decoding-default

August 4, 2025

##Mount Drive

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

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

##Import Required Libraries

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
```

##Install Data profiling

[ ]:
```
#!pip install ydata-profiling
```

##Load Dataset

[ ]:
```
df=pd.read_csv('/content/drive/MyDrive/Lending_Data/lending_club_loan_two.csv')
```

##Data Profiling & Summary

[ ]:
```
# data profiling - Run only once for the first time
#from ydata_profiling import ProfileReport

#profile = ProfileReport(df, title="Data Profiling Report", explorative=True)

#profile.to_file("output.html")
```

[ ]:
```
# Basic Info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
```

```
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object
 5   sub_grade             396030 non-null  object
 6   emp_title             373103 non-null  object
 7   emp_length            377729 non-null  object
 8   home_ownership        396030 non-null  object
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object
 11  issue_d               396030 non-null  object
 12  loan_status           396030 non-null  object
 13  purpose               396030 non-null  object
 14  title                 394274 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object
 23  application_type      396030 non-null  object
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

[ ]:
```
df.describe()
```

[ ]:
```
           loan_amnt       int_rate    installment    annual_inc  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean    14113.888089      13.639400     431.849698  7.420318e+04
std      8357.441341       4.472157     250.727790  6.163762e+04
min       500.000000       5.320000      16.080000  0.000000e+00
25%      8000.000000      10.490000     250.330000  4.500000e+04
50%     12000.000000      13.330000     375.430000  6.400000e+04
75%     20000.000000      16.490000     567.300000  9.000000e+04
max     40000.000000      30.990000    1533.810000  8.706582e+06

                 dti       open_acc        pub_rec     revol_bal  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean       17.379514      11.311153       0.178191  1.584454e+04
std        18.019092       5.137649       0.530671  2.059184e+04
min         0.000000       0.000000       0.000000  0.000000e+00
```

```
25%        11.280000       8.000000       0.000000  6.025000e+03
50%        16.910000      10.000000       0.000000  1.118100e+04
75%        22.980000      14.000000       0.000000  1.962000e+04
max      9999.000000      90.000000      86.000000  1.743266e+06

          revol_util      total_acc      mort_acc  pub_rec_bankruptcies
count  395754.000000  396030.000000  358235.000000         395495.000000
mean       53.791749      25.414744       1.813991              0.121648
std        24.452193      11.886991       2.147930              0.356174
min         0.000000       2.000000       0.000000              0.000000
25%        35.800000      17.000000       0.000000              0.000000
50%        54.800000      24.000000       1.000000              0.000000
75%        72.900000      32.000000       3.000000              0.000000
max       892.300000     151.000000      34.000000              8.000000
```

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

[ ]:
```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5

                 emp_title emp_length home_ownership  annual_inc  …  \
0                Marketing  10+ years           RENT    117000.0  …
1          Credit analyst     4 years       MORTGAGE     65000.0  …
2             Statistician   < 1 year           RENT     43057.0  …
3          Client Advocate    6 years           RENT     54000.0  …
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0  …

  open_acc pub_rec revol_bal revol_util total_acc  initial_list_status  \
0     16.0     0.0   36369.0       41.8      25.0                    w
1     17.0     0.0   20131.0       53.3      27.0                    f
2     13.0     0.0   11987.0       92.2      26.0                    f
3      6.0     0.0    5472.0       21.5      13.0                    f
4     13.0     0.0   24584.0       69.8      43.0                    f

  application_type  mort_acc  pub_rec_bankruptcies  \
0       INDIVIDUAL       0.0                   0.0
1       INDIVIDUAL       3.0                   0.0
2       INDIVIDUAL       0.0                   0.0
3       INDIVIDUAL       0.0                   0.0
4       INDIVIDUAL       1.0                   0.0

                                            address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
```

```
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650

[5 rows x 27 columns]
```

##Data Cleaning

[ ]:
```
df.shape
```

[ ]: (396030, 27)

###Removing Missing Values

[ ]:
```
#Remove missing values from features emp_length,mort_acc, pub_rec_bankruptcies
df.dropna(subset=['emp_length', 'mort_acc', 'pub_rec_bankruptcies'],␣
 ↪inplace=True)
df.shape
```

[ ]: (340990, 27)

###Removing Zeroes

[ ]:
```
#Remove zeroes from features such as annual_inc, revol_bal, revol_util
df = df[df['annual_inc'] != 0]
df = df[df['revol_bal'] != 0]
df = df[df['revol_util'] != 0]
df.shape
```

[ ]: (339541, 27)

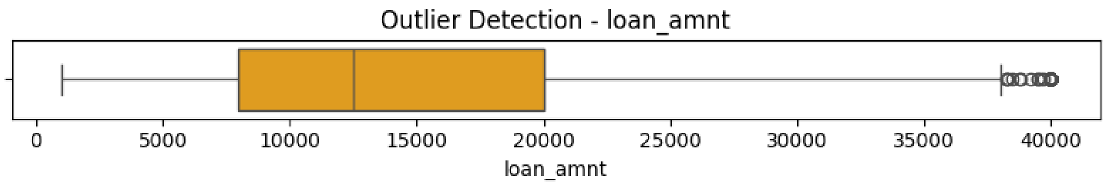
[ ]:
```
#Remove none and other values from the rows of home_ownership
df = df[df['home_ownership'] != 'NONE']
df = df[df['home_ownership'] != 'OTHER']
df.shape
```

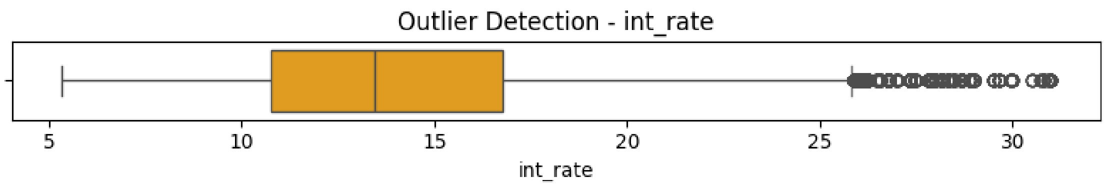
[ ]: (339482, 27)

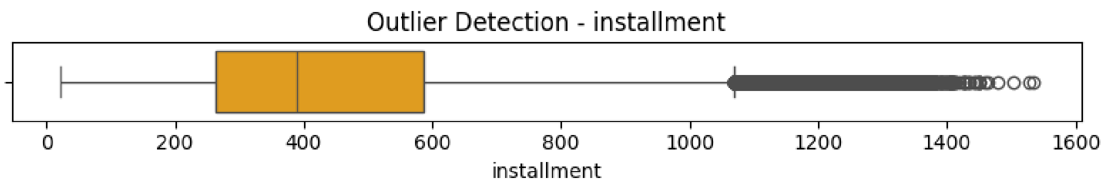
###Plot Outliers

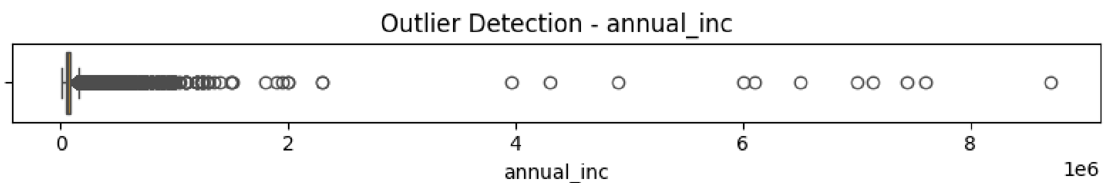
[ ]:
```
#Plot outliers
# Select numerical columns
numeric_cols = df.select_dtypes(include='number').columns

# Plot boxplots for each numeric column
for col in numeric_cols:
    plt.figure(figsize=(8, 1.5))
```

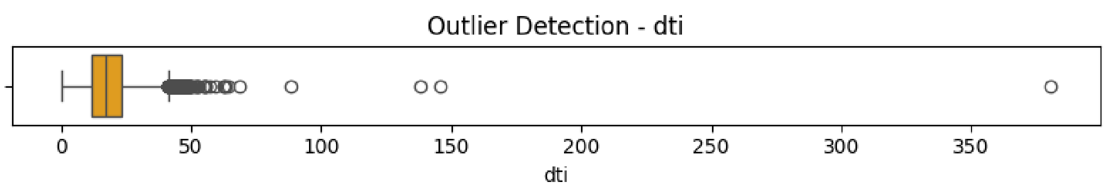
```
    sns.boxplot(x=df[col], color='orange')
    plt.title(f"Outlier Detection - {col}")
    plt.xlabel(col)
    plt.tight_layout()
    plt.show()
```

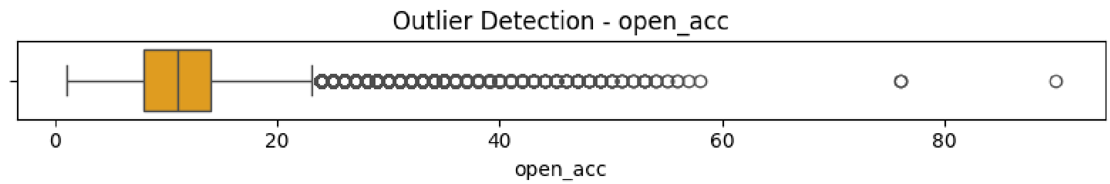


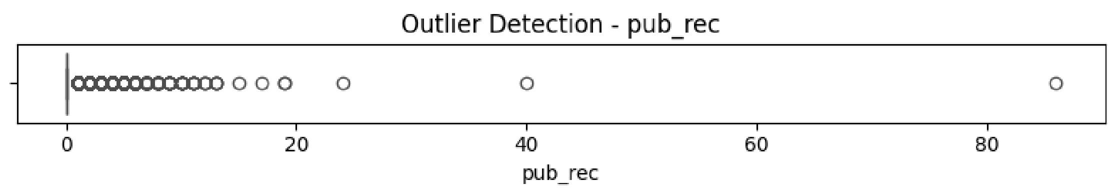


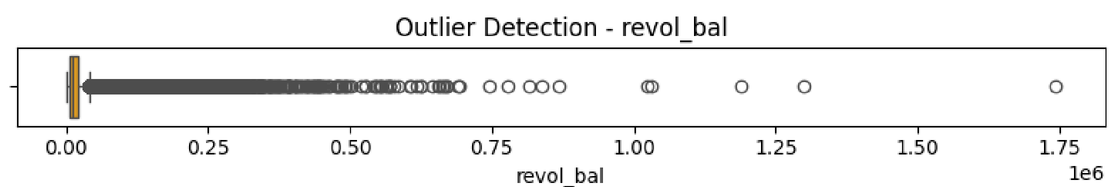


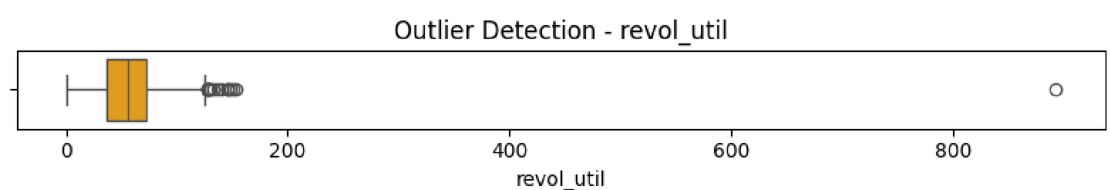


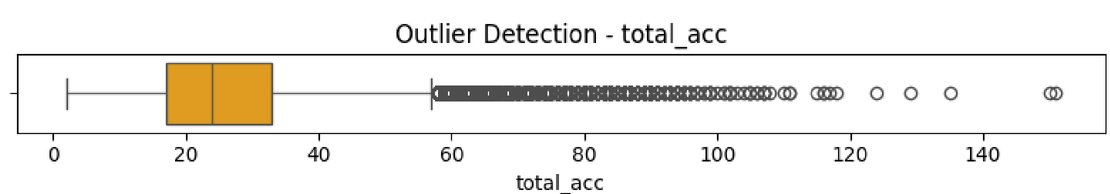


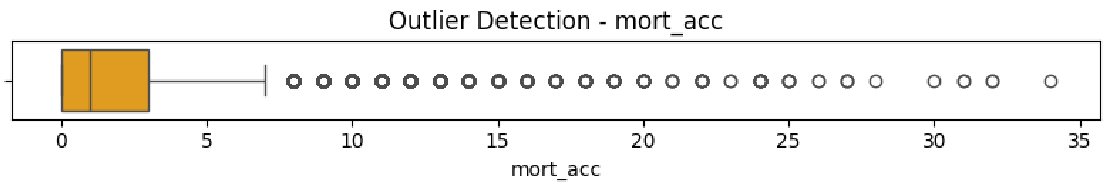

Outlier Detection - open_acc
0
20
40
60
80
open_acc

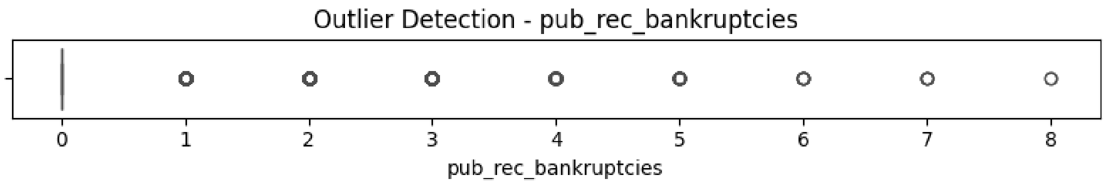

Outlier Detection - pub_rec
0
20
40
60
80
pub_rec


Outlier Detection - revol_bal
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
revol_bal


