# Credit Card Approval Prediction

DS105 – Final Project Presentation

By Jia Yang

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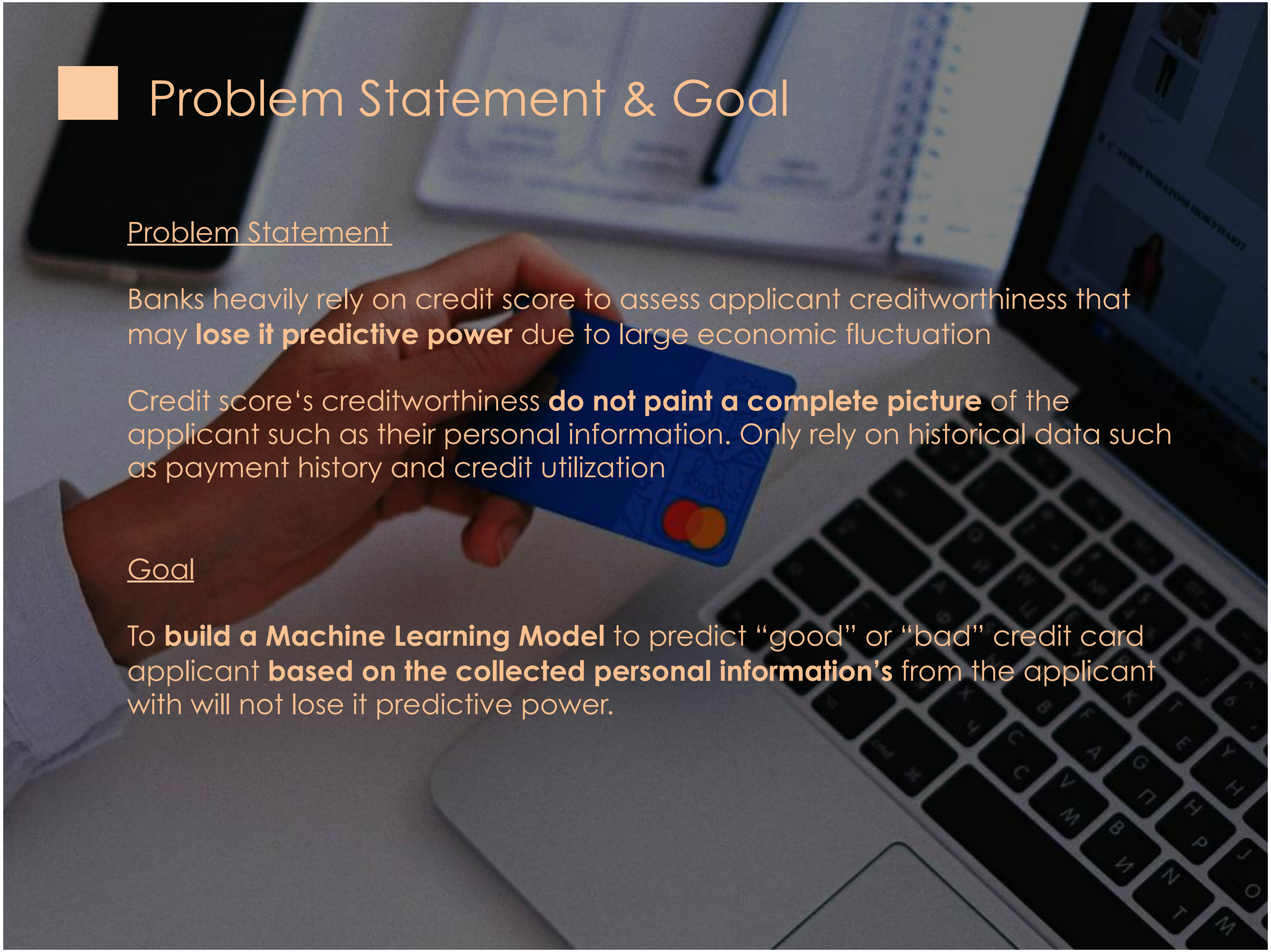


## Problem Statement & Goal

Problem Statement

Banks heavily rely on credit score to assess applicant creditworthiness that may **lose it predictive power** due to large economic fluctuation

Credit score's creditworthiness **do not paint a complete picture** of the applicant such as their personal information. Only rely on historical data such as payment history and credit utilization

Goal

To **build a Machine Learning Model** to predict "good" or "bad" credit card applicant **based on the collected personal information's** from the applicant with will not lose it predictive power.

## Dataset Review

## Dataset Overview

Datasets

1. Application_record.csv
2. Credit_record.csv

*https://www.kaggle.com/rikdifos/credit-card-approval-prediction*

Description

- Datasets are **connected by customer IDs**.
- **Application_record.csv** contains applicant personal information, can be use as **features**. *(Total 18 columns and 439k rows)*
- **Credit_record.csv** records the applicant behaviours of credit card, can be use as **label**. *(Total 3 columns and 1.05m rows)*

# Dataset Overview

## Variable Types - Application_record.csv

| No. | Feature name | Description | Variable Type | Data Type | Variable Category |
|---|---|---|---|---|---|
| 1 | ID | Client number | - | Numeric | Continuous |
| 2 | CODE_GENDER | Gender | Predictor | Numeric | Categorical |
| 3 | FLAG_OWN_CAR | Is there a car | Predictor | Character | Categorical |
| 4 | FLAG_OWN_REALTY | Is there a property | Predictor | Character | Categorical |
| 5 | CNT_CHILDREN | Number of children | Predictor | Numeric | Continuous |
| 6 | AMT_INCOME_TOTAL | Annual income | Predictor | Numeric | Continuous |
| 7 | NAME_INCOME_TYPE | Income category | Predictor | Character | Categorical |
| 8 | NAME_EDUCATION_TYPE | Education level | Predictor | Character | Categorical |
| 9 | NAME_FAMILY_STATUS | Marital status | Predictor | Character | Categorical |
| 10 | NAME_HOUSING_TYPE | Way of living | Predictor | Character | Categorical |
| 11 | DAYS_BIRTH | Birthday count backwards from current day (0), -1 means yesterday | Predictor | Numeric | Continuous |
| 12 | DAYS_EMPLOYED | Start date of employment count backwards from current day(0). If positive, it means the person currently unemployed. | Predictor | Numeric | Continuous |
| 13 | FLAG_MOBIL | Is there a mobile phone | Predictor | Numeric | Categorical |
| 14 | FLAG_WORK_PHONE | Is there a work phone | Predictor | Numeric | Categorical |
| 15 | FLAG_PHONE | Is there a phone | Predictor | Numeric | Categorical |
| 16 | FLAG_EMAIL | Is there an email | Predictor | Numeric | Categorical |
| 17 | OCCUPATION_TYPE | Occupation | Predictor | Character | Categorical |
| 18 | CNT_FAM_MEMBERS | Family size | Predictor | Numeric | Continuous |

Both datasets will be connected with Client Number

## Dataset Overview

### Variable Types - Credit_record.csv

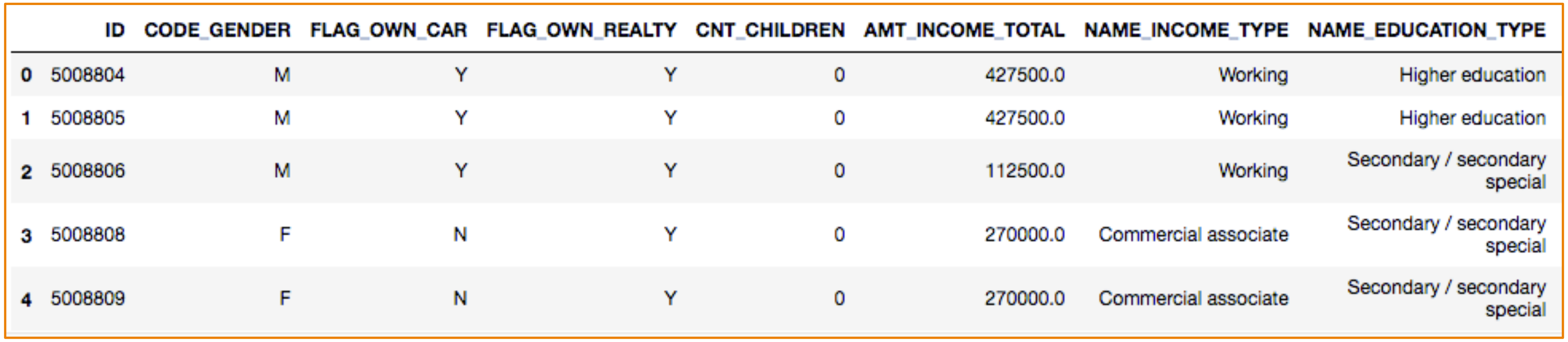
| No. | Feature name | Description | Variable Type | Data Type | Variable Category |
|---|---|---|---|---|---|
| 1 | ID | Client number | - | Numeric | Continuous |
| 2 | MONTHS_BALANCE | The month of the extracted data is the starting point, backwards, 0 is the current month, -1 is the previous month, and so on | Predictor | Numeric | Categorical |
| 3 | STATUS | Payment Status<br>0 : 1-29 days past due<br>1 : 30-59 days past due<br>2 : 60-89 days overdue<br>3 : 90-119 days overdue<br>4 : 120-149 days overdue<br>5 : Overdue or bad debts, write-offs for more than 150 days<br>C : paid off that month<br>X : No loan for the month | Target | Character | Categorical |

Both datasets will be connected with Client Number

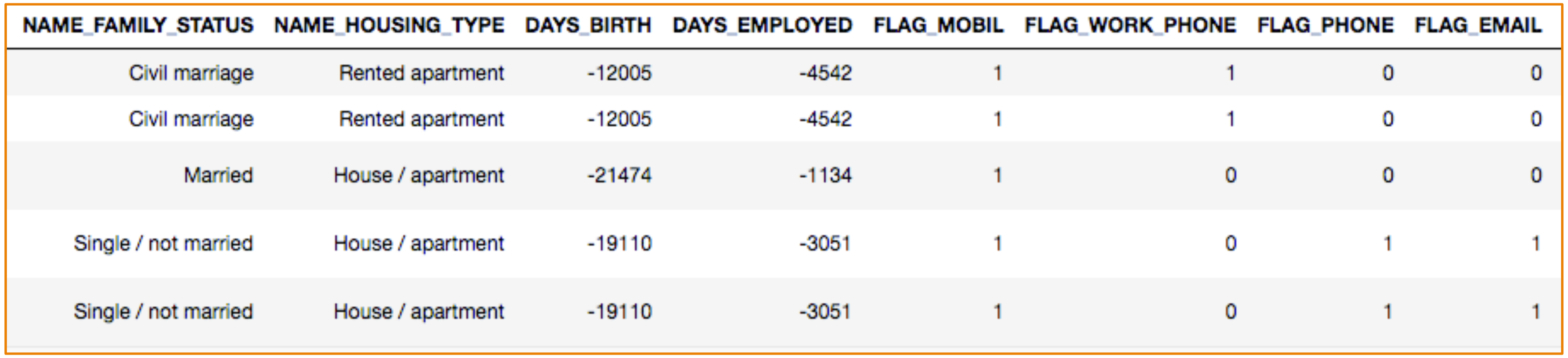
Label for credit card approval based on the acceptable past due range

## Dataset Overview

### Snapshots - Appication_record.csv



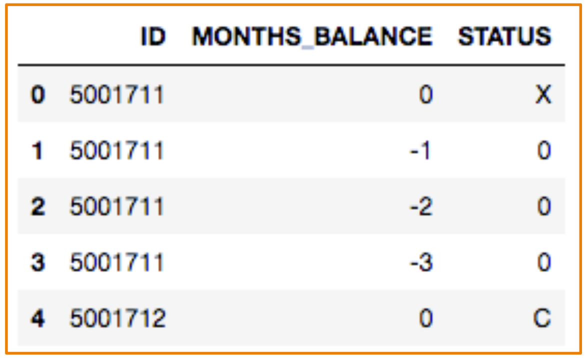
| | ID | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | NAME_INCOME_TYPE | NAME_EDUCATION_TYPE |
|---|---|---|---|---|---|---|---|---|
| **0** | 5008804 | M | Y | Y | 0 | 427500.0 | Working | Higher education |
| **1** | 5008805 | M | Y | Y | 0 | 427500.0 | Working | Higher education |
| **2** | 5008806 | M | Y | Y | 0 | 112500.0 | Working | Secondary / secondary special |
| **3** | 5008808 | F | N | Y | 0 | 270000.0 | Commercial associate | Secondary / secondary special |
| **4** | 5008809 | F | N | Y | 0 | 270000.0 | Commercial associate | Secondary / secondary special |



