```
# importing necessary libraries
import pandas as pd
```

```
df = pd.read_excel("Tillit_Data_Science_Tech_Test.xlsx", sheet_name="data")
df.head()
```

	borrower_id	loan_amnt	term	emp_title	emp_length	home_ownership	annual_inc
0	537185	16075.0	60 months	NaN	NaN	MORTGAGE	50289.0
1	1810804	8000.0	36 months	Graydon Head & Ritchey LLP	10+ years	MORTGAGE	64000.0
2	388855	23700.0	36 months	Director of IT	3 years	RENT	88000.0
3	1137067	1200.0	36 months	NaN	NaN	MORTGAGE	81000.0
4	14585	3500.0	36 months	NaN	NaN	RENT	11736.0

5 rows × 78 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41029 entries, 0 to 41028
Data columns (total 78 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   borrower_id                     41029 non-null  int64
 1   loan_amnt                       41006 non-null  float64
 2   term                            41029 non-null  object
 3   emp_title                       36311 non-null  object
 4   emp_length                      36628 non-null  object
 5   home_ownership                  41029 non-null  object
 6   annual_inc                      41029 non-null  float64
 7   outcome                         41029 non-null  object
 8   purpose                         41029 non-null  object
 9   addr_state                      41029 non-null  object
 10  dti                             41029 non-null  float64
 11  delinq_2yrs                     41029 non-null  int64
 12  earliest_cr_line                41029 non-null  datetime64[ns]
 13  inq_last_6mths                  41029 non-null  int64
 14  mths_since_last_delinq          19875 non-null  float64
 15  mths_since_last_record          6816 non-null   float64
 16  open_acc                        41029 non-null  int64
 17  pub_rec                         41029 non-null  int64
 18  revol_bal                       41029 non-null  int64
 19  revol_util                      41005 non-null  float64
 20  total_acc                       41029 non-null  int64
 21  collections_12_mths_ex_med      41029 non-null  int64
 22  mths_since_last_major_derog     10651 non-null  float64
 23  acc_now_delinq                  41029 non-null  int64
 24  tot_coll_amt                    38625 non-null  float64
 25  tot_cur_bal                     38625 non-null  float64
 26  open_acc_6m                     13351 non-null  float64
 27  open_act_il                     13351 non-null  float64
 28  open_il_12m                     13351 non-null  float64
 29  open_il_24m                     13351 non-null  float64
 30  mths_since_rcnt_il              13015 non-null  float64
 31  total_bal_il                    13351 non-null  float64
 32  il_util                         11674 non-null  float64
 33  open_rv_12m                     13351 non-null  float64
 34  open_rv_24m                     13351 non-null  float64
 35  max_bal_bc                      13351 non-null  float64
 36  all_util                        13349 non-null  float64
 37  total_rev_hi_lim                38625 non-null  float64
 38  inq_fi                          13351 non-null  float64
 39  total_cu_tl                     13351 non-null  float64
 40  inq_last_12m                    13351 non-null  float64
```

```
 41  acc_open_past_24mths            39380 non-null  float64
 42  avg_cur_bal                     38625 non-null  float64
 43  bc_open_to_buy                  38930 non-null  float64
 44  bc_util                         38902 non-null  float64
 45  chargeoff_within_12_mths        41029 non-null  int64
 46  delinq_amnt                     41029 non-null  int64
 47  mo_sin_old_il_acct              37334 non-null  float64
 48  mo_sin_old_rev_tl_op            38625 non-null  float64
 49  mo_sin_rcnt_rev_tl_op           38625 non-null  float64
 50  mo_sin_rcnt_tl                  38625 non-null  float64
 51  mort_acc                        39380 non-null  float64
 52  mths_since_recent_bc            38960 non-null  float64
```