Outlier Detection - revol_util
0
200
400
600
800
revol_util


Outlier Detection - total_acc
0
20
40
60
80
100
120
140
total_acc





###Removing Outliers

[ ]:
```
#Remove outliers from features loan_amnt, int_rate, open_acc, revol_util
# List of target columns to remove outliers from
cols_to_clean = ['loan_amnt', 'int_rate', 'open_acc', 'revol_util']

# Loop through each column and remove outliers using IQR method
for col in cols_to_clean:
    if col in df.columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Filter out outliers
        df = df[(df[col] >= lower_bound) & (df[col] < upper_bound)]

print(f"Outliers removed. New shape of DataFrame: {df.shape}")
```

```
Outliers removed. New shape of DataFrame: (325008, 27)
```

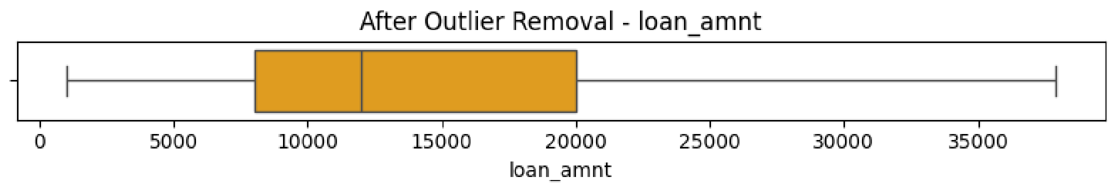
[ ]:
```
#Remove outliers and change upper limit of :
# Remove rows where annual_inc > 20 lakhs
if 'annual_inc' in df.columns:
    df = df[df['annual_inc'] <= 2_000_000]
#Remove rows from total_acc > 110
if 'total_acc' in df.columns:
    df = df[df['total_acc'] <= 110]
#Remove rows from revol_bal > 7.5 lakhs
```

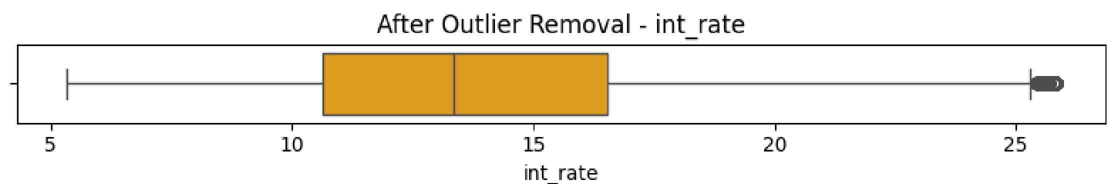
```python
if 'revol_bal' in df.columns:
    df = df[df['revol_bal'] <= 7_500_000]
#Remove rows from mort_acc >15
if 'mort_acc' in df.columns:
    df = df[df['mort_acc'] <= 15]
    #Remove rows from pub_rec >15
if 'pub_rec' in df.columns:
    df = df[df['pub_rec'] <= 15]
    #Remove rows from pub_rec_bankruptcies >15
if 'pub_rec_bankruptcies' in df.columns:
    df = df[df['pub_rec_bankruptcies'] <= 15]
#Remove rows from dti >70
if 'dti' in df.columns:
    df = df[df['dti'] <= 70]
    #Remove rows from installment > 1450
if 'installment' in df.columns:
    df = df[df['installment'] <= 1450]
```

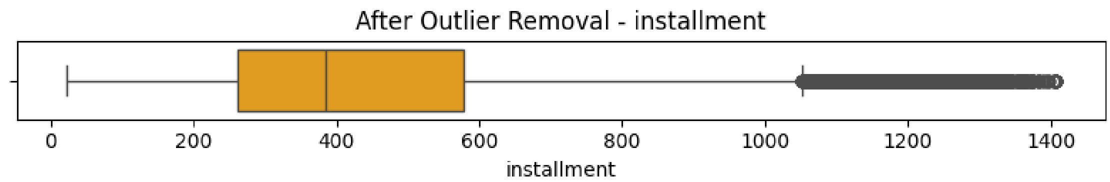
[ ]:
```python
print(f"Outliers removed. New shape of DataFrame: {df.shape}")
```

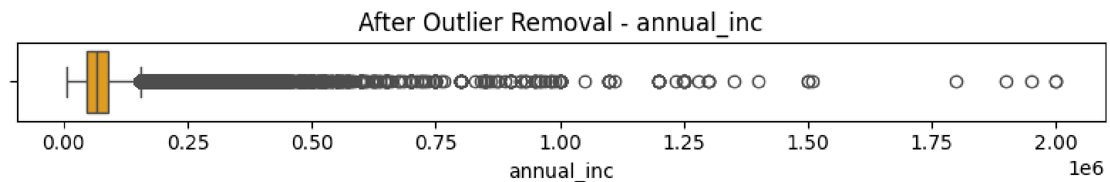
```
Outliers removed. New shape of DataFrame: (324859, 27)
```

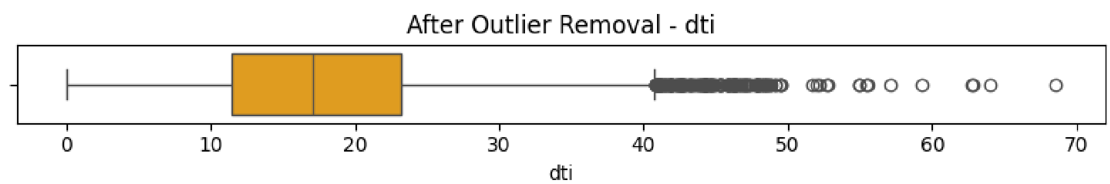
[ ]:
```python
# Plot boxplots for each numeric column after outlier removal
for col in numeric_cols:
    plt.figure(figsize=(8, 1.5))
    sns.boxplot(x=df[col], color='orange')
    plt.title(f"After Outlier Removal - {col}")
    plt.xlabel(col)
    plt.tight_layout()
    plt.show()
```

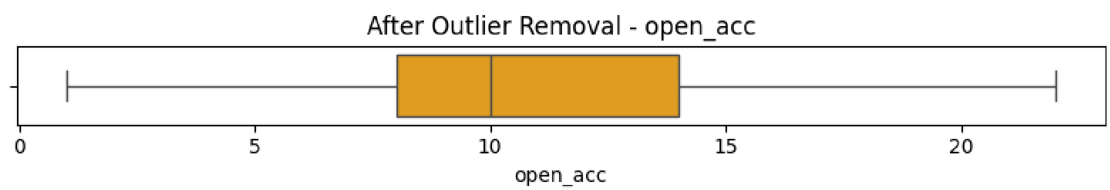


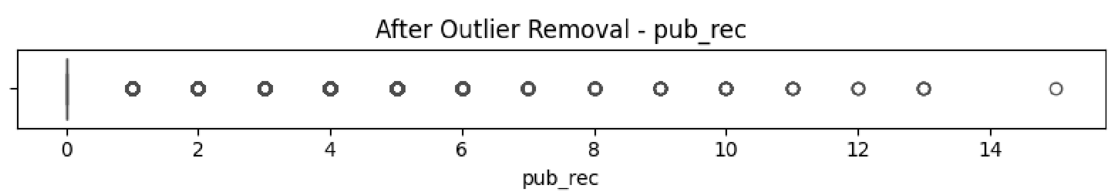


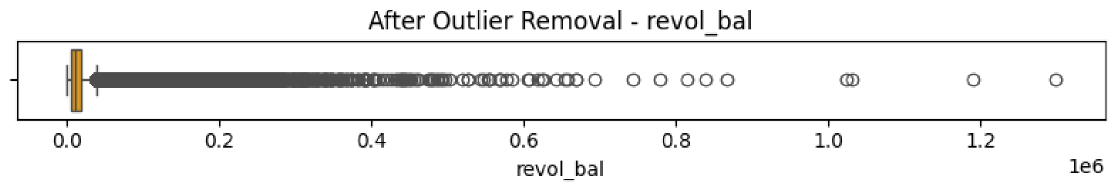

After Outlier Removal - installment
0
200
400
600
800
1000
1200
1400
installment

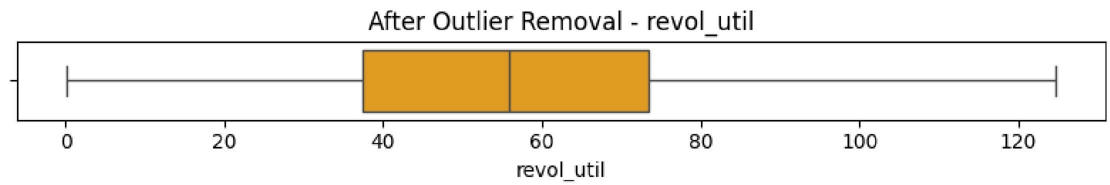

After Outlier Removal - annual_inc
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
1e6
annual_inc

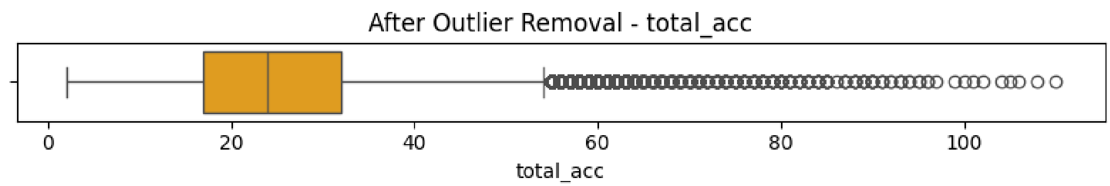

After Outlier Removal - dti
0
10
20
30
40
50
60
70
dti

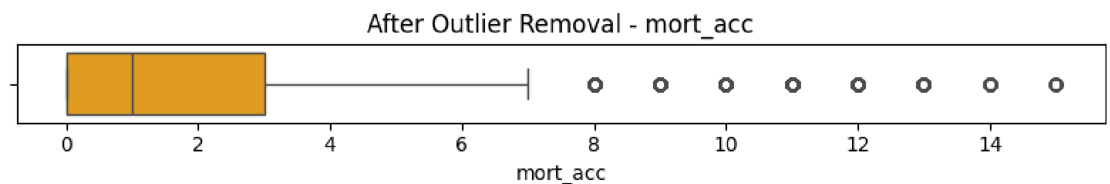

After Outlier Removal - open_acc
0
5
10
15
20
open_acc

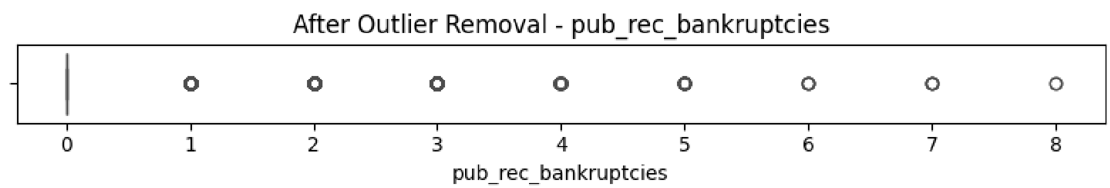

After Outlier Removal - pub_rec
0
2
4
6
8
10
12
14
pub_rec











[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 324859 entries, 0 to 396028
```

```
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             324859 non-null  float64
 1   term                  324859 non-null  object
 2   int_rate              324859 non-null  float64
 3   installment           324859 non-null  float64
 4   grade                 324859 non-null  object
 5   sub_grade             324859 non-null  object
 6   emp_title             321562 non-null  object
 7   emp_length            324859 non-null  object
 8   home_ownership        324859 non-null  object
 9   annual_inc            324859 non-null  float64
 10  verification_status   324859 non-null  object
 11  issue_d               324859 non-null  object
 12  loan_status           324859 non-null  object
 13  purpose               324859 non-null  object
 14  title                 323457 non-null  object
 15  dti                   324859 non-null  float64
 16  earliest_cr_line      324859 non-null  object
 17  open_acc              324859 non-null  float64
 18  pub_rec               324859 non-null  float64
 19  revol_bal             324859 non-null  float64
 20  revol_util            324859 non-null  float64
 21  total_acc             324859 non-null  float64
 22  initial_list_status   324859 non-null  object
 23  application_type      324859 non-null  object
 24  mort_acc              324859 non-null  float64
 25  pub_rec_bankruptcies  324859 non-null  float64
 26  address               324859 non-null  object
dtypes: float64(12), object(15)
memory usage: 69.4+ MB
```

#Feature Engineering

[ ]:
```
#Feature Engineering for address column - extract zipcode from address
# Extract 2-letter state code and 5-digit pincode from address
df['zip_code'] = df['address'].str.extract(r'([A-Z]{2}\s*\d{5})$')
```

##Extract necessary data Conversion to date time format

[ ]:
```
from datetime import datetime
```

[ ]:
```
# Step 1: Convert to datetime (if not already)
df['issue_d'] = pd.to_datetime(df['issue_d'], errors='coerce')
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'], errors='coerce')