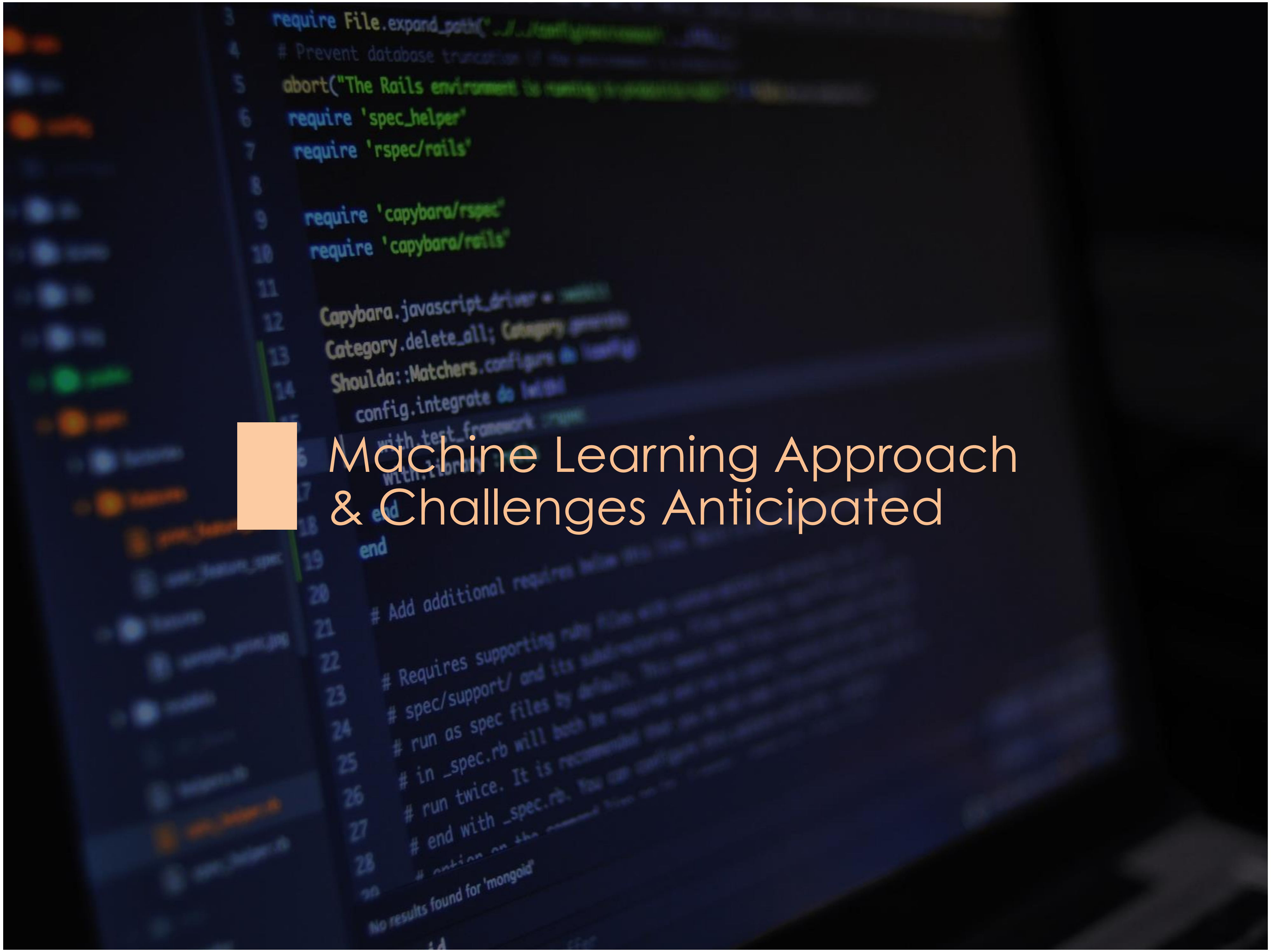
| NAME_FAMILY_STATUS | NAME_HOUSING_TYPE | DAYS_BIRTH | DAYS_EMPLOYED | FLAG_MOBIL | FLAG_WORK_PHONE | FLAG_PHONE | FLAG_EMAIL |
|---|---|---|---|---|---|---|---|
| Civil marriage | Rented apartment | -12005 | -4542 | 1 | 1 | 0 | 0 |
| Civil marriage | Rented apartment | -12005 | -4542 | 1 | 1 | 0 | 0 |
| Married | House / apartment | -21474 | -1134 | 1 | 0 | 0 | 0 |
| Single / not married | House / apartment | -19110 | -3051 | 1 | 0 | 1 | 1 |
| Single / not married | House / apartment | -19110 | -3051 | 1 | 0 | 1 | 1 |

## Dataset Overview

Snapshots - Creidt_record.csv

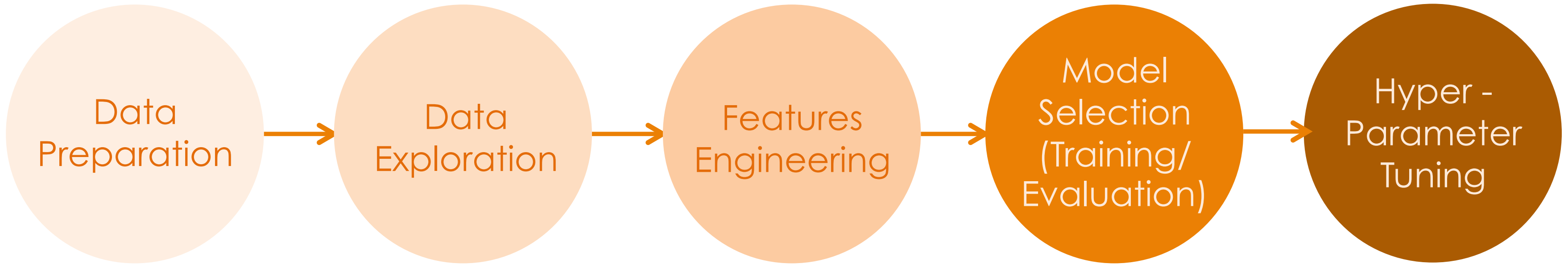


| | ID | MONTHS_BALANCE | STATUS |
|---|---|---|---|
| **0** | 5001711 | 0 | X |
| **1** | 5001711 | -1 | 0 |
| **2** | 5001711 | -2 | 0 |
| **3** | 5001711 | -3 | 0 |
| **4** | 5001712 | 0 | C |



## Machine Learning Approach & Challenges Anticipated

# Machine Learning Approach & Challenges Anticipated



## Challenges

- Null values treatment
- Duplicate records
- Joining of datasets

- Relationship between variables

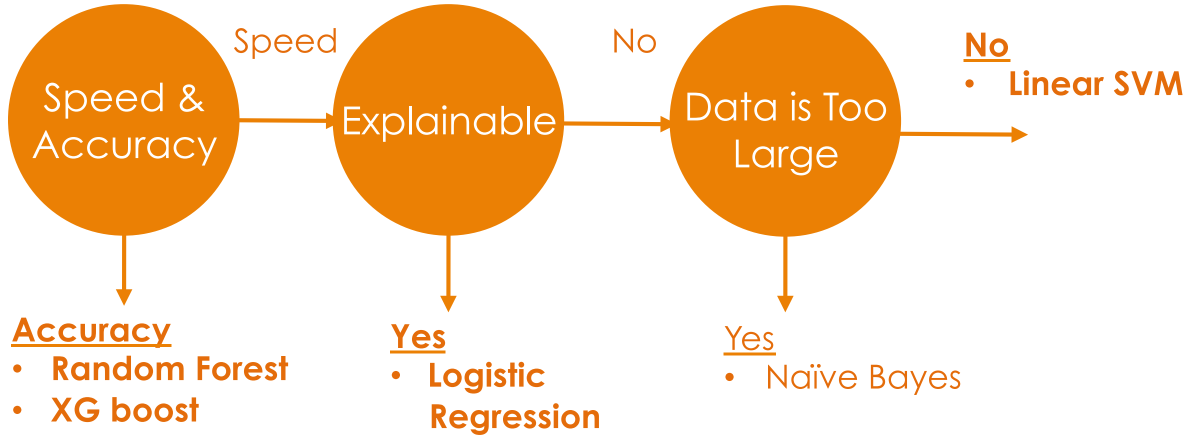
- Create Label
- Create new meaningful features
- Reduce unused features
- Data unbalance.
- Encode categorical features
- Scale overall dataset

