# Capstone Project-2

## Credit card Default Prediction

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# AGENDA


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# Overview

- This project is aimed at predicting the case of customers default payments in Taiwan

- Given is the dataset wherein the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients

- Given are different parameters such as Credit limit, payments done, bill amount etc. to determine the actual probability by building a comprehensive model with the best approach possible

# Goal

- The model we built here will use all possible factors to predict data on customers to find who are  defaulters and non-defaulters next month.
- The goal is to find the whether the clients are able to pay their next month credit amount.
- Identify some potential customers for the financial institution who can settle their credit balance.
- To determine if their customers could make the credit card payments on-time.
- **Default** is the failure to **pay** interest or principal on a loan or credit card payment.

# Approach Design

Preparation of data

Applying models

Comparing the applied models

Evaluation Model

Analyse the best model


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# Dataset Overview

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 1 to 30000
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype 
---  ------                      --------------  ----- 
 0   LIMIT_BAL                   30000 non-null  object
 1   SEX                         30000 non-null  object
 2   EDUCATION                   30000 non-null  object
 3   MARRIAGE                    30000 non-null  object
 4   AGE                         30000 non-null  object
 5   PAY_0                       30000 non-null  object
 6   PAY_2                       30000 non-null  object
 7   PAY_3                       30000 non-null  object
 8   PAY_4                       30000 non-null  object
 9   PAY_5                       30000 non-null  object
 10  PAY_6                       30000 non-null  object
 11  BILL_AMT1                   30000 non-null  object
 12  BILL_AMT2                   30000 non-null  object
 13  BILL_AMT3                   30000 non-null  object
 14  BILL_AMT4                   30000 non-null  object
 15  BILL_AMT5                   30000 non-null  object
 16  BILL_AMT6                   30000 non-null  object
 17  PAY_AMT1                    30000 non-null  object
 18  PAY_AMT2                    30000 non-null  object
 19  PAY_AMT3                    30000 non-null  object
 20  PAY_AMT4                    30000 non-null  object
 21  PAY_AMT5                    30000 non-null  object
 22  PAY_AMT6                    30000 non-null  object
 23  default payment next month  30000 non-null  object
dtypes: object(24)
