# Bank Loan Defaulter Prediction

#### Presented by:

- Ahmad Alharthi
- Faisal Alsufyani
- Yahya Alyoubi

Instructor: Dr.Mejdal Alqahtani

#### Introduction

 Financing is a credit method that enables the client to borrow a certain amount of money to achieve his financial goals, and the client may stumble in paying the installments as a result of a sudden change in his financial situation or mismanagement of benefiting from financing and not allocating part of the income to pay the installments.

### Goals

#### The goals of the project:

- This project aims to classify a customer whether a loan defaulter or not based on multiple factors like loan amount and Interest Rate.
- Finding the factors that affect clients' failure to pay the loan before obtaining it with high accuracy.

### **Penalties**

#### **Penalty for defaulting on loans:**

- Difficulty obtaining another financing shortly.
- Legal accountability and prosecution by creditors.
- Freezing bank accounts.

#### Data Structure

- This data set was collected from Kaggle.com website
- This is a simple overview of the data structure, in which the names of the columns and some rows are explained Columns 35 Rows: 67463 Before cleaning the data:

|       | ID       | Loan<br>Amount | Funded<br>Amount | Funded<br>Amount<br>Investor | Term | Batch<br>Enrolled | Interest<br>Rate | Grade | Sub<br>Grade | Employment<br>Duration | <br>Recoveries  | Collection<br>Recovery<br>Fee | Collection<br>12<br>months<br>Medical | Applicatior<br>Type |
|-------|----------|----------------|------------------|------------------------------|------|-------------------|------------------|-------|--------------|------------------------|-----------------|-------------------------------|---------------------------------------|---------------------|
| 0     | 65087372 | 10000          | 32236            | 12329.36286                  | 59   | BAT2522922        | 11.135007        | В     | C4           | MORTGAGE               | <br>2.498291    | 0.793724                      | 0                                     | INDIVIDUAL          |
| 1     | 1450153  | 3609           | 11940            | 12191.99692                  | 59   | BAT1586599        | 12.237563        | С     | D3           | RENT                   | <br>2.377215    | 0.974821                      | 0                                     | INDIVIDUAL          |
| 2     | 1969101  | 28276          | 9311             | 21603.22455                  | 59   | BAT2136391        | 12.545884        | F     | D4           | MORTGAGE               | <br>4.316277    | 1.020075                      | 0                                     | INDIVIDUAL          |
| 3     | 6651430  | 11170          | 6954             | 17877.15585                  | 59   | BAT2428731        | 16.731201        | С     | C3           | MORTGAGE               | <br>0.107020    | 0.749971                      | 0                                     | INDIVIDUAL          |
| 4     | 14354669 | 16890          | 13226            | 13539.92667                  | 59   | BAT5341619        | 15.008300        | С     | D4           | MORTGAGE               | <br>1294.818751 | 0.368953                      | 0                                     | INDIVIDUAL          |
|       |          |                |                  |                              |      |                   |                  |       |              |                        | <br>            |                               |                                       |                     |
| 67458 | 16164945 | 13601          | 6848             | 13175.28583                  | 59   | BAT3193689        | 9.408858         | С     | A4           | MORTGAGE               | <br>564.614852  | 0.865230                      | 0                                     | INDIVIDUAL          |
| 67459 | 35182714 | 8323           | 11046            | 15637.46301                  | 59   | BAT1780517        | 9.972104         | С     | B3           | RENT                   | <br>2.015494    | 1.403368                      | 0                                     | INDIVIDUAL          |
| 67460 | 16435904 | 15897          | 32921            | 12329.45775                  | 59   | BAT1761981        | 19.650943        | Α     | F3           | MORTGAGE               | <br>5.673092    | 1.607093                      | 0                                     | INDIVIDUAL          |
| 67461 | 5300325  | 16567          | 4975             | 21353.68465                  | 59   | BAT2333412        | 13.169095        | D     | E3           | OWN                    | <br>1.157454    | 0.207608                      | 0                                     | INDIVIDUAL          |
| 67462 | 65443173 | 15353          | 29875            | 14207.44860                  | 59   | BAT1930365        | 16.034631        | В     | D1           | MORTGAGE               | <br>1.856480    | 0.366386                      | 0                                     | INDIVIDUAL          |

