Loan Approval Prediction

Isaac, Fiona, Alex, Kim

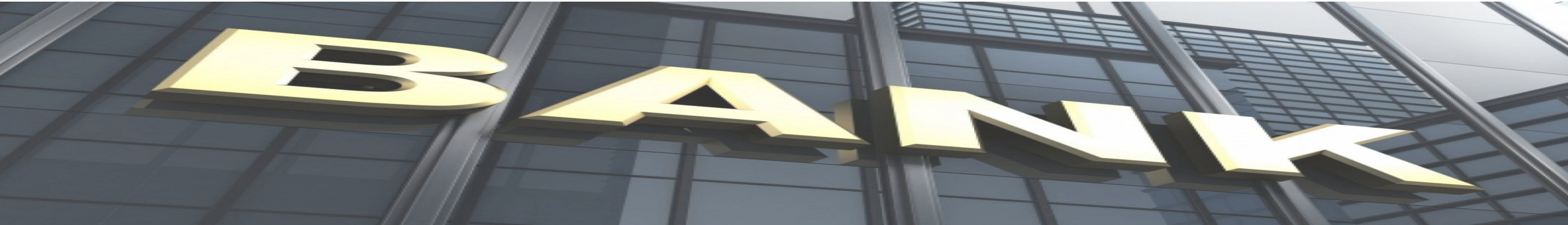


Table of content

Objective

Data from bank loan borrowers dataset

-> Develop a model to predict loan status

Business Value

->> use the model to generate new insights and determine whether a loan should be granted or not

-> make recommendations and help reducing the risk of bad debt from bank and other companies

Dataset Source

https://www.kaggle.com/zaurbegiev/my-dataset?select=credit_train.csv

credit_train.csv (17.94 MB)

Detail Compact **Column** 10 of 19 columns

Loan ID

82000
unique values

Valid	100.0k	99%
Mismatched	0	0%
Missing	514	1%
Unique	82.0k	
Most Common	14dd8831-6...	0%

Customer ID

82000
unique values

Valid	100.0k	99%
Mismatched	0	0%
Missing	514	1%
Unique	82.0k	
Most Common	981165ec-3...	0%

Data preprocessing-Duplicated Value

1.Drop duplicated ‘Loan ID’, as ‘Loan ID’ is unique

```
df = df[~df["Loan ID"].duplicated()]
df = df[~df["Loan ID"].isnull()]
df.head()
```

