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

```
data_file = '/content/credit_risk_dataset.csv'
data = pd.read_csv(data_file)
```

```
data.head()
```

	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loan_grade	loan_amnt	loan_int_rate	loan_status	loan_percent_income	cb_person_default_on_file	cb_person_cred_hist_length
0	22	59000	RENT	123.0	PERSONAL	D	35000	16.02	1	0.59	Y	3
1	21	9600	OWN	5.0	EDUCATION	B	1000	11.14	0	0.10	N	2
2	25	9600	MORTGAGE	1.0	MEDICAL	C	5500	12.87	1	0.57	N	3
3	23	65500	RENT	4.0	MEDICAL	C	35000	15.23	1	0.53	N	2
4	24	54400	RENT	8.0	MEDICAL	C	35000	14.27	1	0.55	Y	4

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

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   person_age                  32581 non-null  int64
 1   person_income               32581 non-null  int64
 2   person_home_ownership       32581 non-null  object
 3   person_emp_length           31686 non-null  float64
 4   loan_intent                 32581 non-null  object
 5   loan_grade                  32581 non-null  object
 6   loan_amnt                   32581 non-null  int64
 7   loan_int_rate               29465 non-null  float64
 8   loan_status                 32581 non-null  int64
 9   loan_percent_income         32581 non-null  float64
 10  cb_person_default_on_file   32581 non-null  object
 11  cb_person_cred_hist_length  32581 non-null  int64
dtypes: float64(3), int64(5), object(4)
memory usage: 3.0+ MB
```

```
data.duplicated().sum()
```

```
165
```

```
data = data.drop_duplicates()
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 32416 entries, 0 to 32580
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   person_age                  32416 non-null  int64
 1   person_income               32416 non-null  int64
 2   person_home_ownership       32416 non-null  object
 3   person_emp_length           31529 non-null  float64
 4   loan_intent                 32416 non-null  object
 5   loan_grade                  32416 non-null  object
 6   loan_amnt                   32416 non-null  int64
 7   loan_int_rate               29321 non-null  float64
 8   loan_status                 32416 non-null  int64
 9   loan_percent_income         32416 non-null  float64
 10  cb_person_default_on_file   32416 non-null  object
 11  cb_person_cred_hist_length  32416 non-null  int64
dtypes: float64(3), int64(5), object(4)
memory usage: 3.2+ MB
```

```
print(data.isnull().sum())
```

```
person_age                      0
person_income                   0
person_home_ownership           0
person_emp_length             887
loan_intent                     0
loan_grade                      0
loan_amnt                       0
loan_int_rate                3095
loan_status                     0
loan_percent_income             0
cb_person_default_on_file       0
cb_person_cred_hist_length      0
dtype: int64
```

```
missing_columns = ['person_emp_length', 'loan_int_rate']

data[missing_columns] = data[missing_columns].fillna(data[missing_columns].median())
```

```
print(data.isnull().sum())
```

```
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_status                   0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
dtype: int64
```

```
categorical_features = ['person_home_ownership', 'loan_intent', 'loan_grade', 'cb_person_default_on_file']

from sklearn.preprocessing import LabelEncoder

label_encoders = {}
for feature in categorical_features:
    le = LabelEncoder()
    data[feature] = le.fit_transform(data[feature])
    label_encoders[feature] = le

for feature, le in label_encoders.items():
    print(f"Feature: {feature}")
    print("Original Categories:", le.classes_)
    print("Encoded Values:", data[feature].unique())
    print()
```

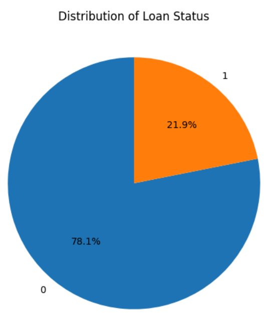
```
Feature: person_home_ownership
Original Categories: ['MORTGAGE' 'OTHER' 'OWN' 'RENT']
Encoded Values: [3 2 0 1]

Feature: loan_intent
Original Categories: ['DEBTCONSOLIDATION' 'EDUCATION' 'HOMEIMPROVEMENT' 'MEDICAL' 'PERSONAL'
 'VENTURE']
Encoded Values: [4 1 3 5 2 0]

Feature: loan_grade
Original Categories: ['A' 'B' 'C' 'D' 'E' 'F' 'G']
Encoded Values: [3 1 2 0 4 5 6]