- Choose the best Classification ML model based on different evaluation method

- Choose the best hyper parameter

# Machine Learning Approach & Challenges Anticipated

## Classification Models Selection



**Accuracy**
- **Random Forest**
- **XG boost**

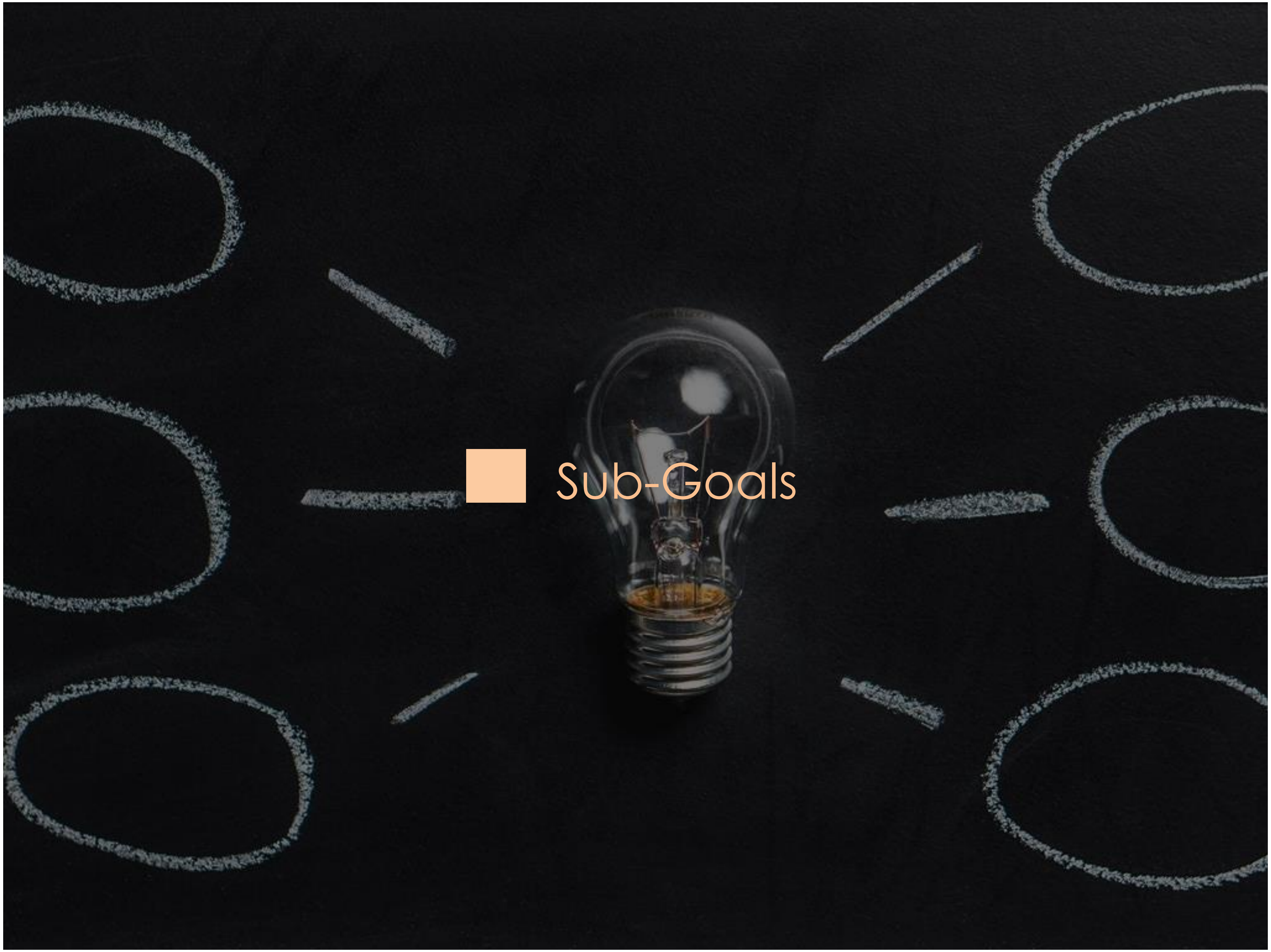
**Yes**
- **Logistic Regression**

Yes
- Naïve Bayes

**No**
- **Linear SVM**

## Evaluation Methods

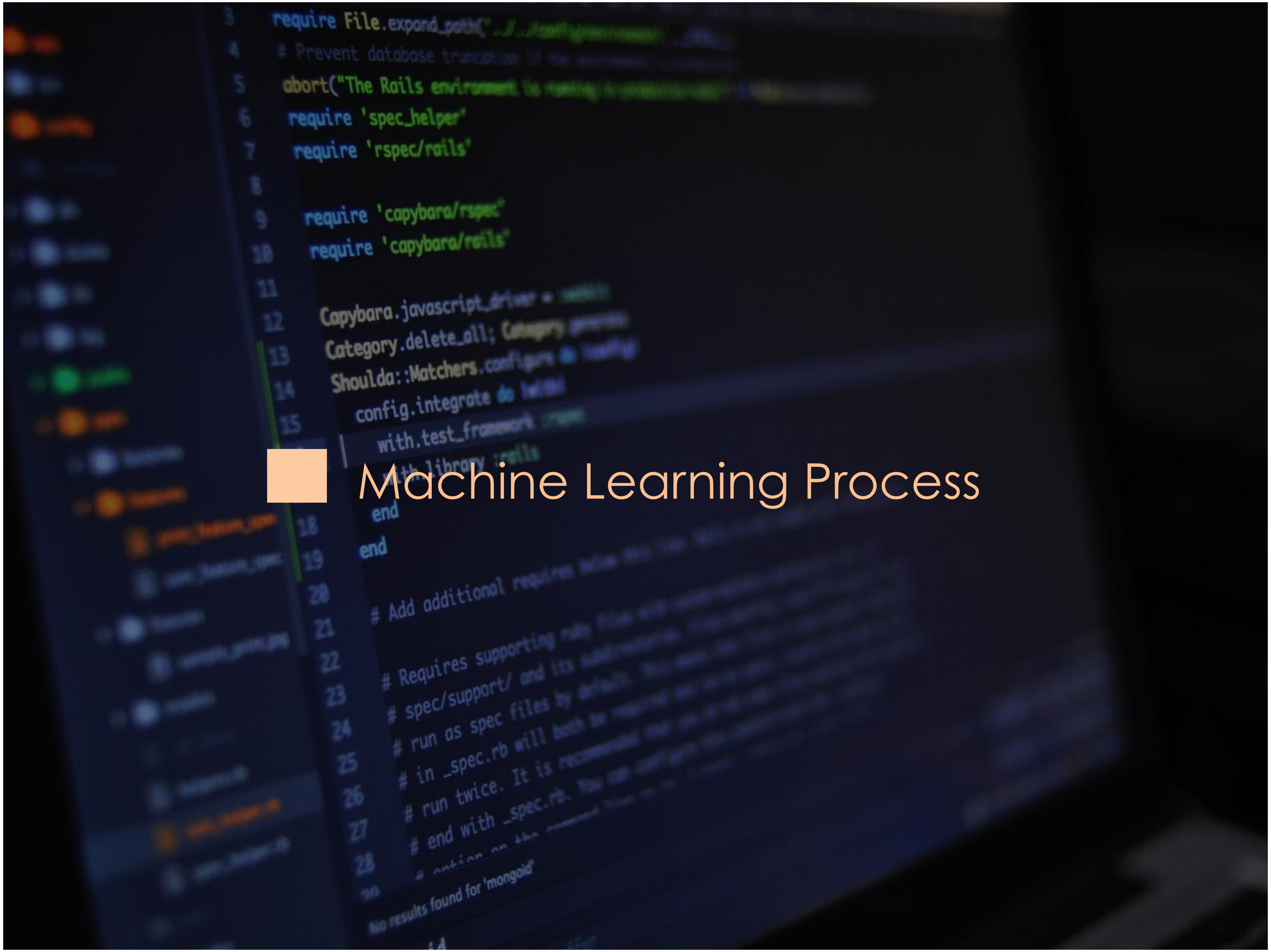
- Accuracy
- F1-Score
- ROC / AUC



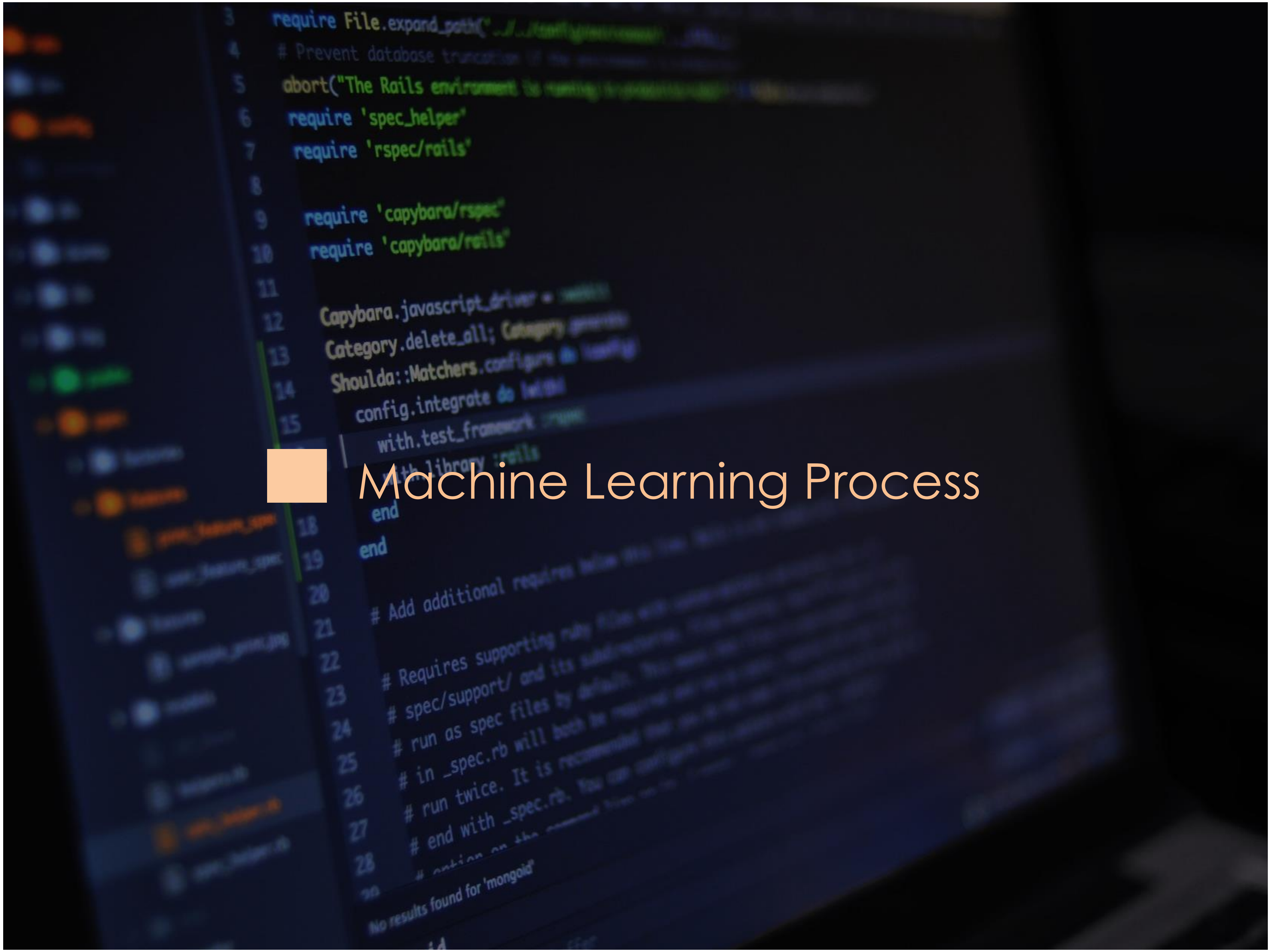
## Sub-Goals

## Sub-Goals

1. Method of creating label from credit_record.csv?
2. Clear segregation between the “good” and “bad” credit card applicants?
3. The best classification machine learning model for prediction?
4. The best hyper-parameters to give the best prediction result?
5. The feature that give the major contribution to the prediction?

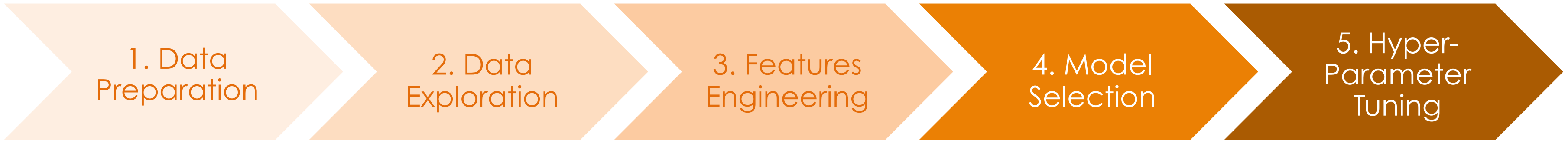


## Machine Learning Process



## Machine Learning Process

## Machine Learning Process



1.1 Checking Of Null Values
1.2 Checking Of Duplicate Records
1.3 Joining Datasets

2.1 Continuous Features
2.2 Categorical Features
2.3 Continuous Vs Continuous Features
2.4 Categorical Vs Categorical Features
2.5 Categorical Vis Continuous Features

3.1 Creating Label
3.2 Change Categorical Data to Frequency
3.3 Check Data Unbalance
3.4 Train-Test Split and MinMaxScalar

4.1 Logistic Regression
4.2 SVM
4.3 Random Forest
4.4 XG boost
4.5 Result Comparison

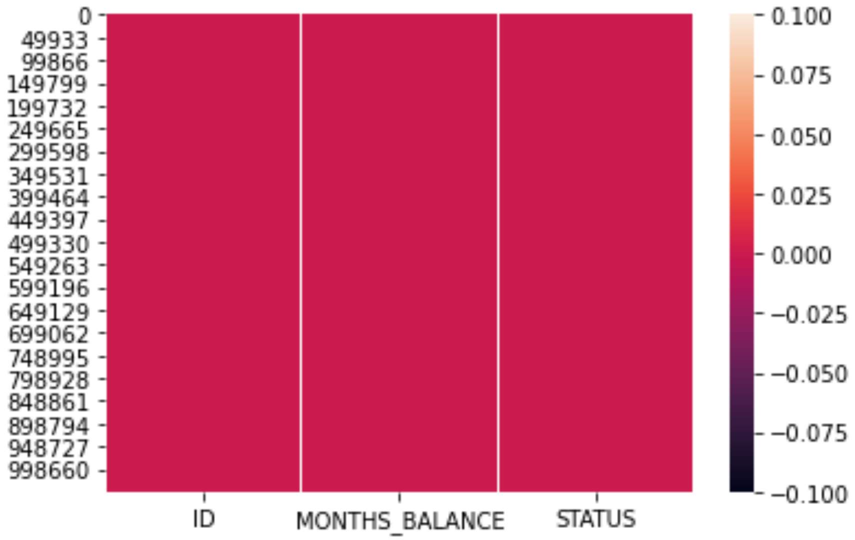
5.1 Tune XGBoost with XGB.cv
5.2 Tune Random Forest with RandomSearch.cv & GridSearch.cv
5.3 Conclusion

# Machine Learning Process

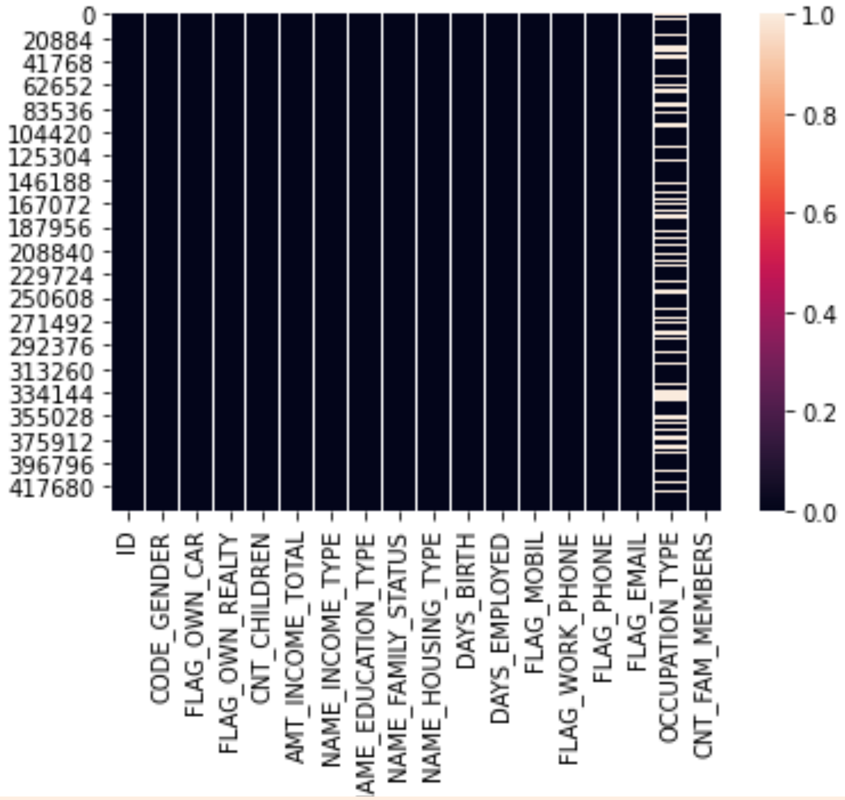
1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 1.1 Checking Of Null Values

credit_record = Credit_record.csv



app_record = Application_record.csv



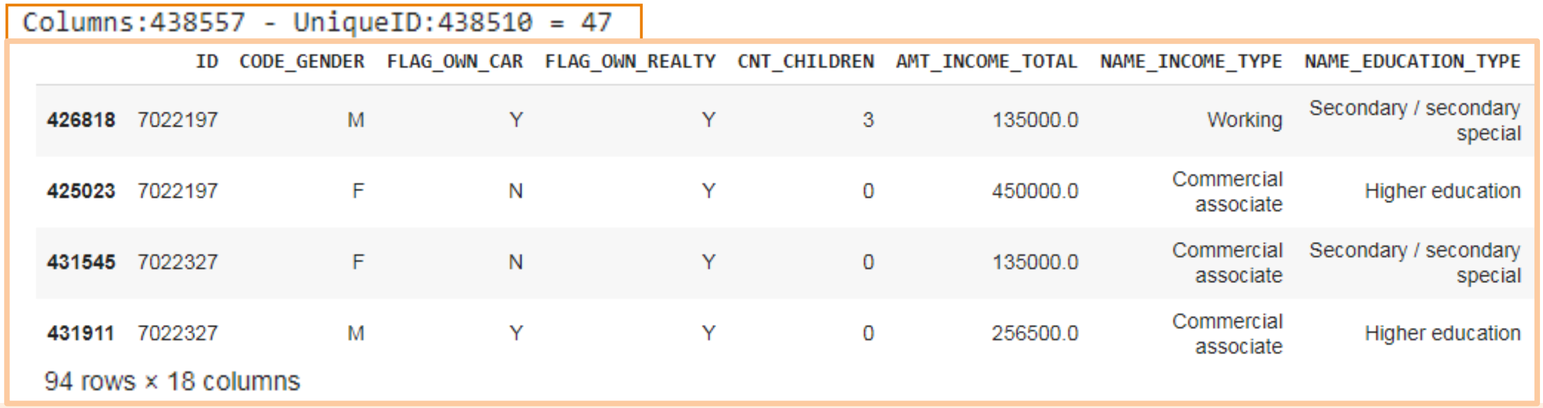
- 30.6% null value in "OCCUPATION_TYPE" column
- <50%, hence, **Fillna** with cat "OTHER"

# Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 1.2 Checking Of Duplicate Records

### app_record



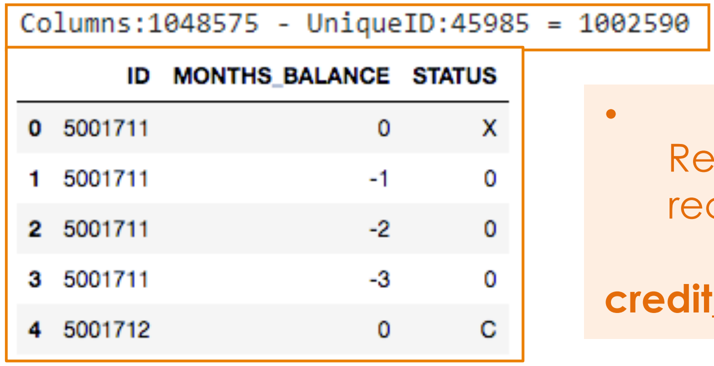
```
Columns:438557 - UniqueID:438510 = 47
```

| | ID | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | NAME_INCOME_TYPE | NAME_EDUCATION_TYPE |
|---|---|---|---|---|---|---|---|---|
| **426818** | 7022197 | M | Y | Y | 3 | 135000.0 | Working | Secondary / secondary special |
| **425023** | 7022197 | F | N | Y | 0 | 450000.0 | Commercial associate | Higher education |
| **431545** | 7022327 | F | N | Y | 0 | 135000.0 | Commercial associate | Secondary / secondary special |
| **431911** | 7022327 | M | Y | Y | 0 | 256500.0 | Commercial associate | Higher education |

94 rows × 18 columns

- **app_record['ID''].duplicated** found duplicate records (47 x 2 = 94 rows)
- Different data in each features, hence, might be issue when assigning IDs to new applicant
- Decided to drop every 2nd record by **app_record.drop_duplicates()**

### credit_record



```
Columns:1048575 - UniqueID:45985 = 1002590
```

| | ID | MONTHS_BALANCE | STATUS |
|---|---|---|---|
| **0** | 5001711 | 0 | X |
| **1** | 5001711 | -1 | 0 |
| **2** | 5001711 | -2 | 0 |
| **3** | 5001711 | -3 | 0 |
| **4** | 5001712 | 0 | C |

- Remove multiple monthly entries and only keep the latest record.

**credit_uniq = credit_record.groupby('ID').max().reset_index()**

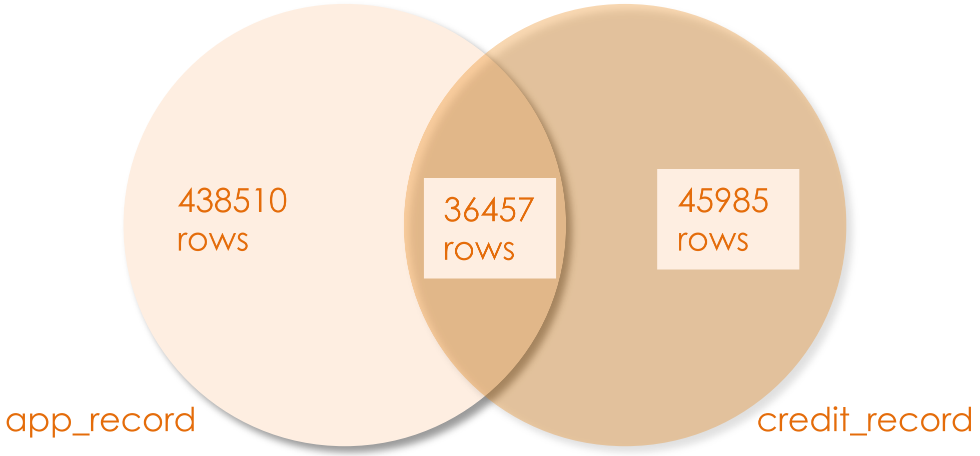
# Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 1.3 Joining Datasets

- Checking how many ID do two datasets share?
  36457 shared the same ID.
  **len(set(app_record['ID']).intersection(set(credit_uniq['ID'])))**

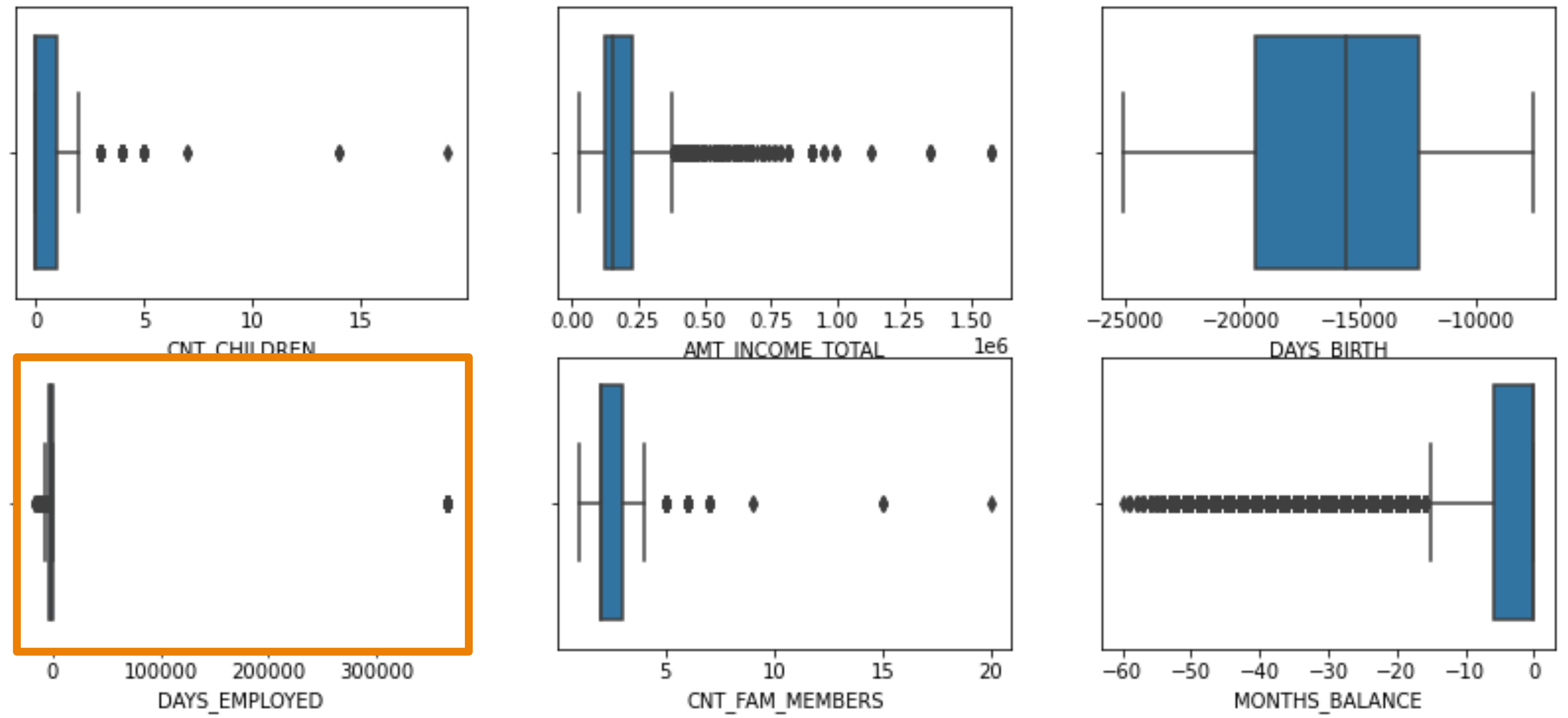
- Inner join both datasets together by ID.
  **df = app_record.join(credit_uniq.set_index('ID'), on='ID', how='inner')**



# Machine Learning Process

1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

## 2.1 Continuous Features (6 columns)



- "DAYS_EMPLOYED" have outliers of >30,0000days (82years) which is impossible.
- Other features have outliers that more then 1.5x IQ however, the values are still reasonable
- Drop all data in "DAYS_EMPLOYED" that > 30,0000days. **df2 = df[df['DAYS_EMPLOYED'] < 300000**]

## Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

### 2.2 Categorical Features (13 columns)

We can use frequency table to understand distribution of each category

```
======== CODE_GENDER ========
    count  percent%
F  19195       63.3
M  11127       36.7

======== FLAG_OWN_CAR ========
    count  percent%
N  17766      58.59
Y  12556      41.41

======== FLAG_OWN_REALTY ========
    count  percent%
Y  19786      65.25
N  10536      34.75

======== NAME_INCOME_TYPE ========
                      count  percent%
Working               18819     62.06
Commercial associate   8490     28.00
State servant          2985      9.84
Pensioner                17      0.06
Student                  11      0.04
```

```
======== NAME_EDUCATION_TYPE ========
                               count  percent%
Secondary / secondary special  19867     65.52
Higher education                8858     29.21
Incomplete higher               1352      4.46
Lower secondary                  214      0.71
Academic degree                   31      0.10

======== NAME_FAMILY_STATUS ========
                      count  percent%
Married               21137     69.71
Single / not married   4148     13.68
Civil marriage         2575      8.49
Separated              1758      5.80
Widow                   704      2.32

======== NAME_FAMILY_STATUS ========
                      count  percent%
Married               21137     69.71
Single / not married   4148     13.68
Civil marriage         2575      8.49
Separated              1758      5.80
Widow                   704      2.32

======== FLAG_MOBIL ========
   count  percent%
1  30322     100.0
```

```
======== FLAG_WORK_PHONE ========
   count  percent%
0  22100     72.88
1   8222     27.12

======== FLAG_PHONE ========
   count  percent%
0  21342     70.38
1   8980     29.62

======== FLAG_EMAIL ========
   count  percent%
0  27265     89.92
1   3057     10.08

======== STATUS ========
   count  percent%
X  16281     53.69
C   9840     32.45
0   3538     11.67
1    574      1.89
5     42      0.14
2     38      0.13
3      7      0.02
4      2      0.01
```

```
======== OCCUPATION_TYPE ========
                       count  percent%
Laborers                6211     20.48
Others                  5188     17.11
Core staff              3591     11.84
Sales staff             3485     11.49
Managers                3012      9.93
Drivers                 2138      7.05
High skill tech staff   1383      4.56
Accountants             1241      4.09
Medicine staff          1207      3.98
Cooking staff            655      2.16
Security staff           592      1.95
Cleaning staff           551      1.82
Private service staff    344      1.13
Low-skill Laborers       175      0.58
Waiters/barmen staff     174      0.57
Secretaries              151      0.50
HR staff                  85      0.28
Realty agents             79      0.26
IT staff                  60      0.20
```

- All of features are important since there is very fine classification in each column.
- Their effectiveness cannot be judged at this moment.
- Will drop "FLAG_MOBIL" as it 100% count 1 which no point to include into the model later on.
  **df3 = df2.drop(["FLAG_MOBIL"],axis='columns')**