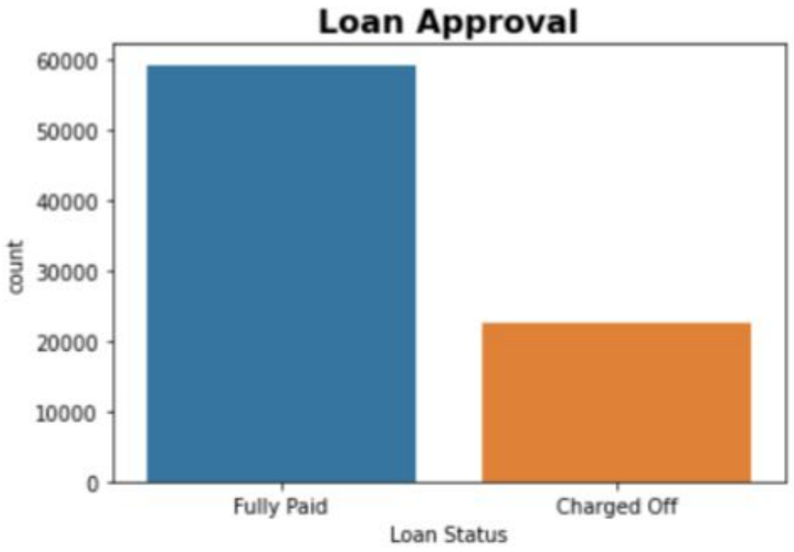
```
df.shape
```

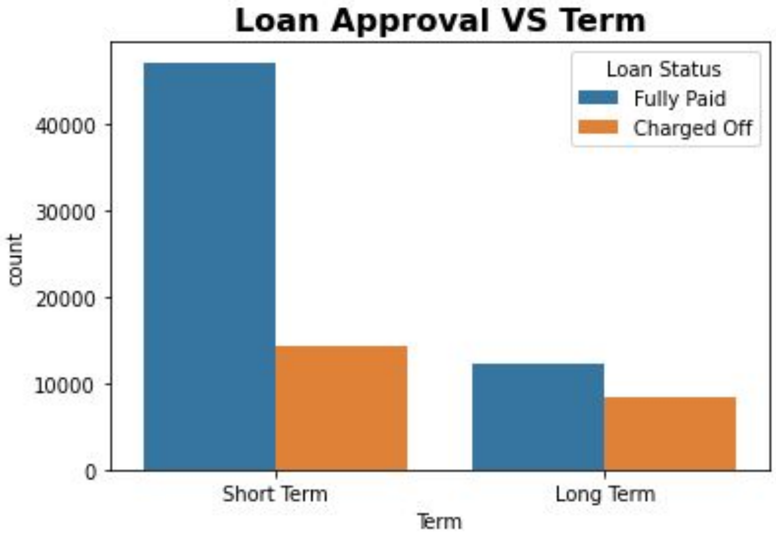
(100514, 19)

```
df.shape
```

(81999, 19)

EDA


Loan Approval
60000
50000
40000
30000
20000
10000
0
count
Fully Paid
Charged Off
Loan Status


Loan Approval VS Term
Loan Status
Fully Paid
Charged Off
40000
30000
20000
10000
0
count
Short Term
Long Term
Term

Data preprocessing-Missing Value

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

Loan ID	0
Customer ID	0
Loan Status	0
Current Loan Amount	0
Term	0
Credit Score	17031
Annual Income	17031
Years in current job	3508
Home Ownership	0
Purpose	0
Monthly Debt	0
Years of Credit History	0
Months since last delinquent	44621
Number of Open Accounts	0
Number of Credit Problems	0
Current Credit Balance	0
Maximum Open Credit	2
Bankruptcies	175
Tax Liens	8

dtype: int64

```
#impute median
df["Credit Score"] = df["Credit Score"].fillna(df["Credit Score"].median())
df["Annual Income"] = df["Annual Income"].fillna(df["Annual Income"].median())
df["Maximum Open Credit"] = df["Maximum Open Credit"].fillna(df["Maximum Open Credit"].median())
df["Years in current job"] = df["Years in current job"].fillna(df["Years in current job"].median())
```

```
#impute mode
df["Tax Liens"] = df["Tax Liens"].fillna(float(df["Tax Liens"].mode()))
df["Bankruptcies"] = df["Bankruptcies"].fillna(float(df["Bankruptcies"].mode()))
```

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

Loan ID	0
Customer ID	0
Loan Status	0
Current Loan Amount	0
Term	0
Credit Score	0
Annual Income	0
Years in current job	0
Home Ownership	0
Purpose	0
Monthly Debt	0
Years of Credit History	0
Number of Open Accounts	0
Number of Credit Problems	0
Current Credit Balance	0
Maximum Open Credit	0
Bankruptcies	0
Tax Liens	0

dtype: int64

Correlation Matrix between categorical variable and target variable

Cramers V statistic is used to calculate the correlation of categorical variables.

```
import scipy.stats as ss

def cramers_v(confusion_matrix):
    """ calculate Cramers V statistic for categorial-categorial association.
        uses correction from Bergsma and Wicher,
        Journal of the Korean Statistical Society 42 (2013): 323-328
    """
    chi2 = ss.chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum()
    phi2 = chi2/n
    r,k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min( (kcorr-1), (rcorr-1)))
```