# Step 2: Strip the time (keep only date)
```

```
df['issue_d'] = df['issue_d'].dt.date
df['earliest_cr_line'] = df['earliest_cr_line'].dt.date
```

```
/tmp/ipython-input-577587950.py:2: UserWarning: Could not infer format, so each
element will be parsed individually, falling back to `dateutil`. To ensure
parsing is consistent and as-expected, please specify a format.
  df['issue_d'] = pd.to_datetime(df['issue_d'], errors='coerce')
/tmp/ipython-input-577587950.py:3: UserWarning: Could not infer format, so each
element will be parsed individually, falling back to `dateutil`. To ensure
parsing is consistent and as-expected, please specify a format.
  df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'],
errors='coerce')
```

[ ]:
```
df['issue_d_year'] = df['issue_d'].apply(lambda x: int(x.strftime('%Y')) if pd.
 ↪notnull(x) else None)
df['issue_d_month'] = df['issue_d'].apply(lambda x: int(x.strftime('%m')) if pd.
 ↪notnull(x) else None)
df['issue_d_day'] = df['issue_d'].apply(lambda x: int(x.strftime('%d')) if pd.
 ↪notnull(x) else None)

df['earliest_cr_line_year'] = df['earliest_cr_line'].apply(lambda x: int(x.
 ↪strftime('%Y')) if pd.notnull(x) else None)
df['earliest_cr_line_month'] = df['earliest_cr_line'].apply(lambda x: int(x.
 ↪strftime('%m')) if pd.notnull(x) else None)
df['earliest_cr_line_day'] = df['earliest_cr_line'].apply(lambda x: int(x.
 ↪strftime('%d')) if pd.notnull(x) else None)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 324859 entries, 0 to 396028
Data columns (total 34 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   loan_amnt              324859 non-null  float64
 1   term                   324859 non-null  object
 2   int_rate               324859 non-null  float64
 3   installment            324859 non-null  float64
 4   grade                  324859 non-null  object
 5   sub_grade              324859 non-null  object
 6   emp_title              321562 non-null  object
 7   emp_length             324859 non-null  object
 8   home_ownership         324859 non-null  object
 9   annual_inc             324859 non-null  float64
 10  verification_status    324859 non-null  object
 11  issue_d                324859 non-null  object
 12  loan_status            324859 non-null  object
```

```
 13  purpose                 324859 non-null  object
 14  title                   323457 non-null  object
 15  dti                     324859 non-null  float64
 16  earliest_cr_line        324859 non-null  object
 17  open_acc                324859 non-null  float64
 18  pub_rec                 324859 non-null  float64
 19  revol_bal               324859 non-null  float64
 20  revol_util              324859 non-null  float64
 21  total_acc               324859 non-null  float64
 22  initial_list_status     324859 non-null  object
 23  application_type        324859 non-null  object
 24  mort_acc                324859 non-null  float64
 25  pub_rec_bankruptcies    324859 non-null  float64
 26  address                 324859 non-null  object
 27  zip_code                324859 non-null  object
 28  issue_d_year            324859 non-null  int64
 29  issue_d_month           324859 non-null  int64
 30  issue_d_day             324859 non-null  int64
 31  earliest_cr_line_year   324859 non-null  int64
 32  earliest_cr_line_month  324859 non-null  int64
 33  earliest_cr_line_day    324859 non-null  int64
dtypes: float64(12), int64(6), object(16)
memory usage: 86.7+ MB
```

[ ]:
```
df.drop(columns =␣
↪['issue_d','earliest_cr_line','emp_title','address','application_type'],␣
↪inplace=True)
```

[ ]:
```
df.shape
```

[ ]:
```
(324859, 29)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 324859 entries, 0 to 396028
Data columns (total 29 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   loan_amnt               324859 non-null  float64
 1   term                    324859 non-null  object
 2   int_rate                324859 non-null  float64
 3   installment             324859 non-null  float64
 4   grade                   324859 non-null  object
 5   sub_grade               324859 non-null  object
 6   emp_length              324859 non-null  object
 7   home_ownership          324859 non-null  object
 8   annual_inc              324859 non-null  float64
```

```
 9   verification_status     324859 non-null  object
 10  loan_status             324859 non-null  object
 11  purpose                 324859 non-null  object
 12  title                   323457 non-null  object
 13  dti                     324859 non-null  float64
 14  open_acc                324859 non-null  float64
 15  pub_rec                 324859 non-null  float64
 16  revol_bal               324859 non-null  float64
 17  revol_util              324859 non-null  float64
 18  total_acc               324859 non-null  float64
 19  initial_list_status     324859 non-null  object
 20  mort_acc                324859 non-null  float64
 21  pub_rec_bankruptcies    324859 non-null  float64
 22  zip_code                324859 non-null  object
 23  issue_d_year            324859 non-null  int64
 24  issue_d_month           324859 non-null  int64
 25  issue_d_day             324859 non-null  int64
 26  earliest_cr_line_year   324859 non-null  int64
 27  earliest_cr_line_month  324859 non-null  int64
 28  earliest_cr_line_day    324859 non-null  int64
dtypes: float64(12), int64(6), object(11)
memory usage: 74.4+ MB
```

[ ]:
```
df['statecode'] = df['zip_code'].str.extract(r'^([A-Z]{2})')
df['zip']=df['zip_code'].str.extract(r'(\d{5})$')
```

[ ]:
```
df.drop(columns = ['zip_code'], inplace=True)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 324859 entries, 0 to 396028
Data columns (total 30 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   loan_amnt               324859 non-null  float64
 1   term                    324859 non-null  object
 2   int_rate                324859 non-null  float64
 3   installment             324859 non-null  float64
 4   grade                   324859 non-null  object
 5   sub_grade               324859 non-null  object
 6   emp_length              324859 non-null  object
 7   home_ownership          324859 non-null  object
 8   annual_inc              324859 non-null  float64
 9   verification_status     324859 non-null  object
 10  loan_status             324859 non-null  object
 11  purpose                 324859 non-null  object
 12  title                   323457 non-null  object
```

```
 13  dti                        324859 non-null  float64
 14  open_acc                   324859 non-null  float64
 15  pub_rec                    324859 non-null  float64
 16  revol_bal                  324859 non-null  float64
 17  revol_util                 324859 non-null  float64
 18  total_acc                  324859 non-null  float64
 19  initial_list_status        324859 non-null  object
 20  mort_acc                   324859 non-null  float64
 21  pub_rec_bankruptcies       324859 non-null  float64
 22  issue_d_year               324859 non-null  int64
 23  issue_d_month              324859 non-null  int64
 24  issue_d_day                324859 non-null  int64
 25  earliest_cr_line_year      324859 non-null  int64
 26  earliest_cr_line_month     324859 non-null  int64
 27  earliest_cr_line_day       324859 non-null  int64
 28  statecode                  324859 non-null  object
 29  zip                        324859 non-null  object
dtypes: float64(12), int64(6), object(12)
memory usage: 76.8+ MB
```

[ ]:
```
df['zip'] = df['zip'].astype(int)
```

[ ]:
```
sorted_unique_values = sorted(df['emp_length'].unique())
sorted_unique_values
```

[ ]:
```
['1 year',
 '10+ years',
 '2 years',
 '3 years',
 '4 years',
 '5 years',
 '6 years',
 '7 years',
 '8 years',
 '9 years',
 '< 1 year']
```

[ ]:
```
#rename <1 year to 0-1 year, 10+ years to 10 years+
df['emp_length'] = df['emp_length'].replace(['< 1 year'], '0-1 year')
df['emp_length'] = df['emp_length'].replace(['10+ years'], '9 years+')
```

[ ]:
```
sorted_unique_values1 = sorted(df['emp_length'].unique())
sorted_unique_values1
```

[ ]:
```
['0-1 year',
 '1 year',
 '2 years',
```

```
 '3 years',
 '4 years',
 '5 years',
 '6 years',
 '7 years',
 '8 years',
 '9 years',
 '9 years+']
```

[ ]:
```python
#save the dataset now
df.to_csv('loan_data_cleaned.csv', index=False)
```

[ ]:
```python
#drop statecode, title columns
#purpose and title are almost similar classes
df.drop(columns = ['statecode','title','sub_grade','dti','pub_rec'],␣
 ↪inplace=True)
```

[ ]:
```python
df.shape
```

[ ]:
```
(324859, 25)
```

##One Hot Encoding

[ ]:
```python
from sklearn.preprocessing import OneHotEncoder
import pandas as pd

# Select the columns you want to encode
cols_to_encode = ['home_ownership', 'purpose']

# Initialize the encoder
ohe = OneHotEncoder(sparse_output = False, handle_unknown='ignore')

# Fit and transform
encoded = ohe.fit_transform(df[cols_to_encode])

# Convert to DataFrame and preserve index
encoded_df = pd.DataFrame(encoded, columns=ohe.
 ↪get_feature_names_out(cols_to_encode), index=df.index)

# Concatenate back with original dataframe (drop the encoded columns first)
df_encoded = pd.concat([df.drop(cols_to_encode, axis=1), encoded_df], axis=1)
```

[ ]:
```python
df_encoded.shape
```

[ ]:
```
(324859, 40)
```

##Label Encoding

[ ]:
```
#Label encoding for categorical features
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df_encoded['term'] = le.fit_transform(df_encoded['term'])
df_encoded['emp_length'] = le.fit_transform(df_encoded['emp_length'])
df_encoded['loan_status'] = le.fit_transform(df_encoded['loan_status'])
df_encoded['grade'] = le.fit_transform(df_encoded['grade'])
df_encoded['verification_status'] = le.
 ↪fit_transform(df_encoded['verification_status'])
df_encoded['initial_list_status'] = le.
 ↪fit_transform(df_encoded['initial_list_status'])
```

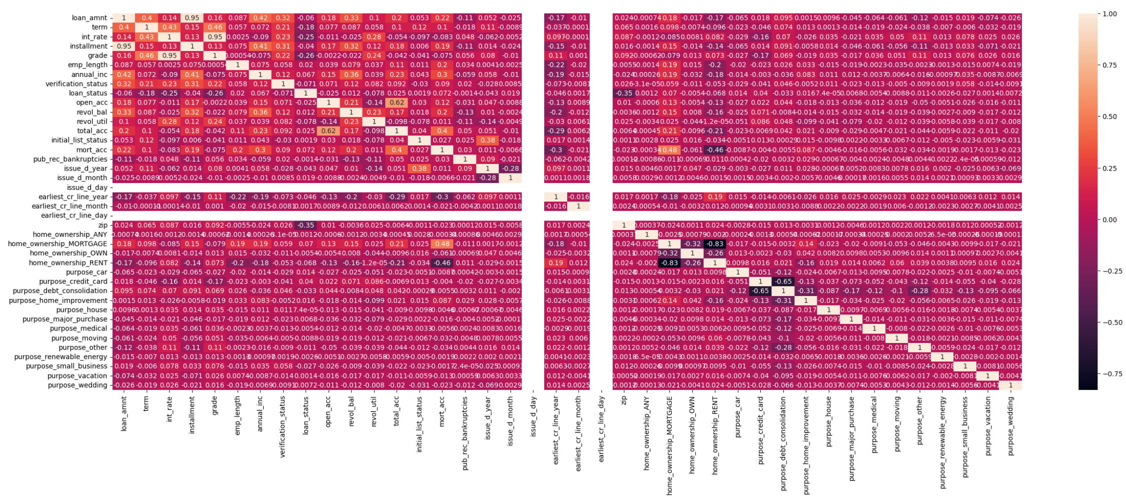
[ ]:
```
df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 324859 entries, 0 to 396028
Data columns (total 40 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   loan_amnt                324859 non-null  float64
 1   term                     324859 non-null  int64
 2   int_rate                 324859 non-null  float64
 3   installment              324859 non-null  float64
 4   grade                    324859 non-null  int64
 5   emp_length               324859 non-null  int64
 6   annual_inc               324859 non-null  float64
 7   verification_status      324859 non-null  int64
 8   loan_status              324859 non-null  int64
 9   open_acc                 324859 non-null  float64
 10  revol_bal                324859 non-null  float64
 11  revol_util               324859 non-null  float64
 12  total_acc                324859 non-null  float64
 13  initial_list_status      324859 non-null  int64
 14  mort_acc                 324859 non-null  float64
 15  pub_rec_bankruptcies     324859 non-null  float64
 16  issue_d_year             324859 non-null  int64
 17  issue_d_month            324859 non-null  int64
 18  issue_d_day              324859 non-null  int64
 19  earliest_cr_line_year    324859 non-null  int64
 20  earliest_cr_line_month   324859 non-null  int64
 21  earliest_cr_line_day     324859 non-null  int64
 22  zip                      324859 non-null  int64
 23  home_ownership_ANY       324859 non-null  float64
 24  home_ownership_MORTGAGE  324859 non-null  float64
 25  home_ownership_OWN       324859 non-null  float64
 26  home_ownership_RENT      324859 non-null  float64
 27  purpose_car              324859 non-null  float64
```