memory usage: 5.5+ MB
```

Dataset Description:
(30000, 24)

No null value count

# Continue

…

Independent variables:

- Customer ID
- Credit limit
- Gender
- Age
- Marital status
- Level of education
- History of their past payments made (April to September) (X6 to X11)
- Amount of bill statement (X12 to X17)
- Amount of previous payment (X18 to X23)

Dependent variables:

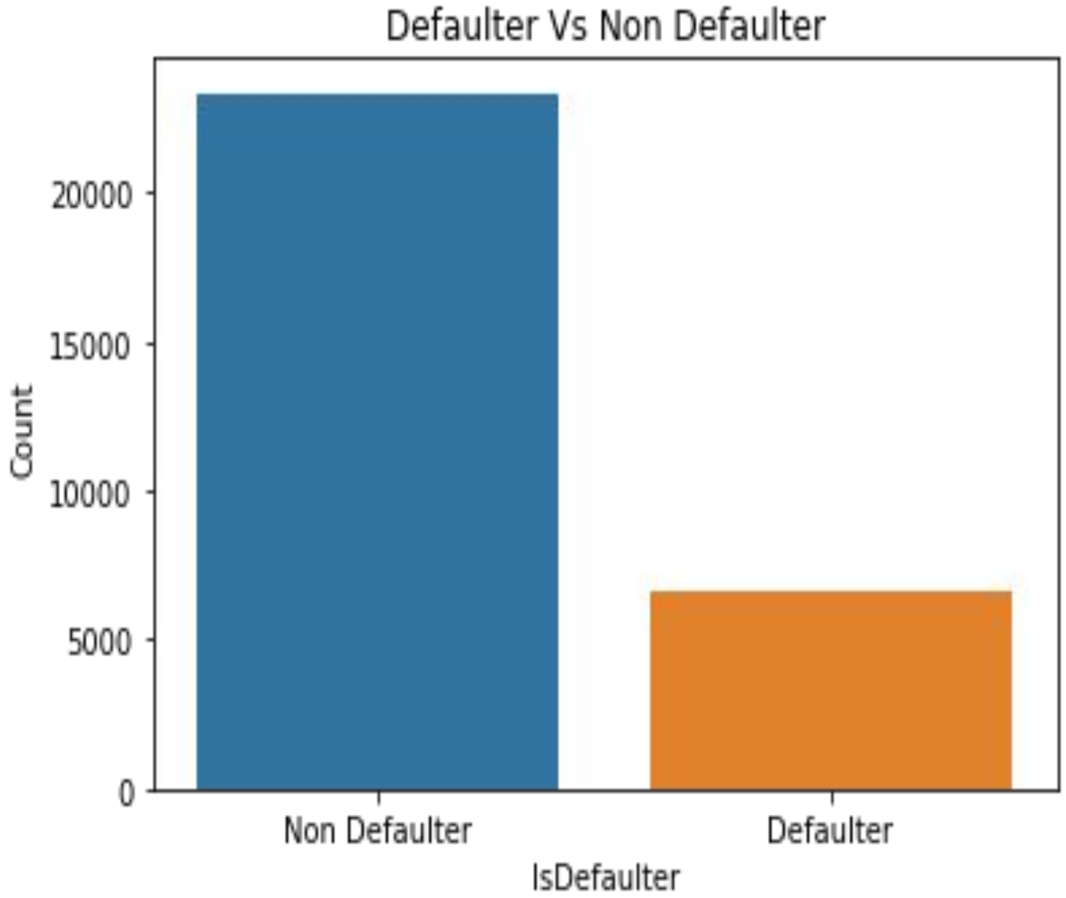
- default – A customer who will be default next month payment (0: no, 1: yes)

# Dataset overview

Graph shows total number of records for defaulters and non-defaulters.

If they would do payment or not (yes=1 no=0) for next month

22% - default
78% - non-default



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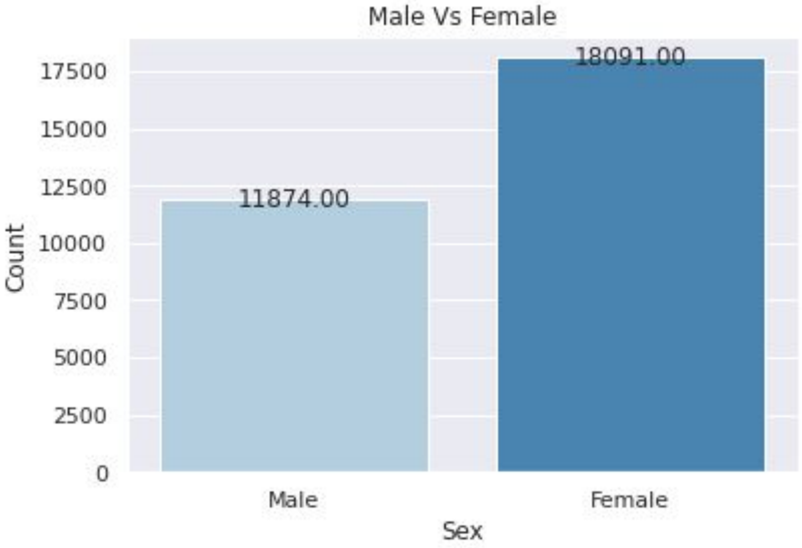
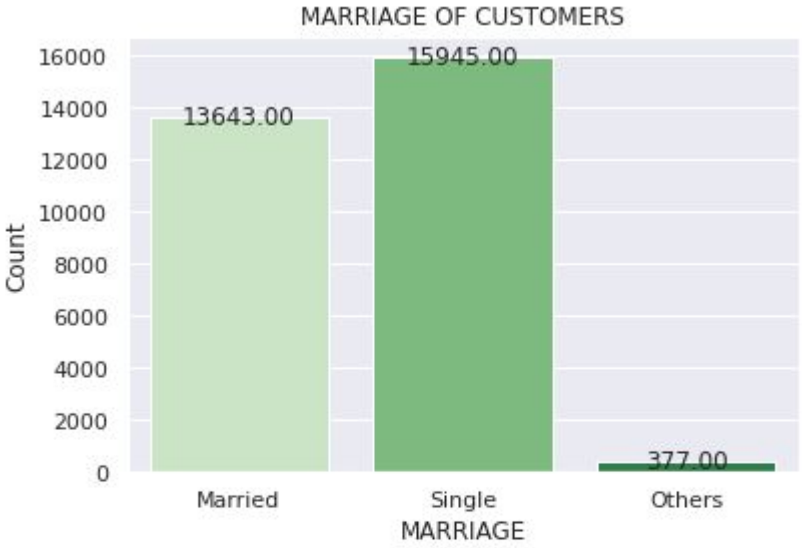



1. It shows count for ‘sex’ attribute




2. It shows default count for ‘marriage’ attribute

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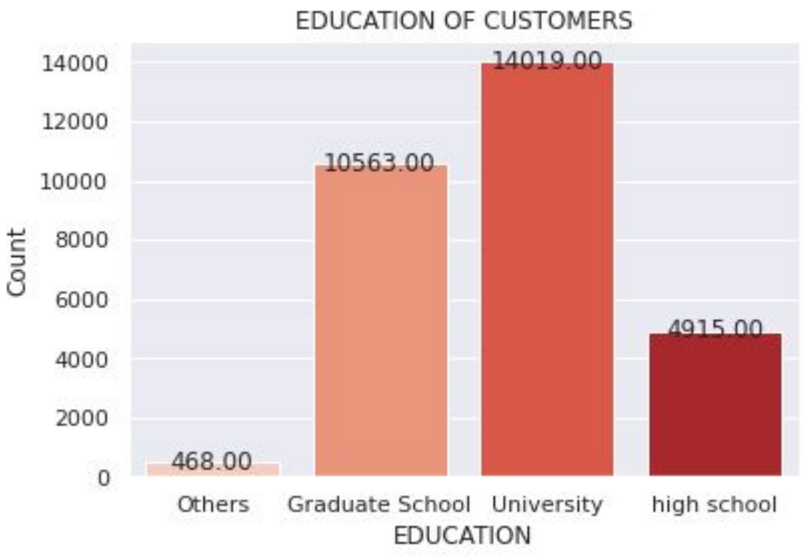


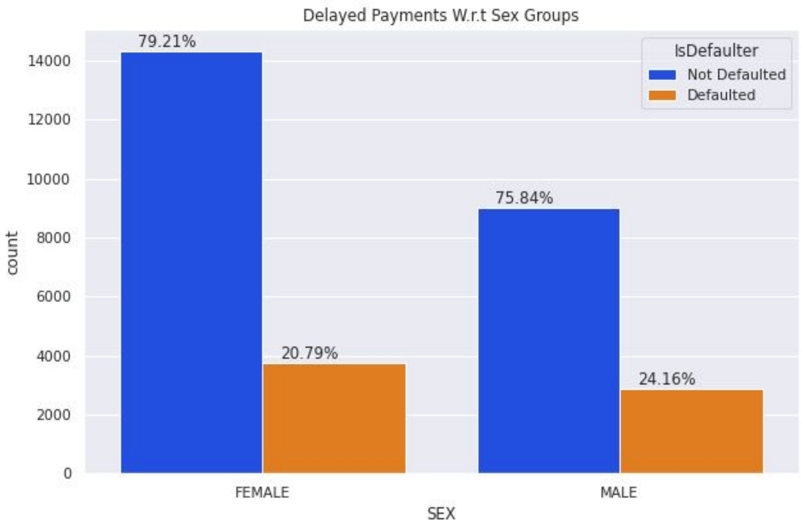


1. It shows count for Education attribute values with respect to credit card count

2. It shows Delayed Payment % wrt Sex.

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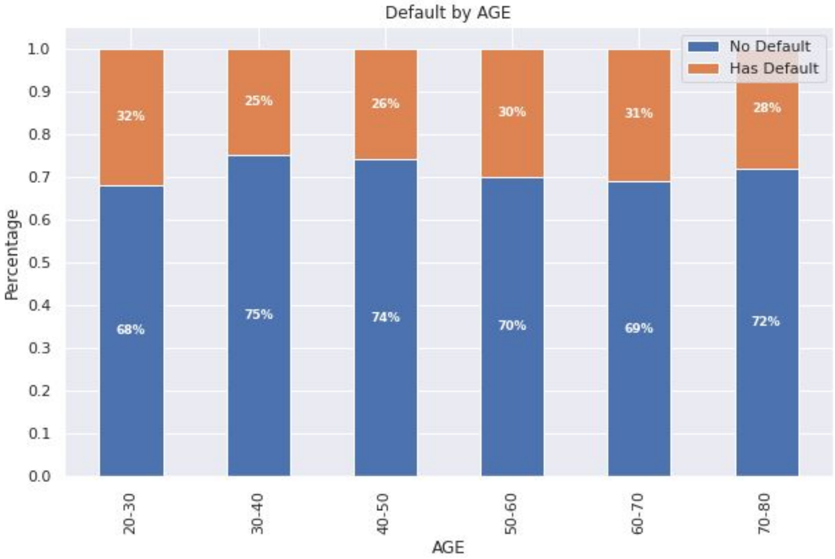
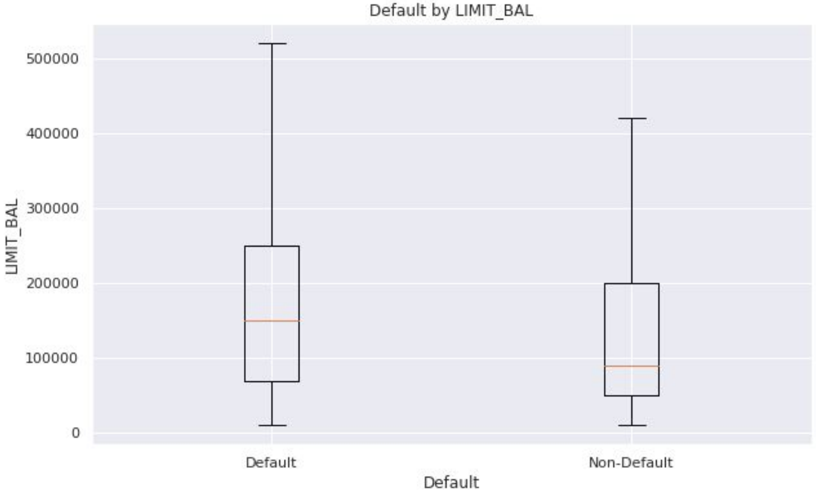



1. It shows %count for Default vs Age

People aged 30-50, and >70 have least default rates