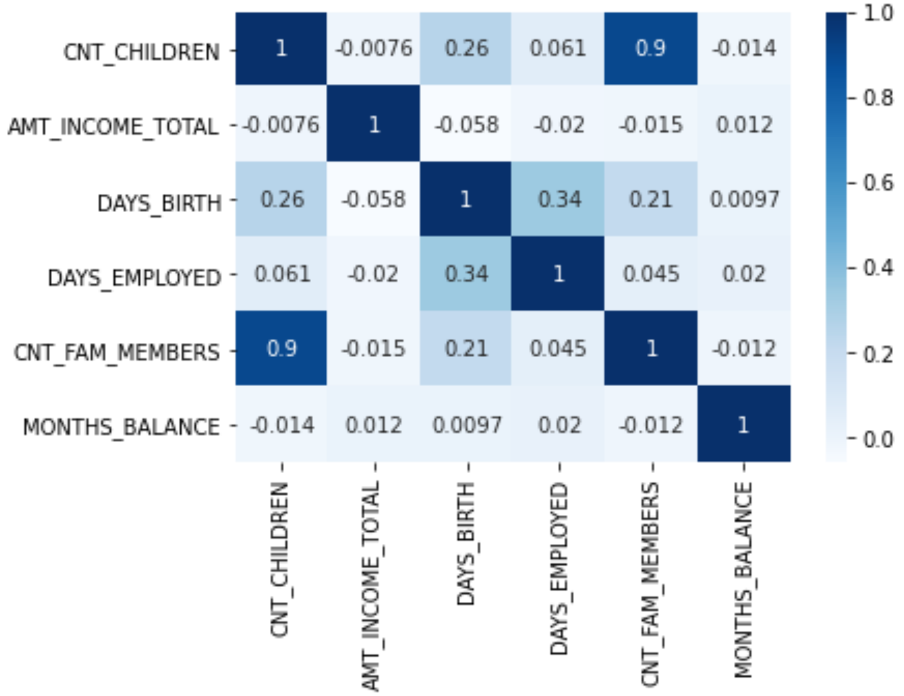
# Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 2.3 Continuous Vs Continuous Features

We can use standard Pearson coefficient **(df.corr)** to understand correlation between each continuous variables

- -1: perfect negative linear correlation
- +1:perfect positive linear correlation and
- 0: No correlation



| | CNT_CHILDREN | AMT_INCOME_TOTAL | DAYS_BIRTH | DAYS_EMPLOYED | CNT_FAM_MEMBERS | MONTHS_BALANCE |
|---|---|---|---|---|---|---|
| CNT_CHILDREN | 1 | -0.0076 | 0.26 | 0.061 | 0.9 | -0.014 |
| AMT_INCOME_TOTAL | -0.0076 | 1 | -0.058 | -0.02 | -0.015 | 0.012 |
| DAYS_BIRTH | 0.26 | -0.058 | 1 | 0.34 | 0.21 | 0.0097 |
| DAYS_EMPLOYED | 0.061 | -0.02 | 0.34 | 1 | 0.045 | 0.02 |
| CNT_FAM_MEMBERS | 0.9 | -0.015 | 0.21 | 0.045 | 1 | -0.012 |
| MONTHS_BALANCE | -0.014 | 0.012 | 0.0097 | 0.02 | -0.012 | 1 |

- "CNT_CHILDREN" & "CNT_FAM_MEMBERS" are more correlated to each other.
- The no. of children is within the count of family members.
- Others are close to no correlation

# Machine Learning Process

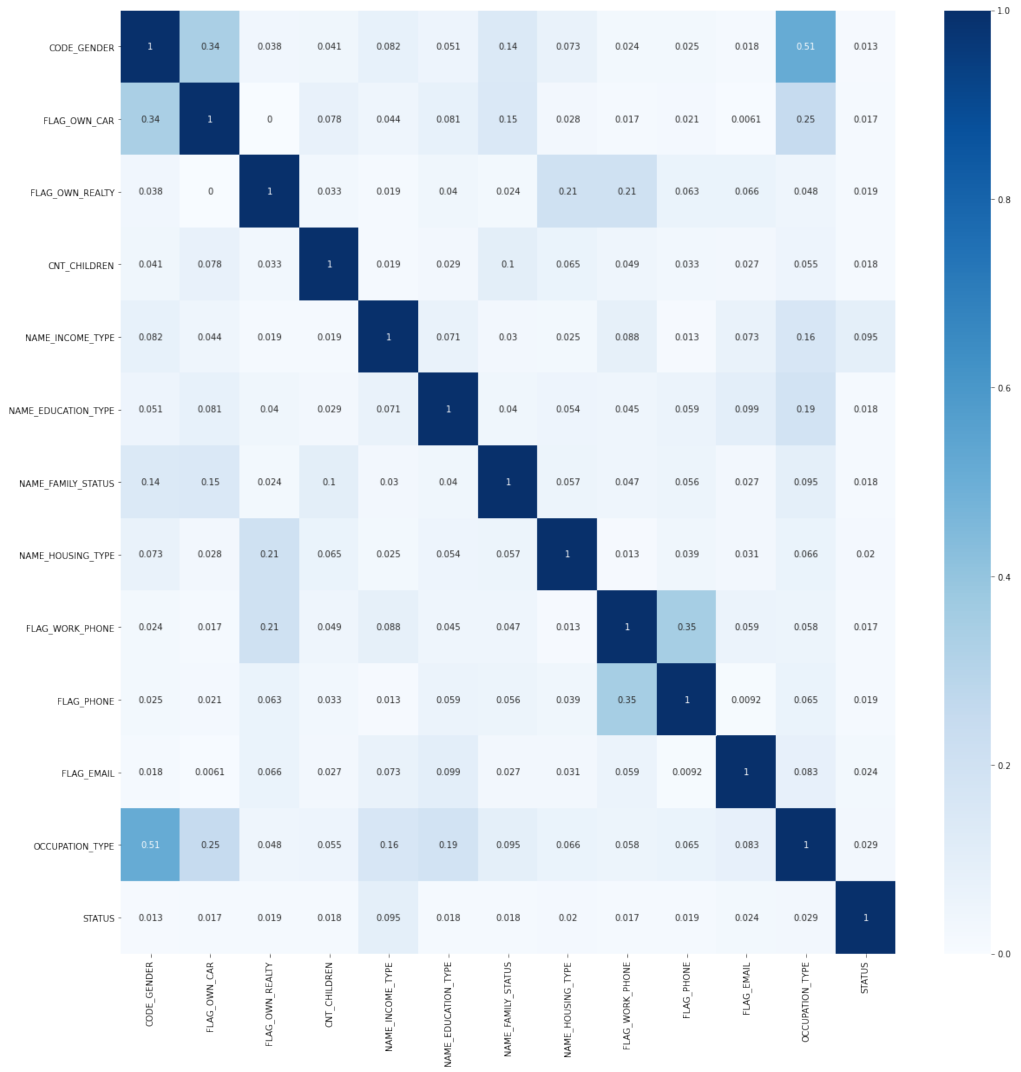
1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

## 2.4 Categorical Vs Categorical Features

We will use "Cramer's V" to find degree of association between categorical variables

- 0: The variables are not associated
- 1: The variables are perfectly associated
- 0.25: The variables are weakly associated
- 0.75: The variables are moderately associated

- Most are weakly associated (<0.25) between columns.
- The highest (0.51) is between Gender & Occupation type
- The next highest are between Gender & Own a car
- Both association lower than moderate (<0.75)



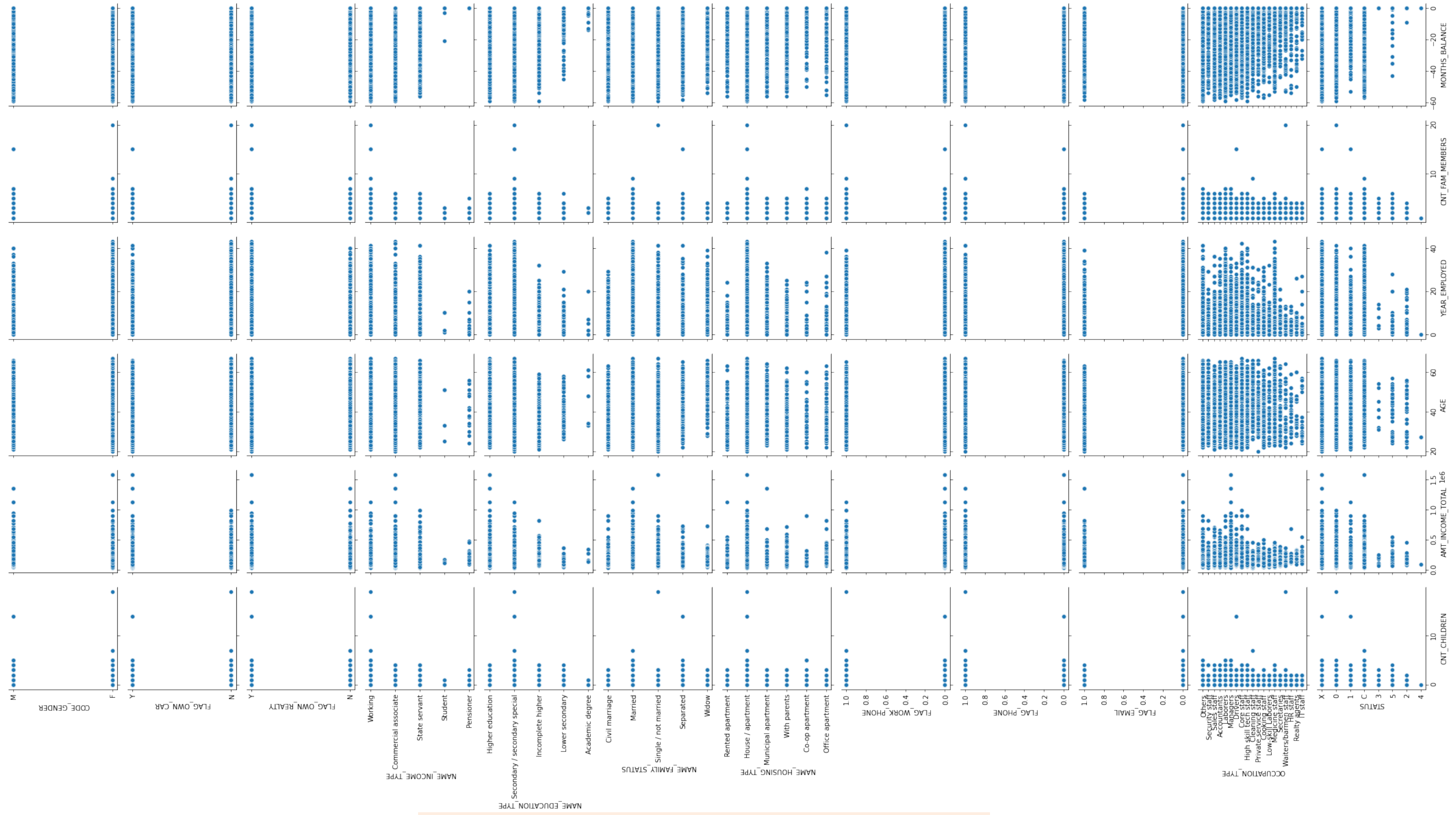
| | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | NAME_INCOME_TYPE | NAME_EDUCATION_TYPE | NAME_FAMILY_STATUS | NAME_HOUSING_TYPE | FLAG_WORK_PHONE | FLAG_PHONE | FLAG_EMAIL | OCCUPATION_TYPE | STATUS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CODE_GENDER | 1 | 0.34 | 0.038 | 0.041 | 0.082 | 0.051 | 0.14 | 0.073 | 0.024 | 0.025 | 0.018 | 0.51 | 0.013 |
| FLAG_OWN_CAR | 0.34 | 1 | 0 | 0.078 | 0.044 | 0.081 | 0.15 | 0.028 | 0.017 | 0.021 | 0.0061 | 0.25 | 0.017 |
| FLAG_OWN_REALTY | 0.038 | 0 | 1 | 0.033 | 0.019 | 0.04 | 0.024 | 0.21 | 0.21 | 0.063 | 0.066 | 0.048 | 0.019 |
| CNT_CHILDREN | 0.041 | 0.078 | 0.033 | 1 | 0.019 | 0.029 | 0.1 | 0.065 | 0.049 | 0.033 | 0.027 | 0.055 | 0.018 |
| NAME_INCOME_TYPE | 0.082 | 0.044 | 0.019 | 0.019 | 1 | 0.071 | 0.03 | 0.025 | 0.088 | 0.013 | 0.073 | 0.16 | 0.095 |
| NAME_EDUCATION_TYPE | 0.051 | 0.081 | 0.04 | 0.029 | 0.071 | 1 | 0.04 | 0.054 | 0.045 | 0.059 | 0.099 | 0.19 | 0.018 |
| NAME_FAMILY_STATUS | 0.14 | 0.15 | 0.024 | 0.1 | 0.03 | 0.04 | 1 | 0.057 | 0.047 | 0.056 | 0.027 | 0.095 | 0.018 |
| NAME_HOUSING_TYPE | 0.073 | 0.028 | 0.21 | 0.065 | 0.025 | 0.054 | 0.057 | 1 | 0.013 | 0.039 | 0.031 | 0.066 | 0.02 |
| FLAG_WORK_PHONE | 0.024 | 0.017 | 0.21 | 0.049 | 0.088 | 0.045 | 0.047 | 0.013 | 1 | 0.35 | 0.059 | 0.058 | 0.017 |
| FLAG_PHONE | 0.025 | 0.021 | 0.063 | 0.033 | 0.013 | 0.059 | 0.056 | 0.039 | 0.35 | 1 | 0.0092 | 0.065 | 0.019 |
| FLAG_EMAIL | 0.018 | 0.0061 | 0.066 | 0.027 | 0.073 | 0.099 | 0.027 | 0.031 | 0.059 | 0.0092 | 1 | 0.083 | 0.024 |
| OCCUPATION_TYPE | 0.51 | 0.25 | 0.048 | 0.055 | 0.16 | 0.19 | 0.095 | 0.066 | 0.058 | 0.065 | 0.083 | 1 | 0.029 |
| STATUS | 0.013 | 0.017 | 0.019 | 0.018 | 0.095 | 0.018 | 0.018 | 0.02 | 0.017 | 0.019 | 0.024 | 0.029 | 1 |

# Machine Learning Process

1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

## 2.5 Categorical Vis Continuous Features

We will use strip plot to understand the distribution of each continuous to categorical variables.