```
 28  purpose_credit_card          324859 non-null  float64
 29  purpose_debt_consolidation   324859 non-null  float64
 30  purpose_home_improvement     324859 non-null  float64
 31  purpose_house                324859 non-null  float64
 32  purpose_major_purchase       324859 non-null  float64
 33  purpose_medical              324859 non-null  float64
 34  purpose_moving               324859 non-null  float64
 35  purpose_other                324859 non-null  float64
 36  purpose_renewable_energy     324859 non-null  float64
 37  purpose_small_business       324859 non-null  float64
 38  purpose_vacation             324859 non-null  float64
 39  purpose_wedding              324859 non-null  float64
dtypes: float64(27), int64(13)
memory usage: 101.6 MB
```

[ ]:
```
#Correlation
corr1 = df_encoded.corr()
plt.figure(figsize=(30,10))
sns.heatmap(corr1, annot=True)
```

[ ]: <Axes: >

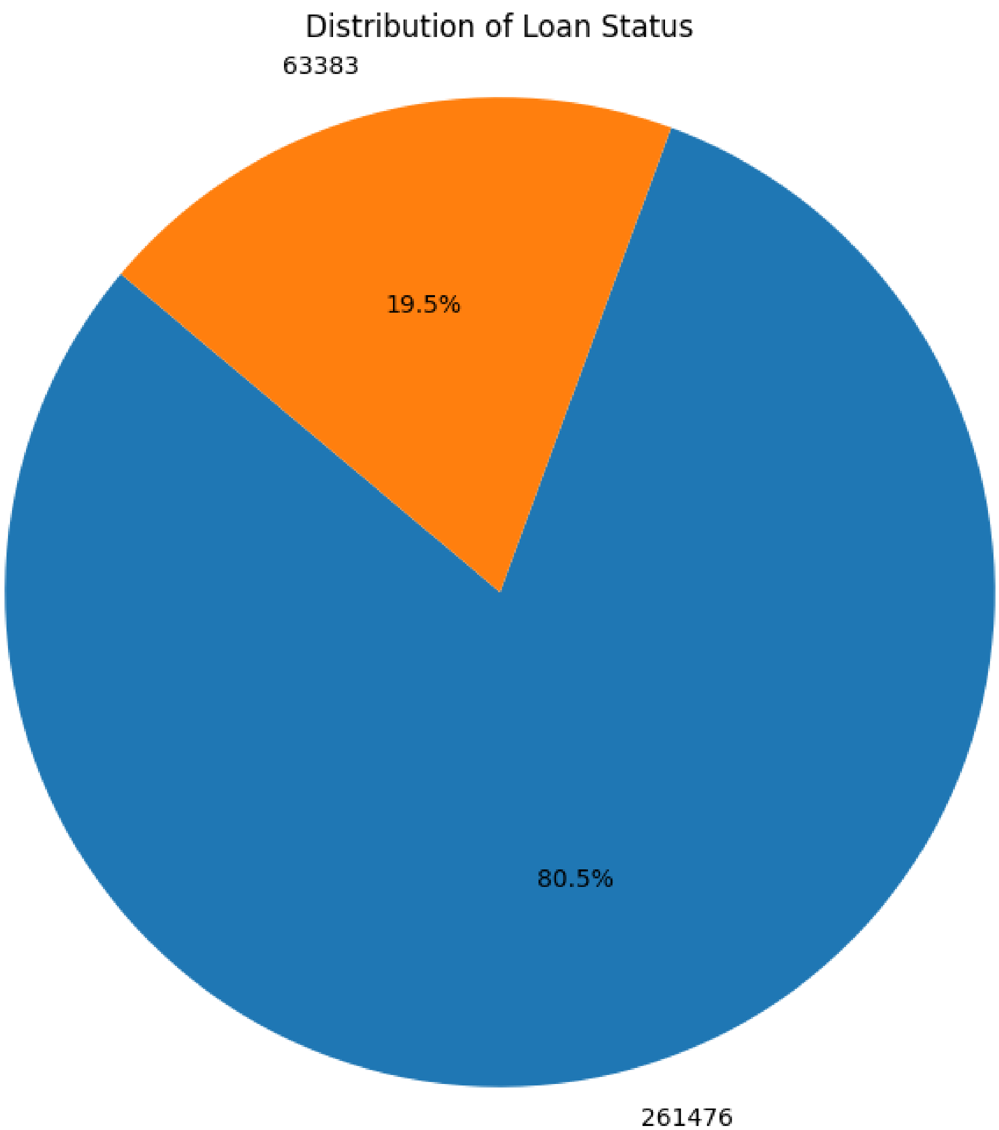


#ML Modelling

[ ]:
```
#X and Y value

# Define the target variable (dependent variable)
y = df_encoded['loan_status']


# Define the feature set (independent variables)
```

```
X = df_encoded.drop('loan_status', axis=1)
```

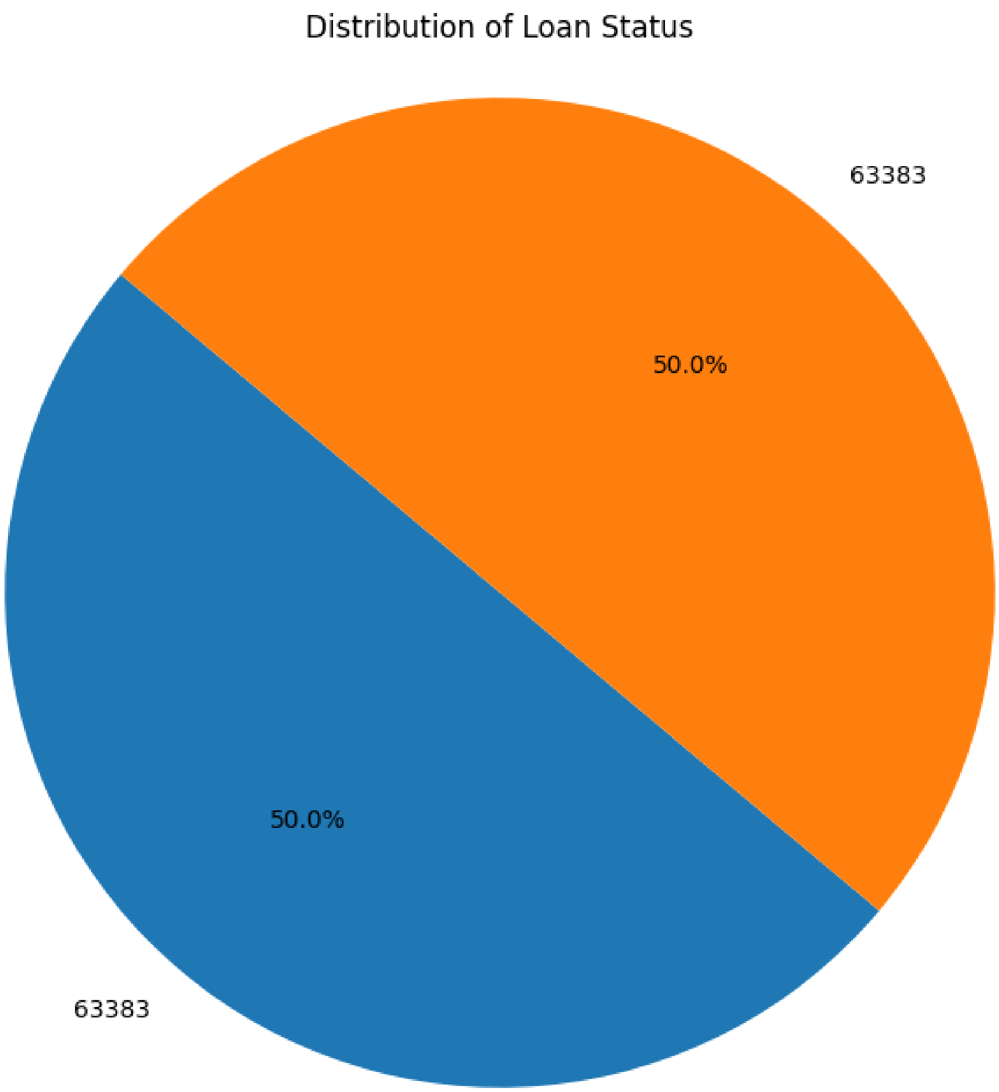
[ ]:
```
#Pie chart for loan_status before SMOTE
loan_status_counts = df_encoded['loan_status'].value_counts()

# Plot
plt.figure(figsize=(8, 8))
labels = loan_status_counts
plt.pie(loan_status_counts, labels=loan_status_counts, autopct='%1.1f%%',␣
 ↪startangle=140)
plt.title('Distribution of Loan Status')
plt.axis('equal')  # Equal aspect ratio ensures the pie is a circle.
plt.show()
```



##SMOTE to handle imbalance data

```
[ ]: #SMOTE to handle imbalance data in loan status feature
from imblearn.under_sampling import RandomUnderSampler
undersampler = RandomUnderSampler(random_state=42)
# Drop columns before undersampling
X = X.drop(['earliest_cr_line_day','issue_d_day'], axis=1)
X_res, y_res = undersampler.fit_resample(X, y)
```

```
[ ]: #Pie chart for loan_status after SMOTE
loan_status_counts1 = y_res.value_counts()

# Plot
plt.figure(figsize=(8, 8))
plt.pie(loan_status_counts1, labels=loan_status_counts1, autopct='%1.1f%%',␣
 ↪startangle=140)
plt.title('Distribution of Loan Status')
plt.axis('equal')  # Equal aspect ratio ensures the pie is a circle.
plt.show()
```



[ ]:
```
X_res.shape
```

[ ]: (126766, 37)

##Machine Learning Algorithms

[ ]:
```
#Test Train data split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.
 ↪2, random_state=42)
```

###Logistic Regression

[ ]:
```
#Logistic Classifier model
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]:
```
LogisticRegression()
```

[ ]:
```
#Predict and find accuracy
from sklearn.metrics import accuracy_score
y_pred_lr = lr.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_lr)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.6684152401987852
```

[ ]:
```
#hyperparameter tuning for logistic regression
..from sklearn.model_selection import GridSearchCV
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga']
}
grid_search = GridSearchCV(estimator=lr, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy')
grid_search.fit(X_train_cv, y_train_cv)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
best_params
```

```
  File "/tmp/ipython-input-3370312101.py", line 2
    ..from sklearn.model_selection import GridSearchCV
    ^
SyntaxError: invalid syntax
```

C=10, penalty='l1', solver='liblinear'

[ ]:
```
best_model = LogisticRegression(C=10, penalty='l1', solver='liblinear')
best_model.fit(X_train, y_train)
```

[ ]:
```
LogisticRegression(C=10, penalty='l1', solver='liblinear')
```

[ ]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

y_pred_lr_best = best_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred_lr_best))
print(confusion_matrix(y_test, y_pred_lr_best))
print(classification_report(y_test, y_pred_lr_best))
```

```
Accuracy: 0.7085666955904394
[[8836 3947]
 [3442 9129]]
              precision    recall  f1-score   support

           0       0.72      0.69      0.71     12783
           1       0.70      0.73      0.71     12571

    accuracy                           0.71     25354
   macro avg       0.71      0.71      0.71     25354
weighted avg       0.71      0.71      0.71     25354
```

Feature Importance for Logistic Regression

[ ]:
```
### 2. Feature Selection using Logistic Regression (L1 penalty) ###
from sklearn.feature_selection import SelectFromModel
import pandas as pd
log_reg = LogisticRegression(penalty='l1', solver='liblinear', C=1.0,␣
↪random_state=42, max_iter=1000)
selector = SelectFromModel(log_reg)
selector.fit(X_train, y_train)

selected_features = X_train.columns[selector.get_support()]
print("\nSelected Features from Logistic Regression (L1):")
print(selected_features.tolist())
```

```
Selected Features from Logistic Regression (L1):
['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'emp_length',
'verification_status', 'open_acc', 'revol_util', 'total_acc',
'initial_list_status', 'mort_acc', 'pub_rec_bankruptcies', 'issue_d_year',
'issue_d_month', 'earliest_cr_line_year', 'earliest_cr_line_month', 'zip',
'home_ownership_MORTGAGE', 'home_ownership_OWN', 'home_ownership_RENT',
```