```
for col in df.columns:
    print(col,":",df[col].isnull().sum())
```

```
total_acc : 0
collections_12_mths_ex_med : 0
mths_since_last_major_derog : 30378
acc_now_delinq : 0
tot_coll_amt : 2404
tot_cur_bal : 2404
open_acc_6m : 27678
open_act_il : 27678
open_il_12m : 27678
open_il_24m : 27678
mths_since_rcnt_il : 28014
total_bal_il : 27678
il_util : 29355
open_rv_12m : 27678
open_rv_24m : 27678
max_bal_bc : 27678
all_util : 27680
total_rev_hi_lim : 2404
inq_fi : 27678
total_cu_tl : 27678
inq_last_12m : 27678
acc_open_past_24mths : 1649
avg_cur_bal : 2404
bc_open_to_buy : 2099
bc_util : 2127
chargeoff_within_12_mths : 0
delinq_amnt : 0
mo_sin_old_il_acct : 3695
mo_sin_old_rev_tl_op : 2404
mo_sin_rcnt_rev_tl_op : 2404
mo_sin_rcnt_tl : 2404
mort_acc : 1649
mths_since_recent_bc : 2069
mths_since_recent_bc_dlq : 31574
mths_since_recent_inq : 5343
mths_since_recent_revol_delinq : 27773
num_accts_ever_120_pd : 2404
num_actv_bc_tl : 2404
num_actv_rev_tl : 2404
num_bc_sats : 1957
num_bc_tl : 2404
num_il_tl : 2404
num_op_rev_tl : 2404
num_rev_accts : 2404
num_rev_tl_bal_gt_0 : 2404
num_sats : 1957
num_tl_120dpd_2m : 4877
num_tl_30dpd : 2404
num_tl_90g_dpd_24m : 2404
num_tl_op_past_12m : 2404
pct_tl_nvr_dlq : 2410
percent_bc_gt_75 : 2110
pub_rec_bankruptcies : 1
tax_liens : 0
tot_hi_cred_lim : 2404
total_bal_ex_mort : 1649
total_bc_limit : 1649
total_il_high_credit_limit : 2404
```

```
categorical_vars = ['term', 'emp_title', 'emp_length', 'home_ownership', 'outcome', 'purpose', 'addr_state']

for var in categorical_vars:
    print(f'Value counts for {var}:')
    print(df[var].value_counts())
    print('\n')
```

```
educational             6
Name: purpose, dtype: int64


Value counts for addr_state:
CA    6180
TX    3409
NY    3262
FL    2755
IL    1576
NJ    1491
GA    1471
PA    1383
OH    1274
NC    1231
VA    1208
MI    1119
MD     970
WA     964
AZ     930
CO     915
MA     855
MN     675
MO     634
IN     629
NV     615
TN     613
CT     589
SC     529
WI     497
OR     492
AL     484
LA     409
KY     399
OK     379
KS     359
UT     312
AR     292
HI     247
NM     240
NH     207
MS     187
WV     178
RI     167
MT     124
DE     117
DC     111
AK     100
WY      96
NE      81
SD      68
VT      65
ME      54
ND      48
ID      39
Name: addr_state, dtype: int64
```

Dropping columns with more than 50% missing values

```
threshold = 0.5
cols_to_drop = df.columns[df.isnull().mean() > threshold]
df.drop(columns=cols_to_drop, inplace=True)
```

Percentage of missing values in the remainging columns

```
for col in df.columns:
    print(col,":",df[col].isnull().sum()/41029*100)
```

```
loan_amnt : 0.05605791025859758
term : 0.0
emp_title : 11.499183504350581
emp_length : 10.726559262960345
home_ownership : 0.0
annual_inc : 0.0
outcome : 0.0
purpose : 0.0
addr_state : 0.0
dti : 0.0
delinq_2yrs : 0.0
earliest_cr_line : 0.0
inq_last_6mths : 0.0
open_acc : 0.0
pub_rec : 0.0
revol_bal : 0.0
revol_util : 0.05849521070462356
total_acc : 0.0
collections_12_mths_ex_med : 0.0
acc_now_delinq : 0.0
tot_coll_amt : 5.85927027224646
tot_cur_bal : 5.85927027224646
total_rev_hi_lim : 5.85927027224646
acc_open_past_24mths : 4.019108435496844
avg_cur_bal : 5.85927027224646
bc_open_to_buy : 5.115893636208535
bc_util : 5.184138048697263
chargeoff_within_12_mths : 0.0
delinq_amnt : 0.0
mo_sin_old_il_acct : 9.005825148066002
mo_sin_old_rev_tl_op : 5.85927027224646
mo_sin_rcnt_rev_tl_op : 5.85927027224646
mo_sin_rcnt_tl : 5.85927027224646
mort_acc : 4.019108435496844
mths_since_recent_bc : 5.042774622827756
mths_since_recent_inq : 13.02249628311682
num_accts_ever_120_pd : 5.85927027224646
num_actv_bc_tl : 5.85927027224646
num_actv_rev_tl : 5.85927027224646
num_bc_sats : 4.769796972872846
num_bc_tl : 5.85927027224646
num_il_tl : 5.85927027224646
num_op_rev_tl : 5.85927027224646
num_rev_accts : 5.85927027224646
num_rev_tl_bal_gt_0 : 5.85927027224646
num_sats : 4.769796972872846
num_tl_120dpd_2m : 11.886714275268712
num_tl_30dpd : 5.85927027224646
num_tl_90g_dpd_24m : 5.85927027224646
num_tl_op_past_12m : 5.85927027224646
pct_tl_nvr_dlq : 5.873894074922616
percent_bc_gt_75 : 5.142703941114822
pub_rec_bankruptcies : 0.0024373004460259817
tax_liens : 0.0
tot_hi_cred_lim : 5.85927027224646
total_bal_ex_mort : 4.019108435496844
total_bc_limit : 4.019108435496844
total_il_high_credit_limit : 5.85927027224646
```

By analysing the percentage of missing values in the remaining columns, the highest missing value percentage is 13%. So we can impute these missing values using SimpleImputer

Imputing missing values for numerical columns