67463 rows x 35 columns

#### **Exploratory Data Analysis**

- Delete columns
- Duplicate values
- Check for NaN values

|       | Loan<br>Amount | Funded<br>Amount | Funded<br>Amount<br>Investor | Interest<br>Rate |
|-------|----------------|------------------|------------------------------|------------------|
| 0     | 10000          | 32236            | 12329.36286                  | 11.135007        |
| 1     | 3609           | 11940            | 12191.99692                  | 12.237563        |
| 2     | 28276          | 9311             | 21603.22455                  | 12.545884        |
| 3     | 11170          | 6954             | 17877.15585                  | 16.731201        |
| 4     | 16890          | 13226            | 13539.92667                  | 15.008300        |
|       |                |                  |                              |                  |
| 67458 | 13601          | 6848             | 13175.28583                  | 9.408858         |
| 67459 | 8323           | 11046            | 15637.46301                  | 9.972104         |
| 67460 | 15897          | 32921            | 12329.45775                  | 19.650943        |
| 67461 | 16567          | 4975             | 21353.68465                  | 13.169095        |
| 67462 | 15353          | 29875            | 14207.44860                  | 16.034631        |

67463 rows × 27 columns

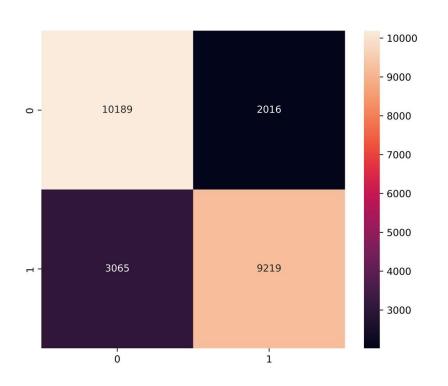
# Exploratory Data Analysis



Fig. 1 A plot of imbalanced class distribution

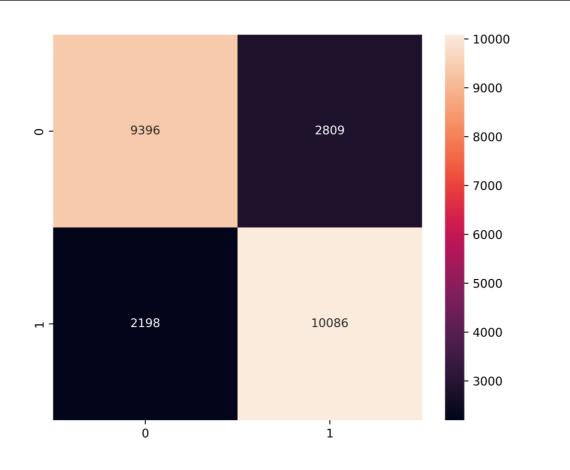
Fig. 2 A plot of a balanced class distribution after applying SMOTE method

# Logistic Regression



```
[13] # Logistic Regression
     from sklearn.metrics import classification report
     labels = ['Not loan defaulter','loan defaulter']
     print(classification_report(y_test, y_pred, target_names=labels))
                         precision
                                      recall f1-score
                                                         support
    Not loan defaulter
                              0.77
                                        0.83
                                                  0.80
                                                           12205
        loan defaulter
                              0.82
                                        0.75
                                                  0.78
                                                           12284
                                                  0.79
                                                           24489
               accuracy
                              0.79
                                        0.79
                                                  0.79
                                                           24489
              macro avg
           weighted avg
                              0.79
                                        0.79
                                                  0.79
                                                           24489
```

#### Decision Tree Classifier



```
[14] # DecisionTreeClassifier
     from sklearn.metrics import classification_report
     labels = ['Not a loan defaulter','A loan defaulter']
     print(classification report(y test, y pred, target names=labels))
                           precision
                                        recall f1-score
                                                           support
     Not a loan defaulter
                                0.81
                                          0.77
                                                    0.79
                                                             12205
                                          0.82
        A loan defaulter
                                0.78
                                                    0.80
                                                             12284
                 accuracy
                                                    0.80
                                                             24489
                                                    0.80
                macro avq
                                0.80
                                          0.80
                                                             24489
```

