```
import numpy as np
import pandas as pd
from google.colab import drive
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
```

```
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
dataset_path = '/content/drive/MyDrive/credit_train.csv'
```

```
df=pd.read_csv(dataset_path)
```

```
df.head()
```

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	s d
0	14dd8831-6af5-400b-83ec-68e61888a048	981165ec-3274-42f5-a3b4-d104041a9ca9	Fully Paid	445412.0	Short Term	709.0	1167493.0	8 years	Home Mortgage	Home Improvements	5214.74	17.2	
1	4771cc26-131a-45db-b5aa-537ea4ba5342	2de017a3-2e01-49cb-a581-08169e83be29	Fully Paid	262328.0	Short Term	NaN	NaN	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	
2	4eed4e6a-aa2f-4c91-8651-ce984ee8fb26	5efb2b2b-bf11-4dfd-a572-3761a2694725	Fully Paid	99999999.0	Short Term	741.0	2231892.0	8 years	Own Home	Debt Consolidation	29200.53	14.9	
3	77598f7b-32e7-4e3b-a6e5-06ba0d98fe8a	e777faab-98ae-45af-9a86-7ce5b33b1011	Fully Paid	347666.0	Long Term	721.0	806949.0	3 years	Own Home	Debt Consolidation	8741.90	12.0	
4	d4062e70-befa-4995-8643-a0de73938182	81536ad9-5ccf-4eb8-befb-47a4d608658e	Fully Paid	176220.0	Short Term	NaN	NaN	5 years	Rent	Debt Consolidation	20639.70	6.1	

```
df.columns
```

```
Index(['Loan ID', 'Customer ID', 'Loan Status', 'Current Loan Amount', 'Term',
       'Credit Score', 'Annual Income', 'Years in current job',
       'Home Ownership', 'Purpose', 'Monthly Debt', 'Years of Credit History',
       'Months since last delinquent', 'Number of Open Accounts',
       'Number of Credit Problems', 'Current Credit Balance',
       'Maximum Open Credit', 'Bankruptcies', 'Tax Liens'],
      dtype='object')
```

```
df.shape
```

```
(100514, 19)
```

```
df.describe()
```

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	Number of Credit Problems	Curr Cre Bala
count	1.000000e+05	80846.000000	8.084600e+04	100000.000000	100000.000000	46859.000000	100000.00000	100000.000000	1.000000e
mean	1.176045e+07	1076.456089	1.378277e+06	18472.412336	18.199141	34.901321	11.12853	0.168310	2.946374e
std	3.178394e+07	1475.403791	1.081360e+06	12174.992609	7.015324	21.997829	5.00987	0.482705	3.761709e
min	1.080200e+04	585.000000	7.662700e+04	0.000000	3.600000	0.000000	0.00000	0.000000	0.000000e
25%	1.796520e+05	705.000000	8.488440e+05	10214.162500	13.500000	16.000000	8.00000	0.000000	1.126700e
50%	3.122460e+05	724.000000	1.174162e+06	16220.300000	16.900000	32.000000	10.00000	0.000000	2.098170e
75%	5.249420e+05	741.000000	1.650663e+06	24012.057500	21.700000	51.000000	14.00000	0.000000	3.679588e
max	1.000000e+08	7510.000000	1.655574e+08	435843.280000	70.500000	176.000000	76.00000	15.000000	3.287897e

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

	0
Loan ID	514
Customer ID	514
Loan Status	514
Current Loan Amount	514
Term	514
Credit Score	19668
Annual Income	19668
Years in current job	4736
Home Ownership	514
Purpose	514
Monthly Debt	514
Years of Credit History	514
Months since last delinquent	53655
Number of Open Accounts	514
Number of Credit Problems	514
Current Credit Balance	514
Maximum Open Credit	516
Bankruptcies	718
Tax Liens	524

dtype: int64

```
df.dtypes
df.drop(['Customer ID'],axis=1,inplace=True)
df.drop(['Loan ID'],axis=1,inplace=True)
```

```
unique_values = df['Loan Status'].unique()
print("Unique values in 'Loan status':", unique_values)

status_mapping = {
    'Fully Paid': 1,
    'Charged Off': 0
}

df['Loan Status'] = df['Loan Status'].map(status_mapping)

df.head()
```

```
Unique values in 'Loan status': ['Fully Paid' 'Charged Off' nan]
```

	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	Numbe o Credi Problem
0	1.0	445412.0	Short Term	709.0	1167493.0	8 years	Home Mortgage	Home Improvements	5214.74	17.2	NaN	6.0	1.
1	1.0	262328.0	Short Term	NaN	NaN	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	8.0	35.0	0.
2	1.0	99999999.0	Short Term	741.0	2231892.0	8 years	Own Home	Debt Consolidation	29200.53	14.9	29.0	18.0	1.
3	1.0	347666.0	Long Term	721.0	806949.0	3 years	Own Home	Debt Consolidation	8741.90	12.0	NaN	9.0	0.
4	1.0	176220.0	Short Term	NaN	NaN	5 years	Rent	Debt Consolidation	20639.70	6.1	NaN	15.0	0.

```
df = df.dropna(subset=['Loan Status'])
```

```
df[['Credit Score', 'Loan Status']].corr()
```

	Credit Score	Loan Status
Credit Score	1.000000	-0.467328
Loan Status	-0.467328	1.000000

```
# df = df.dropna(subset=['Credit Score'])
# print(df.isnull().sum())
# # print(df['Months since last delinquent'].unique())
# # print((df['Months since last delinquent']==0).sum())
# print('*******************************************************')
# print(df.nunique())


mean_credit_score_approved = df[df['Loan Status'] == 1]['Credit Score'].mean()

mean_credit_score_not_approved = df[df['Loan Status'] == 0]['Credit Score'].mean()

df.loc[(df['Loan Status'] == 1) & (df['Credit Score'].isnull()), 'Credit Score'] = mean_credit_score_approved

df.loc[(df['Loan Status'] == 0) & (df['Credit Score'].isnull()), 'Credit Score'] = mean_credit_score_not_approved
```

```
Start coding or generate with AI.
```

```
df.head()
```

	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	Nu Cr Prot
0	1.0	445412.0	Short Term	709.000000	1167493.0	8 years	Home Mortgage	Home Improvements	5214.74	17.2	NaN	6.0	
1	1.0	262328.0	Short Term	717.889874	NaN	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	8.0	35.0	
2	1.0	99999999.0	Short Term	741.000000	2231892.0	8 years	Own Home	Debt Consolidation	29200.53	14.9	29.0	18.0	
3	1.0	347666.0	Long Term	721.000000	806949.0	3 years	Own Home	Debt Consolidation	8741.90	12.0	NaN	9.0	
4	1.0	176220.0	Short Term	717.889874	NaN	5 years	Rent	Debt Consolidation	20639.70	6.1	NaN	15.0	

Next steps: Generate code with df View recommended plots New interactive sheet

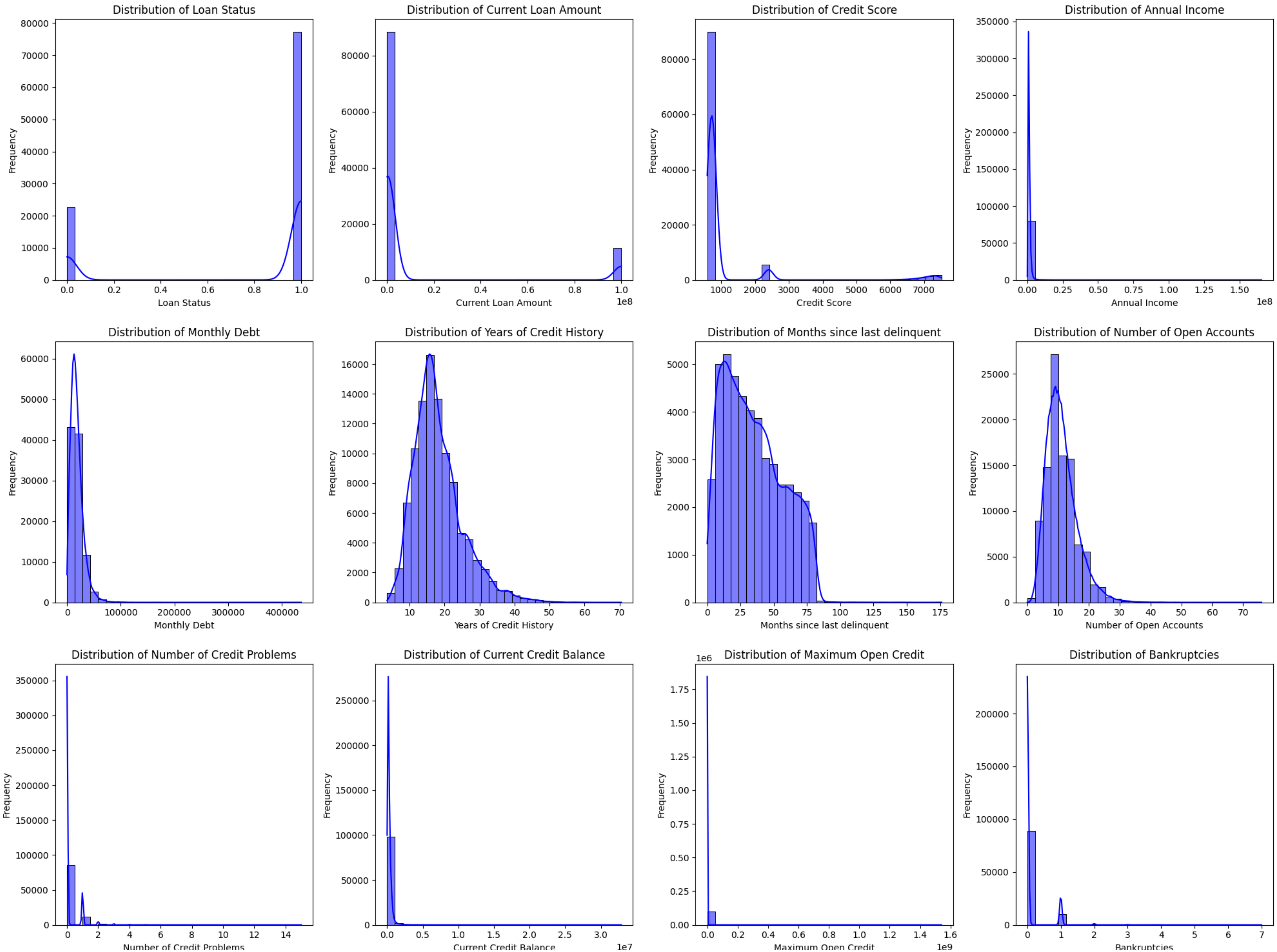
```
df.dtypes
```

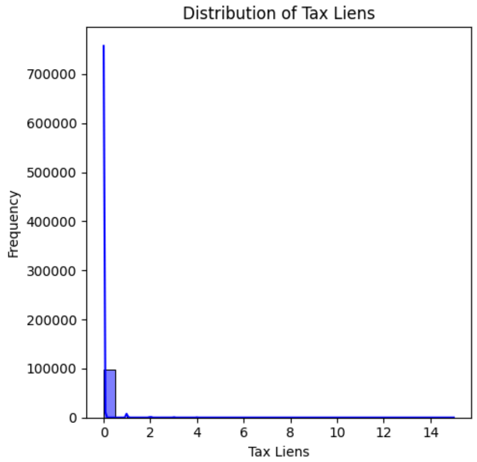
	0
Loan Status	float64
Current Loan Amount	float64
Term	object
Credit Score	float64
Annual Income	float64
Years in current job	object
Home Ownership	object
Purpose	object
Monthly Debt	float64
Years of Credit History	float64
Months since last delinquent	float64
Number of Open Accounts	float64
Number of Credit Problems	float64
Current Credit Balance	float64
Maximum Open Credit	float64
Bankruptcies	float64
Tax Liens	float64