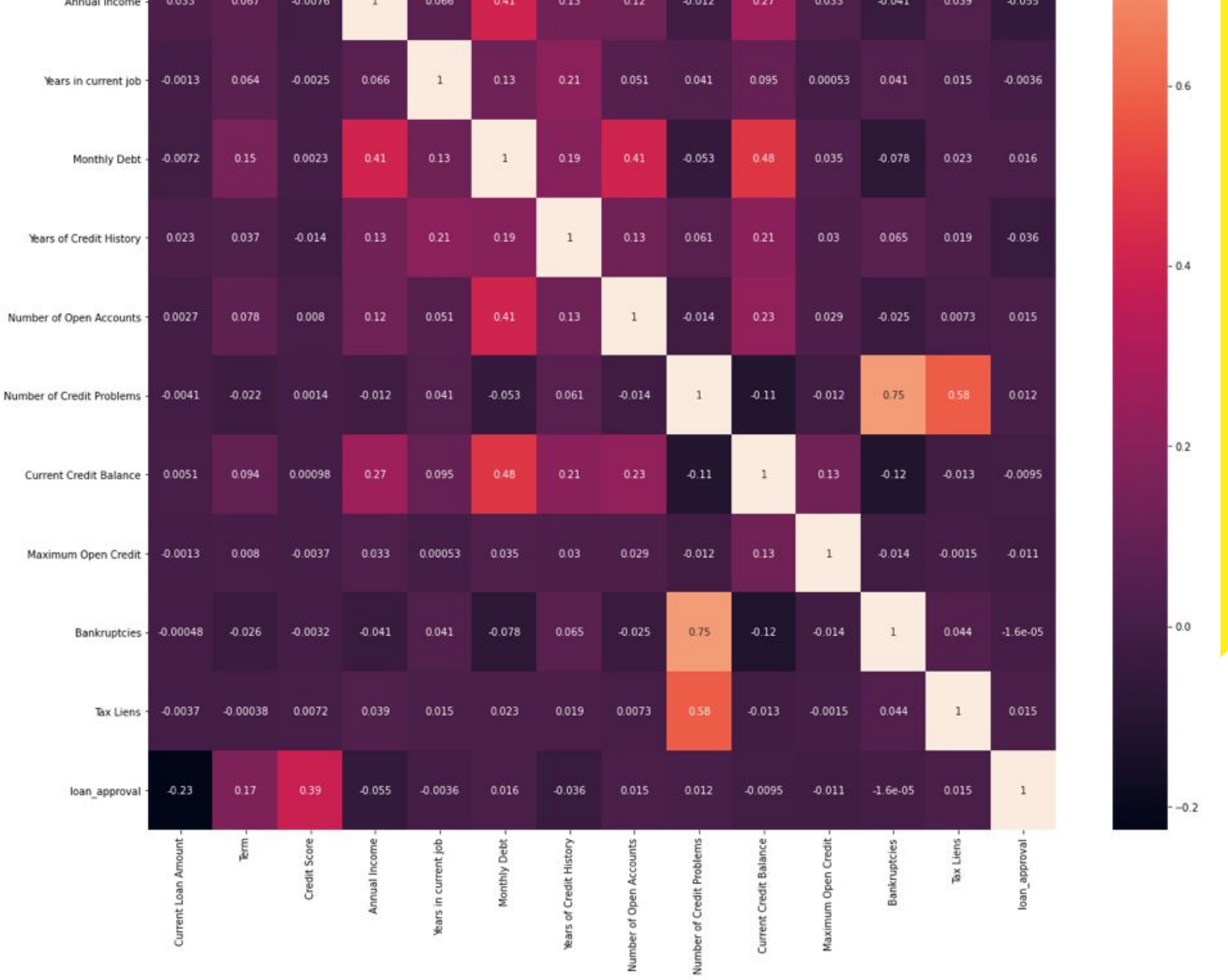
```
#checking correlation between Home Ownership & Loan Stauts
confusion_matrix = pd.crosstab(df1['Home Ownership'], df1["Loan Status"])
cramers_v(confusion_matrix.values)
```

```
0.05317824870623\82
```

```
#checking correlation between Purpose & Loan Stauts
confusion_matrix = pd.crosstab(df1['Purpose'], df1["Loan Status"])
cramers_v(confusion_matrix.values)
```

```
0.045696536787389
```

