

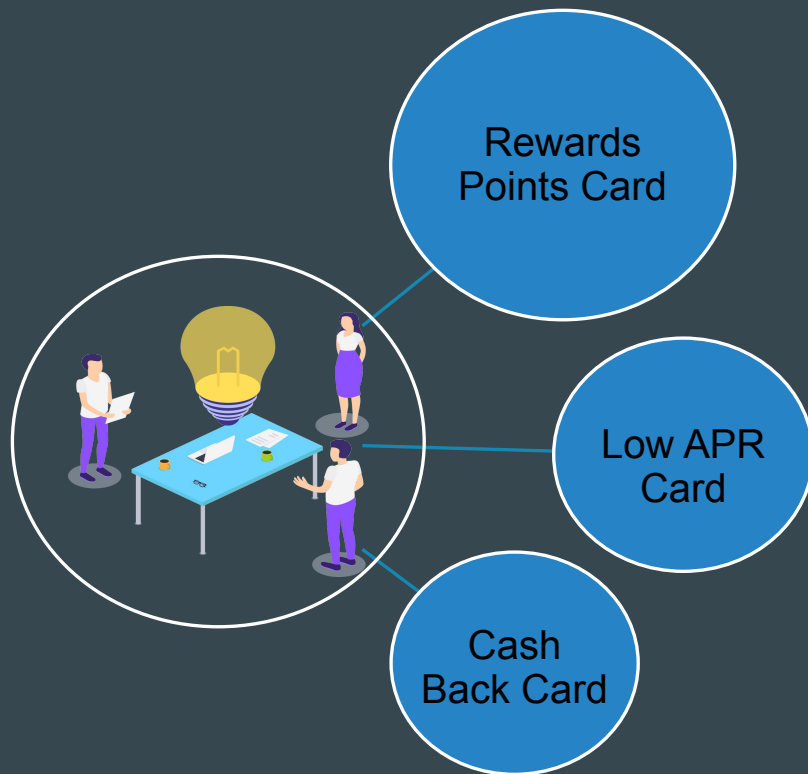


Credit Card Approval Prediction

September, 2021

Introduction

All over the world people use credit card to purchase, it is essential part of the modern society, but credit cards present opportunities and challenge for banks and other lending institutions. On one hand, credit cards create revenue with fees and interest they generated, on the other hand, there is risk that consumers won't repay the balance, and the banks will lose money. With machine learning, will we be able to help a financial institution to decide whether to issue a credit card to an applicant or not?



Overview of the Project

In this project, we will use Python and Machine learning to focus on recognizing, assessing and reducing the financial or other risks that could lead to loss involved in the transaction.

Machine Learning can process a large amount of data to arrive at a single decision; whether or not to approve futur credit card applications.



Understanding the problem

what are the standard requirements for an individual to be approved for a credit card?



Project: Credit Card Approval Prediction

Technology Stack

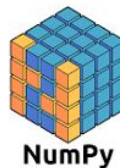
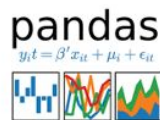
Dataset: downloaded from  <https://www.kaggle.com/rikdifos/credit-card-approval-prediction/code>