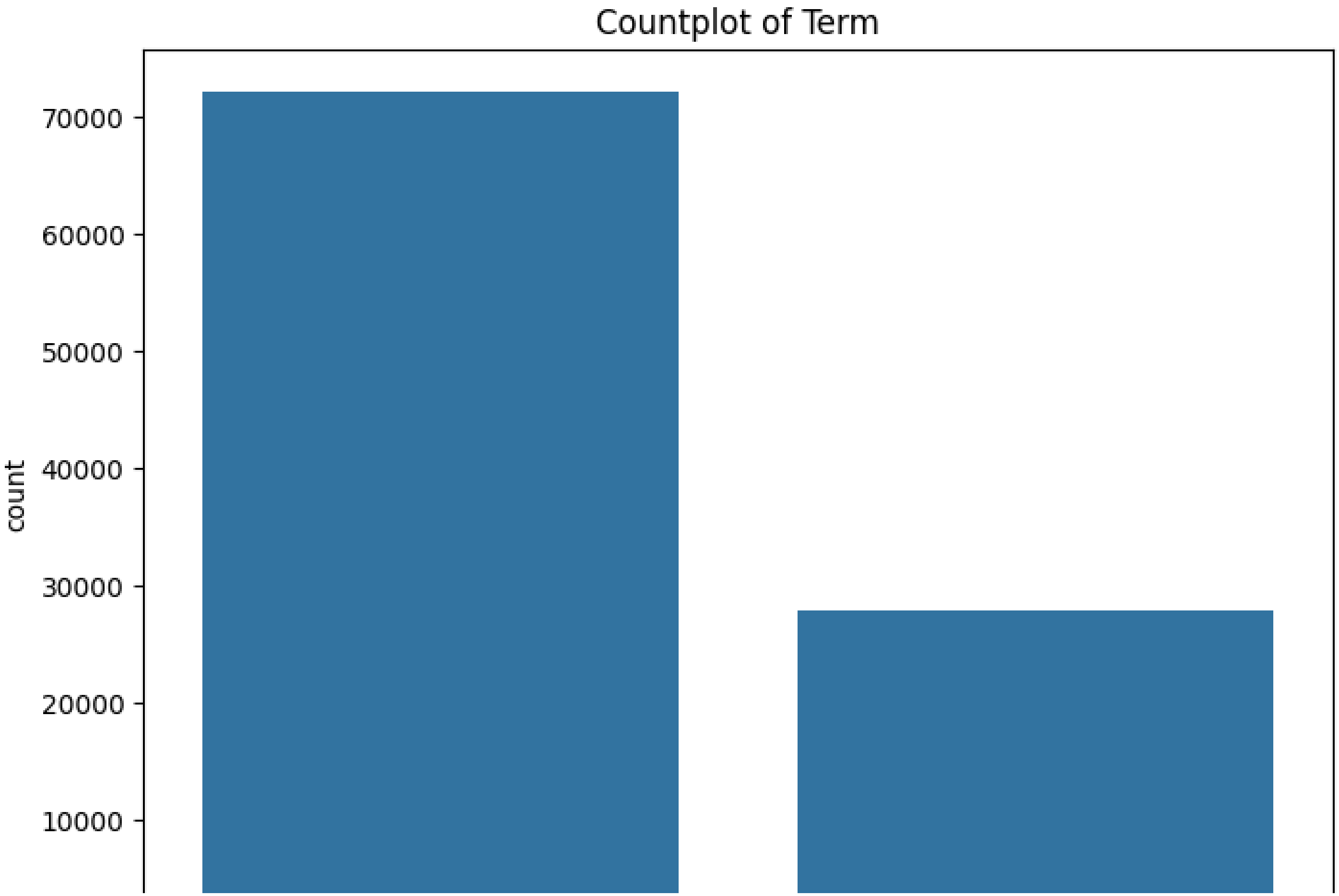
dtype: object

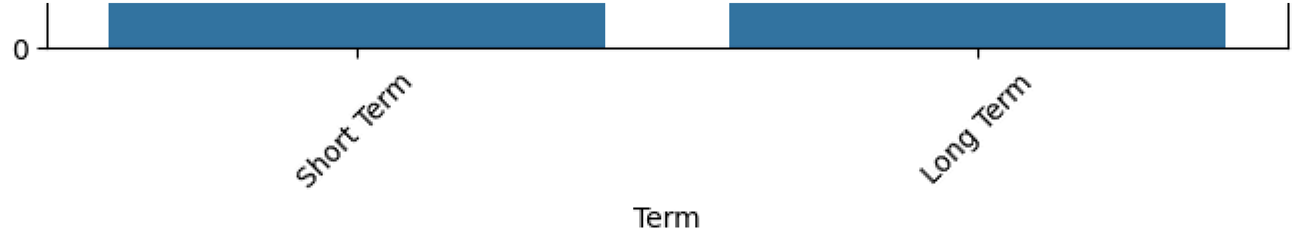
```
import seaborn as sns
import matplotlib.pyplot as plt

numerical_columns = [
```

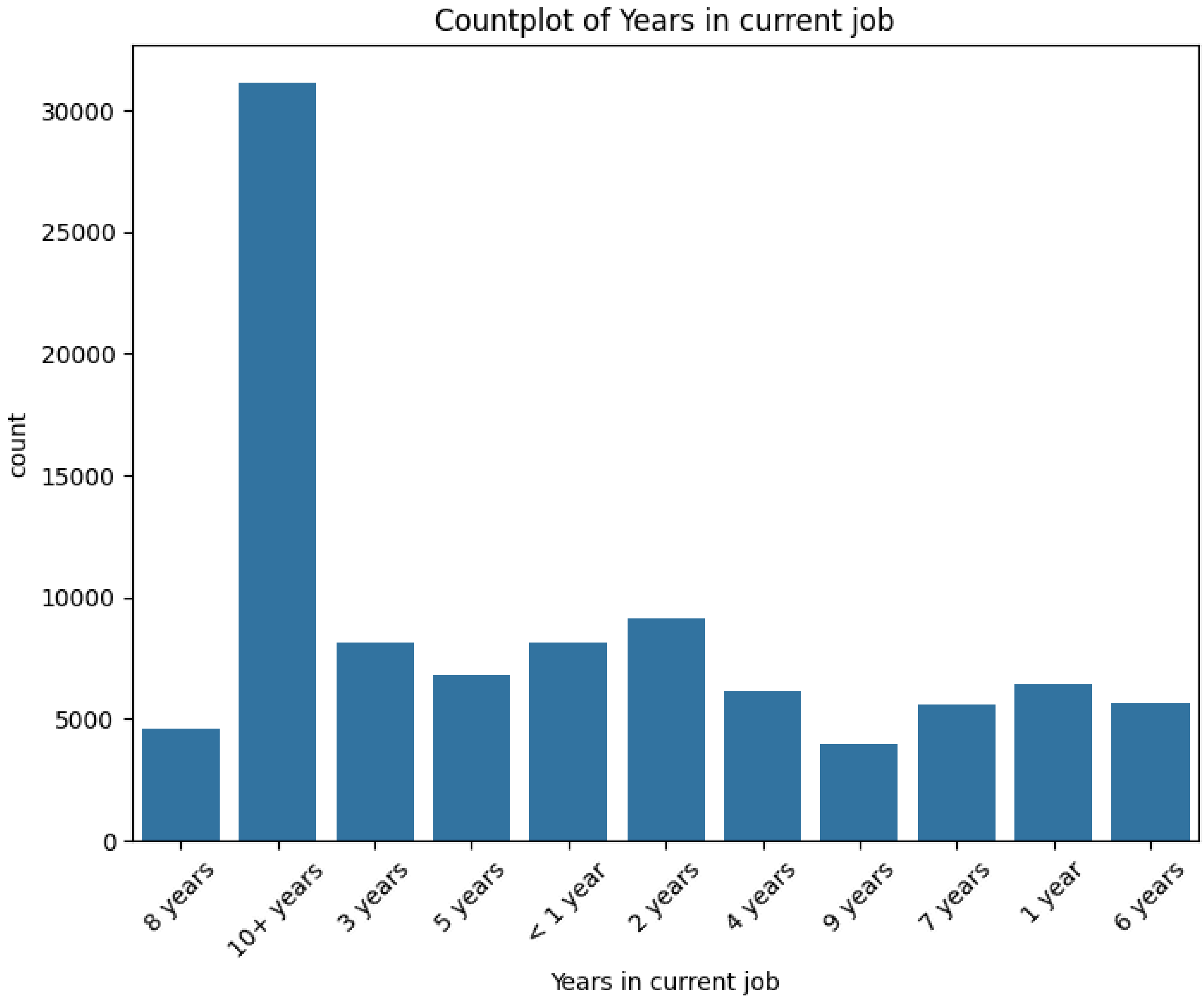
```
    'Loan Status', 'Current Loan Amount', 'Credit Score', 'Annual Income',
    'Monthly Debt', 'Years of Credit History', 'Months since last delinquent',
    'Number of Open Accounts', 'Number of Credit Problems', 'Current Credit Balance',
    'Maximum Open Credit', 'Bankruptcies', 'Tax Liens'
]

plt.figure(figsize=(20, 20))

for i, col in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    sns.histplot(df[col], kde=True, bins=30, color='blue')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()

categorical_columns = ['Term', 'Years in current job', 'Home Ownership', 'Purpose']

for col in categorical_columns:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=df[col])
    plt.title(f'Countplot of {col}')
    plt.xticks(rotation=45)
    plt.show()
```