```
'purpose_car', 'purpose_credit_card', 'purpose_home_improvement',
'purpose_house', 'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
'purpose_other', 'purpose_renewable_energy', 'purpose_small_business',
'purpose_vacation', 'purpose_wedding']
```

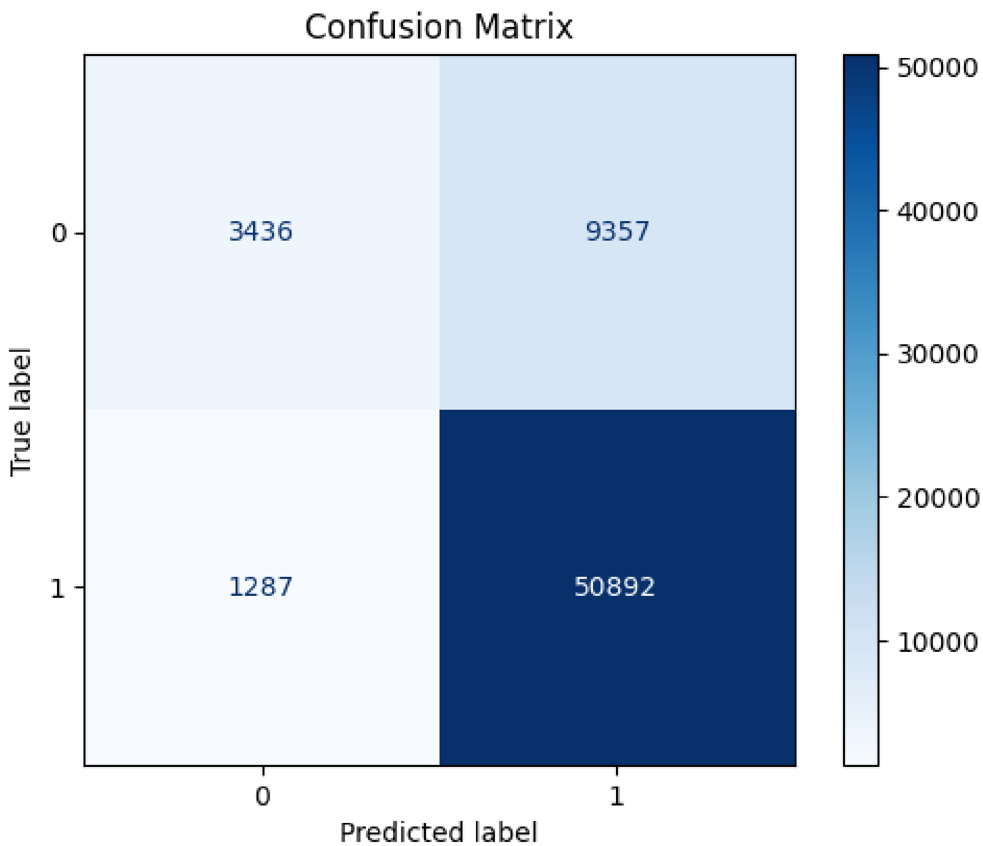
[ ]:
```
#Top features from Logistic Regression (L1) to new df
# Include 'loan_status' in the selection
# Sort the selected_features index and take the top 15
top_lr_features = selected_features.sort_values(ascending=False).tolist()[:15]
new_lr_df = df_encoded[top_lr_features + ['loan_status']]
```

[ ]:
```
#Split to X and y, test and train data and run LR model
y_new_df = new_lr_df['loan_status']
X_new_df = new_lr_df.drop('loan_status', axis=1)

X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_new_df,␣
↪y_new_df, test_size=0.2, random_state=42)

#LR model
lr_new = LogisticRegression()
lr_new.fit(X_new_train, y_new_train)

#predict accuracy
y_pred_lr_new = lr_new.predict(X_new_test)
accuracy = accuracy_score(y_new_test, y_pred_lr_new)
print("Accuracy:", accuracy)
print(classification_report(y_new_test, y_pred_lr_new))
```

```
Accuracy: 0.836175583328203
              precision    recall  f1-score   support

           0       0.73      0.27      0.39     12793
           1       0.84      0.98      0.91     52179

    accuracy                           0.84     64972
   macro avg       0.79      0.62      0.65     64972
weighted avg       0.82      0.84      0.80     64972


/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
```

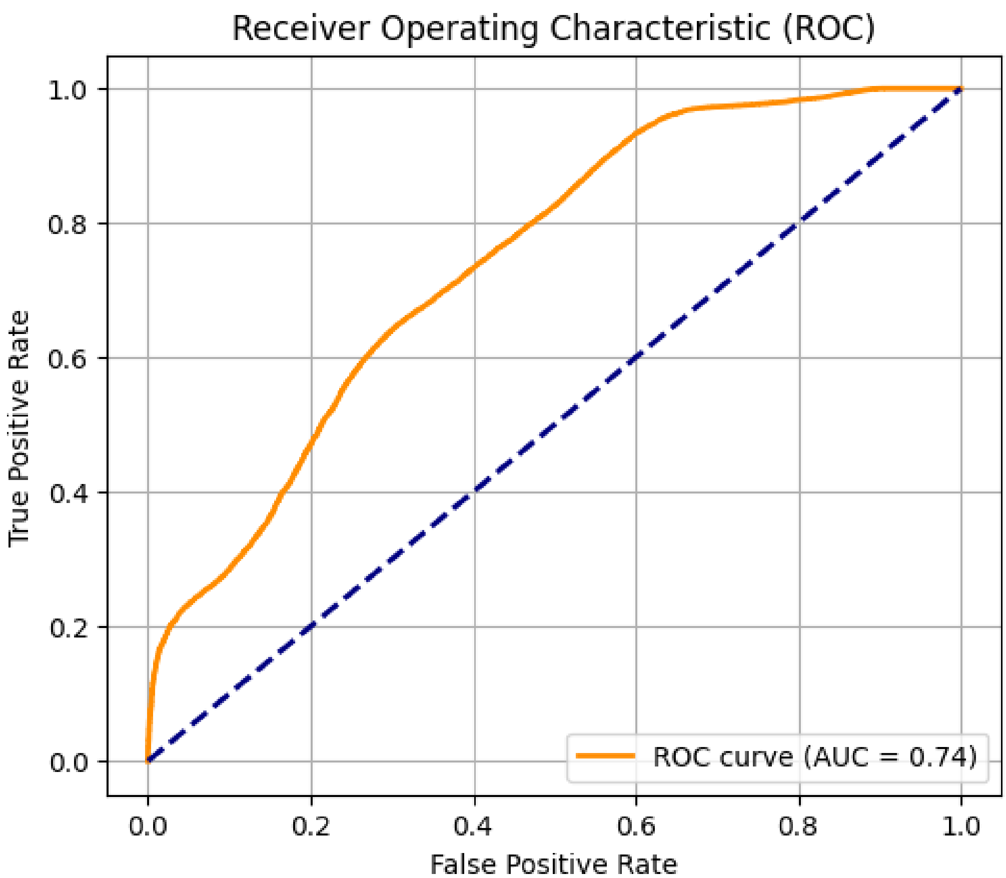
```
n_iter_i = _check_optimize_result(
```

[ ]:
```python
#Confusion Matrix and AUC-ROC curve code
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve, auc,␣
↪ConfusionMatrixDisplay
# Confusion Matrix
cm = confusion_matrix(y_new_test, y_pred_lr_new)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```



[ ]:
```python
# 6. ROC Curve and AUC
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Calculate predicted probabilities for the positive class
y_proba = lr_new.predict_proba(X_new_test)[:, 1]
```

```
fpr, tpr, thresholds = roc_curve(y_new_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %␣
↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



[ ]:
```
#save lr model
#import joblib
#joblib.dump(lr_new, 'lr_model.pkl')
```

###Gradient Boosting Method

[ ]:
```
#GBM machine learning model
from sklearn.ensemble import GradientBoostingClassifier
gbm = GradientBoostingClassifier()
gbm.fit(X_train, y_train)
```

[ ]:
```
GradientBoostingClassifier()
```

[ ]:
```
#Predict and find accuracy
from sklearn.metrics import accuracy_score
y_pred_gbm = gbm.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_gbm)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.8063027530172754
```

[ ]:
```
#hyperparameter tuning for GBM model
from sklearn.model_selection import GridSearchCV
param_grid = {
     'n_estimators': [100, 150],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 4]
}
grid_search = GridSearchCV(estimator=gbm, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy')
grid_search.fit(X_train_cv, y_train_cv)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
best_params
```

learning_rate=0.1, max_depth=4, n_estimators=150

[ ]:
```
#GBM machine learning model
from sklearn.ensemble import GradientBoostingClassifier
gbm_h = GradientBoostingClassifier(learning_rate=0.1, max_depth=4,␣
 ↪n_estimators=150)
gbm_h.fit(X_train, y_train)
```

[ ]:
```
GradientBoostingClassifier(max_depth=4, n_estimators=150)
```

[ ]:
```
#Predict and find accuracy
from sklearn.metrics import accuracy_score
y_pred_gbm_h = gbm_h.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_gbm_h)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.8082748284294391
```

```
[ ]: #Classification matrix or F1-score
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_gbm))
```

```
              precision    recall  f1-score   support

           0       0.80      0.82      0.81     12783
           1       0.81      0.79      0.80     12571

    accuracy                           0.81     25354
   macro avg       0.81      0.81      0.81     25354
weighted avg       0.81      0.81      0.81     25354
```

Feature Importance for GBM

```
[ ]: # 1. Feature importance using Gradient Boosting Machine (GBM)
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.feature_selection import SelectFromModel
import pandas as pd

# Assuming 'gbm' model is already trained
# gbm = GradientBoostingClassifier()
# gbm.fit(X_train, y_train)


feature_importance_gbm = pd.Series(gbm.feature_importances_, index=X_train.
 ↪columns)
print("\nTop Features from GBM:")
print(feature_importance_gbm.sort_values(ascending=False).head(15))
```

```
Top Features from GBM:
zip                        0.829751
grade                      0.106077
int_rate                   0.015608
term                       0.014113
issue_d_year               0.010837
annual_inc                 0.007725
issue_d_month              0.003024
mort_acc                   0.002483
installment                0.001929
revol_util                 0.001684
home_ownership_RENT        0.001611
loan_amnt                  0.001484
open_acc                   0.001239
home_ownership_MORTGAGE    0.001130
verification_status        0.000569
```

```
dtype: float64
```

```
[ ]: #Top features from GBM to new df
     # Include 'loan_status' in the selection
     new_df = df_encoded[feature_importance_gbm.sort_values(ascending=False).
      ↪head(15).index.tolist() + ['loan_status']]
```

```
[ ]: new_df.head()
```

```
[ ]:     zip  grade  int_rate  term  issue_d_year  annual_inc  issue_d_month  \
     0  22690      1     11.44     0          2015    117000.0              1
     1   5113      1     11.99     0          2015     65000.0              1
     2   5113      1     10.49     0          2015     43057.0              1
     3    813      0      6.49     0          2014     54000.0             11
     4  11650      2     17.27     1          2013     55000.0              4

        mort_acc  installment  revol_util  home_ownership_RENT  loan_amnt  \
     0       0.0       329.48        41.8                  1.0    10000.0
     1       3.0       265.68        53.3                  0.0     8000.0
     2       0.0       506.97        92.2                  1.0    15600.0
     3       0.0       220.65        21.5                  1.0     7200.0
     4       1.0       609.33        69.8                  0.0    24375.0

        open_acc  home_ownership_MORTGAGE  verification_status  loan_status
     0      16.0                      0.0                    0            1
     1      17.0                      1.0                    0            1
     2      13.0                      0.0                    1            1
     3       6.0                      0.0                    0            1
     4      13.0                      1.0                    2            0
```

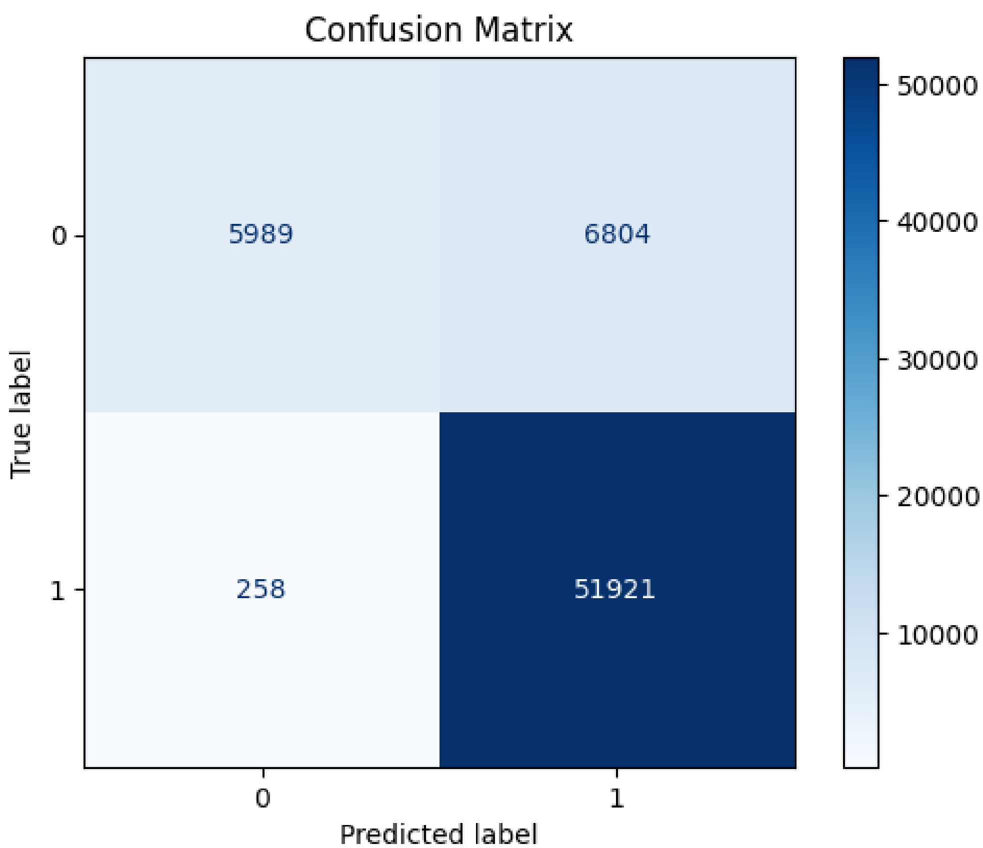
```
[ ]: #Split to X and y, test and train data and run GBM model
     y_new_df = new_df['loan_status']
     X_new_df = new_df.drop('loan_status', axis=1)