Feature: cb_person_default_on_file
Original Categories: ['N' 'Y']
Encoded Values: [1 0]
```

```
# Define target and feature columns
target = 'loan_status'
features = data.drop(target, axis=1).columns.tolist()

# Identify categorical and numerical features
numerical_features = list(set(features) - set(categorical_features))

# Summary statistics for numerical features
numerical_summary = data[numerical_features].describe().T
print("Summary Statistics for Numerical Features:")
print(numerical_summary)

# Summary statistics for categorical features (including label-encoded ones)
categorical_summary = data[categorical_features].describe().T
print("\nSummary Statistics for Categorical Features:")
print(categorical_summary)
```

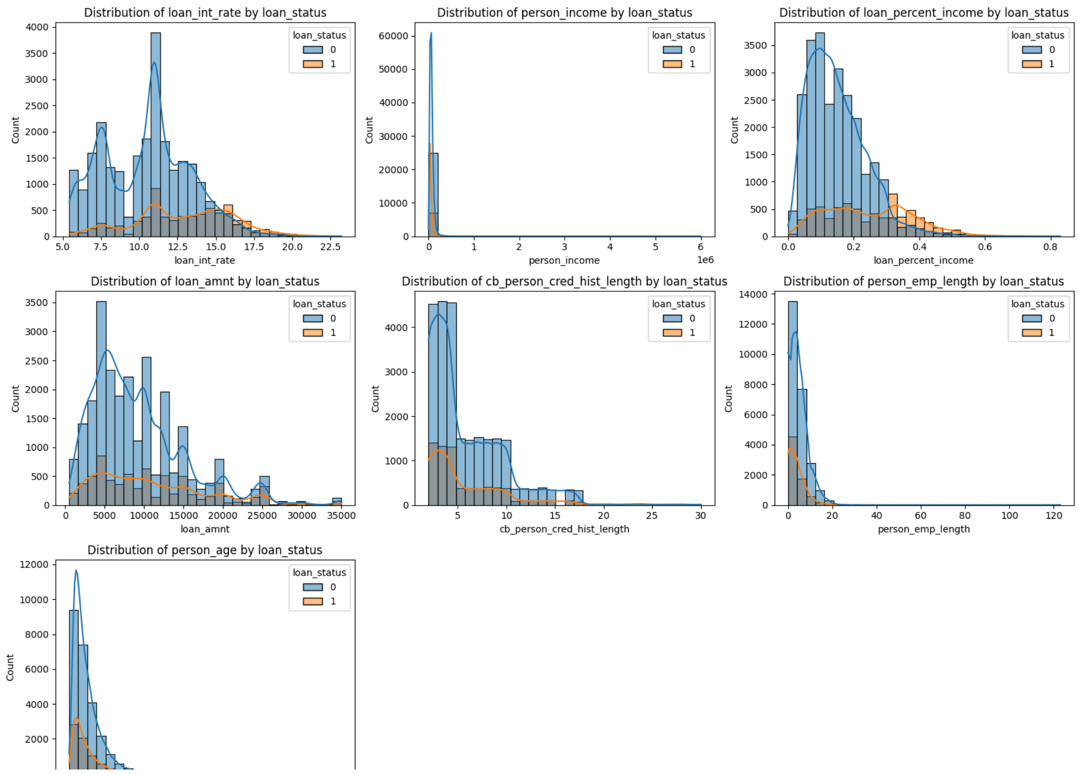
```
Summary Statistics for Numerical Features:
                              count          mean           std      min  \
loan_int_rate               32416.0     11.014662      3.083050     5.42
person_income               32416.0  66091.640826  62015.580269  4000.00
loan_percent_income         32416.0      0.170250      0.106812     0.00
loan_amnt                   32416.0   9593.845632   6322.730241   500.00
cb_person_cred_hist_length  32416.0      5.811297      4.059030     2.00
person_emp_length           32416.0      4.768880      4.090411     0.00
person_age                  32416.0     27.747008      6.354100    20.00
```

```
                            25%       50%       75%         max
loan_int_rate              8.49     10.99     13.11       23.22
person_income          38542.00  55000.00  79218.00  6000000.00
loan_percent_income        0.09      0.15      0.23        0.83
loan_amnt               5000.00   8000.00  12250.00    35000.00
cb_person_cred_hist_length  3.00      4.00      8.00       30.00
person_emp_length          2.00      4.00      7.00      123.00
person_age                23.00     26.00     30.00      144.00