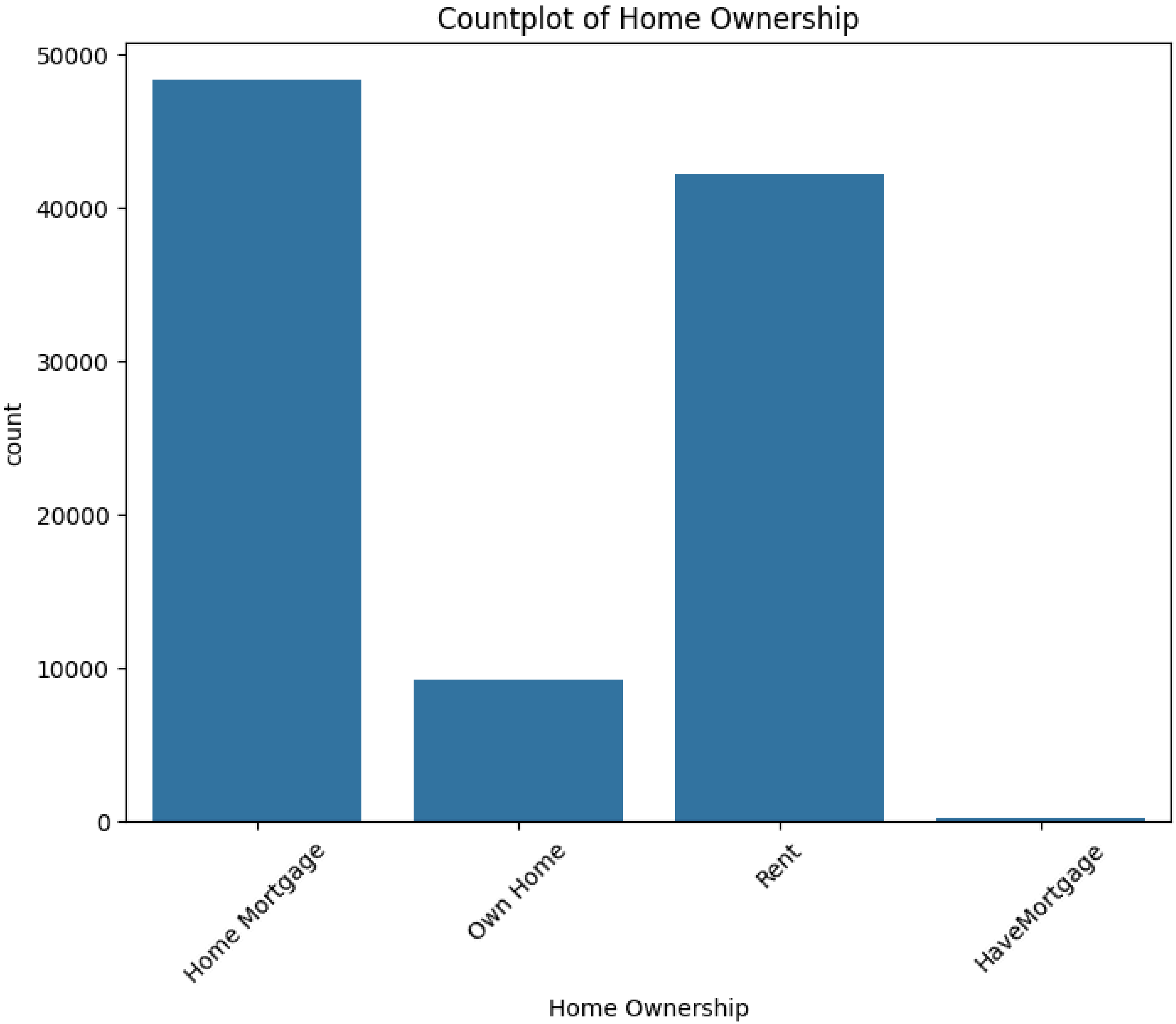

Distribution of Loan Status
Frequency
Loan Status
Distribution of Current Loan Amount
Frequency
Current Loan Amount
1e8
Distribution of Credit Score
Frequency
Credit Score
Distribution of Annual Income
Frequency
Annual Income
1e8
Distribution of Monthly Debt
Frequency
Monthly Debt
Distribution of Years of Credit History
Frequency
Years of Credit History
Distribution of Months since last delinquent
Frequency
Months since last delinquent
Distribution of Number of Open Accounts
Frequency
Number of Open Accounts
Distribution of Number of Credit Problems
Frequency
Number of Credit Problems
Distribution of Current Credit Balance
Frequency
Current Credit Balance
1e7
Distribution of Maximum Open Credit
1e6
Frequency
Maximum Open Credit
1e9
Distribution of Bankruptcies
Frequency
Bankruptcies

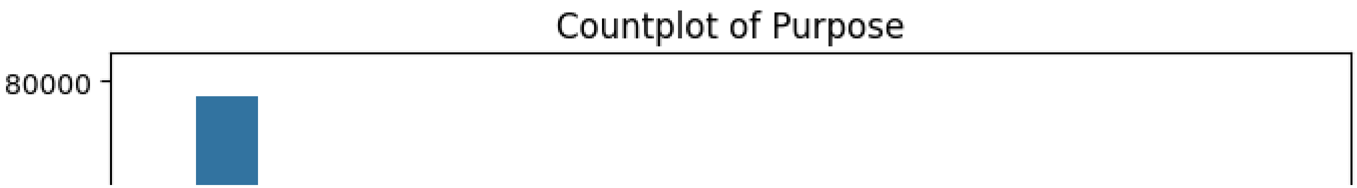

Distribution of Tax Liens
Frequency
Tax Liens
0
100000
200000
300000
400000
500000
600000
700000
0
2
4
6
8
10
12
14

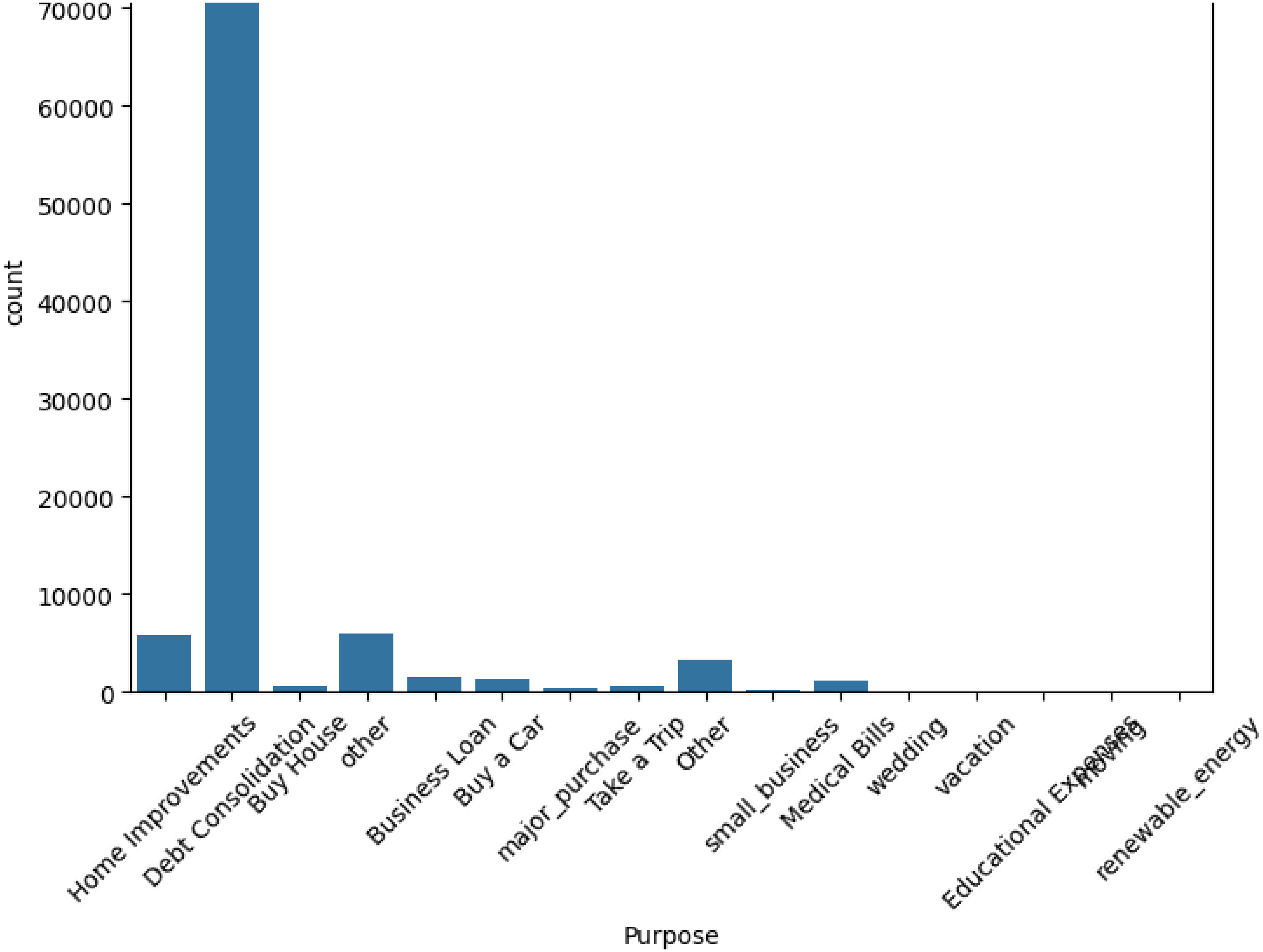

Countplot of Term
count
70000
60000
50000
40000
30000
20000
10000


0
Short Term
Long Term
Term

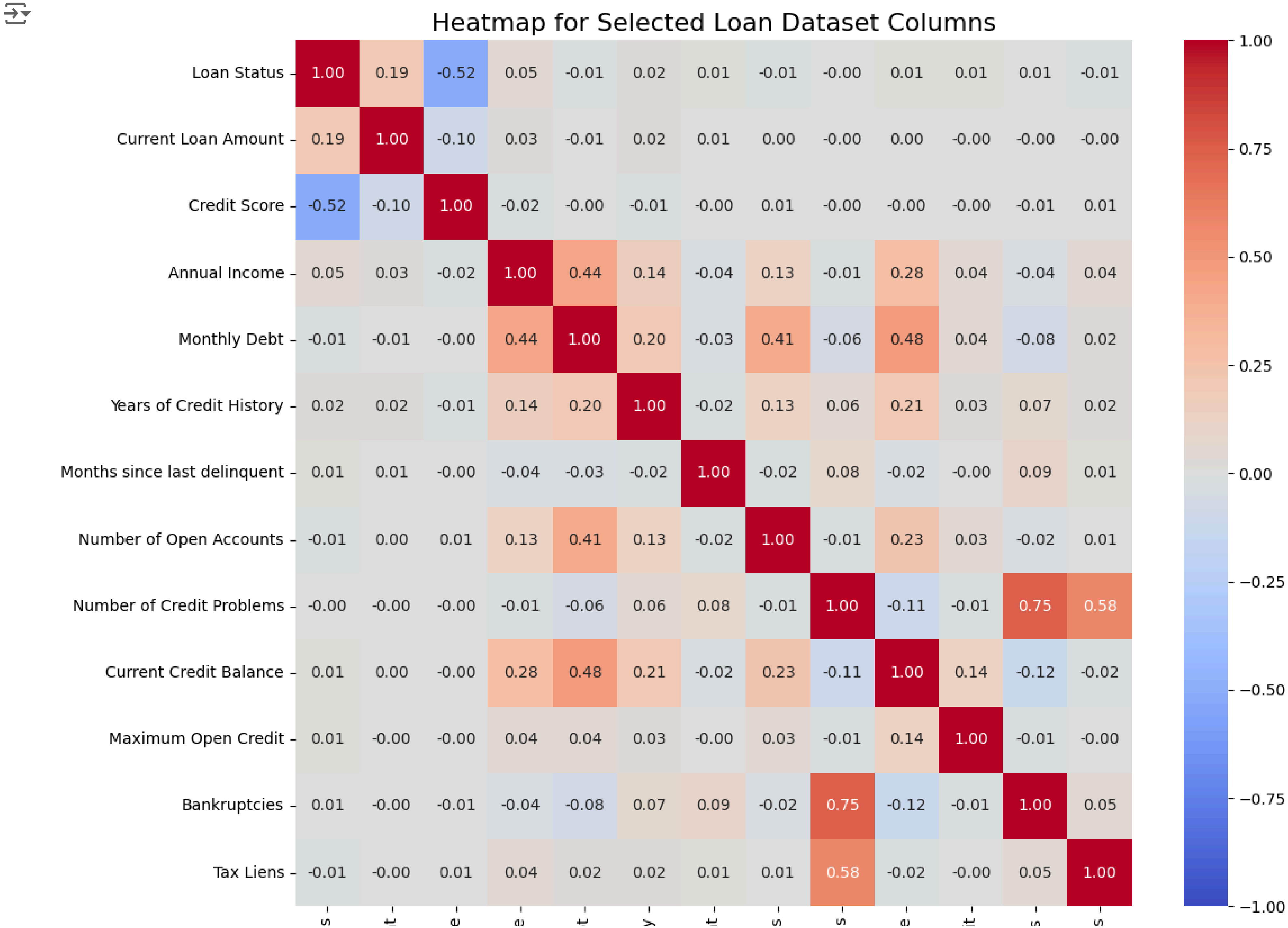

Countplot of Years in current job
count
30000
25000
20000
15000
10000
5000
0
8 years
10+ years
3 years
5 years
< 1 year
2 years
4 years
9 years
7 years
1 year
6 years
Years in current job

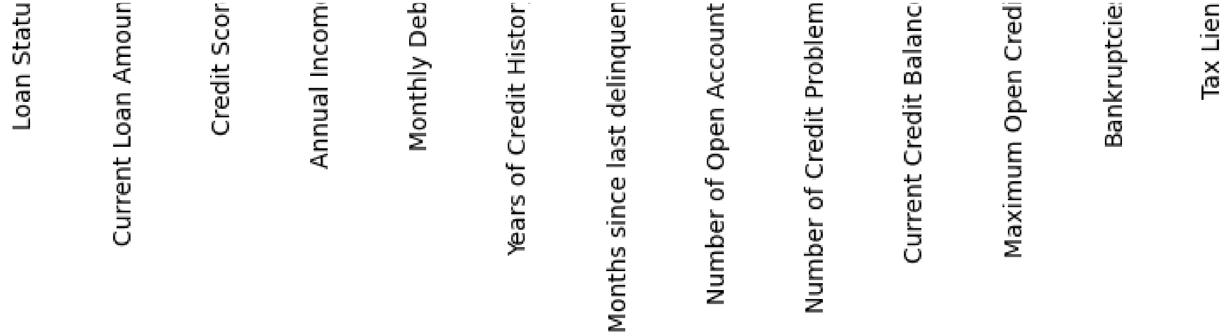

Countplot of Home Ownership
count
50000
40000
30000
20000
10000
0
Home Mortgage
Own Home
Rent
HaveMortgage
Home Ownership