     X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_new_df,␣
      ↪y_new_df, test_size=0.2, random_state=42)

     #GBM model
     gbm_new = GradientBoostingClassifier()
     gbm_new.fit(X_new_train, y_new_train)

     #predict accuracy
     y_pred_gbm_new = gbm_new.predict(X_new_test)
     accuracy = accuracy_score(y_new_test, y_pred_gbm_new)
     print("Accuracy:", accuracy)
```

```
Accuracy: 0.8913070245644278
```

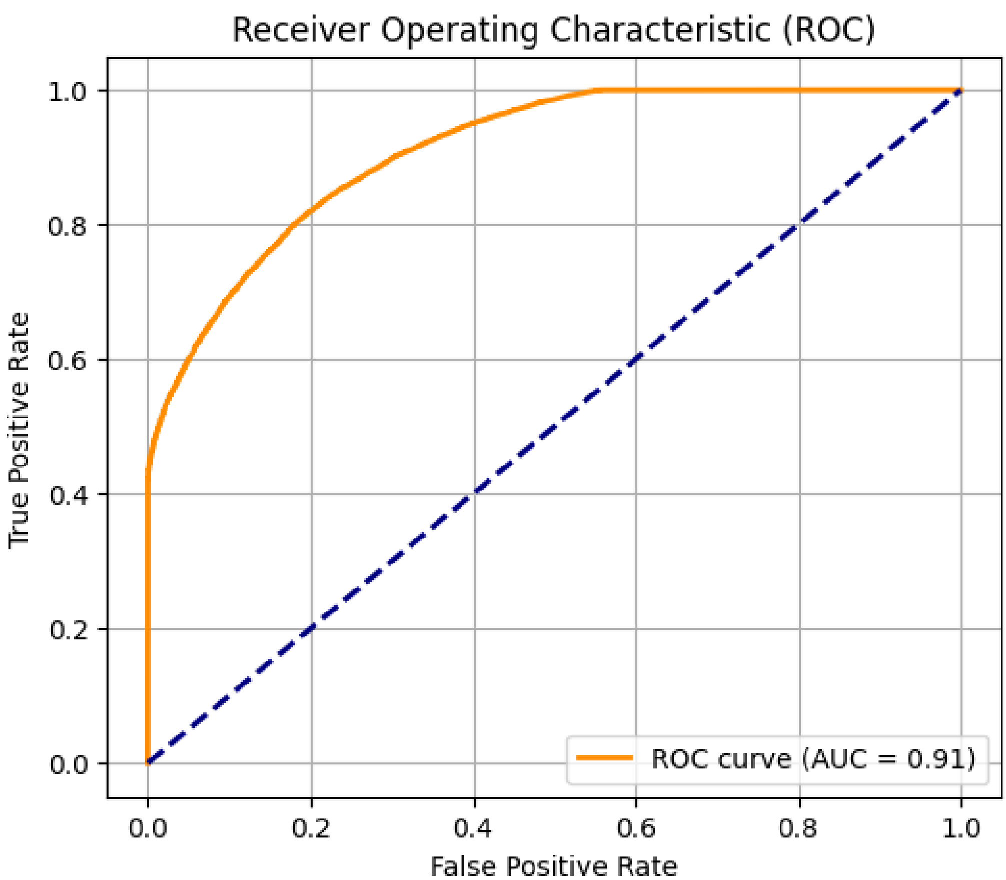
```
[ ]: print(classification_report(y_new_test, y_pred_gbm_new))
```

```
              precision    recall  f1-score   support

           0       0.96      0.47      0.63     12793
           1       0.88      1.00      0.94     52179

    accuracy                           0.89     64972
   macro avg       0.92      0.73      0.78     64972
weighted avg       0.90      0.89      0.88     64972
```

```
[ ]: # Confusion Matrix
cm = confusion_matrix(y_new_test, y_pred_gbm_new)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```



```
[ ]: # 6. ROC Curve and AUC
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Calculate predicted probabilities for the positive class
y_proba = gbm_new.predict_proba(X_new_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_new_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



```
[ ]: #save gbm model
     #import joblib
     #joblib.dump(gbm_new, 'gbm_model.pkl')
```

###Random Forest

```
[ ]: #Random Forest model
     from sklearn.ensemble import RandomForestClassifier
     rf = RandomForestClassifier()
     rf.fit(X_train, y_train)
```

```
[ ]: RandomForestClassifier()
```

```
[ ]: #Predict and find accuracy
     from sklearn.metrics import accuracy_score
     y_pred_rf = rf.predict(X_test)
     accuracy = accuracy_score(y_test, y_pred_rf)
     print("Accuracy:", accuracy)
```

```
Accuracy: 0.7964818174646998
```

```
[ ]: #Hyperparameter tuning for Random Forest
     from sklearn.model_selection import GridSearchCV
     param_grid = {
         'n_estimators': [100, 150, 200],
         'max_depth': [None, 10, 20],
         'min_samples_split': [2, 5, 10],
         'min_samples_leaf': [ 1, 2, 4]
     }
     grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5,␣
      ↪scoring='accuracy')
     grid_search.fit(X_train_cv, y_train_cv)
     best_params = grid_search.best_params_
     best_model = grid_search.best_estimator_
     best_params
```

{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 10, 'n_estimators': 150}

```
[ ]: rf_h = RandomForestClassifier(max_depth=None,
      min_samples_leaf=1,
      min_samples_split=10,
      n_estimators=150)
     rf_h.fit(X_train, y_train)
```

```
[ ]: RandomForestClassifier(min_samples_split=10, n_estimators=150)
```

[ ]:
```
#Predict and find accuracy
from sklearn.metrics import accuracy_score
y_pred_rf = rf_h.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_rf)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7966790250059163
```

Feature Importance for Random Forest

[ ]:
```
# 1. Feature importance using Random Forest
from sklearn.feature_selection import SelectKBest, f_classif

feature_importances = pd.Series(rf.feature_importances_, index=X_train.columns)
important_features_rf = feature_importances.sort_values(ascending=False)

print("\nTop Features from Random Forest:")
print(important_features_rf.head(10))
```

```
Top Features from Random Forest:
zip                     0.307047
int_rate                0.069580
revol_util              0.053619
annual_inc              0.052212
revol_bal               0.051842
installment             0.049085
grade                   0.046517
total_acc               0.041708
loan_amnt               0.040311
earliest_cr_line_year   0.039036
dtype: float64
```

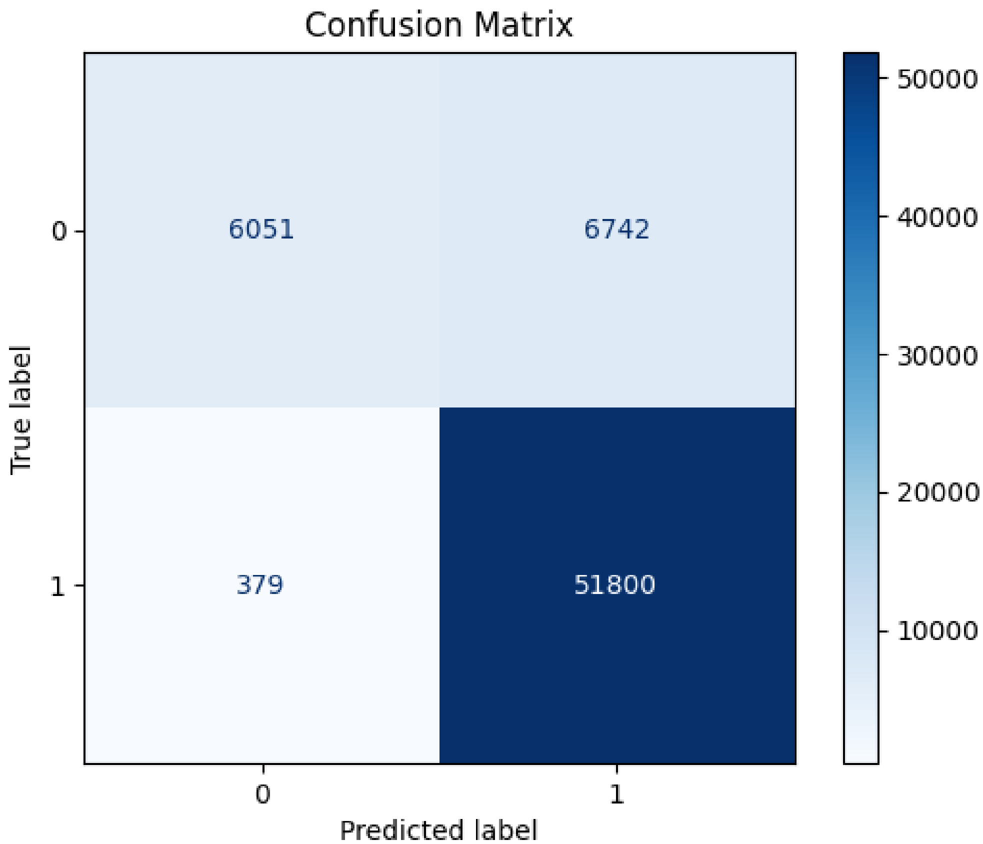
[ ]:
```
top_rf_features = important_features_rf.sort_values(ascending=False).head(15).
 ↪index.tolist()
new_rf_df = df_encoded[top_rf_features + ['loan_status']]
```

[ ]:
```
#Split to X and y, test and train data and run RF model
y_new_df = new_rf_df['loan_status']
X_new_df = new_rf_df.drop('loan_status', axis=1)

X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_new_df,␣
 ↪y_new_df, test_size=0.2, random_state=42)

#LR model
rf_new = RandomForestClassifier()
rf_new.fit(X_new_train, y_new_train)
```

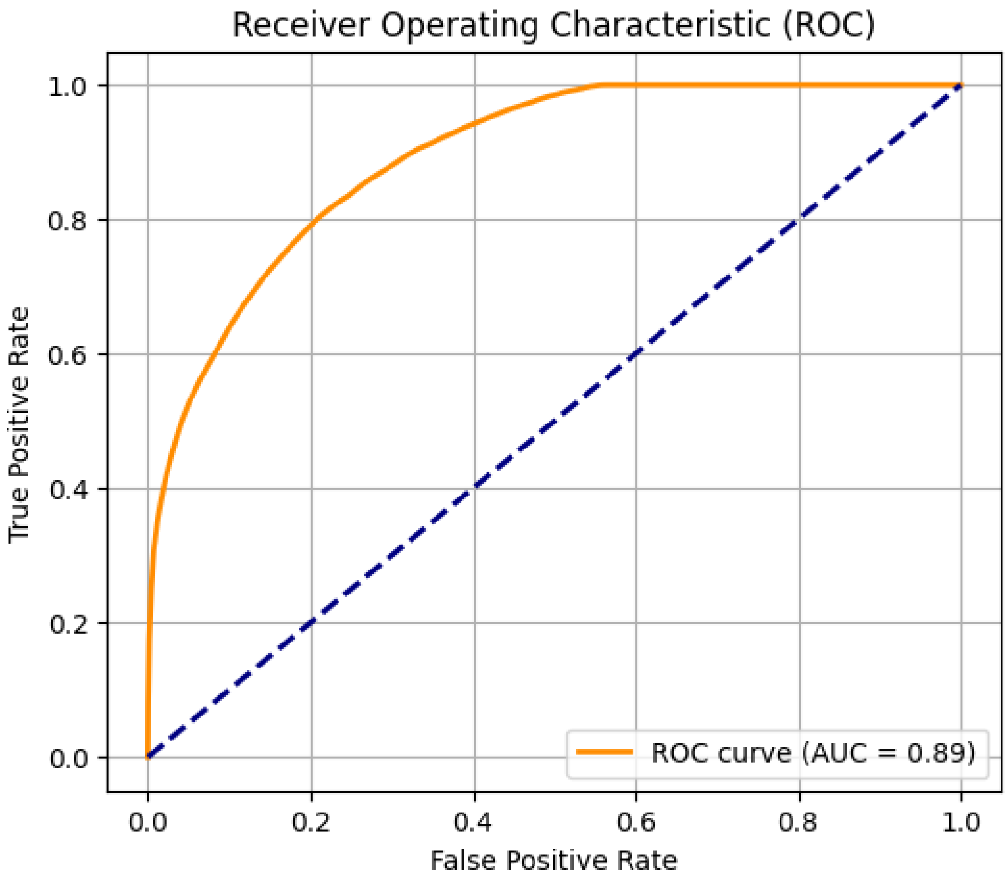
```python
#predict accuracy
y_pred_rf_new = rf_new.predict(X_new_test)
accuracy = accuracy_score(y_new_test, y_pred_rf_new)
print("Accuracy:", accuracy)
print(classification_report(y_new_test, y_pred_rf_new))
```

```
Accuracy: 0.8903989410823124
              precision    recall  f1-score   support

           0       0.94      0.47      0.63     12793
           1       0.88      0.99      0.94     52179

    accuracy                           0.89     64972
   macro avg       0.91      0.73      0.78     64972
weighted avg       0.90      0.89      0.88     64972
```

[ ]:
```python
#Confusion Matrix and AUC-ROC curve code
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve, auc,␣
 ↪ConfusionMatrixDisplay
# Confusion Matrix
cm = confusion_matrix(y_new_test, y_pred_rf_new)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```