Correlation Matrix between **numeric** variable and **target** variable



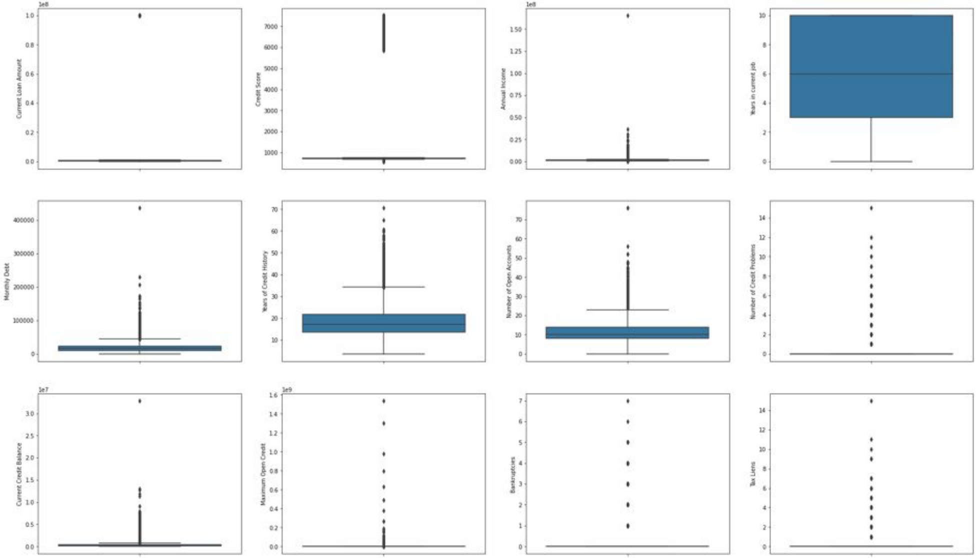
Data preprocessing-Encoding Method

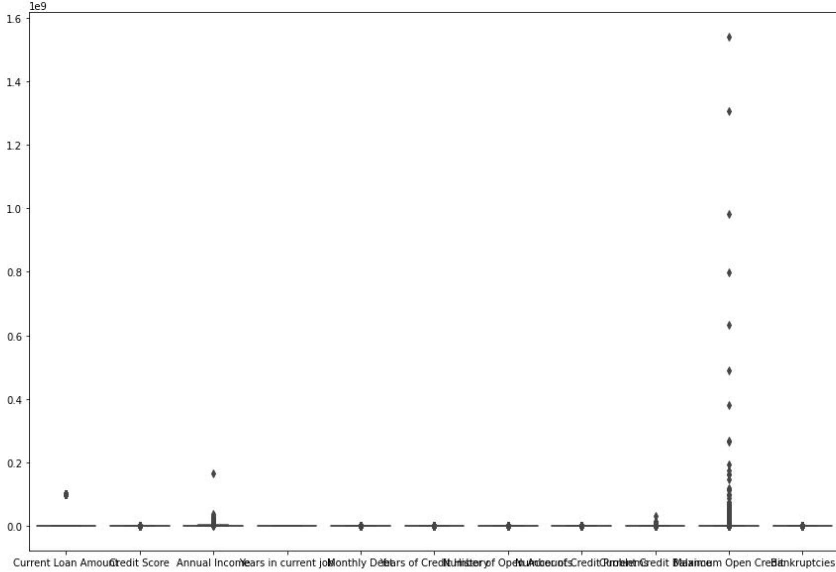
OneHotEncoder: Home Ownership,Purpose

Ordinal Encoder: Term

Label Encoder: Loan Status

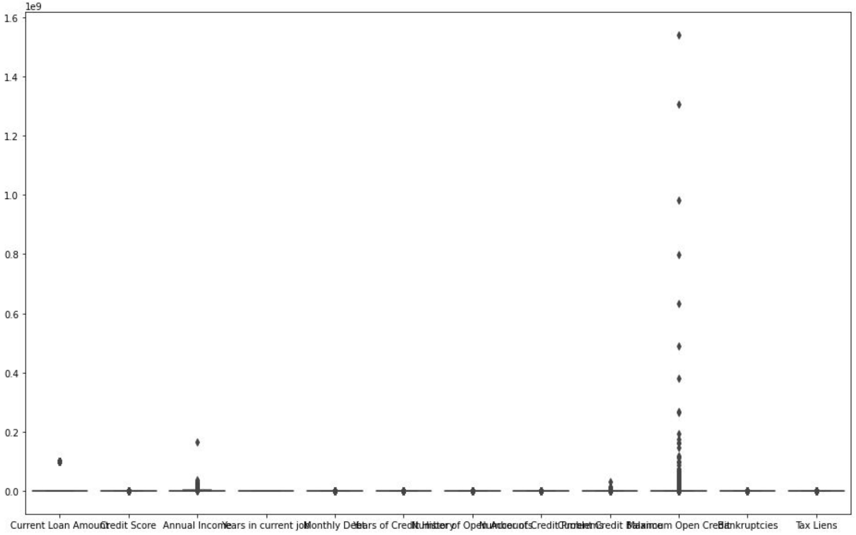
Data preprocessing -MinMaxScaler



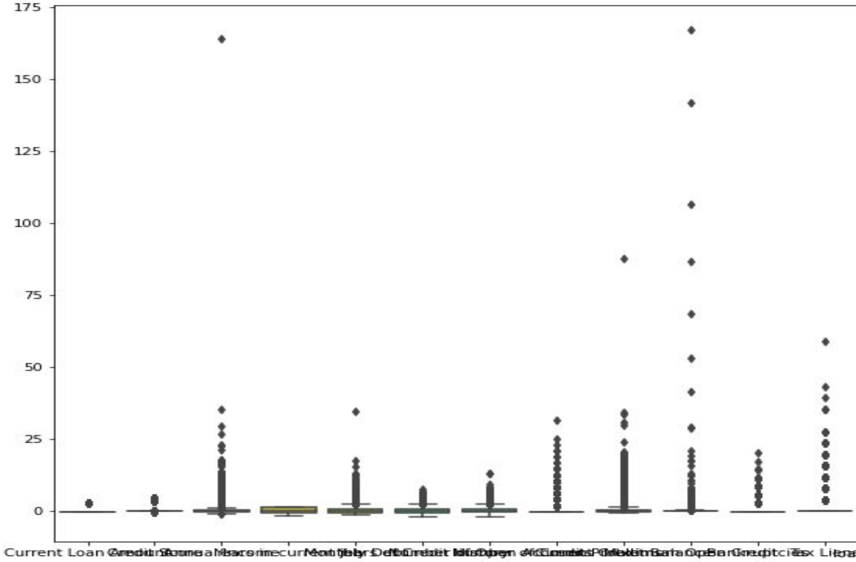


Data preprocessing-MinMaxScaler

Before Scaling



After Scaling



Model Selection

- X (features) = All features (Annual income, no. of credit card, current credit balance etc)
- y (target) = Default (1), Passed (0)

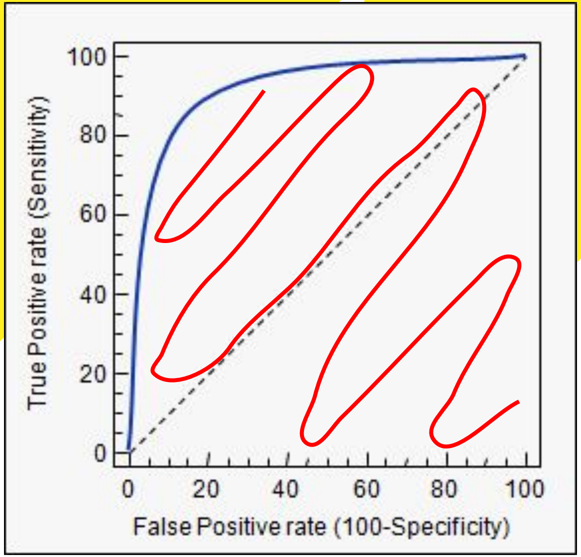
1. Logistic Regression
2. KNN Classifier
3. Decision Tree Classifier
4. Random Forest Classifier
5. AdaBoost Classifier
6. XGBoost Classifier

Model Selection

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=df["Loan Status"])
```

- GridSearchCV to find the best parameters for each classifier model for prediction

- Comparison of ‘ROC_AUC’ score
    - The higher the AUC score, the higher predictability
    - Different thresholds score



GridSearchCV

```
from sklearn.linear_model import LogisticRegression
parameters = {'C' : np.linspace(0.1,100,10),"penalty":["l1","l2"]}
```

```
from sklearn.neighbors import KNeighborsClassifier
parameters = {'n_neighbors': np.arange(1, 12, 2),
              'weights': ['uniform', 'distance']}
```

```
from sklearn.tree import DecisionTreeClassifier

parameters={"criterion": ["gini", "entropy"],
            "min_samples_split": [10, 20, 40],
            "max_depth": [2, 6, 8],
            "min_samples_leaf": [20, 40, 100],
            "max_leaf_nodes": [5, 20, 100],
            }
```

```
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier()
parameters = {'n_estimators': [300, 400],
              'learning_rate': [0.3, 0.4]
             }
```

```
from sklearn.ensemble import RandomForestClassifier
parameters={
            "n_estimators"      : [30,40,50],
            "max_features"      : ["sqrt", "log2"],
            "min_samples_split" : [6,8,10,12,14]
            }
```