Countplot of Purpose
80000


70000
60000
50000
40000
30000
20000
10000
0
count
Home Improvements
Debt Consolidation
Buy House
other
Business Loan
Buy a Car
major_purchase
Take a Trip
Other
small_business
Medical Bills
wedding
vacation
Educational Expenses
moving
renewable_energy
Purpose

```
columns = [
    'Loan Status', 'Current Loan Amount', 'Credit Score', 'Annual Income',
    'Monthly Debt', 'Years of Credit History', 'Months since last delinquent',
    'Number of Open Accounts', 'Number of Credit Problems', 'Current Credit Balance',
    'Maximum Open Credit', 'Bankruptcies', 'Tax Liens'
]

df_filtered = df[columns]

df_cleaned = df_filtered.fillna(df_filtered.median())

correlation_matrix = df_cleaned.corr()

plt.figure(figsize=(12, 10))
sns.heatmap(
    correlation_matrix,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    vmin=-1, vmax=1
)
plt.title("Heatmap for Selected Loan Dataset Columns", fontsize=16)
plt.show()
```


Heatmap for Selected Loan Dataset Columns
Loan Status
Current Loan Amount
Credit Score
Annual Income
Monthly Debt
Years of Credit History
Months since last delinquent
Number of Open Accounts
Number of Credit Problems
Current Credit Balance
Maximum Open Credit
Bankruptcies
Tax Liens
1.00 0.19 -0.52 0.05 -0.01 0.02 0.01 -0.01 -0.00 0.01 0.01 0.01 -0.01
0.19 1.00 -0.10 0.03 -0.01 0.02 0.01 0.00 -0.00 0.00 -0.00 -0.00 -0.00
-0.52 -0.10 1.00 -0.02 -0.00 -0.01 -0.00 0.01 -0.00 -0.00 -0.00 -0.01 0.01
0.05 0.03 -0.02 1.00 0.44 0.14 -0.04 0.13 -0.01 0.28 0.04 -0.04 0.04
-0.01 -0.01 -0.00 0.44 1.00 0.20 -0.03 0.41 -0.06 0.48 0.04 -0.08 0.02
0.02 0.02 -0.01 0.14 0.20 1.00 -0.02 0.13 0.06 0.21 0.03 0.07 0.02
0.01 0.01 -0.00 -0.04 -0.03 -0.02 1.00 -0.02 0.08 -0.02 -0.00 0.09 0.01
-0.01 0.00 0.01 0.13 0.41 0.13 -0.02 1.00 -0.01 0.23 0.03 -0.02 0.01
-0.00 -0.00 -0.00 -0.01 -0.06 0.06 0.08 -0.01 1.00 -0.11 -0.01 0.75 0.58
0.01 0.00 -0.00 0.28 0.48 0.21 -0.02 0.23 -0.11 1.00 0.14 -0.12 -0.02
0.01 -0.00 -0.00 0.04 0.04 0.03 -0.00 0.03 -0.01 0.14 1.00 -0.01 -0.00
0.01 -0.00 -0.01 -0.04 -0.08 0.07 0.09 -0.02 0.75 -0.12 -0.01 1.00 0.05
-0.01 -0.00 0.01 0.04 0.02 0.02 0.01 0.01 0.58 -0.02 -0.00 0.05 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Loan Statu
Current Loan Amoun
Credit Scor
Annual Incom
Monthly Deb
Years of Credit Histor
Months since last delinquen
Number of Open Account
Number of Credit Problem
Current Credit Balanc
Maximum Open Credi
Bankruptcie
Tax Lien

```
purpose_counts = df['Purpose'].value_counts()
print(purpose_counts)
```

```
Purpose
Debt Consolidation      78552
other                    6037
Home Improvements        5839
Other                    3250
Business Loan            1569
Buy a Car                1265
Medical Bills            1127
Buy House                 678
Take a Trip               573
major_purchase            352
small_business            283
moving                    150
wedding                   115
vacation                  101
Educational Expenses       99
renewable_energy           10
Name: count, dtype: int64
```

```
print(f"Original shape: {df.shape}")
valid_purposes = purpose_counts[purpose_counts >= 100].index
df = df[df['Purpose'].isin(valid_purposes)]
print(f"Shape after filtering: {df.shape}")
```

```
Original shape: (100000, 17)
Shape after filtering: (99891, 17)
```

```
ownership_counts = df['Home Ownership'].value_counts()
print(ownership_counts)
```

```
Home Ownership
Home Mortgage    48376
Rent             42129
```

```
Own Home          9172
HaveMortgage       214
Name: count, dtype: int64
```

```
print(f"Original shape: {df.shape}")
valid_ownerships = ownership_counts[ownership_counts >= 200].index
df = df[df['Home Ownership'].isin(valid_ownerships)]
print(f"Shape after filtering: {df.shape}")
```

```
Original shape: (99891, 17)
Shape after filtering: (99891, 17)
```

```
df.shape
```

```
(99891, 17)
```

```
unique_values = df['Years in current job'].unique()
print("Unique values in 'Years in current job':", unique_values)
# mapping = {
#     '10+ years': 10,
#     '9 years': 9,
#     '8 years': 8,
#     '7 years': 7,
#     '6 years': 6,
#     '5 years': 5,
#     '4 years': 4,
#     '3 years': 3,
#     '2 years': 2,
#     '1 year': 1,
#     '< 1 year': 0.5
# }

# df['Years in current job'] = df['Years in current job'].map(mapping)
# df.head()
```

```
df = pd.get_dummies(df, columns=['Years in current job'], prefix='Years in current job', drop_first=True)

df.head()
```

```
Unique values in 'Years in current job': ['8 years' '10+ years' '3 years' '5 years' '< 1 year' '2 years' '4 years'
 '9 years' '7 years' '1 year' nan '6 years']
```

	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Months since last delinquent	...	Years in current job_10+ years	Years in current job_2 years
0	1.0	445412.0	Short Term	709.000000	1167493.0	Home Mortgage	Home Improvements	5214.74	17.2	NaN	...	False	False
1	1.0	262328.0	Short Term	717.889874	NaN	Home Mortgage	Debt Consolidation	33295.98	21.1	8.0	...	True	False
2	1.0	99999999.0	Short Term	741.000000	2231892.0	Own Home	Debt Consolidation	29200.53	14.9	29.0	...	False	False
3	1.0	347666.0	Long Term	721.000000	806949.0	Own Home	Debt Consolidation	8741.90	12.0	NaN	...	False	False
4	1.0	176220.0	Short Term	717.889874	NaN	Rent	Debt Consolidation	20639.70	6.1	NaN	...	False	False

5 rows × 26 columns

```
# term_mapping = {
#     'Short Term': 0,
#     'Long Term': 1
# }

# df['Term'] = df['Term'].map(term_mapping)

# df.head()
```

```
df = pd.get_dummies(df, columns=['Term'], prefix='Term', drop_first=True)

df.head()
```

	Loan Status	Current Loan Amount	Credit Score	Annual Income	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	...	Years in current job_2 years	Yea curre job yea
0	1.0	445412.0	709.000000	1167493.0	Home Mortgage	Home Improvements	5214.74	17.2	NaN	6.0	...	False	Fal
1	1.0	262328.0	717.889874	NaN	Home Mortgage	Debt Consolidation	33295.98	21.1	8.0	35.0	...	False	Fal
2	1.0	99999999.0	741.000000	2231892.0	Own Home	Debt Consolidation	29200.53	14.9	29.0	18.0	...	False	Fal
3	1.0	347666.0	721.000000	806949.0	Own Home	Debt Consolidation	8741.90	12.0	NaN	9.0	...	False	Tr
4	1.0	176220.0	717.889874	NaN	Rent	Debt Consolidation	20639.70	6.1	NaN	15.0	...	False	Fal

5 rows × 26 columns

Start coding or generate with AI.

```
unique_values = df['Home Ownership'].unique()
print("Unique values in 'Home Ownership':", unique_values)

# owner_mapping = {
#     'Home Mortgage':1,
#     'Own Home':2,
#      'Rent':3,
```

```
#     'HaveMortgage':4
# }

# df['Home Ownership'] = df['Home Ownership'].map(owner_mapping)

# df.head()

df = pd.get_dummies(df, columns=['Home Ownership'], prefix='Home Ownership', drop_first=True)

df.head()
```

```
Unique values in 'Home Ownership': ['Home Mortgage' 'Own Home' 'Rent' 'HaveMortgage']
```

	Loan Status	Current Loan Amount	Credit Score	Annual Income	Purpose	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	Number of Credit Problems	...	Years in current job_5 years	Year i curren job_ year
0	1.0	445412.0	709.000000	1167493.0	Home Improvements	5214.74	17.2	NaN	6.0	1.0	...	False	Fals
1	1.0	262328.0	717.889874	NaN	Debt Consolidation	33295.98	21.1	8.0	35.0	0.0	...	False	Fals
2	1.0	99999999.0	741.000000	2231892.0	Debt Consolidation	29200.53	14.9	29.0	18.0	1.0	...	False	Fals
3	1.0	347666.0	721.000000	806949.0	Debt Consolidation	8741.90	12.0	NaN	9.0	0.0	...	False	Fals
4	1.0	176220.0	717.889874	NaN	Debt Consolidation	20639.70	6.1	NaN	15.0	0.0	...	True	Fals

5 rows × 28 columns

```
unique_values = df['Purpose'].unique()
print("Unique values in 'Purpose':", unique_values)
```

```
# Purpose_mapping = {
#     'Home Mortgage':1,
#     'Own Home':2,
#      'Rent':3,
#      'HaveMortgage':4
# }

# df['Purpose'] = df['Purpose'].map(Purpose_mapping)

# df.head()

df = pd.get_dummies(df, columns=['Purpose'], prefix='Purpose', drop_first=True)

df.head()
```

```
Unique values in 'Purpose': ['Home Improvements' 'Debt Consolidation' 'Buy House' 'other'
 'Business Loan' 'Buy a Car' 'major_purchase' 'Take a Trip' 'Other'
 'small_business' 'Medical Bills' 'wedding' 'vacation' 'moving']
```

	Loan Status	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	...	Purpose_Home Improvements	Purpo
0	1.0	445412.0	709.000000	1167493.0	5214.74	17.2	NaN	6.0	1.0	228190.0	...	True	
1	1.0	262328.0	717.889874	NaN	33295.98	21.1	8.0	35.0	0.0	229976.0	...	False	
2	1.0	99999999.0	741.000000	2231892.0	29200.53	14.9	29.0	18.0	1.0	297996.0	...	False	
3	1.0	347666.0	721.000000	806949.0	8741.90	12.0	NaN	9.0	0.0	256329.0	...	False	
4	1.0	176220.0	717.889874	NaN	20639.70	6.1	NaN	15.0	0.0	253460.0	...	False	