```
from sklearn.impute import SimpleImputer
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns
imputer = SimpleImputer(strategy='median')
```

```
imputer = SimpleImputer(strategy='median')
df[numerical_cols] = imputer.fit_transform(df[numerical_cols])
```

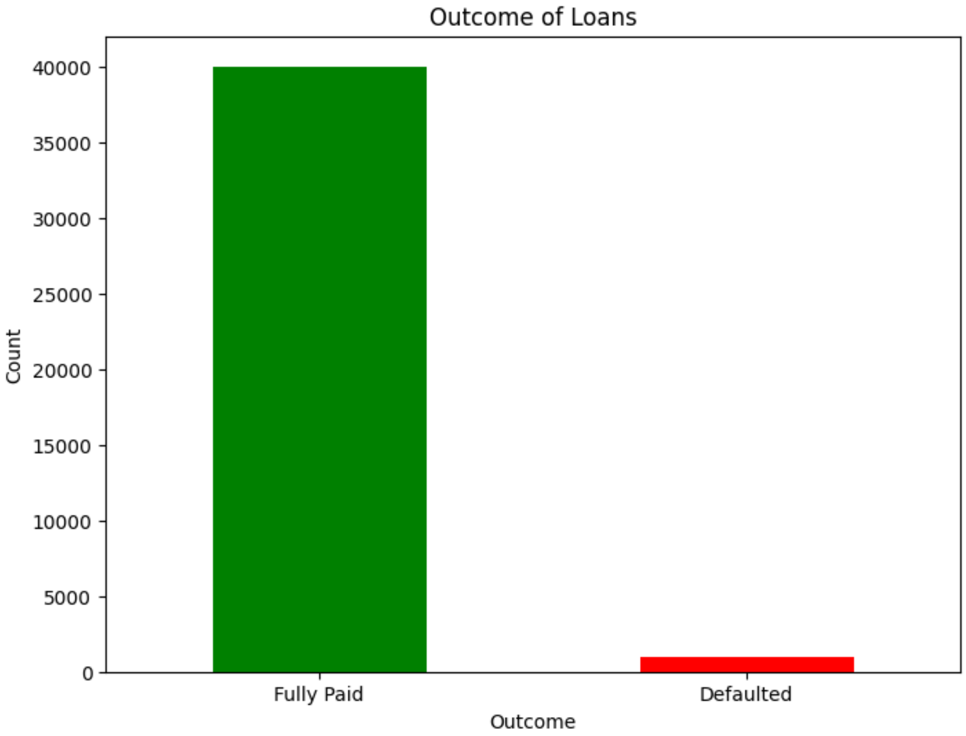
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41029 entries, 0 to 41028
Data columns (total 59 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   borrower_id                 41029 non-null  float64
 1   loan_amnt                   41029 non-null  float64
 2   term                        41029 non-null  object
 3   emp_title                   36311 non-null  object
 4   emp_length                  36628 non-null  object
 5   home_ownership              41029 non-null  object
 6   annual_inc                  41029 non-null  float64
 7   outcome                     41029 non-null  object
 8   purpose                     41029 non-null  object
 9   addr_state                  41029 non-null  object
 10  dti                         41029 non-null  float64
 11  delinq_2yrs                 41029 non-null  float64
 12  earliest_cr_line            41029 non-null  datetime64[ns]
 13  inq_last_6mths              41029 non-null  float64
 14  open_acc                    41029 non-null  float64
 15  pub_rec                     41029 non-null  float64
 16  revol_bal                   41029 non-null  float64
 17  revol_util                  41029 non-null  float64
 18  total_acc                   41029 non-null  float64
 19  collections_12_mths_ex_med  41029 non-null  float64
 20  acc_now_delinq              41029 non-null  float64
 21  tot_coll_amt                41029 non-null  float64
 22  tot_cur_bal                 41029 non-null  float64
 23  total_rev_hi_lim            41029 non-null  float64
 24  acc_open_past_24mths        41029 non-null  float64
 25  avg_cur_bal                 41029 non-null  float64
 26  bc_open_to_buy              41029 non-null  float64
 27  bc_util                     41029 non-null  float64
 28  chargeoff_within_12_mths    41029 non-null  float64
 29  delinq_amnt                 41029 non-null  float64
 30  mo_sin_old_il_acct          41029 non-null  float64
 31  mo_sin_old_rev_tl_op        41029 non-null  float64
 32  mo_sin_rcnt_rev_tl_op       41029 non-null  float64
 33  mo_sin_rcnt_tl              41029 non-null  float64
 34  mort_acc                    41029 non-null  float64
 35  mths_since_recent_bc        41029 non-null  float64
 36  mths_since_recent_inq       41029 non-null  float64
 37  num_accts_ever_120_pd       41029 non-null  float64
 38  num_actv_bc_tl              41029 non-null  float64
 39  num_actv_rev_tl             41029 non-null  float64