[ ]:
```python
# 6. ROC Curve and AUC
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Calculate predicted probabilities for the positive class
y_proba = rf_new.predict_proba(X_new_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_new_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



[ ]:
```
#save rf model
#import joblib
#joblib.dump(rf, 'rf_model.pkl')
```

###Support Vector Machine

[ ]:
```
from sklearn.svm import LinearSVC
from sklearn.calibration import CalibratedClassifierCV

# LinearSVC does NOT support predict_proba directly
base_model = LinearSVC(random_state=42, max_iter=10000)
svm = CalibratedClassifierCV(base_model)

svm.fit(X_train, y_train)
```

[ ]:
```
CalibratedClassifierCV(estimator=LinearSVC(max_iter=10000, random_state=42))
```

[ ]:
```
#Predict and find accuracy
from sklearn.metrics import accuracy_score
```

```
y_pred_svm = svm.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_svm)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7016644316478662
```

[ ]:
```
#Hyperparameter tuning for SVM
from sklearn.model_selection import GridSearchCV
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto']
}
grid_search = GridSearchCV(estimator=svm, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy')
grid_search.fit(X_train_cv, y_train_cv)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
best_params
```

Feature Importance for SVM

[ ]:
```
from sklearn.inspection import permutation_importance

#  Use a smaller sample from X_test if dataset is large
sample_size = 500  # Adjust as needed
X_test_sample = X_test[:sample_size]
y_test_sample = y_test[:sample_size]

result = permutation_importance(
    svm,
    X_test_sample,
    y_test_sample,
    n_repeats=5,
    random_state=42,
    n_jobs=-1
)

# If using NumPy array instead of DataFrame
if isinstance(X_test_sample, pd.DataFrame):
    feature_names = X_test_sample.columns
else:
    feature_names = [f"Feature_{i}" for i in range(X_test_sample.shape[1])]

# Organize and sort importances
perm_importance_svm = pd.Series(result.importances_mean, index=feature_names)
perm_importance_svm = perm_importance_svm.sort_values(ascending=False)
```

```
# Print top features
print("\nTop Feature Importances from Permutation Importance (SVM):")
print(perm_importance_svm.head(10))
```

```
Top Feature Importances from Permutation Importance (SVM):
zip              0.1296
installment      0.0272
int_rate         0.0184
loan_amnt        0.0160
annual_inc       0.0116
open_acc         0.0084
total_acc        0.0080
issue_d_month    0.0064
emp_length       0.0060
mort_acc         0.0056
dtype: float64
```

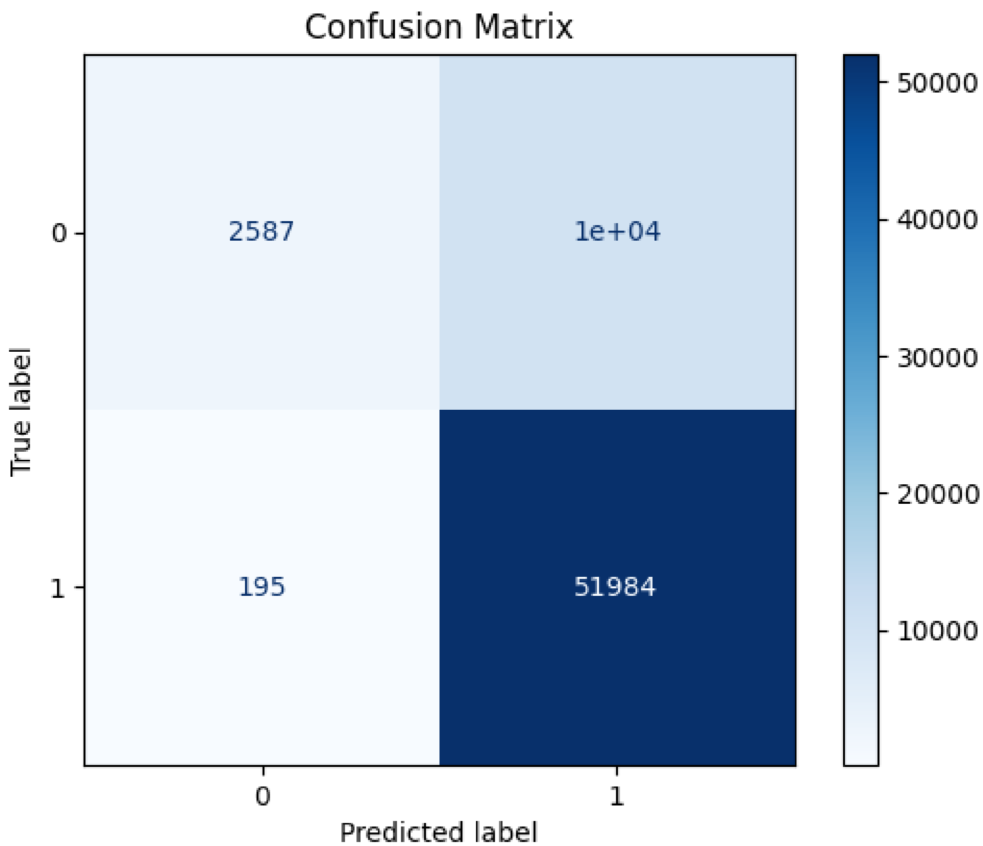
[ ]:
```
top_svm_features = perm_importance_svm.sort_values(ascending=False).head(15).
    ↪index.tolist()
new_svm_df = df_encoded[top_svm_features + ['loan_status']]
```

[ ]:
```
#Split to X and y, test and train data and run SVM model
y_new_df = new_svm_df['loan_status']
X_new_df = new_svm_df.drop('loan_status', axis=1)

X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_new_df,␣
    ↪y_new_df, test_size=0.2, random_state=42)

#SVM model
svm_new = LinearSVC(random_state=42, max_iter=10000)
svm_new.fit(X_new_train, y_new_train)

#predict accuracy
y_pred_svm_new = svm_new.predict(X_new_test)
accuracy = accuracy_score(y_new_test, y_pred_svm_new)
print("Accuracy:", accuracy)
print(classification_report(y_new_test, y_pred_svm_new))
```

```
Accuracy: 0.8399156559748815
              precision    recall  f1-score   support

           0       0.93      0.20      0.33     12793
           1       0.84      1.00      0.91     52179

    accuracy                           0.84     64972
```

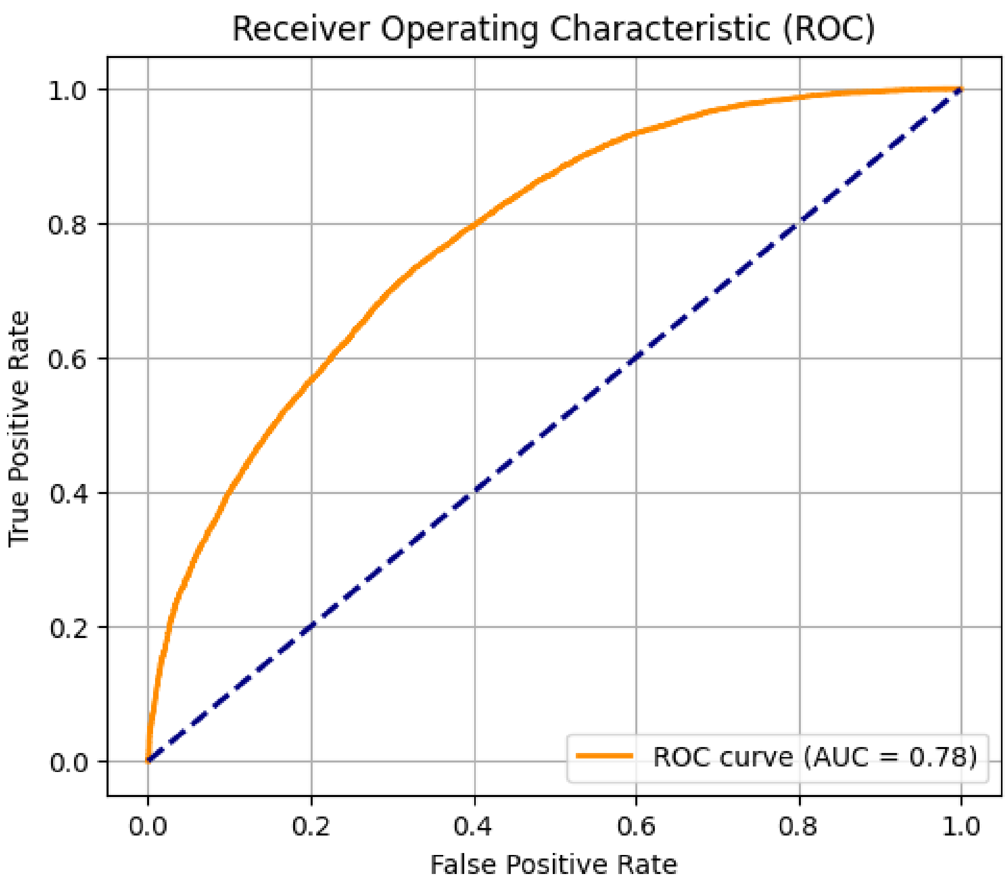
```
   macro avg       0.88      0.60      0.62     64972
weighted avg       0.85      0.84      0.80     64972
```

[ ]:
```
#Confusion Matrix and AUC-ROC curve code
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve, auc,␣
↪ConfusionMatrixDisplay
# Confusion Matrix
cm = confusion_matrix(y_new_test, y_pred_svm_new)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```



[ ]:
```
# 6. ROC Curve and AUC
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Calculate predicted probabilities for the positive class
```

```
y_proba = svm.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



[ ]:
```
#save svm model
#import joblib
#joblib.dump(svm, 'svm_model.pkl')
```

#ANN (Deep Learning)

```
[ ]: #Run ANN for the current dataset
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

#Artificial Neural network model
model = Sequential()
model.add(Dense(64, activation='relu', input_dim=X_new_train.shape[1]))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

#predict ANN accuracy
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
model.fit(X_new_train, y_new_train, epochs=20, batch_size=32,␣
 ↪validation_split=0.2)
loss, accuracy = model.evaluate(X_new_test, y_new_test)
print(f"Test Loss: {loss:.4f}, Test Accuracy: {accuracy:.4f}")
```

```
Epoch 1/20
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
6498/6498             18s 3ms/step -
accuracy: 0.7302 - loss: 66.3755 - val_accuracy: 0.8278 - val_loss: 8.9592
Epoch 2/20
6498/6498             22s 3ms/step -
accuracy: 0.7620 - loss: 13.9426 - val_accuracy: 0.8104 - val_loss: 7.6403
Epoch 3/20
6498/6498             20s 3ms/step -
accuracy: 0.7820 - loss: 5.7421 - val_accuracy: 0.8221 - val_loss: 7.3997
Epoch 4/20
6498/6498             23s 3ms/step -
accuracy: 0.7950 - loss: 1.8184 - val_accuracy: 0.8843 - val_loss: 0.4140
Epoch 5/20
6498/6498             18s 3ms/step -
accuracy: 0.8438 - loss: 0.5632 - val_accuracy: 0.8768 - val_loss: 0.3450
Epoch 6/20
6498/6498             17s 3ms/step -
accuracy: 0.8723 - loss: 0.3405 - val_accuracy: 0.8149 - val_loss: 0.4267
Epoch 7/20
```

```
6498/6498                17s 3ms/step -
accuracy: 0.8240 - loss: 0.4129 - val_accuracy: 0.8076 - val_loss: 0.4417
Epoch 8/20
6498/6498                21s 3ms/step -
accuracy: 0.8287 - loss: 0.4048 - val_accuracy: 0.8193 - val_loss: 0.4161
Epoch 9/20
6498/6498                17s 3ms/step -
accuracy: 0.8163 - loss: 0.4211 - val_accuracy: 0.8040 - val_loss: 0.4769
Epoch 10/20
6498/6498                28s 4ms/step -
accuracy: 0.8174 - loss: 0.4212 - val_accuracy: 0.8215 - val_loss: 0.4125
Epoch 11/20
6498/6498                35s 3ms/step -
accuracy: 0.8220 - loss: 0.4141 - val_accuracy: 0.8039 - val_loss: 0.4560
Epoch 12/20
6498/6498                18s 3ms/step -
accuracy: 0.8054 - loss: 0.4378 - val_accuracy: 0.8039 - val_loss: 0.4361
Epoch 13/20
6498/6498                20s 3ms/step -
accuracy: 0.8046 - loss: 0.4361 - val_accuracy: 0.8039 - val_loss: 0.4361
Epoch 14/20
6498/6498                21s 3ms/step -
accuracy: 0.8052 - loss: 0.4356 - val_accuracy: 0.8039 - val_loss: 0.4361
Epoch 15/20
6498/6498                17s 3ms/step -
accuracy: 0.8046 - loss: 0.4369 - val_accuracy: 0.8039 - val_loss: 0.4360
Epoch 16/20
6498/6498                17s 3ms/step -
accuracy: 0.8051 - loss: 0.4358 - val_accuracy: 0.8039 - val_loss: 0.4360
Epoch 17/20
6498/6498                23s 3ms/step -
accuracy: 0.8067 - loss: 0.4336 - val_accuracy: 0.8039 - val_loss: 0.4360
Epoch 18/20
6498/6498                16s 3ms/step -
accuracy: 0.8060 - loss: 0.4349 - val_accuracy: 0.8039 - val_loss: 0.4360
Epoch 19/20
6498/6498                22s 3ms/step -
accuracy: 0.8076 - loss: 0.4326 - val_accuracy: 0.8039 - val_loss: 0.4360
Epoch 20/20
6498/6498                17s 3ms/step -
accuracy: 0.8059 - loss: 0.4349 - val_accuracy: 0.8039 - val_loss: 0.4360
2031/2031                3s 2ms/step -
accuracy: 0.8032 - loss: 0.4375
Test Loss: 0.4385, Test Accuracy: 0.8031
```

[ ]:
```
# 1. Scaling
scaler = StandardScaler()
```