5 rows × 40 columns

```
print(df.columns)
```

```
Index(['Loan Status', 'Current Loan Amount', 'Credit Score', 'Annual Income',
       'Monthly Debt', 'Years of Credit History',
       'Months since last delinquent', 'Number of Open Accounts',
       'Number of Credit Problems', 'Current Credit Balance',
       'Maximum Open Credit', 'Bankruptcies', 'Tax Liens',
       'Years in current job_10+ years', 'Years in current job_2 years',
       'Years in current job_3 years', 'Years in current job_4 years',
       'Years in current job_5 years', 'Years in current job_6 years',
       'Years in current job_7 years', 'Years in current job_8 years',
       'Years in current job_9 years', 'Years in current job_< 1 year',
       'Term_Short Term', 'Home Ownership_Home Mortgage',
       'Home Ownership_Own Home', 'Home Ownership_Rent', 'Purpose_Buy House',
       'Purpose_Buy a Car', 'Purpose_Debt Consolidation',
       'Purpose_Home Improvements', 'Purpose_Medical Bills', 'Purpose_Other',
       'Purpose_Take a Trip', 'Purpose_major_purchase', 'Purpose_moving',
       'Purpose_other', 'Purpose_small_business', 'Purpose_vacation',
       'Purpose_wedding'],
      dtype='object')
```

```
df.dtypes
```

	0
Loan Status	float64
Current Loan Amount	float64
Credit Score	float64
Annual Income	float64
Monthly Debt	float64
Years of Credit History	float64
Months since last delinquent	float64
Number of Open Accounts	float64
Number of Credit Problems	float64
Current Credit Balance	float64
Maximum Open Credit	float64
Bankruptcies	float64
Tax Liens	float64
Years in current job_10+ years	bool
Years in current job_2 years	bool
Years in current job_3 years	bool
Years in current job_4 years	bool
Years in current job_5 years	bool
Years in current job_6 years	bool
Years in current job_7 years	bool
Years in current job_8 years	bool
Years in current job_9 years	bool

Years in current job_< 1 year	bool
Term_Short Term	bool
Home Ownership_Home Mortgage	bool
Home Ownership_Own Home	bool
Home Ownership_Rent	bool
Purpose_Buy House	bool
Purpose_Buy a Car	bool
Purpose_Debt Consolidation	bool
Purpose_Home Improvements	bool
Purpose_Medical Bills	bool
Purpose_Other	bool
Purpose_Take a Trip	bool
Purpose_major_purchase	bool
Purpose_moving	bool
Purpose_other	bool
Purpose_small_business	bool
Purpose_vacation	bool
Purpose_wedding	bool

dtype: object

```
mean_annual_approved = df[df['Loan Status'] == 1]['Annual Income'].mean()

mean_annual_not_approved = df[df['Loan Status'] == 0]['Annual Income'].mean()

df.loc[(df['Loan Status'] == 1) & (df['Annual Income'].isnull()), 'Annual Income'] = mean_annual_approved

df.loc[(df['Loan Status'] == 0) & (df['Annual Income'].isnull()), 'Annual Income'] = mean_annual_not_approved
```

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

```
Loan Status                         0
Current Loan Amount                 0
Credit Score                        0
Annual Income                       0
Monthly Debt                        0
Years of Credit History             0
Months since last delinquent    53083
Number of Open Accounts              0
Number of Credit Problems           0
Current Credit Balance              0
Maximum Open Credit                 2
Bankruptcies                      198
Tax Liens                           9
Years in current job_10+ years      0
Years in current job_2 years        0
Years in current job_3 years        0
Years in current job_4 years        0
Years in current job_5 years        0
Years in current job_6 years        0
Years in current job_7 years        0
Years in current job_8 years        0
Years in current job_9 years        0
Years in current job_< 1 year       0
Term_Short Term                     0
Home Ownership_Home Mortgage        0
Home Ownership_Own Home             0
Home Ownership_Rent                 0
Purpose_Buy House                   0
```

```
Purpose_Buy a Car                0
Purpose_Debt Consolidation       0
Purpose_Home Improvements        0
Purpose_Medical Bills            0
Purpose_Other                    0
Purpose_Take a Trip              0
Purpose_major_purchase           0
Purpose_moving                   0
Purpose_other                    0
Purpose_small_business           0
Purpose_vacation                 0
Purpose_wedding                  0
dtype: int64
```

```
Start coding or generate with AI.
```

```
correlation = df['Months since last delinquent'].corr(df['Loan Status'])
print(f"Correlation between 'Months since last delinquent' and 'Loan Status': {correlation}")
```

```
Correlation between 'Months since last delinquent' and 'Loan Status': 0.013648753642806554
```

```
df.drop(['Months since last delinquent'],axis=1,inplace=True)
```

```
df.dropna(subset=['Bankruptcies'], inplace=True)
```

```
df.dropna(subset=['Tax Liens'], inplace=True)
```

```
df.dropna(subset=['Maximum Open Credit'], inplace=True)
```

```
df.shape
```

```
(99691, 39)
```

```
df.head()
```

	Loan Status	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	Maximum Open Credit	...	Purpose_Home Improvements	Purp
0	1.0	445412.0	709.000000	1.167493e+06	5214.74	17.2	6.0	1.0	228190.0	416746.0	...	True	
1	1.0	262328.0	717.889874	1.408456e+06	33295.98	21.1	35.0	0.0	229976.0	850784.0	...	False	
2	1.0	99999999.0	741.000000	2.231892e+06	29200.53	14.9	18.0	1.0	297996.0	750090.0	...	False	
3	1.0	347666.0	721.000000	8.069490e+05	8741.90	12.0	9.0	0.0	256329.0	386958.0	...	False	
4	1.0	176220.0	717.889874	1.408456e+06	20639.70	6.1	15.0	0.0	253460.0	427174.0	...	False	

5 rows × 39 columns

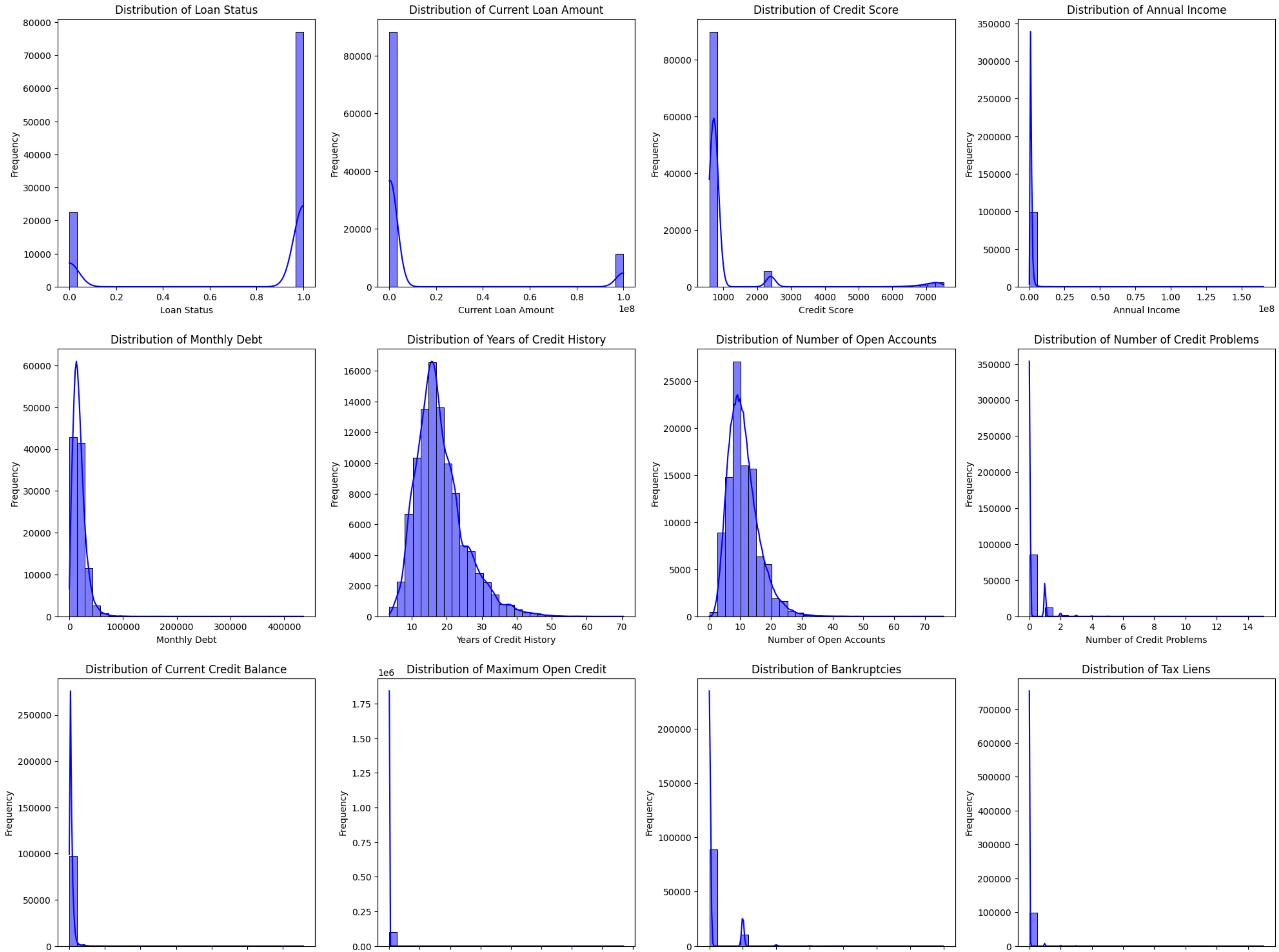
```
df.nunique()
```

	0
Loan Status	2
Current Loan Amount	21987
Credit Score	326
Annual Income	36099
Monthly Debt	65598
Years of Credit History	506
Number of Open Accounts	51
Number of Credit Problems	14
Current Credit Balance	32676
Maximum Open Credit	44511
Bankruptcies	8
Tax Liens	12
Years in current job_10+ years	2
Years in current job_2 years	2
Years in current job_3 years	2
Years in current job_4 years	2
Years in current job_5 years	2
Years in current job_6 years	2
Years in current job_7 years	2
Years in current job_8 years	2
Years in current job_9 years	2
Years in current job_< 1 year	2

Term_Short Term	2
Home Ownership_Home Mortgage	2
Home Ownership_Own Home	2
Home Ownership_Rent	2
Purpose_Buy House	2
Purpose_Buy a Car	2
Purpose_Debt Consolidation	2
Purpose_Home Improvements	2
Purpose_Medical Bills	2
Purpose_Other	2
Purpose_Take a Trip	2
Purpose_major_purchase	2
Purpose_moving	2
Purpose_other	2
Purpose_small_business	2
Purpose_vacation	2
Purpose_wedding	2