Continuous Features (6 columns)

Categorical Features (13 columns)

# Machine Learning Process

1. Data Preparation → 2. Data Exploration → **3. Features Engineering** → 4. Model Selection → 5. Hyper-Parameter Tuning

## 3.1 Creating Label

- We will be creating binary label. (1 : Bad Customer, 0 : Good Customer)
- Refer to distribution table of ‘STATUS”. Almost 98% users have not more than 29 days overdue (only 2% for >29 days overdue), which is too common, thus, it's inappropriate to be our standard.
- Whereas if we use >89 days overdue(in most bank standard), its only 0.17%. If we use that, we will left out many bad customers from our analysis.
- Hence, we will define that overdue >1day will be the bad customer

**Payment Status :**

X : No loan for the month

C : paid off that month

0 : 1-29 days past due

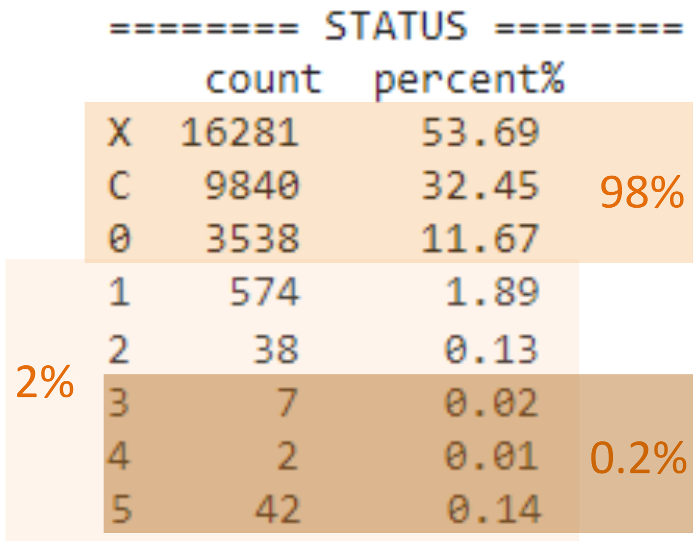
1 : 30-59 days past due

2 : 60-89 days overdue

3 : 90-119 days overdue

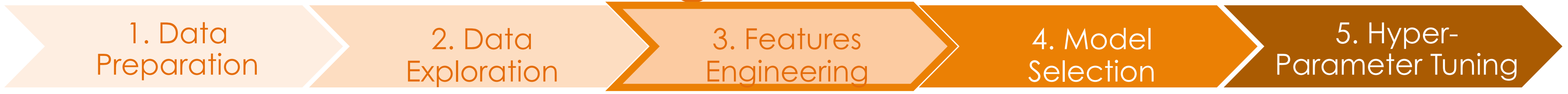
4 : 120-149 days overdue

5. >150 days



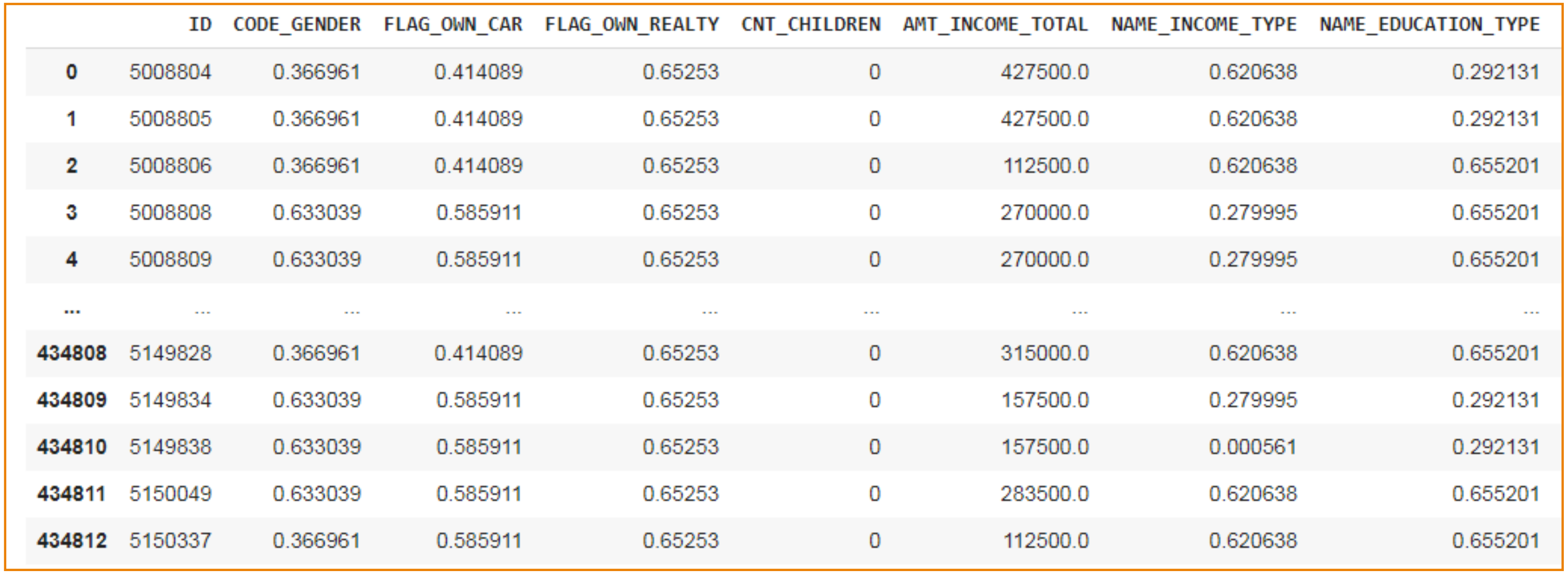
```
======== STATUS ========
     count   percent%
X    16281      53.69
C     9840      32.45
0     3538      11.67
1      574       1.89
2       38       0.13
3        7       0.02
4        2       0.01
5       42       0.14
```

## Machine Learning Process



### 3.2 Change Categorical Data to Frequency

We will use frequency encoder as the categorical data are all nominal type.



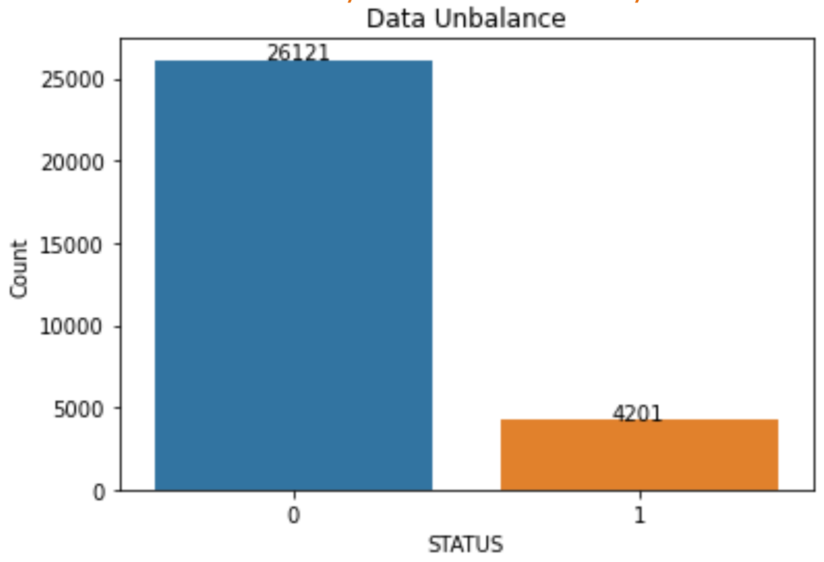
| | ID | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | NAME_INCOME_TYPE | NAME_EDUCATION_TYPE |
|---|---|---|---|---|---|---|---|---|
| **0** | 5008804 | 0.366961 | 0.414089 | 0.65253 | 0 | 427500.0 | 0.620638 | 0.292131 |
| **1** | 5008805 | 0.366961 | 0.414089 | 0.65253 | 0 | 427500.0 | 0.620638 | 0.292131 |
| **2** | 5008806 | 0.366961 | 0.414089 | 0.65253 | 0 | 112500.0 | 0.620638 | 0.655201 |
| **3** | 5008808 | 0.633039 | 0.585911 | 0.65253 | 0 | 270000.0 | 0.279995 | 0.655201 |
| **4** | 5008809 | 0.633039 | 0.585911 | 0.65253 | 0 | 270000.0 | 0.279995 | 0.655201 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **434808** | 5149828 | 0.366961 | 0.414089 | 0.65253 | 0 | 315000.0 | 0.620638 | 0.655201 |
| **434809** | 5149834 | 0.633039 | 0.585911 | 0.65253 | 0 | 157500.0 | 0.279995 | 0.292131 |
| **434810** | 5149838 | 0.633039 | 0.585911 | 0.65253 | 0 | 157500.0 | 0.000561 | 0.292131 |
| **434811** | 5150049 | 0.633039 | 0.585911 | 0.65253 | 0 | 283500.0 | 0.620638 | 0.655201 |
| **434812** | 5150337 | 0.366961 | 0.585911 | 0.65253 | 0 | 112500.0 | 0.620638 | 0.655201 |

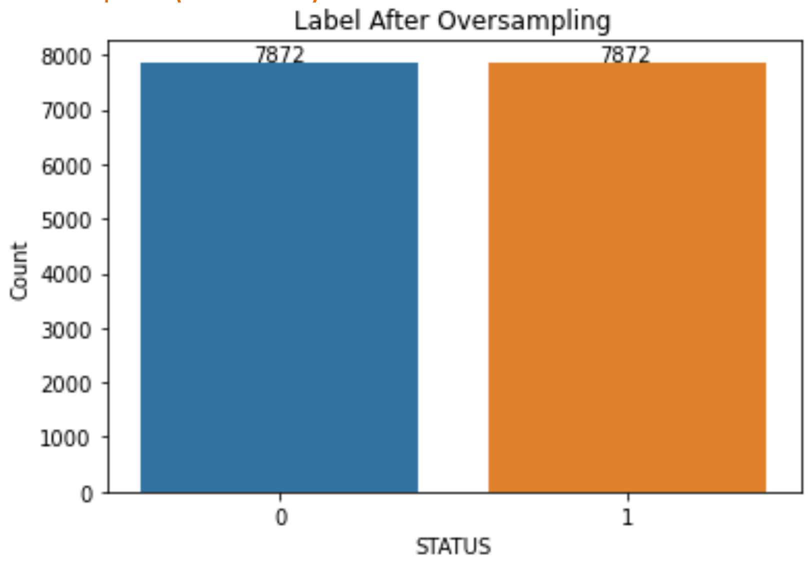
# Machine Learning Process

1. Data Preparation → 2. Data Exploration → 3. Features Engineering → 4. Model Selection → 5. Hyper-Parameter Tuning

## 3.3 Check Data Unbalance

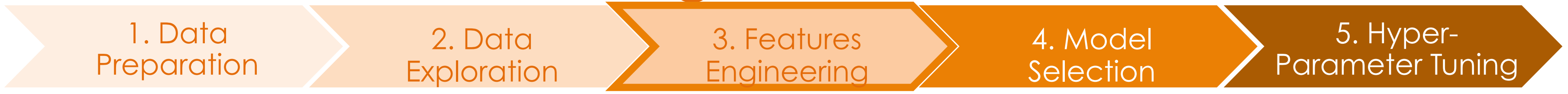
- The dataset is imbalanced.
- Classification model will give a false accuracy rate as the prediction uses the most common class without performing any analysis of the features.
- We will use Synthetic Minority Oversampling TEchnique (SMOTE) to make the dataset balance





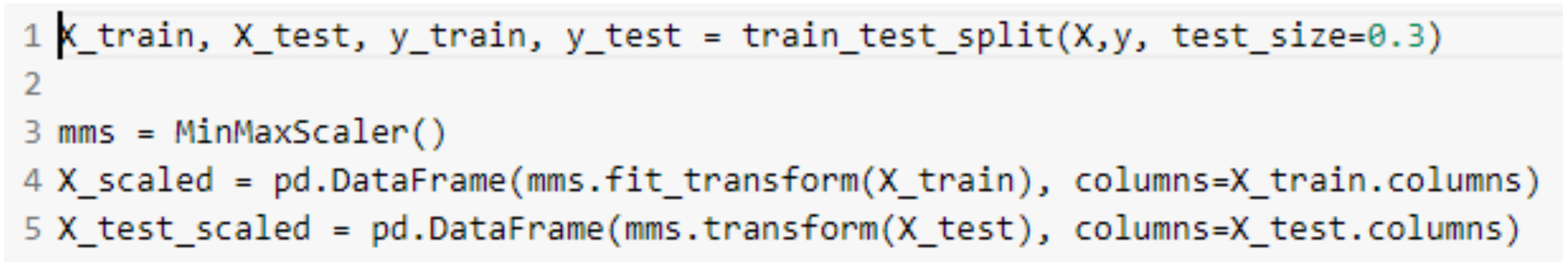
```
oversample = SMOTE()
X_balanced, y_balanced = oversample.fit_resample(X_scaled, y_train)
X_test_balanced, y_test_balanced= oversample.fit_resample(X_test_scaled, y_test)
```

# Machine Learning Process



## 3.4 Train-Test Split and MinMaxScalar

- Split the data for 70% training and 30% testing.
- Fit and transform the data into a scaler for accurate reading and results.