0.80

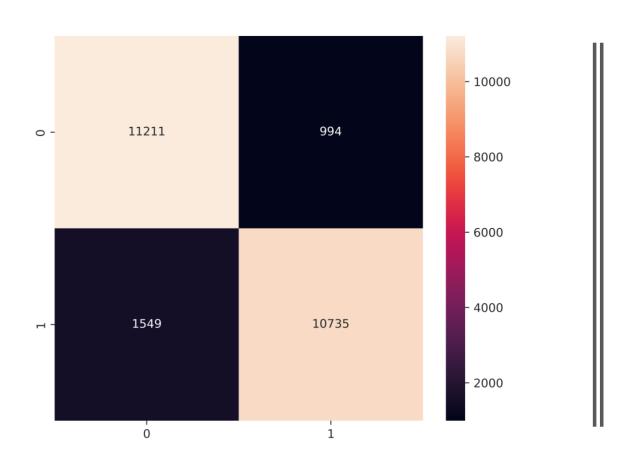
0.80

24489

0.80

weighted avg

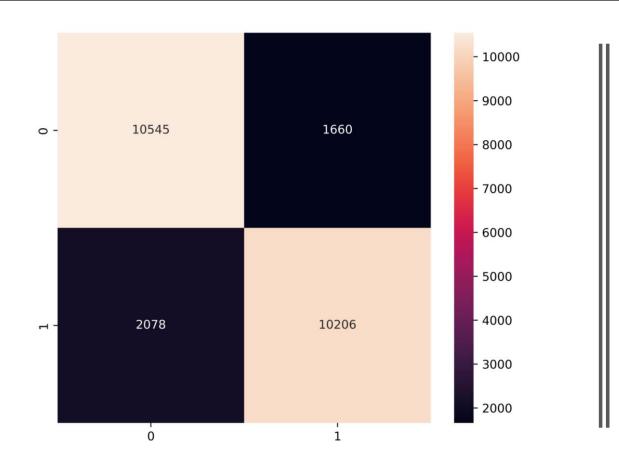
#### Random Forest Classifier



```
[9] # RandomForestClassifier
    from sklearn.metrics import classification_report
    labels = ['Not loan defaulter', 'loan defaulter']
    print(classification_report(y_test, y_pred, target_names=labels))
```

|                    | precision | recall | f1-score | support |
|--------------------|-----------|--------|----------|---------|
|                    |           |        |          |         |
| Not loan defaulter | 0.88      | 0.92   | 0.90     | 12205   |
| loan defaulter     | 0.92      | 0.87   | 0.89     | 12284   |
|                    |           |        |          |         |
| accuracy           |           |        | 0.90     | 24489   |
| macro avg          | 0.90      | 0.90   | 0.90     | 24489   |
| weighted avg       | 0.90      | 0.90   | 0.90     | 24489   |

## XGBoost Classifier



```
[39] # XGBClassifier
    from sklearn.metrics import classification_report
    labels = ['Not a loan defaulter','A loan defaulter']
    print(classification_report(y_test,xgb_classifier.predict(X_test),target_names=labels))
                          precision
                                       recall f1-score
                                                          support
    Not a loan defaulter
                                         0.86
                                                   0.85
                                                            12205
        A loan defaulter
                               0.86
                                         0.83
                                                   0.85
                                                            12284
                accuracy
                                                   0.85
                                                            24489
```

0.85

24489

24489

0.85

0.85

macro avg

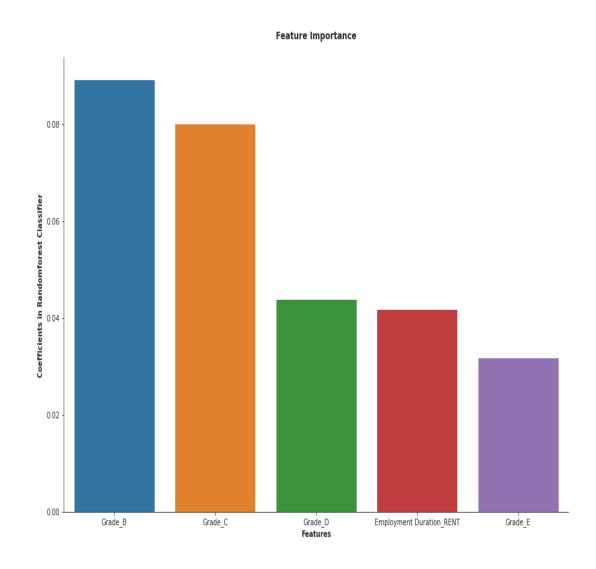
weighted avg

0.85

0.85

#### Conclusion & Future Work

- Model Selection
- Random Forest Classifier
  - with precision which 92% and recall 87%
- Able to predict the person who might be a loan defaulter
- Feature generation needed to improve the accuracy



# Thank You Any Question?