2. It shows Default vs Limit balance

Customers with high credit limit tends to have higher default rate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# Feature Engineering

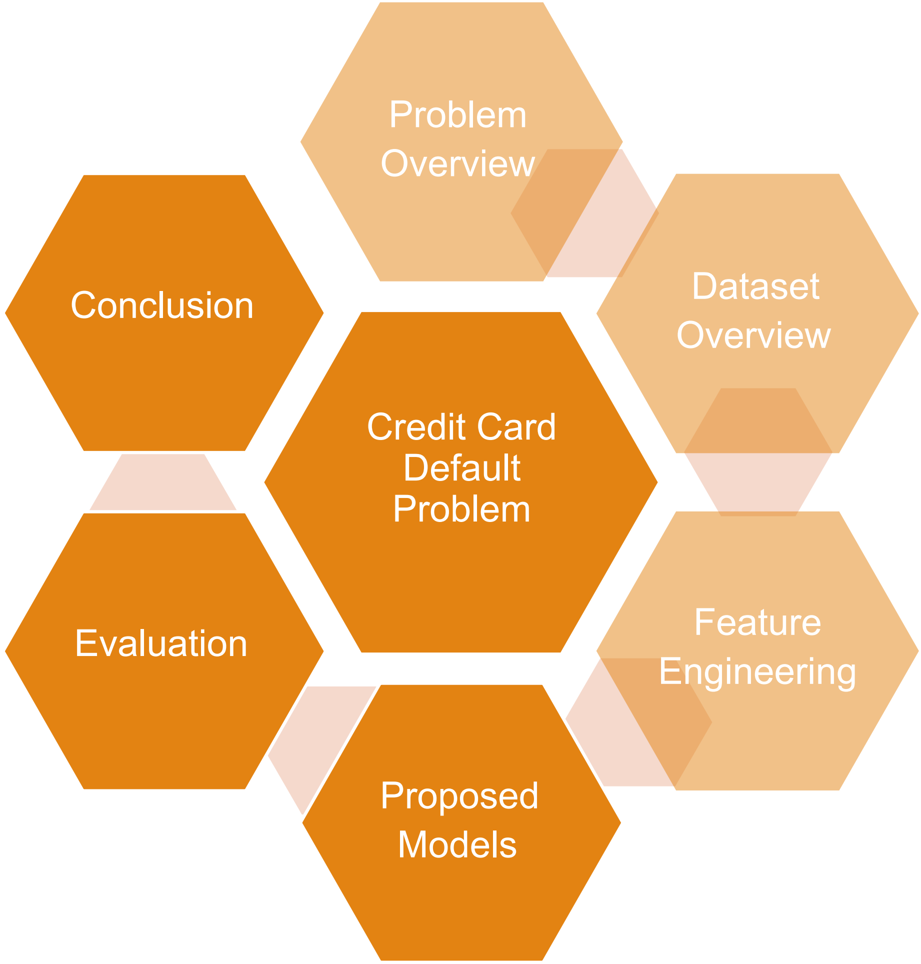
- In this Feature Engineering we have made a separate column for balance of defaulters and got that we have got the result that there are 46670 defaulters.

- We have also done the Label Encoding on the gender section which says Female as 0 and Male as 1

- We have also done One hot encoding on Education and marriage and also divided the age column into 7 groups (21, 30, 40, 50, 60, 70, 80).

- We have separated the Independent Feature and dependent Feature and made a separate columns for Independent Feature.

- Also rescaled the Independent Feature using StandardScaler.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# Proposed Models

## Logistic Regression

- It is used for Binary classification.
- Outputs have a nice probabilistic interpretation, and the algorithm can be regularized to avoid over fitting.
- In logistic regression the hypothesis is that the conditional probability p of class belongs to ”1”
- if probability is greater than threshold probability, generally 0.5, else it belongs to the class ”0”.

$$\text{Ex. } Y(i) = \begin{cases} 1, p \geq 0.5 \\ 0, p < 0.5 \end{cases}$$

## Random Forest Classifier

- Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset
- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result
- The predictions from each tree must have very low correlations

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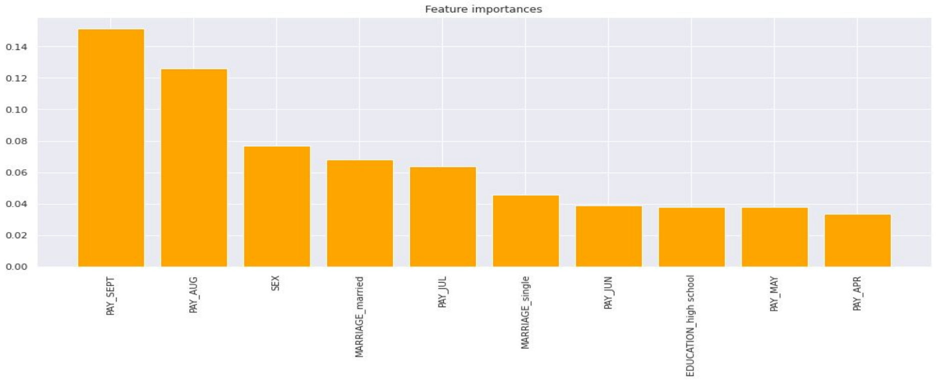
## XGBoost

- It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems
- It's vital to an understanding of XGBoost to first grasp the machine learning concepts and algorithms that XGBoost builds upon supervised machine learning, decision trees, ensemble learning, and gradient boosting.



# Evaluation Process

Evaluation Metrics:

- **Accuracy:** Accuracy determine how often the model predicts default and non-default correctly.
- **Precision:** Precision calculates whenever our models predicts it is default how often it is correct.
- **Recall:** Recall regulate the actual default that the model is actually predict.
- **Precision Recall Curve:** PRC will display the tradeoff between precision and recall threshold.

# Confusion Matrix

**True Positive – A person who is defaulter and predicted as defaulter.**
True Negative – A person who is non-defaulter and predicted as non-defaulter.  False Positive – A person who is predicted defaulter is non-defaulter.

| # | Non-defaulter (predicted) - 0 | Defaulter (predicted) - 1 |
|---|---|---|
| **Non-defaulter (actual) - 0** | TN | FP |
| **Defaulter (actual) - 1** | **FN** | TP |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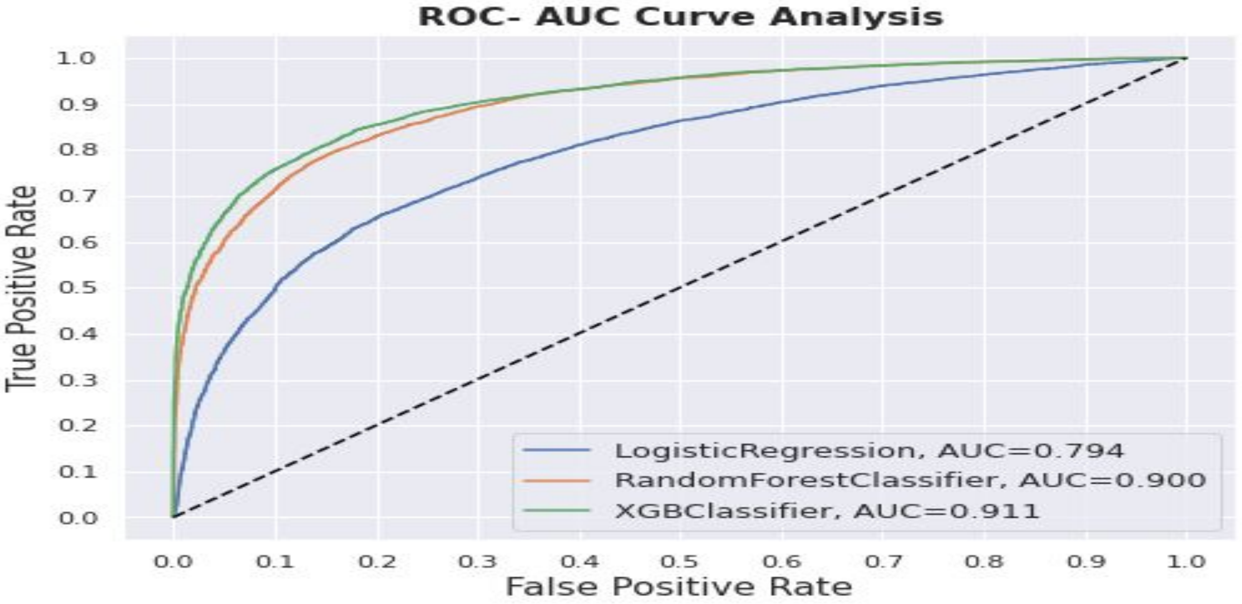