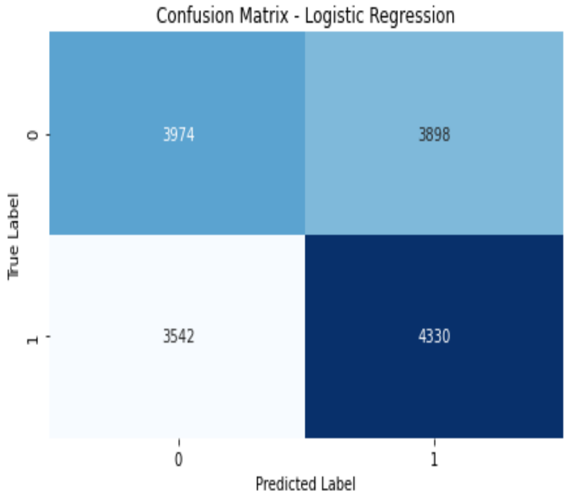
```python
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3)

mms = MinMaxScaler()
X_scaled = pd.DataFrame(mms.fit_transform(X_train), columns=X_train.columns)
X_test_scaled = pd.DataFrame(mms.transform(X_test), columns=X_test.columns)
```

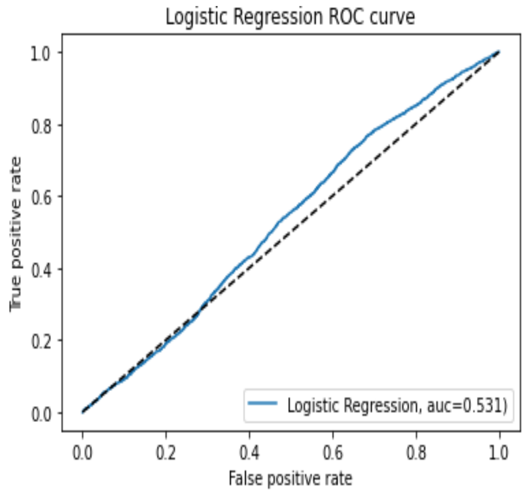
# Machine Learning Process

| 1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning |
|---|---|---|---|---|

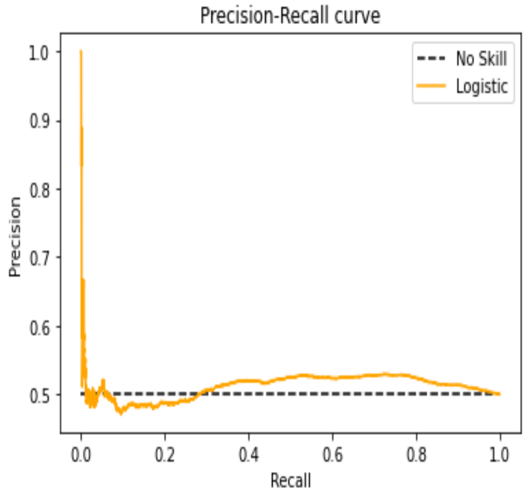
## 4.1 Logistic Regression

| Metrics | Result |
|---|---|
| Accuracy | 0.53 |
| Precision | 0.53 |
| Recall | 0.55 |
| F1-Score | 0.54 |
| AUC | 0.53 |





Classifier is not able to distinguish between Positive and Negative



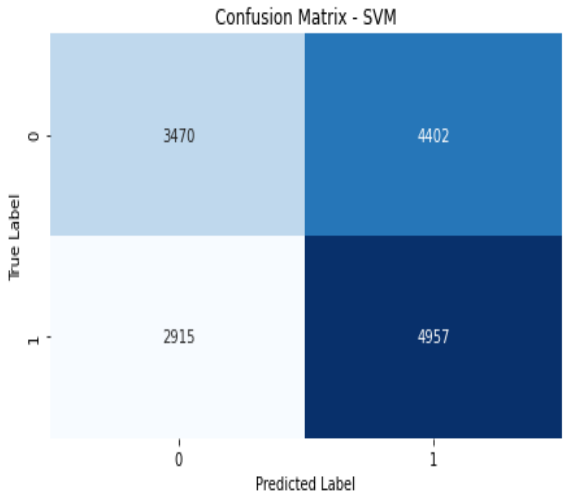
Both 0 & 1 close to overlapping each other.

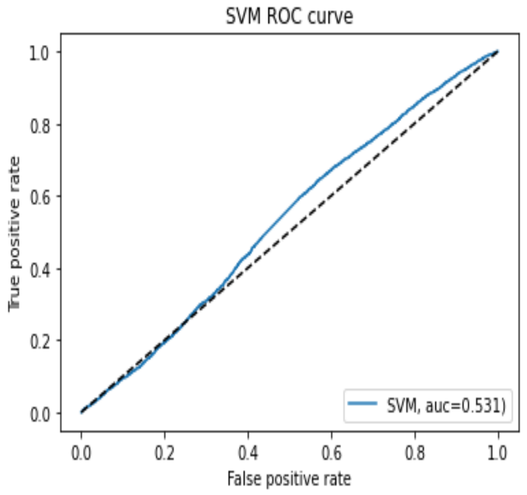
# Machine Learning Process

1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

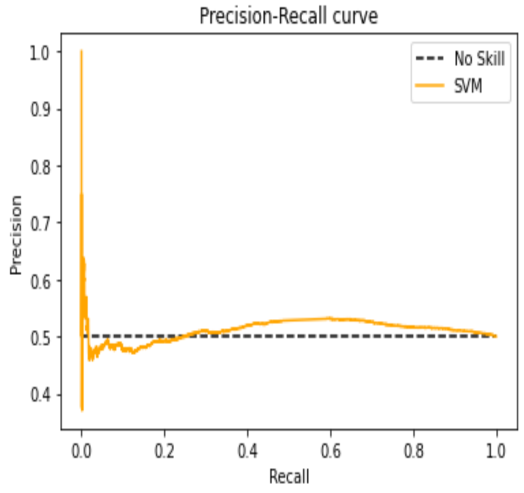
## 4.2 Support Vector Machine

| Metrics | Result |
|---|---|
| Accuracy | 0.54 |
| Precision | 0.53 |
| Recall | 0.63 |
| F1-Score | 0.58 |
| AUC | 0.53 |





Classifier is not able to distinguish between Positive and Negative



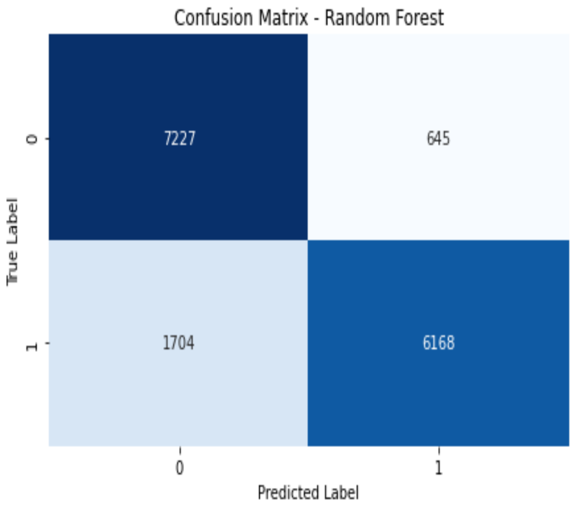
Both 0 & 1 close to overlapping each other.

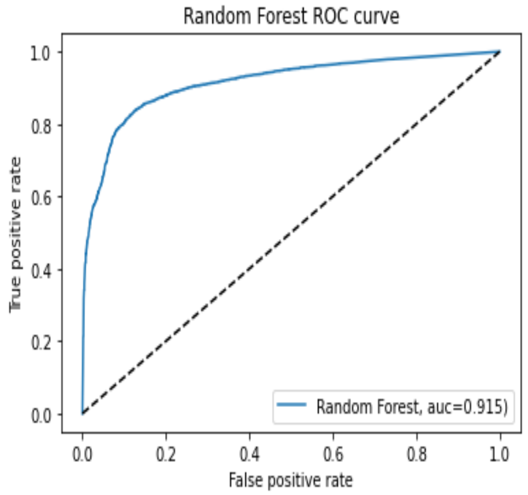
# Machine Learning Process

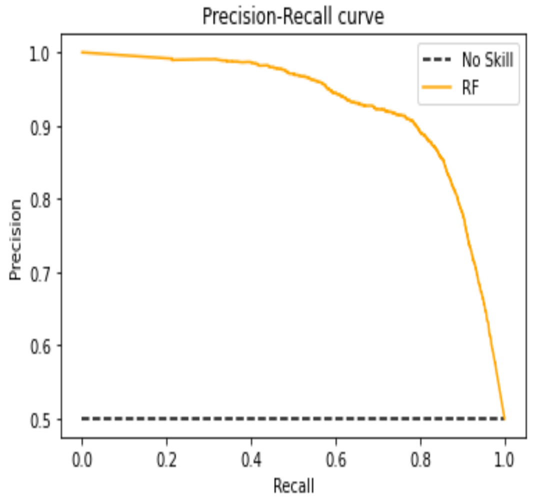
1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

## 4.3 Random Forest

| Metrics | Result |
|---|---|
| Accuracy | 0.85 |
| Precision | 0.91 |
| Recall | 0.78 |
| F1-Score | 0.84 |
| AUC | 0.91 |





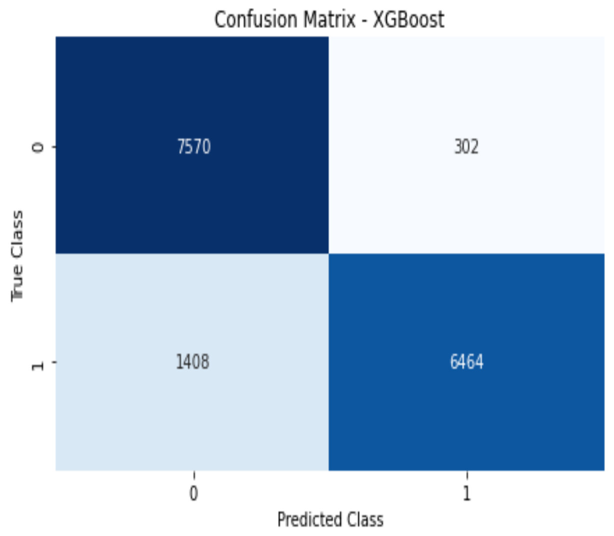


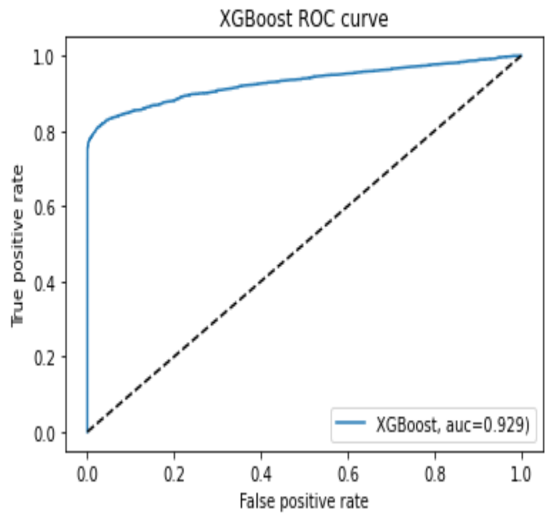
# Machine Learning Process

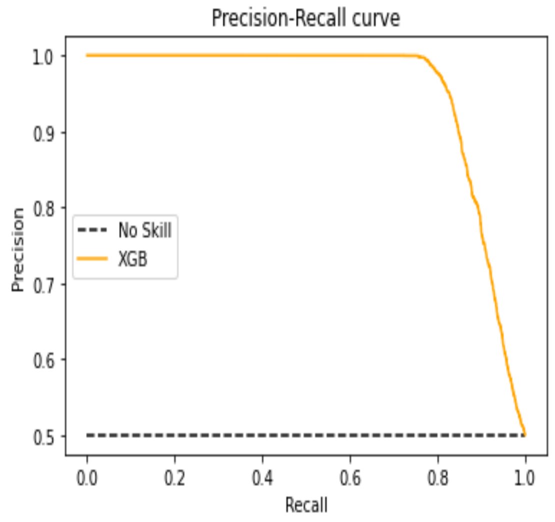
1. Data Preparation
2. Data Exploration
3. Features Engineering
4. Model Selection
5. Hyper-Parameter Tuning