 40  num_bc_sats                 41029 non-null  float64
 41  num_bc_tl                   41029 non-null  float64
 42  num_il_tl                   41029 non-null  float64
 43  num_op_rev_tl               41029 non-null  float64
 44  num_rev_accts               41029 non-null  float64
 45  num_rev_tl_bal_gt_0         41029 non-null  float64
 46  num_sats                    41029 non-null  float64
 47  num_tl_120dpd_2m            41029 non-null  float64
 48  num_tl_30dpd                41029 non-null  float64
 49  num_tl_90g_dpd_24m          41029 non-null  float64
 50  num_tl_op_past_12m          41029 non-null  float64
 51  pct_tl_nvr_dlq              41029 non-null  float64
 52  percent_bc_gt_75            41029 non-null  float64
```

```
import matplotlib.pyplot as plt

outcome_counts = df['outcome'].value_counts()

plt.figure(figsize=(8, 6))
outcome_counts.plot(kind='bar', color=['green', 'red'])
plt.title('Outcome of Loans')
plt.xlabel('Outcome')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```



We can say that the data is imbalanced

First building a model to find out the accuracy and then if the accuracy is less then we can balance the data

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings("ignore")
```

```
df.drop(columns=['borrower_id'], inplace=True)
X = df.drop(columns=['outcome'])
y = df['outcome']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Define numeric and categorical features
numeric_features = X_train.select_dtypes(include=['float64', 'int64']).columns
categorical_features = X_train.select_dtypes(include=['object']).columns

# Define transformers for numeric and categorical features
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])

# Combine transformers using ColumnTransformer
```

```
# Combine transformers using ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ])
```

```
# Define the classifier
classifier = LogisticRegression()

# Create the pipeline
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('classifier', classifier)])

# Fit the pipeline
pipeline.fit(X_train, y_train)

# Make predictions
y_pred = pipeline.predict(X_test)
```

```
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.9786741408725322

Classification Report:
               precision    recall  f1-score   support

   Defaulted       0.00      0.00      0.00       175
  Fully Paid       0.98      1.00      0.99      8031

    accuracy                           0.98      8206
   macro avg       0.49      0.50      0.49      8206
weighted avg       0.96      0.98      0.97      8206
```

The accuracy of the model is 97.87% but it seems that the model is performing poorly in predicting minority class "Defaulted" as the precision, recall and f1-score of Defaulted class are all zero