Summary Statistics for Categorical Features:
                           count      mean       std  min  25%  50%  75%  \
person_home_ownership     32416.0  1.677135  1.433183  0.0  0.0  3.0  3.0
loan_intent               32416.0  2.533533  1.730862  0.0  1.0  3.0  4.0
loan_grade                32416.0  1.220508  1.167293  0.0  0.0  1.0  2.0
cb_person_default_on_file 32416.0  0.176765  0.381475  0.0  0.0  0.0  0.0

                          max
person_home_ownership     3.0
loan_intent               5.0
loan_grade                6.0
cb_person_default_on_file 1.0
```

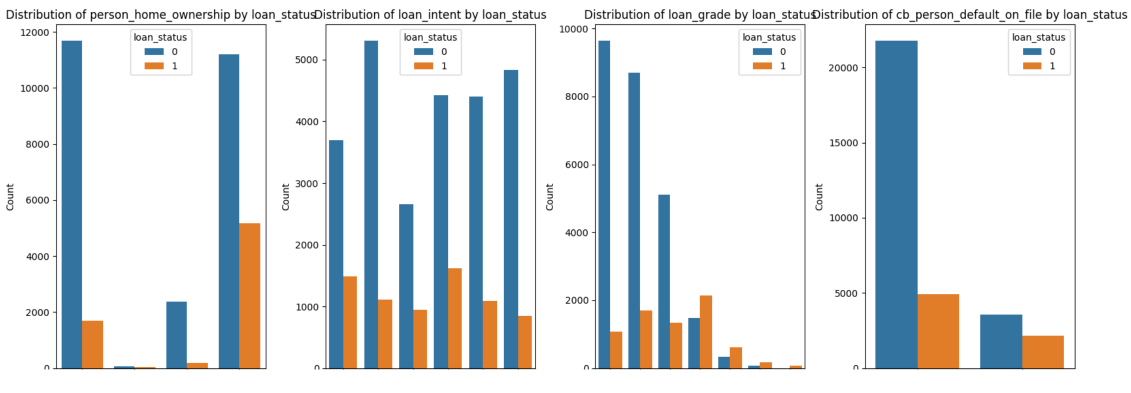
```
plt.figure(figsize=(8, 6))
data['loan_status'].value_counts().plot(
    kind='pie',
    autopct='%1.1f%%',
    startangle=90
)
plt.title('Distribution of Loan Status')
plt.ylabel('')
plt.show()
```



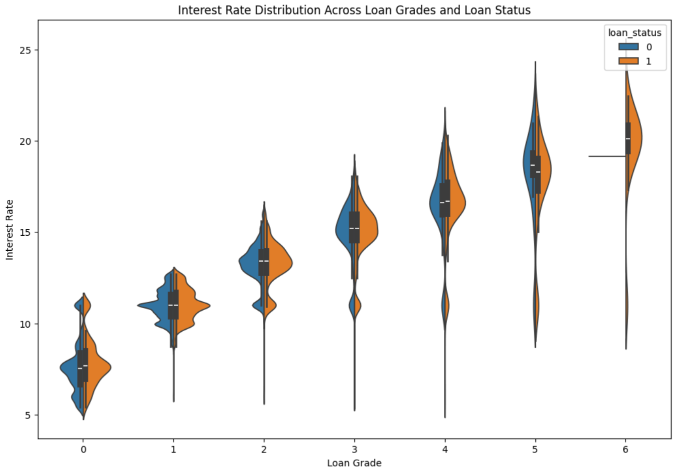

```
plt.figure(figsize=(16, 12))

for i, col in enumerate(numerical_features):
    plt.subplot(3, 3, i+1)
    sns.histplot(data=data, x=col, hue=target, kde=True, bins=30)
    plt.title(f'Distribution of {col} by {target}')
    plt.xlabel(col)
    plt.ylabel('Count')