dtype: int64

```
numerical_columns = [
    'Loan Status', 'Current Loan Amount', 'Credit Score', 'Annual Income',
    'Monthly Debt', 'Years of Credit History',
    'Number of Open Accounts', 'Number of Credit Problems', 'Current Credit Balance',
    'Maximum Open Credit', 'Bankruptcies', 'Tax Liens'
]

plt.figure(figsize=(20, 20))

for i, col in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    sns.histplot(df[col], kde=True, bins=30, color='blue')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```


Distribution of Loan Status
Loan Status
Frequency
Distribution of Current Loan Amount
Current Loan Amount
1e8
Distribution of Credit Score
Credit Score
Distribution of Annual Income
Annual Income
1e8
Distribution of Monthly Debt
Monthly Debt
Distribution of Years of Credit History
Years of Credit History
Distribution of Number of Open Accounts
Number of Open Accounts
Distribution of Number of Credit Problems
Number of Credit Problems
Distribution of Current Credit Balance
1e6
Distribution of Maximum Open Credit
Distribution of Bankruptcies
Distribution of Tax Liens


0.0 0.5 1.0 1.5 2.0 2.5 3.0
Current Credit Balance
1e7
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6
Maximum Open Credit
1e9
0 1 2 3 4 5 6 7
Bankruptcies
0 2 4 6 8 10 12 14
Tax Liens

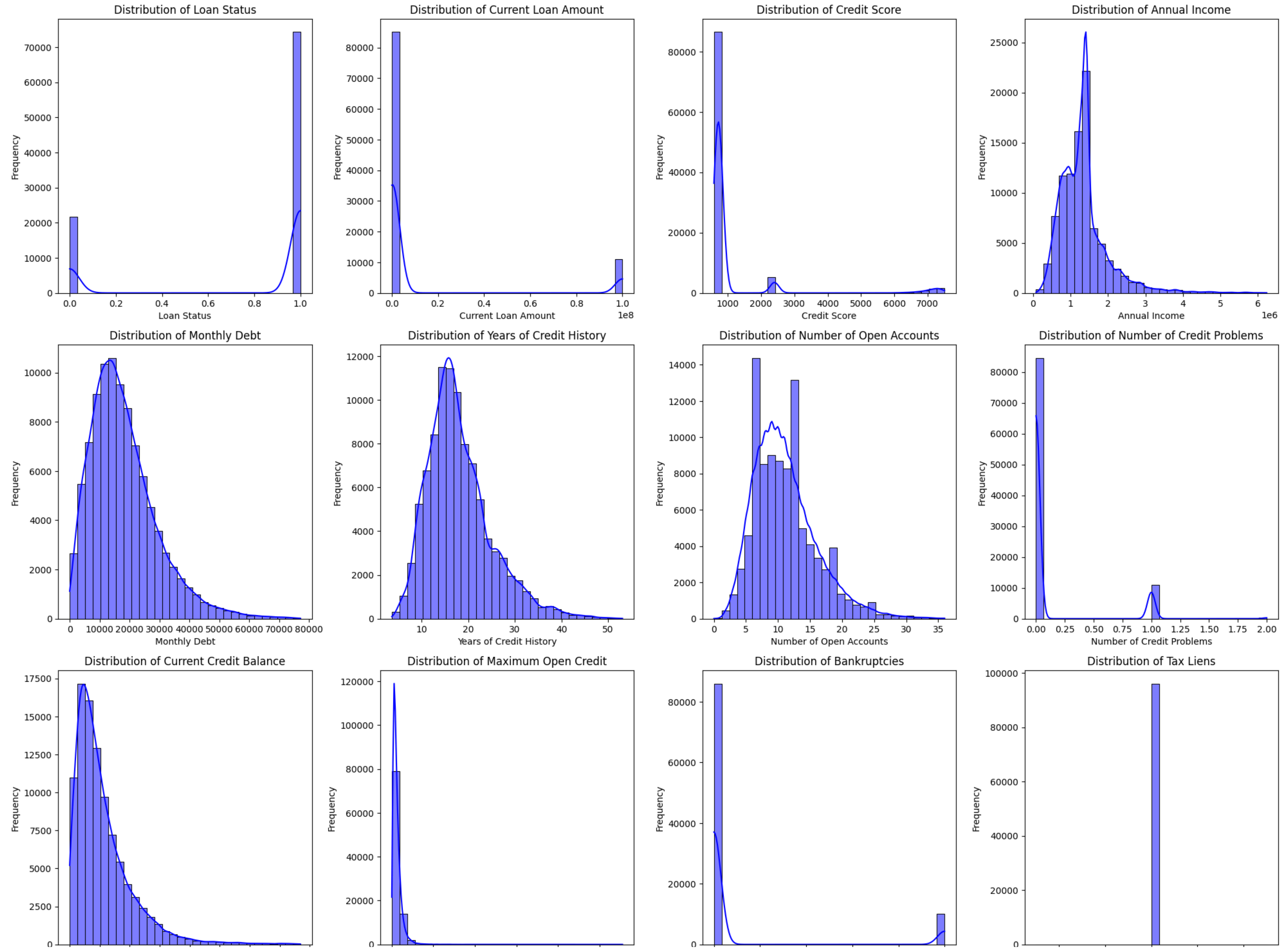
```
# max_credit_score = df[df['Credit Score'] <= 1000]['Credit Score'].max()

# df['Credit Score'] = df['Credit Score'].apply(lambda x: max_credit_score if x > 1000 else x)

# print(df[df['Credit Score'] > 1000])
```

```
def remove_outliers_std(df, columns, std_multiplier=5):
    for col in columns:
        mean = df[col].mean()
        std = df[col].std()

        lower_bound = mean - std_multiplier * std
        upper_bound = mean + std_multiplier * std

        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]

    return df

print(f"Original shape: {df.shape}")

df = remove_outliers_std(df, numerical_columns)

print(f"Shape after removing outliers: {df.shape}")
```

```
Original shape: (99691, 39)
Shape after removing outliers: (96068, 39)
```

```
numerical_columns = [
    'Loan Status', 'Current Loan Amount', 'Credit Score', 'Annual Income',
    'Monthly Debt', 'Years of Credit History',
    'Number of Open Accounts', 'Number of Credit Problems', 'Current Credit Balance',
    'Maximum Open Credit', 'Bankruptcies', 'Tax Liens'
```

```
]

plt.figure(figsize=(20, 20))

for i, col in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    sns.histplot(df[col], kde=True, bins=30, color='blue')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```


Distribution of Loan Status
Loan Status
Frequency
Distribution of Current Loan Amount
Current Loan Amount
1e8
Distribution of Credit Score
Credit Score
Distribution of Annual Income
Annual Income
1e6
Distribution of Monthly Debt
Monthly Debt
Distribution of Years of Credit History
Years of Credit History
Distribution of Number of Open Accounts
Number of Open Accounts
Distribution of Number of Credit Problems
Number of Credit Problems
Distribution of Current Credit Balance
Distribution of Maximum Open Credit
Distribution of Bankruptcies
Distribution of Tax Liens


0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
Current Credit Balance
1e6
0.0 0.5 1.0 1.5 2.0 2.5
Maximum Open Credit
1e7
0.0 0.2 0.4 0.6 0.8 1.0
Bankruptcies
−0.4 −0.2 0.0 0.2 0.4
Tax Liens

```
X = df.drop(columns=['Loan Status'])
y = df['Loan Status']
```

```
X.describe()
```

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	Maximum Open Credit
count	9.606800e+04	96068.000000	9.606800e+04	96068.000000	96068.000000	96068.000000	96068.000000	9.606800e+04	9.606800e+04
mean	1.172616e+07	1099.559611	1.338335e+06	18103.294486	18.094578	11.066089	0.122705	2.754761e+05	6.217404e+05
std	3.174507e+07	1369.326795	6.480467e+05	11172.280902	6.943097	4.899561	0.339360	2.403756e+05	7.214159e+05
min	1.542200e+04	585.000000	7.662700e+04	0.000000	3.600000	0.000000	0.000000	0.000000e+00	0.000000e+00
25%	1.793000e+05	711.000000	9.276940e+05	10166.520000	13.400000	8.000000	0.000000	1.132400e+05	2.736085e+05
50%	3.106730e+05	721.000000	1.268138e+06	16117.605000	16.900000	10.000000	0.000000	2.097410e+05	4.666860e+05
75%	5.204650e+05	741.000000	1.496744e+06	23754.607500	21.600000	14.000000	0.000000	3.641445e+05	7.744660e+05

```
scaler = StandardScaler()

numerical_cols = X.select_dtypes(include=['float64', 'int64']).columns

X[numerical_cols] = scaler.fit_transform(X[numerical_cols])

print("Data after scaling with StandardScaler:")
print(X.head())
```

```
Data after scaling with StandardScaler:
   Current Loan Amount  Credit Score  Annual Income  Monthly Debt  \
```

```
0        -0.355356   -0.285222    -0.263628   -1.153625
1        -0.361124   -0.278729     0.108204    1.359862
2         2.780725   -0.261852     1.378853    0.993288
3        -0.358435   -0.276458    -0.819986   -0.837917
4        -0.363836   -0.278729     0.108204    0.227028

   Years of Credit History  Number of Open Accounts  \
0                -0.128845                -1.033994
1                 0.432867                 4.884935
2                -0.460111                 1.415218
3                -0.877794                -0.421691
4                -1.727563                 0.802915

   Number of Credit Problems  Current Credit Balance  Maximum Open Credit  \
0                   2.585162               -0.196719            -0.284157
1                  -0.361579               -0.189289             0.317493
2                   2.585162                0.093687             0.177914
3                  -0.361579               -0.079655            -0.325448
4                  -0.361579               -0.091591            -0.269702

   Bankruptcies  ...  Purpose_Home Improvements  Purpose_Medical Bills  \
0      2.923466  ...                       True                  False
1     -0.342060  ...                      False                  False
2     -0.342060  ...                      False                  False
3     -0.342060  ...                      False                  False
4     -0.342060  ...                      False                  False

   Purpose_Other  Purpose_Take a Trip  Purpose_major_purchase  Purpose_moving  \
0          False                False                   False           False
1          False                False                   False           False
2          False                False                   False           False
3          False                False                   False           False
4          False                False                   False           False

   Purpose_other  Purpose_small_business  Purpose_vacation  Purpose_wedding
0          False                   False             False            False
1          False                   False             False            False
2          False                   False             False            False
3          False                   False             False            False
4          False                   False             False            False
```

```
[5 rows x 38 columns]
```

```
X.columns
```

```
Index(['Current Loan Amount', 'Credit Score', 'Annual Income', 'Monthly Debt',
       'Years of Credit History', 'Number of Open Accounts',
       'Number of Credit Problems', 'Current Credit Balance',
       'Maximum Open Credit', 'Bankruptcies', 'Tax Liens',
       'Years in current job_10+ years', 'Years in current job_2 years',
       'Years in current job_3 years', 'Years in current job_4 years',
       'Years in current job_5 years', 'Years in current job_6 years',
       'Years in current job_7 years', 'Years in current job_8 years',
       'Years in current job_9 years', 'Years in current job_< 1 year',
       'Term_Short Term', 'Home Ownership_Home Mortgage',
       'Home Ownership_Own Home', 'Home Ownership_Rent', 'Purpose_Buy House',
       'Purpose_Buy a Car', 'Purpose_Debt Consolidation',
       'Purpose_Home Improvements', 'Purpose_Medical Bills', 'Purpose_Other',
       'Purpose_Take a Trip', 'Purpose_major_purchase', 'Purpose_moving',
       'Purpose_other', 'Purpose_small_business', 'Purpose_vacation',
       'Purpose_wedding'],
      dtype='object')
```

```
X.head()
```

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	Maximum Open Credit	Bankruptcies	...	Purpose_Home Improvements	P
0	-0.355356	-0.285222	-0.263628	-1.153625	-0.128845	-1.033994	2.585162	-0.196719	-0.284157	2.923466	...	True	
1	-0.361124	-0.278729	0.108204	1.359862	0.432867	4.884935	-0.361579	-0.189289	0.317493	-0.342060	...	False	
2	2.780725	-0.261852	1.378853	0.993288	-0.460111	1.415218	2.585162	0.093687	0.177914	-0.342060	...	False	
3	-0.358435	-0.276458	-0.819986	-0.837917	-0.877794	-0.421691	-0.361579	-0.079655	-0.325448	-0.342060	...	False	
4	-0.363836	-0.278729	0.108204	0.227028	-1.727563	0.802915	-0.361579	-0.091591	-0.269702	-0.342060	...	False	

5 rows × 38 columns

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
log_reg = LogisticRegression()

log_reg.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
y_pred = log_reg.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