```
xgmodel = XGBClassifier()

params = {'learning_rate': [0.001, 0.01, 0.1],
          'max_depth': [3,4]
         }
```

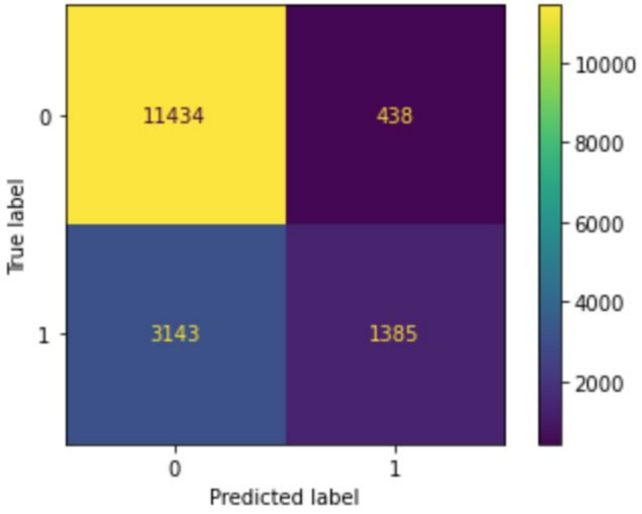
GridSearchCV

	'ROC_AUC' score	
Tuned parameters	LogisticRegression 0.5944481309444813 KNeighborsClassifier 0.6104537478559476 DecisionTreeClassifier 0.6028633780355367 RandomForestClassifier 0.6122866884601849 AdaBoostClassifier 0.598215846324359 XGBClassifier 0.5970091886672886	**Random Forest Classifier**
Default parameters	{'logreg': 0.600191054403627, 'knn': 0.6190772837236768, 'tree': 0.6251851313897117, 'rf': 0.6298774084938996, 'ada': 0.6164253212118903, 'xgb': 0.6344905136532911}	**XGBoost Classifier**

Model Evaluation

XGBoost Classifier

Confusion Matrix:
(0: Pass, 1: Default)



Threshold = 0.5
Test dataset(Total): 16,400 samples:

True Positive(TP) = 1,385
False Negative(FN) = 3,143

True Negative(TN) = 11,434
False Positive(FP) = 438

Accuracy	**Precision**	**Recall / True Positive Rate**	**False Positive Rate**
(TP+TN) / (Total) = (1,385+11,434) / (16,400) = **0.7816**	(TP) / (TN+FP) = (1,385) / (11,434+438) = **0.7597**	(TP) / (TP+FN) = (1,385) / (1,385+3,143) = **0.3058** → **Adjust Threshold**	(FP) / (FP+TN) = (438) / (11,434+438) = **0.0369**