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



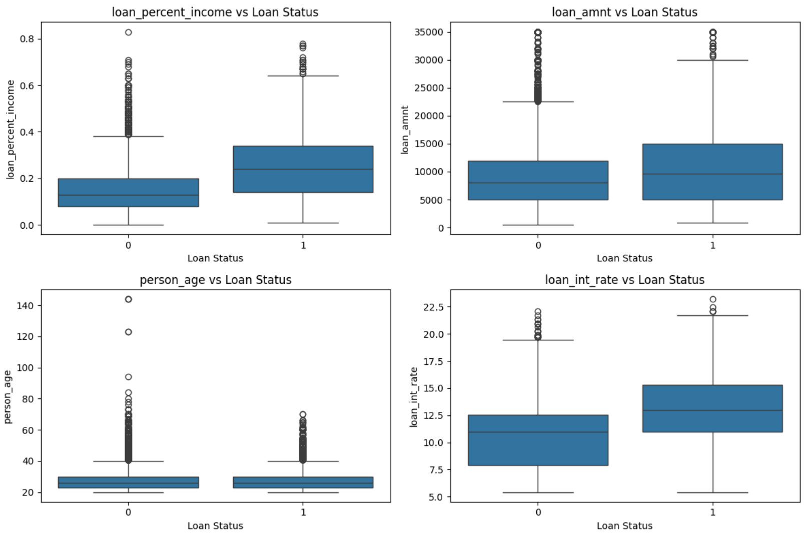

```
plt.figure(figsize=(16, 6))

for i, col in enumerate(categorical_features):
    plt.subplot(1, len(categorical_features), i+1)
    sns.countplot(x=col, data=data, hue=target)
    plt.title(f'Distribution of {col} by {target}')
    plt.xlabel(col)
    plt.ylabel('Count')

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



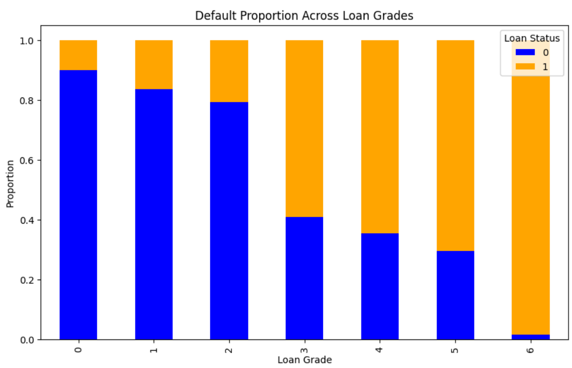
```
plt.figure(figsize=(12, 8))

sns.violinplot(x='loan_grade', y='loan_int_rate', hue='loan_status', data=data, split=True)
plt.title('Interest Rate Distribution Across Loan Grades and Loan Status')
plt.xlabel('Loan Grade')
plt.ylabel('Interest Rate')
plt.show()
```




```
plt.figure(figsize=(12, 8))

for i, col in enumerate(['loan_percent_income', 'loan_amnt', 'person_age', 'loan_int_rate']):
    plt.subplot(2, 2, i + 1)
    sns.boxplot(x='loan_status', y=col, data=data)
    plt.title(f'{col} vs Loan Status')
    plt.xlabel('Loan Status')
    plt.ylabel(col)

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

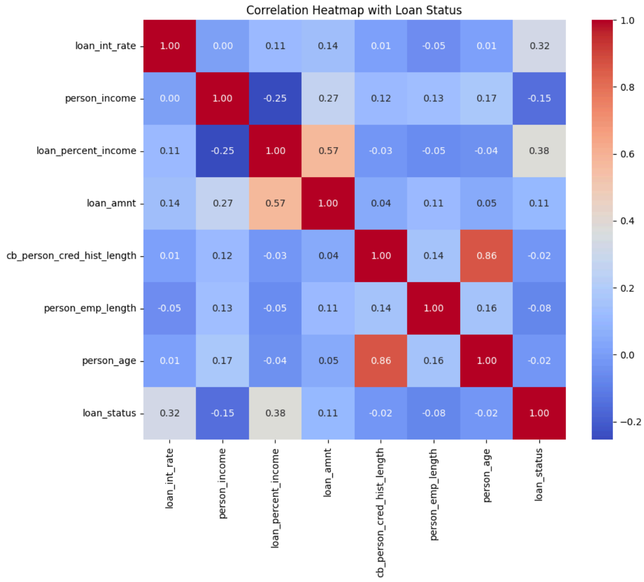



```
grade_dist = data.groupby(['loan_grade', 'loan_status']).size().unstack()
grade_dist = grade_dist.div(grade_dist.sum(axis=1), axis=0)

grade_dist.plot(kind='bar', stacked=True, color=['blue', 'orange'], figsize=(10, 6))
plt.title('Default Proportion Across Loan Grades')
plt.xlabel('Loan Grade')
plt.ylabel('Proportion')
plt.legend(title='Loan Status', loc='upper right')
plt.show()
```