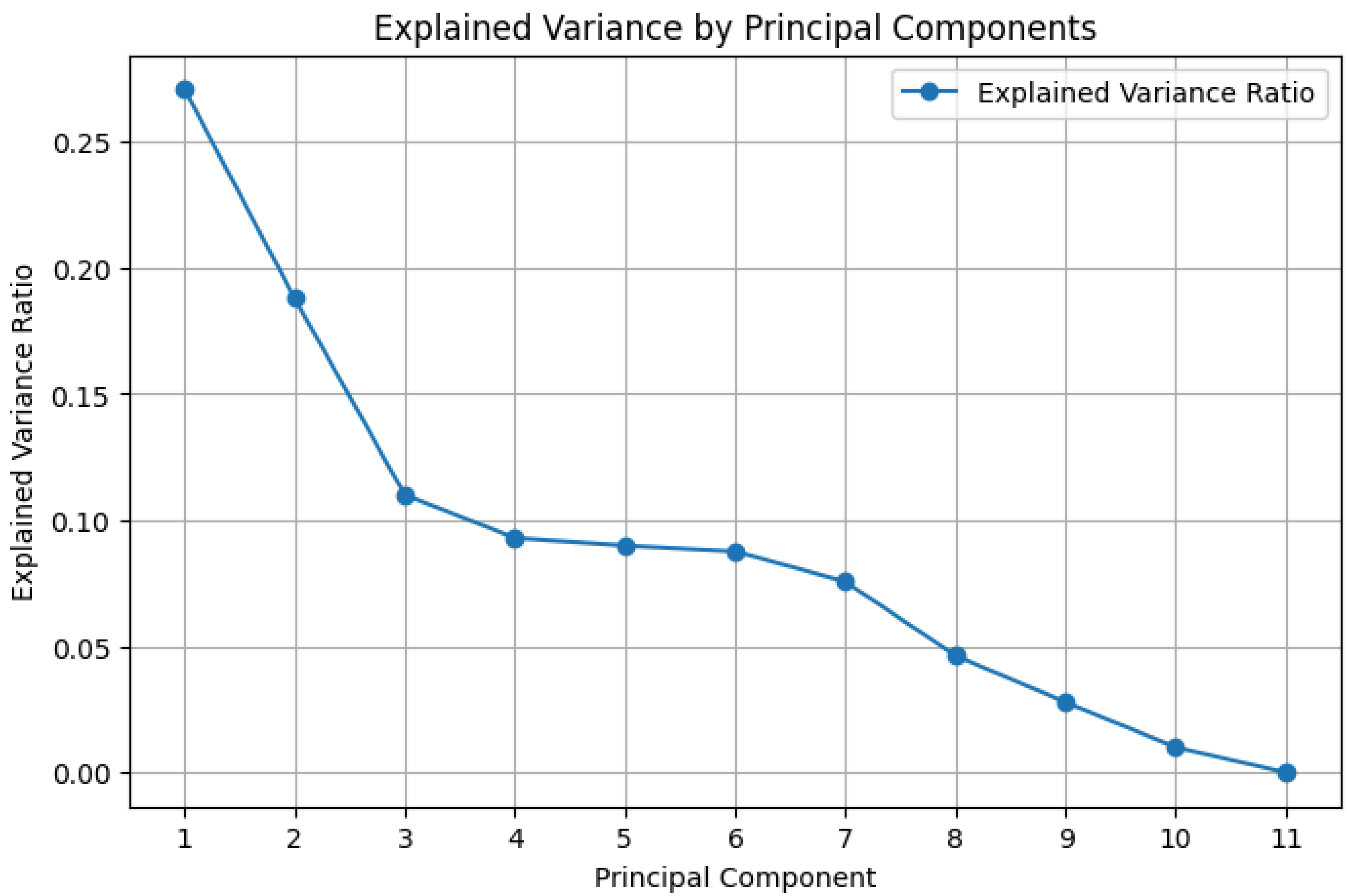
```
Accuracy: 87.35%
Confusion Matrix:
[[ 2902  3641]
 [    6 22272]]
```

```
import numpy as np

class PCA:
    def __init__(self, n_components):
        self.n_components = n_components
        self.components = None
        self.mean = None

    def fit(self, X):
        self.mean = np.mean(X, axis=0)
        X = X - self.mean

        cov_matrix = np.cov(X, rowvar=False)

        eigenvalues, eigenvectors = np.linalg.eig(cov_matrix)

        eigenvectors = eigenvectors.T
        idxs = np.argsort(eigenvalues)[::-1]
        eigenvalues = eigenvalues[idxs]
        eigenvectors = eigenvectors[idxs]

        self.components = eigenvectors[:self.n_components]

    def transform(self, X):
        X = X - self.mean
        return np.dot(X, self.components.T)


n_components = 11
pca = PCA(n_components=n_components)
X_train_numeric = X_train.select_dtypes(include=np.number).astype(np.float64)
pca.fit(X_train_numeric.values)
```

```
X_train_pca = pca.transform(X_train_numeric.values)

X_test_numeric = X_test.select_dtypes(include=np.number).astype(np.float64)
X_test_pca = pca.transform(X_test_numeric.values)

print(f"Transformed X_train shape: {X_train_pca.shape}")
print(f"Transformed X_test shape: {X_test_pca.shape}")
```

```
Transformed X_train shape: (67247, 11)
Transformed X_test shape: (28821, 11)
```

```
import matplotlib.pyplot as plt

# Calculate explained variance
eigenvalues = np.var(X_train_pca, axis=0)
explained_variance_ratio = eigenvalues / np.sum(eigenvalues)

# Plot explained variance
plt.figure(figsize=(8, 5))
plt.plot(range(1, len(explained_variance_ratio) + 1), explained_variance_ratio, marker='o', label='Explained Variance Ratio')
plt.title("Explained Variance by Principal Components")
plt.xlabel("Principal Component")
plt.ylabel("Explained Variance Ratio")
plt.xticks(range(1, len(explained_variance_ratio) + 1))
plt.grid()
plt.legend()
plt.show()
```

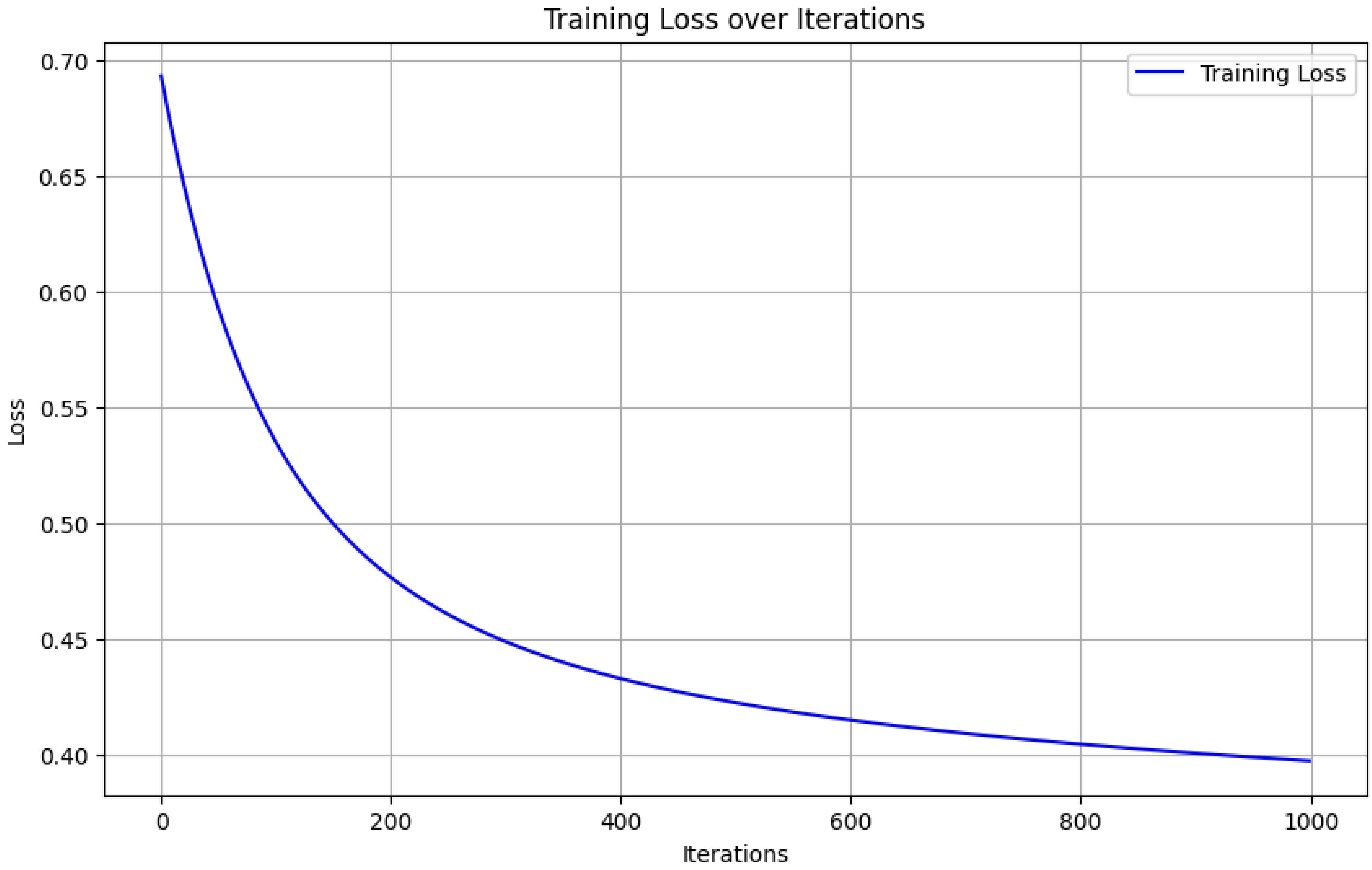



```
import numpy as np

class LogisticRegressionCustom:
    def __init__(self, learning_rate=0.01, n_iters=1000):
        self.lr = learning_rate
        self.n_iters = n_iters
        self.weights = None
        self.bias = None
        self.losses = []

    def fit(self, X, y):
```

```
        X = X.astype(np.float64)

        n_samples, n_features = X.shape

        self.weights = np.zeros(n_features)
        self.bias = 0

        for iteration in range(self.n_iters):
            linear_model = np.dot(X, self.weights) + self.bias
            y_predicted = self._sigmoid(linear_model)

            dw = (1 / n_samples) * np.dot(X.T, (y_predicted - y))
            db = (1 / n_samples) * np.sum(y_predicted - y)

            self.weights -= self.lr * dw
            self.bias -= self.lr * db

            loss = - (1 / n_samples) * np.sum(
                y * np.log(np.clip(y_predicted, 1e-15, 1 - 1e-15)) +
                (1 - y) * np.log(np.clip(1 - y_predicted, 1e-15, 1 - 1e-15))
            )
            self.losses.append(loss)
            # if iteration % 100 == 0:
            #     loss = - (1 / n_samples) * np.sum(
            #         y * np.log(np.clip(y_predicted, 1e-15, 1 - 1e-15)) +
            #         (1 - y) * np.log(np.clip(1 - y_predicted, 1e-15, 1 - 1e-15))
            #     )
            #     print(f"Loss at iteration {iteration}: {loss}")

    def predict(self, X):
        X = X.astype(np.float64)

        linear_model = np.dot(X, self.weights) + self.bias
        y_predicted = self._sigmoid(linear_model)
        return (y_predicted > 0.5).astype(int)

    def _sigmoid(self, x):
```

```
        x = np.array(x, dtype=np.float64)

        x = np.clip(x, -500, 500)
        return 1 / (1 + np.exp(-x))

custom_log_reg = LogisticRegressionCustom(learning_rate=0.01, n_iters=1000)
custom_log_reg.fit(X_train.values, y_train.values)
y_pred_log_reg = custom_log_reg.predict(X_test.values)
accuracy_log_reg = np.sum(y_pred_log_reg == y_test.values) / len(y_test)
accuracy_log_reg = round(accuracy_log_reg * 100, 2)
print(f"Accuracy of custom logistic regression: {accuracy_log_reg}%")

# Visualizing the training loss
plt.figure(figsize=(10, 6))
plt.plot(range(custom_log_reg.n_iters), custom_log_reg.losses, label="Training Loss", color="blue")
plt.xlabel("Iterations")
plt.ylabel("Loss")
plt.title("Training Loss over Iterations")
plt.legend()
plt.grid()
plt.show()
```

```
Accuracy of custom logistic regression: 83.19%
```




```
import numpy as np

class SVM:
    def __init__(self, learning_rate=0.01, lambda_param=0.01, n_iters=500):
        self.lr = learning_rate
        self.lambda_param = lambda_param
```

```
        self.n_iters = n_iters
        self.w = None
        self.b = None
        self.losses = []

    def fit(self, X, y):
        X = X.astype(np.float64)
        n_samples, n_features = X.shape

        y_ = np.where(y <= 0, -1, 1)

        self.w = np.random.randn(n_features) * 0.01
        self.b = 0

        for iteration in range(self.n_iters):
            gradients_w = np.zeros_like(self.w)
            gradients_b = 0
            for idx, x_i in enumerate(X):
                condition = y_[idx] * (np.dot(x_i, self.w) - self.b) >= 1
                if condition:
                    gradients_w += 2 * self.lambda_param * self.w
                else:
                    gradients_w += 2 * self.lambda_param * self.w - np.dot(x_i, y_[idx])
                    gradients_b += -y_[idx]

            self.w -= self.lr * gradients_w / n_samples
            self.b -= self.lr * gradients_b / n_samples

            loss = self.hinge_loss(X, y_)
            self.losses.append(loss)
            # if iteration % 100 == 0:
            #     loss = self.hinge_loss(X, y_)
            #     print(f"Loss at iteration {iteration}: {loss}")

    def predict(self, X):
        approx = np.dot(X, self.w) - self.b
        predictions = np.sign(approx)
```

```
        # Change here to convert -1 to 0
        predictions = np.where(predictions == -1, 0, predictions)
        return predictions

    def hinge_loss(self, X, y):
        loss = 0
        for idx, x_i in enumerate(X):
            loss += max(0, 1 - y[idx] * (np.dot(x_i, self.w) - self.b))
        loss /= len(X)
        return loss


svm = SVM()
svm.fit(X_train.values, y_train.values)
y_pred_svm = svm.predict(X_test.values)

def accuracy(y_true, y_pred):
    accuracy = np.sum(y_true == y_pred) / len(y_true)
    return accuracy

accuracy_svm = accuracy(y_test, y_pred_svm)
accuracy_svm = round(accuracy_svm * 100, 2)
print("SVM classification accuracy", accuracy_svm)

plt.figure(figsize=(10, 6))
plt.plot(range(svm.n_iters), svm.losses, label="Hinge Loss", color="blue")
plt.xlabel("Iterations")
plt.ylabel("Hinge Loss")
plt.title("SVM Training: Hinge Loss over Iterations")
plt.legend()
plt.grid()
plt.show()
```

```
SVM classification accuracy 81.74
```


```
import numpy as np

class NaiveBayes:
    def __init__(self):
        self.prior = None
        self.likelihood = None
```

```
        self.classes = None

    def fit(self, X, y):
        self.classes = np.unique(y)
        self.prior = np.zeros(len(self.classes))
        self.likelihood = {}
        n_samples, n_features = X.shape

        for i, c in enumerate(self.classes):
            X_c = X[y == c]
            self.prior[i] = len(X_c) / len(X)

            for j in range(n_features):
                if j not in self.likelihood:
                    self.likelihood[j] = {}

                values = np.unique(X[:, j])
                for v in values:
                    self.likelihood[j][(c, v)] = (np.sum(X_c[:, j] == v) + 1) / (len(X_c) + len(values))

    def _calculate_loss(self, X, y):
        n_samples = X.shape[0]
        loss = 0
        for i, x in enumerate(X):
            true_class = y[i]
            posterior_sum = 0
            for c in self.classes:
                posterior = self.prior[np.where(self.classes == c)[0][0]]
                for j in range(len(x)):
                    posterior *= self.likelihood[j].get((c, x[j]), 1e-9)
                posterior_sum += posterior

            true_posterior = self.prior[np.where(self.classes == true_class)[0][0]]
            for j in range(len(x)):
                true_posterior *= self.likelihood[j].get((true_class, x[j]), 1e-9)

            loss += -np.log(true_posterior / (posterior_sum + 1e-9))
```

```
        return loss / n_samples

    def predict(self, X):
        predictions = []
        for x in X:
            posteriors = []
            for c in self.classes:
                posterior = self.prior[np.where(self.classes == c)[0][0]]
                for j in range(len(x)):
                    posterior *= self.likelihood[j].get((c, x[j]), 1e-9)
                posteriors.append(posterior)
            predictions.append(self.classes[np.argmax(posteriors)])
        return np.array(predictions)


nb = NaiveBayes()

chunk_size = 100
n_chunks = (len(X_train) + chunk_size - 1) // chunk_size
for i in range(n_chunks):
    start = i * chunk_size
    end = min((i + 1) * chunk_size, len(X_train))
    X_chunk, y_chunk = X_train.values[start:end], y_train.values[start:end]
    nb.fit(X_chunk, y_chunk)

    # if i % 100 == 0 or i == n_chunks - 1:
    #     loss = nb._calculate_loss(X_train.values, y_train.values)
    #     print(f"Loss at iteration {i}: {loss:.4f}")

y_pred_nb = nb.predict(X_test.values)

accuracy_nb = np.sum(y_pred_nb == y_test.values) / len(y_test)
accuracy_nb = round(accuracy_nb * 100, 2)
print(f"Accuracy of Naive Bayes: {accuracy_nb}%")
```