Double-click (or enter) to edit

Using SMOTE to balance the data

```
df[categorical_vars] = df[categorical_vars].astype(str)
label_encoder = LabelEncoder()
df_encoded = df.copy()
for col in categorical_vars:
    df_encoded[col] = label_encoder.fit_transform(df[col])
```

```
import joblib
joblib.dump(label_encoder, 'label_encoder.pkl')
```

```
['label_encoder.pkl']
```

```
X = df_encoded.drop('outcome', axis=1)
y = df_encoded['outcome']
```

```
X.dtypes
```

```
loan_amnt                                float64
term                                       int64
emp_title                                  int64
emp_length                                 int64
home_ownership                             int64
annual_inc                               float64
purpose                                    int64
addr_state                                 int64
dti                                      float64
delinq_2yrs                              float64
earliest_cr_line                  datetime64[ns]
inq_last_6mths                           float64
open_acc                                 float64
pub_rec                                  float64
revol_bal                                float64
revol_util                               float64
total_acc                                float64
collections_12_mths_ex_med               float64
acc_now_delinq                           float64
tot_coll_amt                             float64
tot_cur_bal                              float64
total_rev_hi_lim                         float64
acc_open_past_24mths                     float64
avg_cur_bal                              float64
bc_open_to_buy                           float64
bc_util                                  float64
chargeoff_within_12_mths                 float64
delinq_amnt                              float64
mo_sin_old_il_acct                       float64
mo_sin_old_rev_tl_op                     float64
mo_sin_rcnt_rev_tl_op                    float64
mo_sin_rcnt_tl                           float64
mort_acc                                 float64
mths_since_recent_bc                     float64
mths_since_recent_inq                    float64
num_accts_ever_120_pd                    float64
num_actv_bc_tl                           float64
num_actv_rev_tl                          float64
num_bc_sats                              float64
num_bc_tl                                float64
num_il_tl                                float64
num_op_rev_tl                            float64
num_rev_accts                            float64
num_rev_tl_bal_gt_0                      float64
num_sats                                 float64
num_tl_120dpd_2m                         float64
num_tl_30dpd                             float64
num_tl_90g_dpd_24m                       float64
num_tl_op_past_12m                       float64
pct_tl_nvr_dlq                           float64
percent_bc_gt_75                         float64
pub_rec_bankruptcies                     float64
tax_liens                                float64
tot_hi_cred_lim                          float64
total_bal_ex_mort                        float64
total_bc_limit                           float64
total_il_high_credit_limit               float64
dtype: object
```

```
y.dtype
```

```
dtype('int64')
```

```
X = X.drop(columns=['earliest_cr_line'])
```

```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.5994254309268049
              precision    recall  f1-score   support

           0       0.58      0.71      0.64      7995
           1       0.63      0.49      0.55      8017

    accuracy                           0.60     16012
   macro avg       0.60      0.60      0.59     16012
weighted avg       0.60      0.60      0.59     16012
```

The accuracy was dropped but still got a good recall, precision and f1-score for two classes

Trying out other methods

```
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)
rf_y_pred = rf_classifier.predict(X_test)
print("Random Forest Classifier:")
print(classification_report(y_test, rf_y_pred))
```

```
Random Forest Classifier:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99      7995
           1       0.98      1.00      0.99      8017

    accuracy                           0.99     16012
   macro avg       0.99      0.99      0.99     16012
weighted avg       0.99      0.99      0.99     16012
```

```
from sklearn.ensemble import GradientBoostingClassifier
gb_classifier = GradientBoostingClassifier(n_estimators=100, random_state=42)
gb_classifier.fit(X_train, y_train)
gb_y_pred = gb_classifier.predict(X_test)
print("Gradient Boosting Classifier:")
print(classification_report(y_test, gb_y_pred))
```

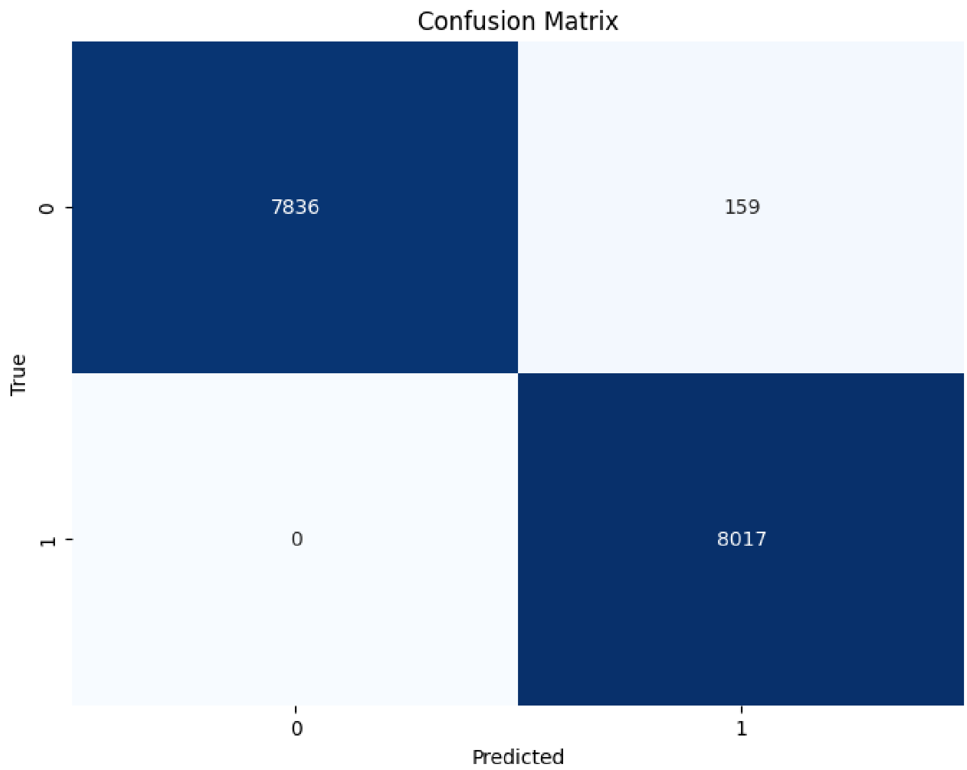
```
Gradient Boosting Classifier:
              precision    recall  f1-score   support

           0       1.00      0.94      0.97      7995
           1       0.95      1.00      0.97      8017

    accuracy                           0.97     16012
   macro avg       0.97      0.97      0.97     16012
weighted avg       0.97      0.97      0.97     16012
```