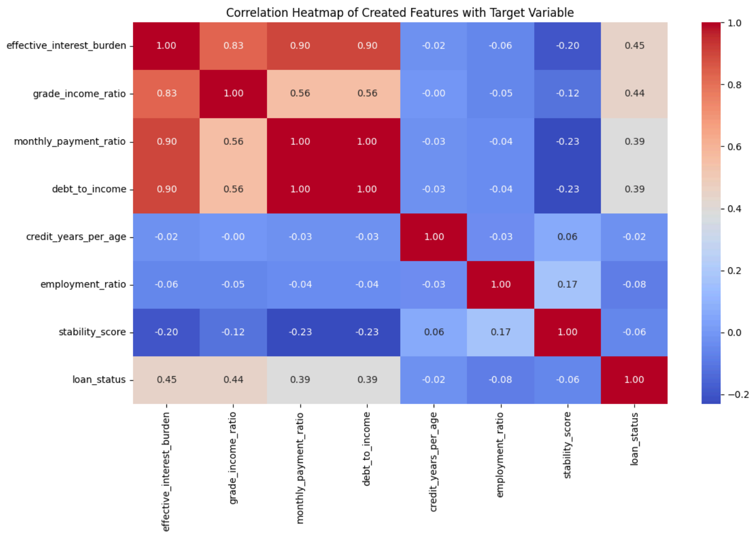



```
# Calculate correlations between numerical features and the target
correlations = data[numerical_features + ['loan_status']].corr()

# Extract correlations of features with the target
target_corr = correlations['loan_status'].drop('loan_status')

# Display correlations
print(target_corr.sort_values(ascending=False))

# Plot heatmap for numerical features and target
plt.figure(figsize=(10, 8))
sns.heatmap(correlations, annot=True, cmap='coolwarm', fmt='.2f', cbar=True)
plt.title('Correlation Heatmap with Loan Status')
plt.show()
```

```
loan_percent_income           0.379697
loan_int_rate                 0.320081
loan_amnt                     0.105736
cb_person_cred_hist_length   -0.016498
person_age                   -0.022698
person_emp_length            -0.082517
person_income                -0.145005
Name: loan_status, dtype: float64
```




```
# Create new features
data['effective_interest_burden'] = (data['loan_int_rate'] * data['loan_amnt']) / data['person_income']
data['grade_income_ratio'] = data['loan_grade'] * data['loan_percent_income']
data['monthly_payment_ratio'] = data['loan_amnt'] / (data['person_income'] / 12)
data['debt_to_income'] = data['loan_amnt'] / data['person_income']
data['credit_years_per_age'] = data['cb_person_cred_hist_length'] / data['person_age']
data['employment_ratio'] = data['person_emp_length'] / data['person_age']
data['stability_score'] = (data['person_emp_length'] * data['person_income']) / \
                          (data['loan_amnt'] * data['loan_percent_income'])

# Correlation map for newly created features
created_features = [
    'effective_interest_burden', 'grade_income_ratio', 'monthly_payment_ratio',
    'debt_to_income', 'credit_years_per_age', 'employment_ratio', 'stability_score'
]

# Calculate correlations including the target variable
correlations = data[created_features + ['loan_status']].corr()

# Plot correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlations, annot=True, cmap='coolwarm', fmt='.2f', cbar=True)
plt.title('Correlation Heatmap of Created Features with Target Variable')
plt.tight_layout()
plt.show()

# Filter features with correlation > 0.4
selected_features = correlations['loan_status'].loc[correlations['loan_status'] > 0.4].index.tolist()

# Display selected features and their correlations
print("Selected Features with Correlation > 0.4:\n", correlations['loan_status'][selected_features])
```




```
Selected Features with Correlation > 0.4:
 effective_interest_burden    0.454224
grade_income_ratio           0.442093
loan_status                  1.000000
Name: loan_status, dtype: float64
```

```
original_features = [  # Assuming your original features are in this list
    'loan_amnt', 'person_income', 'loan_int_rate', 'loan_grade',
    'loan_percent_income', 'cb_person_cred_hist_length',
    'person_age', 'person_emp_length'
]

# Adding new features
updated_features = original_features + ['effective_interest_burden', 'grade_income_ratio']
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Preparing data
X = data[updated_features]
y = data['loan_status']

# Splitting data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardizing the data (optional)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Logistic Regression
logistic_model = LogisticRegression()
logistic_model.fit(X_train_scaled, y_train)
y_pred_logistic = logistic_model.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred_logistic)
classification_rep = classification_report(y_test, y_pred_logistic)
```

```
# Print Results
print("Logistic Regression Results:")
print(f"Accuracy: {accuracy:.2f}")  # Formats accuracy to two decimal places
print("\nClassification Report:\n", classification_rep)
```

```
Logistic Regression Results:
Accuracy: 0.84

Classification Report:
               precision    recall  f1-score   support

           0       0.86      0.95      0.90      5073
           1       0.69      0.45      0.54      1411

    accuracy                           0.84      6484
   macro avg       0.78      0.70      0.72      6484
weighted avg       0.82      0.84      0.82      6484
```