```
[1385, 438]
[3143, 11434]
The accuracy_score: 0.78164
precision: 0.75973669775096
recall: 0.30587455830388693
```

ROC and Precision Recall AUC

Threshold	Recall	Precision	Successsful find-out (e.g. 10 Real Default Cases)	False Positive Rate	True Positive Rate
0.1	0.9759	0.3347	~ 9 - 10	0.74	0.9759
0.2	0.845	0.3911	~ 8 - 9	0.5018	0.845
0.3	0.6151	0.4959	~ 6	0.2385	0.6151
0.4	0.4218	0.6122	~ 4	0.1019	0.4218
0.5	0.3059	0.7597	~ 3	0.0369	0.3059
0.6	0.2405	0.8993	~ 2 - 3	0.0103	0.2405
0.7	0.2102	0.9714	~ 2	0.0024	0.2102
0.8	0.2008	0.9945	~ 2	0.0004	0.2008
0.9	0.1999	1	~ 0	0	0.1999

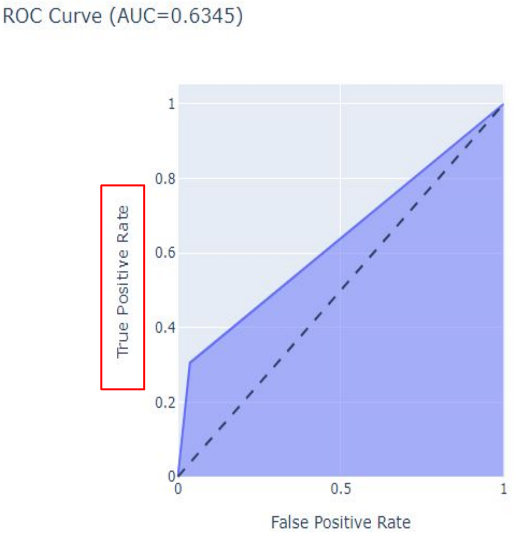
Extremely strict

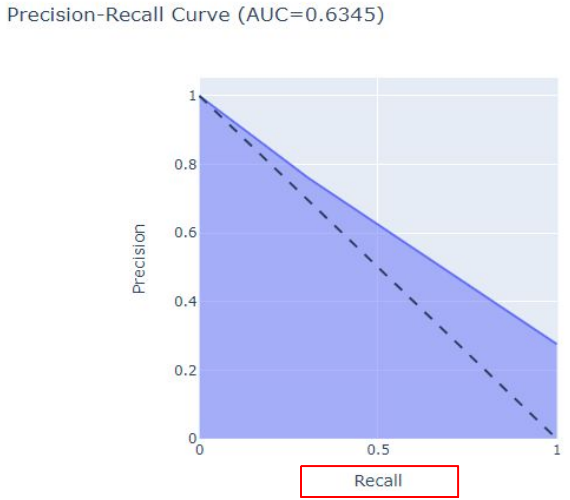
Strict

moderate

Loose

Extremely loose





Tradeoff & Threshold

- Make **own preference / risk tolerance** on the balance between Precision and Recall Rate

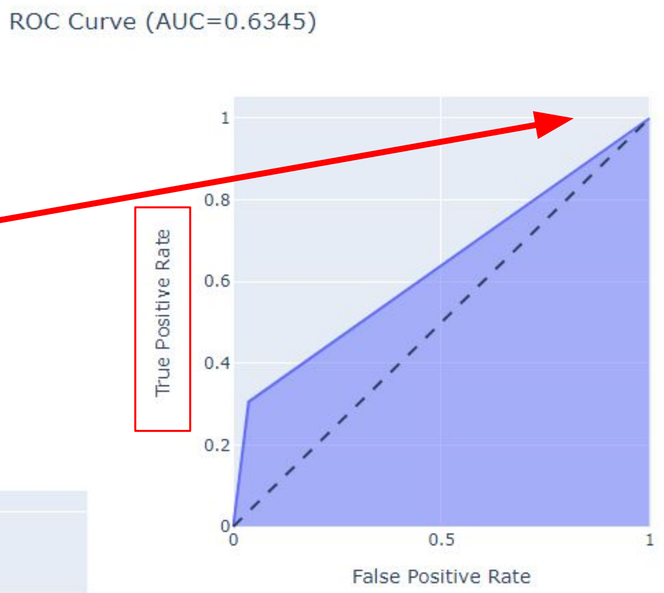
- A bank aim to **minimize default risk strictly**

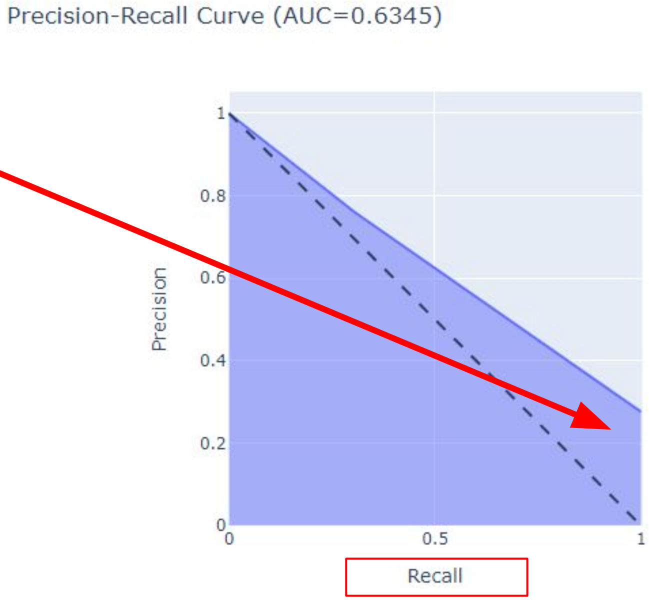
  -> **lower** the model **threshold**

  = **higher Recall Rate**
  = **more cases rejected**

Tradeoff:

- Less chance to approve th loan application
- Revenue may affect





Limitation & Reflection

- Many other factors would affect the default rate,
  not only the factors/ features in individual level,
  perhaps the factors in other aspects,

  E.g. Economy situation
  -> Business worse -> Unemployment -> Default rate increase.

- However, our dataset is limited in the personal aspect only,
  We ignored the influence of other factors

Thank you!