Random Forest Classifer is the best of both and it is classifying both models with highest accuracy

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
cm = confusion_matrix(y_test, rf_y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```




```
import joblib
joblib.dump(rf_classifier, 'random_forest_model.pkl')
```

```
    ['random_forest_model.pkl']
```

```
X_test.columns
```

```
    Index(['loan_amnt', 'term', 'emp_title', 'emp_length', 'home_ownership',
           'annual_inc', 'purpose', 'addr_state', 'dti', 'delinq_2yrs',
           'inq_last_6mths', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util',
           'total_acc', 'collections_12_mths_ex_med', 'acc_now_delinq',
           'tot_coll_amt', 'tot_cur_bal', 'total_rev_hi_lim',
           'acc_open_past_24mths', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
           'chargeoff_within_12_mths', 'delinq_amnt', 'mo_sin_old_il_acct',
           'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
           'mort_acc', 'mths_since_recent_bc', 'mths_since_recent_inq',
           'num_accts_ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl',
           'num_bc_sats', 'num_bc_tl', 'num_il_tl', 'num_op_rev_tl',
           'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats', 'num_tl_120dpd_2m',
           'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12m',
           'pct_tl_nvr_dlq', 'percent_bc_gt_75', 'pub_rec_bankruptcies',
           'tax_liens', 'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
           'total_il_high_credit_limit'],
          dtype='object')
```

```
import joblib
import numpy as np

# Load the saved model
```

```
loaded_model = joblib.load('random_forest_model.pkl')

test_data_index = 10
test_data = X_test.iloc[test_data_index].values.reshape(1, -1)
print(test_data)

# Predict using the loaded model
prediction = loaded_model.predict(test_data)
print("Prediction:", prediction)
lab=['Defaulted','Fully Paid']
print("value: ",lab[prediction[0]])
```

```
[[6.04045967e+03 0.00000000e+00 1.59210000e+04 0.00000000e+00
  5.00000000e+00 3.00229833e+04 2.00000000e+00 4.00000000e+00
  3.50171316e+01 2.02298335e-01 0.00000000e+00 8.19080666e+00
  0.00000000e+00 5.69251892e+03 7.70469219e+01 1.11908067e+01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 1.74496350e+04
  7.48206850e+03 1.80919334e+00 2.30139198e+03 1.03253070e+03
  9.00494591e+01 0.00000000e+00 0.00000000e+00 5.23816133e+01
  6.86827849e+01 6.39310500e+00 6.39310500e+00 0.00000000e+00
  6.39310500e+00 9.22528168e+00 2.02298335e-01 3.79770167e+00
  4.59540333e+00 3.79770167e+00 5.59540333e+00 3.20229833e+00
  6.19080666e+00 7.98850833e+00 4.59540333e+00 8.19080666e+00
  0.00000000e+00 0.00000000e+00 2.02298335e-01 1.20229833e+00
  1.00000000e+02 7.97701665e+01 0.00000000e+00 0.00000000e+00
  3.82497861e+04 1.74496350e+04 5.80689500e+03 3.07677176e+04]]
Prediction: [0]
value:  Defaulted
```

Start coding or generate with AI.