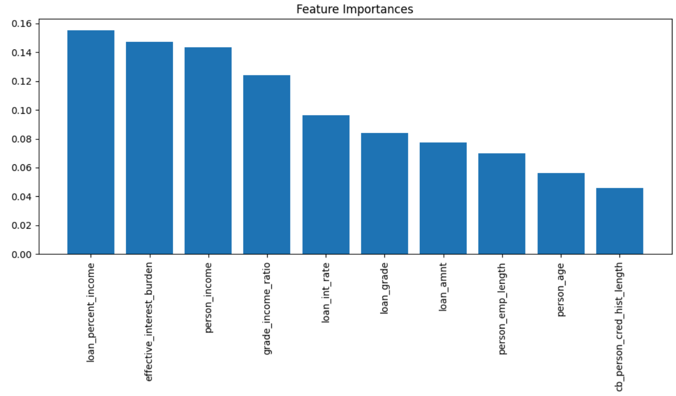
```
from sklearn.ensemble import RandomForestClassifier

# Random Forest
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train_scaled, y_train)
y_pred_rf = random_forest_model.predict(X_test_scaled)

# Evaluate Random Forest
rf_accuracy = accuracy_score(y_test, y_pred_rf)
rf_classification_rep = classification_report(y_test, y_pred_rf)

# Print Results
print("Random Forest Results:")
print(f"Accuracy: {rf_accuracy:.2f}")
print("\nClassification Report:\n", rf_classification_rep)
```

```
Random Forest Results:
Accuracy: 0.89

Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.95      0.93      5073
           1       0.79      0.66      0.72      1411

    accuracy                           0.89      6484
   macro avg       0.85      0.80      0.82      6484
weighted avg       0.88      0.89      0.88      6484
```

```
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

# XGBoost
xgb_model = XGBClassifier()
xgb_model.fit(X_train_scaled, y_train)
y_pred_xgb = xgb_model.predict(X_test_scaled)

# Evaluate XGBoost
xgb_accuracy = accuracy_score(y_test, y_pred_xgb)
xgb_classification_rep = classification_report(y_test, y_pred_xgb)

# Print Results
print("XGBoost Results:")
print(f"Accuracy: {xgb_accuracy:.2f}")
print("\nClassification Report:\n", xgb_classification_rep)
```

```
XGBoost Results:
Accuracy: 0.88

Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.95      0.93      5073
           1       0.77      0.64      0.70      1411

    accuracy                           0.88      6484
   macro avg       0.84      0.79      0.81      6484
weighted avg       0.88      0.88      0.88      6484
```

```
# Use the existing Random Forest model (make sure it's trained)
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Feature Importances
importances = rf_model.feature_importances_
sorted_indices = np.argsort(importances)[::-1]
features = X.columns

# Plot
plt.figure(figsize=(10, 6))
plt.bar(range(len(features)), importances[sorted_indices], align='center')
plt.xticks(range(len(features)), features[sorted_indices], rotation=90)
plt.title("Feature Importances")
plt.tight_layout()
plt.show()
```




```
top_features = features[sorted_indices[:5]]

print("Top 5 Important Features:")
print(top_features)
```

```
Top 5 Important Features:
Index(['cb_person_cred_hist_length', 'person_income', 'loan_percent_income',
       'loan_int_rate', 'person_age'],
      dtype='object')
```