# Evaluation Result

| No. | Algorithms | Train/Test Accuracy(%) | Precision(%) | Recall(%) | Confusion Metrix |
|---|---|---|---|---|---|
| 1 | Logistic Regression | 72.00/72.09 | 72.04 | 72.11 | $\begin{bmatrix} 5100 & 2000 \\ 2000 & 5000 \end{bmatrix}$ |
| 2 | Random Forest | 95.23/81.88 | 79.72 | 83.31 | $\begin{bmatrix} 5900 & 1100 \\ 1400 & 5600 \end{bmatrix}$ |
| 3 | XGBoost | 94.61/83.02 | 80.98 | 84.42 | $\begin{bmatrix} 6000 & 1000 \\ 1300 & 5700 \end{bmatrix}$ |

# ROC-AUC Curve

ROC-AUC curve analysis for the Models

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# Conclusion

- We investigated the data, checking for data unbalancing, visualizing the features and understanding the relationship between different features.

- We used both train-validation split and cross-validation to evaluate the model effectiveness to predict the target value, i.e. detecting if a credit card client will default next month.

- We then investigated three predictive models:
    - We started with Logistic Regression, Random Forest and XG Boost. Among them random forest and XGBoost classifier accuracy is almost same.
    - We choose based model based on **minimum value of False Negative value** i.e. the XG Boost
    - This would also inform the issuer's decisions on who to **give a credit card** to and what **credit limit** to provide.

# THANK YOU