## 4.4 XG Boost

| Metrics | Result |
|---|---|
| Accuracy | 0.89 |
| Precision | 0.96 |
| Recall | 0.82 |
| F1-Score | 0.88 |
| AUC | 0.93 |





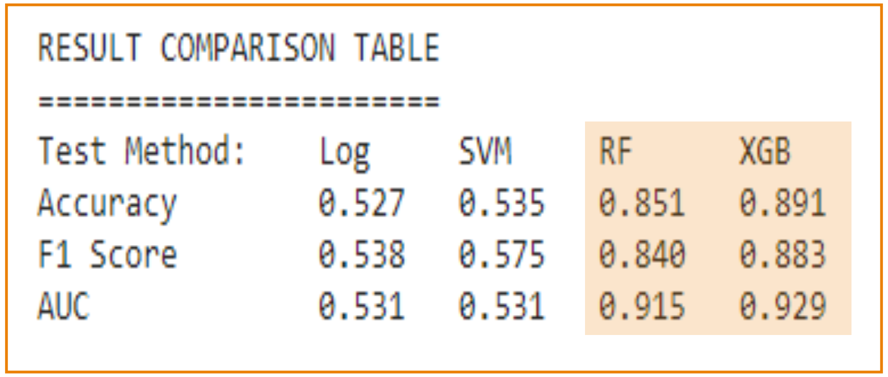


# Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | **5. Hyper-Parameter Tuning**

## 4.5 Result Comparison

- Random Forest and XG Boost has the close and best performance according to our classification metrics (Accuracy, F1-score and AUC).
- Next, we can further improved the both models by tuning hyper-parameters.



```
RESULT COMPARISON TABLE
=======================
Test Method:     Log     SVM     RF      XGB
Accuracy         0.527   0.535   0.851   0.891
F1 Score         0.538   0.575   0.840   0.883
AUC              0.531   0.531   0.915   0.929
```

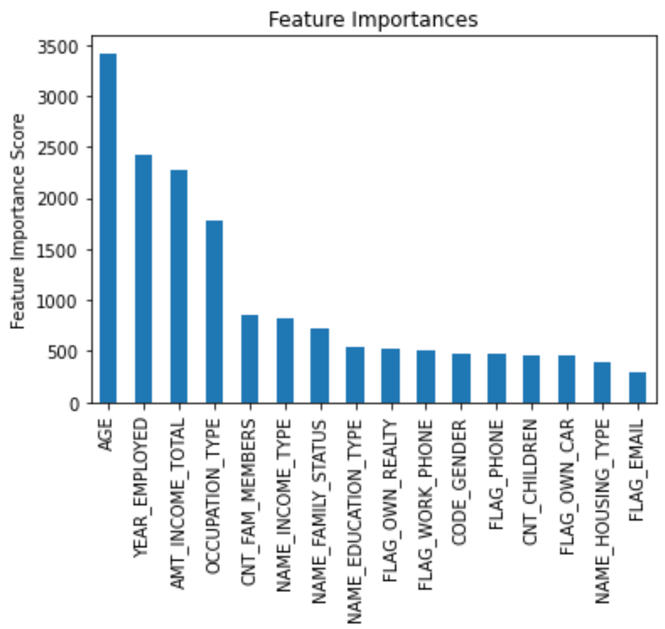
# Machine Learning Process

1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

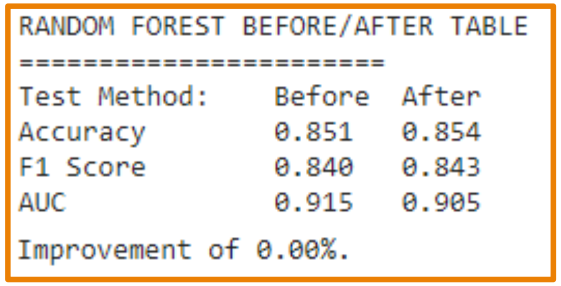
## 5.1 Tune XG Boost with XGB.cv

Hyper-parameters to tune:

- **Min_child_weight** - Defines the minimum sum of weights of all observations required in a child.
- **Max_depth** - The maximum depth of a tree.
- **Subsample** - Denotes the fraction of observations to be randomly samples for each tree.
- **Colsample_bytree** - Denotes the fraction of columns to be randomly samples for each tree.
- **ETA** - Parameter controls the learning rate. Makes the model more robust by shrinking the weights on each step.



- All features have contribution to our target.
- No need to remove any feature to improve the model



```
RANDOM FOREST BEFORE/AFTER TABLE
========================
Test Method:     Before   After
Accuracy         0.851    0.854
F1 Score         0.840    0.843
AUC              0.915    0.905
Improvement of 0.00%.
```

# Machine Learning Process

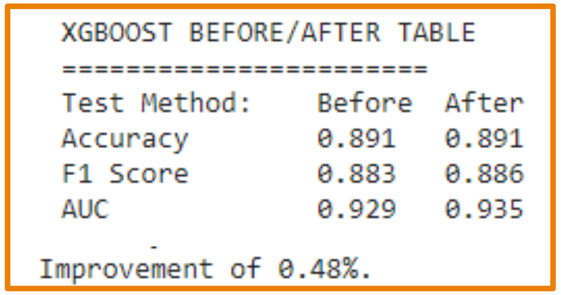
1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 5.2 Tune Random Forest with RandomSearch.cv & GridSearch.cv

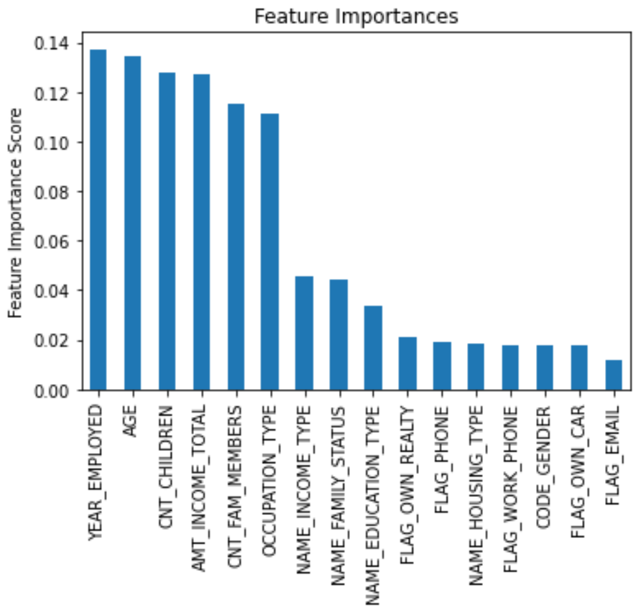
We will use Randomsearch.cv to get the parameter range. Then, we will use Gridsearch.cv to further select the best parameter.

Hyper-parameters to tune:

- **N_estimators** - Number of trees in random forest
- **Max_features** - Number of features to consider at every split
- **Max_depth** - Maximum number of levels in tree
- **Min_samples_split** - Minimum number of samples required to split a node
- **Min_samples_leaf** - Minimum number of samples required at each leaf node
- **Bootstrap** - Method of selecting samples for training each tree



```
XGBOOST BEFORE/AFTER TABLE
=======================
Test Method:     Before   After
Accuracy         0.891    0.891
F1 Score         0.883    0.886
AUC              0.929    0.935

Improvement of 0.48%.
```



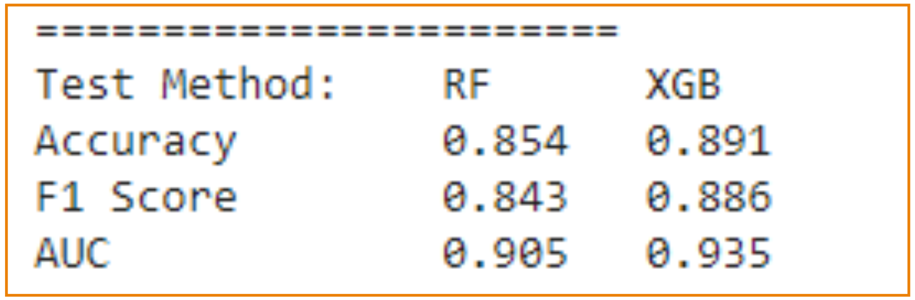
- All features have contribution to our target.
- No need to remove any feature to improve t he model

# Machine Learning Process

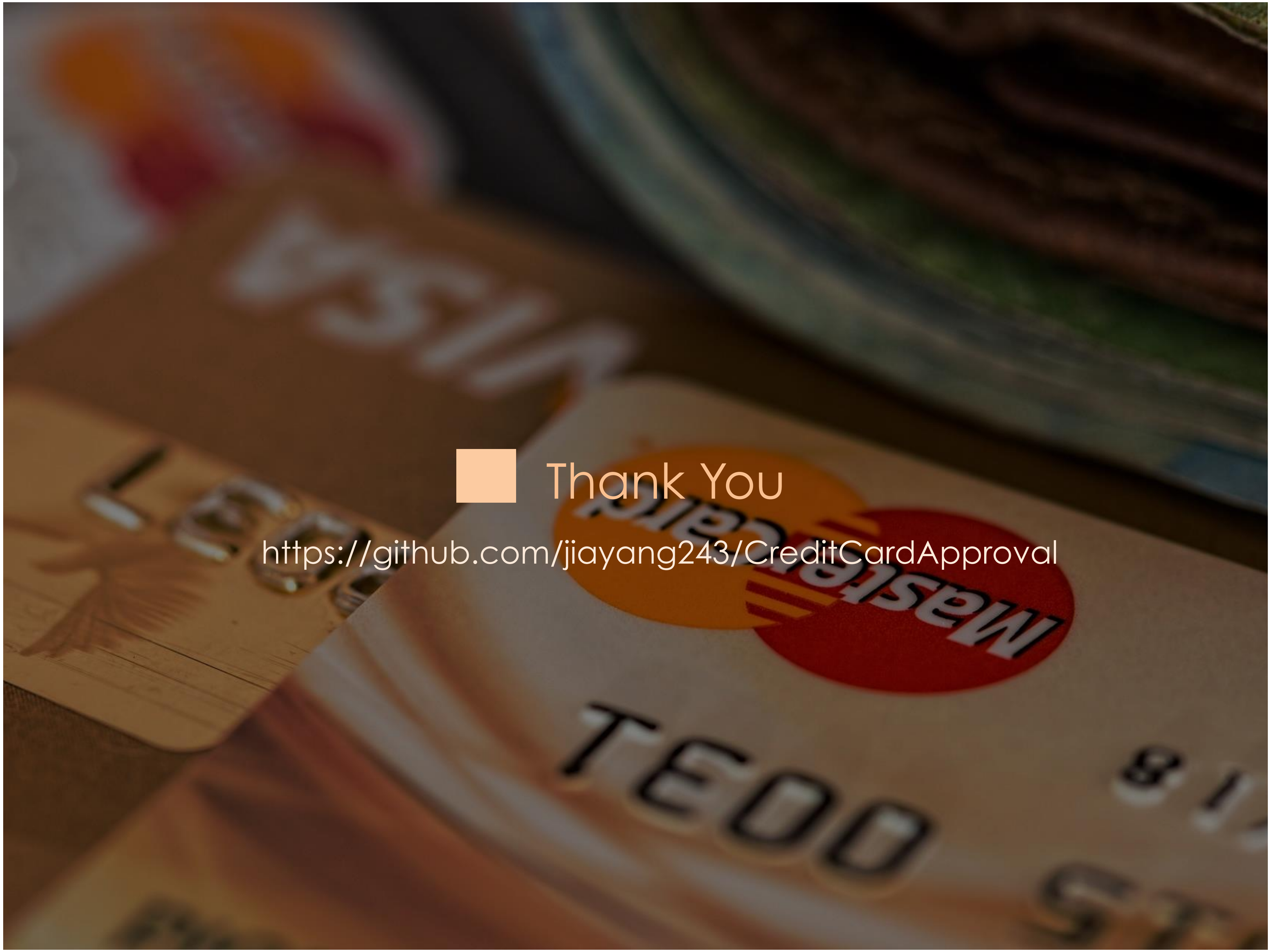
1. Data Preparation | 2. Data Exploration | 3. Features Engineering | 4. Model Selection | 5. Hyper-Parameter Tuning

## 5.3 Conclusion

- The best model to identify good/bad applicant for credit card approval will be XG Boost model with test of ~89% accuracy.
- We will be using XG Boost to predict our values.
- For future work, we could look into:
  - Other value range for parameter tuning
  - We can also  look into using ensemble of XG Boost and Random Forest to get a more accurate prediction.
  - Look into the feature importance for the top features
  - Do Cost Benefit Analysis to further enhance the practical use of the model



```
=========================
Test Method:      RF       XGB
Accuracy          0.854    0.891
F1 Score          0.843    0.886
AUC               0.905    0.935
```



## Thank You

https://github.com/jiayang243/CreditCardApproval