```python
X_train_scaled = scaler.fit_transform(X_new_train)
X_test_scaled = scaler.transform(X_new_test)

# 2. Model
model = Sequential()
model.add(Dense(128, activation='relu', input_dim=X_new_train.shape[1]))
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

# 3. Compile
model.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

# 4. Optional: class weights
from sklearn.utils import class_weight
class_weights = class_weight.compute_class_weight(class_weight='balanced',␣
↪classes=np.unique(y_train), y=y_new_train)
class_weight_dict = dict(enumerate(class_weights))

# 5. Train
model.fit(X_train_scaled, y_new_train, epochs=50, batch_size=32,␣
↪validation_split=0.2, class_weight=class_weight_dict)

# 6. Evaluate
loss, accuracy = model.evaluate(X_test_scaled, y_new_test)
print(f"Test Loss: {loss:.4f}, Test Accuracy: {accuracy:.4f}")
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Epoch 1/50
6498/6498                 21s 3ms/step -
accuracy: 0.7400 - loss: 0.5232 - val_accuracy: 0.7733 - val_loss: 0.4225
Epoch 2/50
6498/6498                 22s 3ms/step -
accuracy: 0.8042 - loss: 0.3907 - val_accuracy: 0.8208 - val_loss: 0.3663
Epoch 3/50
6498/6498                 23s 3ms/step -
accuracy: 0.8055 - loss: 0.3888 - val_accuracy: 0.8115 - val_loss: 0.3709
Epoch 4/50
6498/6498                 41s 3ms/step -
accuracy: 0.8054 - loss: 0.3855 - val_accuracy: 0.8056 - val_loss: 0.3822
Epoch 5/50
6498/6498                 38s 3ms/step -
```

```
accuracy: 0.8098 - loss: 0.3820 - val_accuracy: 0.7939 - val_loss: 0.3835
Epoch 6/50
6498/6498             22s 3ms/step -
accuracy: 0.8052 - loss: 0.3820 - val_accuracy: 0.8017 - val_loss: 0.3782
Epoch 7/50
6498/6498             20s 3ms/step -
accuracy: 0.8082 - loss: 0.3781 - val_accuracy: 0.8095 - val_loss: 0.3662
Epoch 8/50
6498/6498             21s 3ms/step -
accuracy: 0.8094 - loss: 0.3699 - val_accuracy: 0.8037 - val_loss: 0.3617
Epoch 9/50
6498/6498             19s 3ms/step -
accuracy: 0.8088 - loss: 0.3586 - val_accuracy: 0.8168 - val_loss: 0.3417
Epoch 10/50
6498/6498             19s 3ms/step -
accuracy: 0.8038 - loss: 0.3559 - val_accuracy: 0.8266 - val_loss: 0.3318
Epoch 11/50
6498/6498             21s 3ms/step -
accuracy: 0.8072 - loss: 0.3524 - val_accuracy: 0.8111 - val_loss: 0.3434
Epoch 12/50
6498/6498             18s 3ms/step -
accuracy: 0.8046 - loss: 0.3499 - val_accuracy: 0.8117 - val_loss: 0.3359
Epoch 13/50
6498/6498             18s 3ms/step -
accuracy: 0.8066 - loss: 0.3476 - val_accuracy: 0.8058 - val_loss: 0.3435
Epoch 14/50
6498/6498             22s 3ms/step -
accuracy: 0.8064 - loss: 0.3478 - val_accuracy: 0.8132 - val_loss: 0.3380
Epoch 15/50
6498/6498             19s 3ms/step -
accuracy: 0.8040 - loss: 0.3471 - val_accuracy: 0.8001 - val_loss: 0.3538
Epoch 16/50
6498/6498             18s 3ms/step -
accuracy: 0.8065 - loss: 0.3487 - val_accuracy: 0.8032 - val_loss: 0.3474
Epoch 17/50
6498/6498             21s 3ms/step -
accuracy: 0.8084 - loss: 0.3482 - val_accuracy: 0.7980 - val_loss: 0.3525
Epoch 18/50
6498/6498             41s 3ms/step -
accuracy: 0.8043 - loss: 0.3462 - val_accuracy: 0.8045 - val_loss: 0.3593
Epoch 19/50
6498/6498             40s 3ms/step -
accuracy: 0.8100 - loss: 0.3473 - val_accuracy: 0.7995 - val_loss: 0.3538
Epoch 20/50
6498/6498             18s 3ms/step -
accuracy: 0.8083 - loss: 0.3467 - val_accuracy: 0.7967 - val_loss: 0.3541
Epoch 21/50
6498/6498             21s 3ms/step -
```

```
accuracy: 0.8064 - loss: 0.3454 - val_accuracy: 0.8045 - val_loss: 0.3470
Epoch 22/50
6498/6498            19s 3ms/step -
accuracy: 0.8043 - loss: 0.3468 - val_accuracy: 0.8070 - val_loss: 0.3532
Epoch 23/50
6498/6498            18s 3ms/step -
accuracy: 0.8083 - loss: 0.3461 - val_accuracy: 0.8198 - val_loss: 0.3375
Epoch 24/50
6498/6498            18s 3ms/step -
accuracy: 0.8081 - loss: 0.3455 - val_accuracy: 0.7904 - val_loss: 0.3620
Epoch 25/50
6498/6498            18s 3ms/step -
accuracy: 0.8069 - loss: 0.3457 - val_accuracy: 0.8150 - val_loss: 0.3413
Epoch 26/50
6498/6498            21s 3ms/step -
accuracy: 0.8084 - loss: 0.3445 - val_accuracy: 0.7964 - val_loss: 0.3525
Epoch 27/50
6498/6498            18s 3ms/step -
accuracy: 0.8102 - loss: 0.3423 - val_accuracy: 0.8081 - val_loss: 0.3441
Epoch 28/50
6498/6498            21s 3ms/step -
accuracy: 0.8092 - loss: 0.3433 - val_accuracy: 0.8072 - val_loss: 0.3496
Epoch 29/50
6498/6498            18s 3ms/step -
accuracy: 0.8077 - loss: 0.3445 - val_accuracy: 0.8109 - val_loss: 0.3443
Epoch 30/50
6498/6498            18s 3ms/step -
accuracy: 0.8099 - loss: 0.3418 - val_accuracy: 0.8115 - val_loss: 0.3432
Epoch 31/50
6498/6498            18s 3ms/step -
accuracy: 0.8083 - loss: 0.3435 - val_accuracy: 0.7989 - val_loss: 0.3535
Epoch 32/50
6498/6498            21s 3ms/step -
accuracy: 0.8088 - loss: 0.3452 - val_accuracy: 0.7991 - val_loss: 0.3552
Epoch 33/50
6498/6498            18s 3ms/step -
accuracy: 0.8107 - loss: 0.3436 - val_accuracy: 0.8173 - val_loss: 0.3320
Epoch 34/50
6498/6498            21s 3ms/step -
accuracy: 0.8095 - loss: 0.3415 - val_accuracy: 0.8077 - val_loss: 0.3493
Epoch 35/50
6498/6498            20s 3ms/step -
accuracy: 0.8117 - loss: 0.3422 - val_accuracy: 0.8079 - val_loss: 0.3436
Epoch 36/50
6498/6498            20s 3ms/step -
accuracy: 0.8121 - loss: 0.3385 - val_accuracy: 0.8075 - val_loss: 0.3538
Epoch 37/50
6498/6498            20s 3ms/step -
```

```
accuracy: 0.8109 - loss: 0.3429 - val_accuracy: 0.7822 - val_loss: 0.3772
Epoch 38/50
6498/6498               18s 3ms/step -
accuracy: 0.8094 - loss: 0.3432 - val_accuracy: 0.8053 - val_loss: 0.3533
Epoch 39/50
6498/6498               23s 3ms/step -
accuracy: 0.8096 - loss: 0.3405 - val_accuracy: 0.7841 - val_loss: 0.3806
Epoch 40/50
6498/6498               17s 3ms/step -
accuracy: 0.8103 - loss: 0.3432 - val_accuracy: 0.7910 - val_loss: 0.3664
Epoch 41/50
6498/6498               18s 3ms/step -
accuracy: 0.8088 - loss: 0.3420 - val_accuracy: 0.7994 - val_loss: 0.3526
Epoch 42/50
6498/6498               18s 3ms/step -
accuracy: 0.8101 - loss: 0.3383 - val_accuracy: 0.8082 - val_loss: 0.3518
Epoch 43/50
6498/6498               19s 3ms/step -
accuracy: 0.8133 - loss: 0.3366 - val_accuracy: 0.8005 - val_loss: 0.3621
Epoch 44/50
6498/6498               18s 3ms/step -
accuracy: 0.8126 - loss: 0.3400 - val_accuracy: 0.8010 - val_loss: 0.3523
Epoch 45/50
6498/6498               18s 3ms/step -
accuracy: 0.8107 - loss: 0.3371 - val_accuracy: 0.8125 - val_loss: 0.3420
Epoch 46/50
6498/6498               18s 3ms/step -
accuracy: 0.8099 - loss: 0.3388 - val_accuracy: 0.8112 - val_loss: 0.3436
Epoch 47/50
6498/6498               20s 3ms/step -
accuracy: 0.8094 - loss: 0.3403 - val_accuracy: 0.7897 - val_loss: 0.3711
Epoch 48/50
6498/6498               18s 3ms/step -
accuracy: 0.8112 - loss: 0.3387 - val_accuracy: 0.8021 - val_loss: 0.3556
Epoch 49/50
6498/6498               20s 3ms/step -
accuracy: 0.8120 - loss: 0.3396 - val_accuracy: 0.8137 - val_loss: 0.3471
Epoch 50/50
6498/6498               19s 3ms/step -
accuracy: 0.8132 - loss: 0.3387 - val_accuracy: 0.7915 - val_loss: 0.3610
2031/2031               3s 2ms/step -
accuracy: 0.7916 - loss: 0.3622
Test Loss: 0.3630, Test Accuracy: 0.7922
```

#Best Model Evaluation

[ ]:
```
import pandas as pd
import numpy as np
```

```
import os
import joblib
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score

# ------------------- Load Dataset -------------------
df_path = "/content/loan_data_cleaned.csv"
df = pd.read_csv(df_path)

# ------------------- Extract Year from Date Column -------------------
if 'earliest_cr_line' in df.columns:
    df['earliest_cr_line_year'] = pd.to_datetime(
        df['earliest_cr_line'], errors='coerce').dt.year

# ------------------- Define Feature Set -------------------
possible_features = [
    'zip',  # optional
    'earliest_cr_line_year',
    'int_rate', 'revol_bal', 'revol_util',
    'annual_inc', 'installment', 'total_acc',
    'loan_amnt', 'open_acc'
]

# Use only existing features
features = [col for col in possible_features if col in df.columns]
missing = [col for col in possible_features if col not in df.columns]

print(f"  Using features: {features}")
if missing:
    print(f"  Skipping missing columns: {missing}")

# ------------------- Target Processing -------------------
target = 'loan_status'
if df[target].dtype == 'object':
    le = LabelEncoder()
    df[target] = le.fit_transform(df[target])

# ------------------- Feature / Target Split -------------------
X = df[features]
y = df[target]

# ------------------- Train-Test Split -------------------
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# -------------------- Define Pipeline --------------------
pipeline = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler()),  # Optional but good for many ML models
    ('model', GradientBoostingClassifier())
])

# -------------------- Train Model --------------------
pipeline.fit(X_train, y_train)

# -------------------- Evaluate Model --------------------
y_pred = pipeline.predict(X_test)
print("\n Classification Report:\n", classification_report(y_test, y_pred))
print(f" Accuracy: {accuracy_score(y_test, y_pred)*100:.2f}%")

# -------------------- Save Pipeline & Features --------------------
os.makedirs("models", exist_ok=True)
joblib.dump(pipeline, "models/gbm_pipeline.pkl")
joblib.dump(features, "models/model_columns.pkl")
print("\n Pipeline saved as 'models/gbm_pipeline.pkl'")
print(" Feature columns saved as 'models/model_columns.pkl'")
```

```
 Using features: ['zip', 'earliest_cr_line_year', 'int_rate', 'revol_bal',
'revol_util', 'annual_inc', 'installment', 'total_acc', 'loan_amnt', 'open_acc']

 Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.45      0.62     12793
           1       0.88      1.00      0.94     52179

    accuracy                           0.89     64972
   macro avg       0.94      0.72      0.78     64972
weighted avg       0.90      0.89      0.87     64972

 Accuracy: 89.04%

 Pipeline saved as 'models/gbm_pipeline.pkl'
 Feature columns saved as 'models/model_columns.pkl'
```