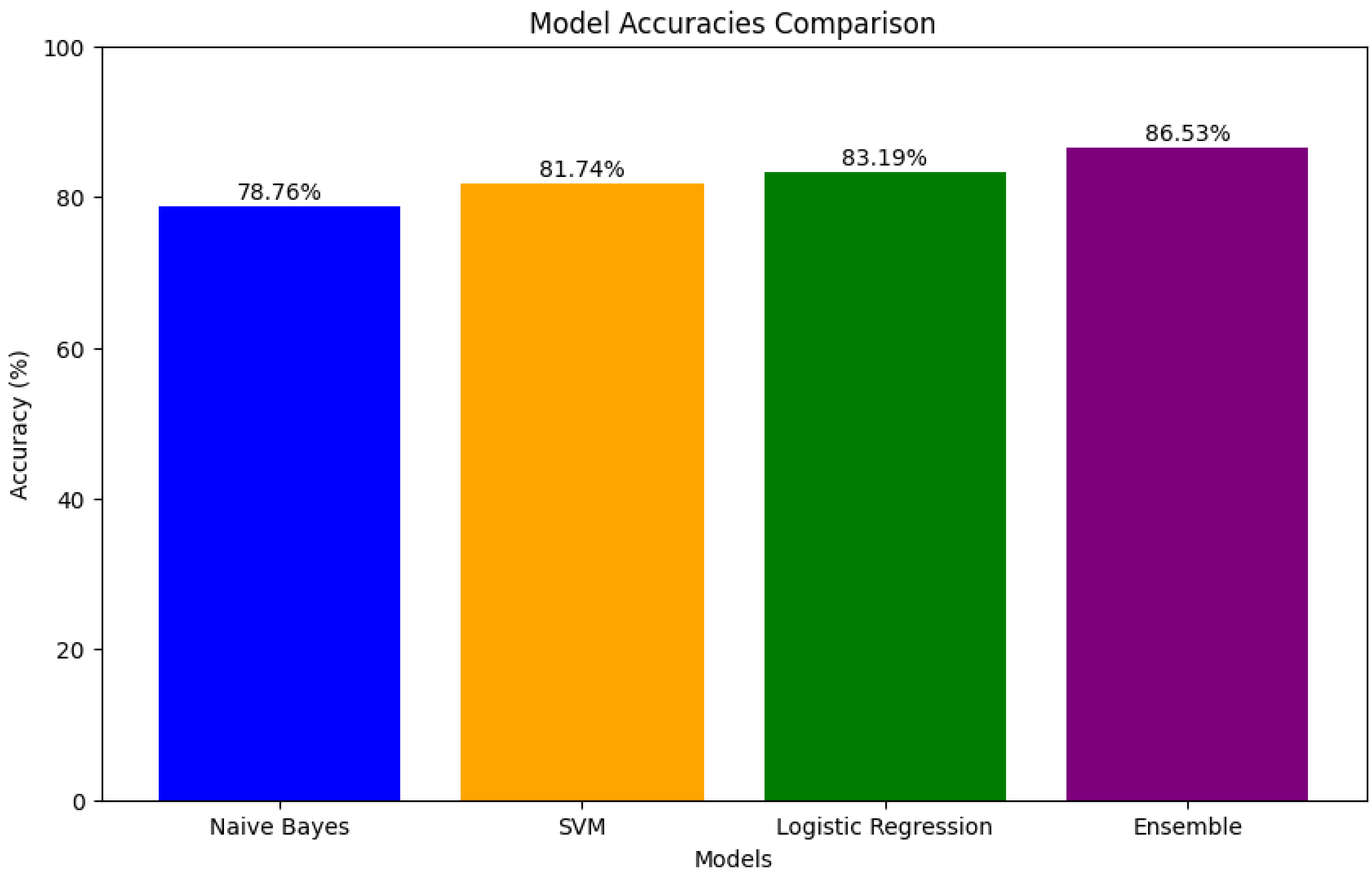
```
Accuracy of Naive Bayes: 78.76%
```

```
import numpy as np

class EnsembleModel:
    def __init__(self, models):
        self.models = models

    def predict(self, X):
        predictions = np.array([model.predict(X) for model in self.models])
        predictions = predictions.T

        predictions = np.clip(predictions, 0, 1)

        predictions = predictions.astype(int)

        y_pred = [np.bincount(row).argmax() for row in predictions]
        return np.array(y_pred)

ensemble = EnsembleModel(models=[svm, log_reg, nb])

y_pred_ensemble = ensemble.predict(X_test.values)

accuracy_ensemble = np.sum(y_pred_ensemble == y_test.values) / len(y_test)
accuracy_ensemble = round(accuracy_ensemble * 100, 2)
print(f"Ensemble Model Accuracy: {accuracy_ensemble}%")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493: UserWarning: X does not have valid feature names, but LogisticRegre
  warnings.warn(
Ensemble Model Accuracy: 86.53%
```

```
import matplotlib.pyplot as plt

models = ['Naive Bayes','SVM','Logistic Regression', 'Ensemble']
accuracies = [accuracy_nb,accuracy_svm,accuracy_log_reg, accuracy_ensemble]
```

```
plt.figure(figsize=(10, 6))
plt.bar(models, accuracies, color=['blue', 'orange', 'green', 'purple'])
plt.xlabel('Models')
plt.ylabel('Accuracy (%)')
plt.title('Model Accuracies Comparison')
plt.ylim(0, 100)
for i, v in enumerate(accuracies):
    plt.text(i, v + 1, f"{v:.2f}%", ha='center', fontsize=10, color='black')
plt.show()
```




```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Dictionary to store results
metrics = {
    "Model": [],
    "Accuracy": [],
    "Precision": [],
```

```
    "Recall": [],
    "F1 Score": []
}

def evaluate_model(y_true, y_pred, model_name):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='weighted', zero_division=0)
    recall = recall_score(y_true, y_pred, average='weighted', zero_division=0)
    f1 = f1_score(y_true, y_pred, average='weighted', zero_division=0)

    metrics["Model"].append(model_name)
    metrics["Accuracy"].append(accuracy)
    metrics["Precision"].append(precision)
    metrics["Recall"].append(recall)
    metrics["F1 Score"].append(f1)

# Evaluate SVM
y_pred_svm_fixed = np.clip(y_pred_svm, 0, 1).astype(int)
evaluate_model(y_test.values, y_pred_svm_fixed, "SVM")

# Evaluate Logistic Regression
evaluate_model(y_test.values, y_pred_log_reg, "Logistic Regression")

# Evaluate Naive Bayes
evaluate_model(y_test.values, y_pred_nb, "Naive Bayes")

# Evaluate Ensemble
evaluate_model(y_test.values, y_pred_ensemble, "Ensemble Model")

# Display all metrics
import pandas as pd
metrics_df = pd.DataFrame(metrics)
print(metrics_df)
```

```
                 Model  Accuracy  Precision    Recall  F1 Score
0                  SVM  0.817390   0.801434  0.817390  0.801108
1  Logistic Regression  0.831893   0.861922  0.831893  0.790721
```

2	Naive Bayes	0.787620	0.761020	0.787620	0.763616
3	Ensemble Model	0.865307	0.872365	0.865307	0.846699