Exploratory Data Analysis



 **matplotlib**

Database, Data
Wrangling & Feature
Engineering



Machine
Learning Pipeline



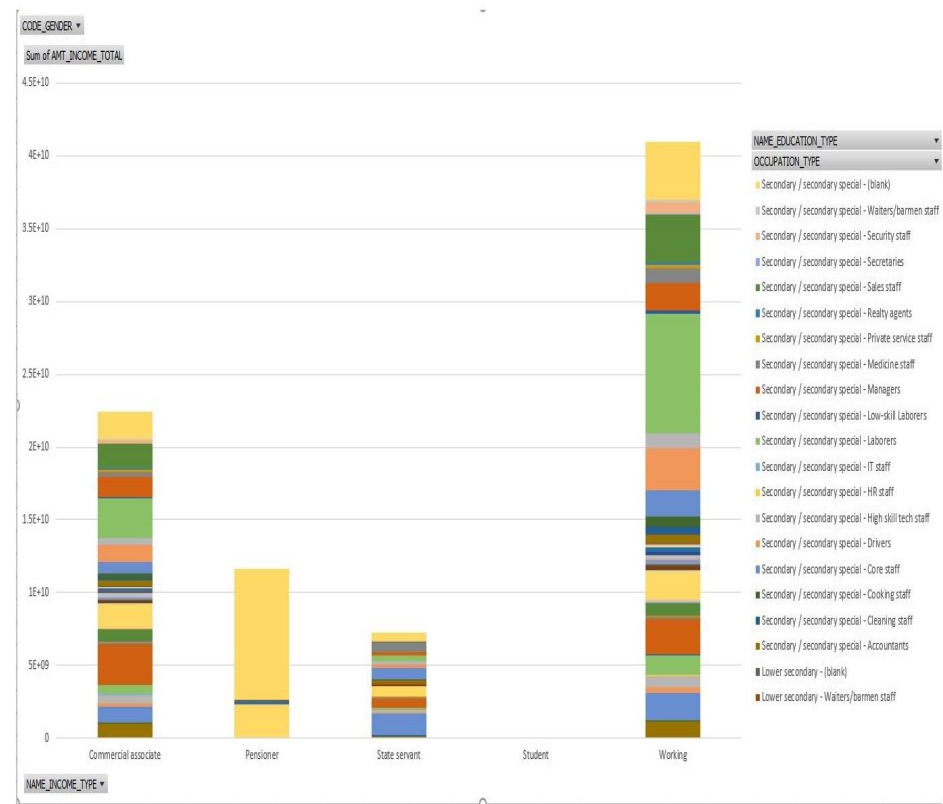
Dashboard
Presentation



DataSweeper_Project

Data

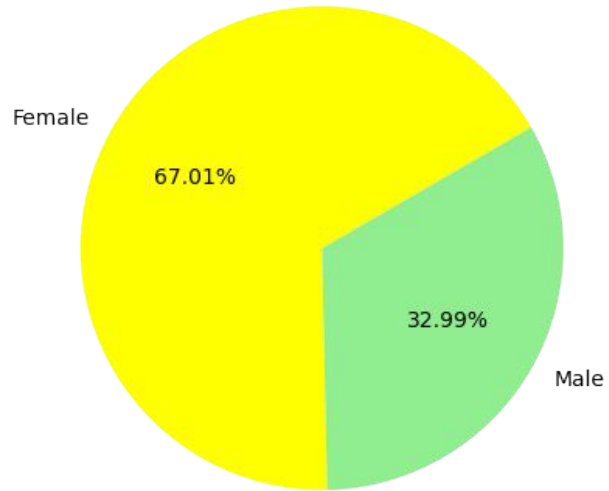
Exploration



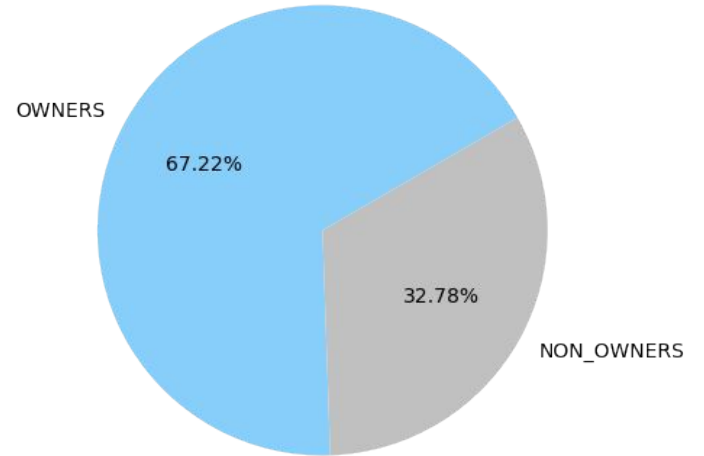
DATASET DEMOGRAPHICS

Gender Distribution and Realty Ownership

Gender Distribution

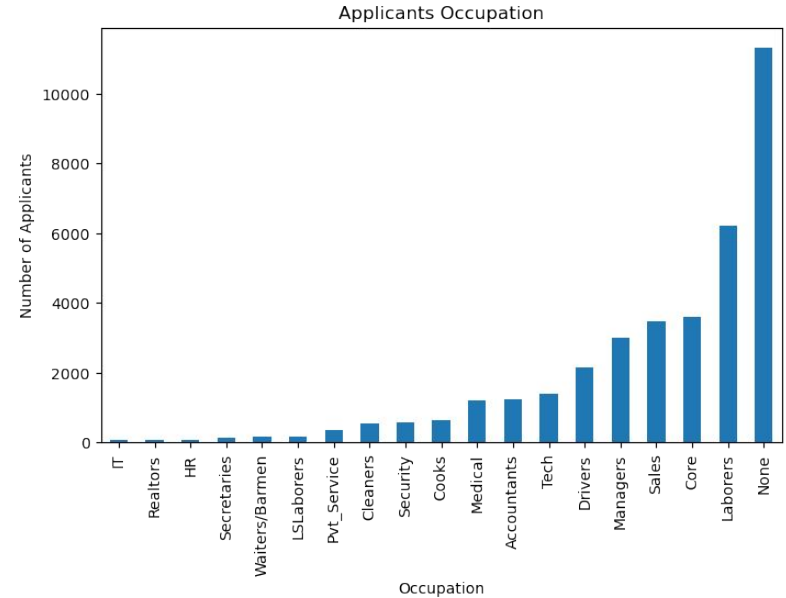
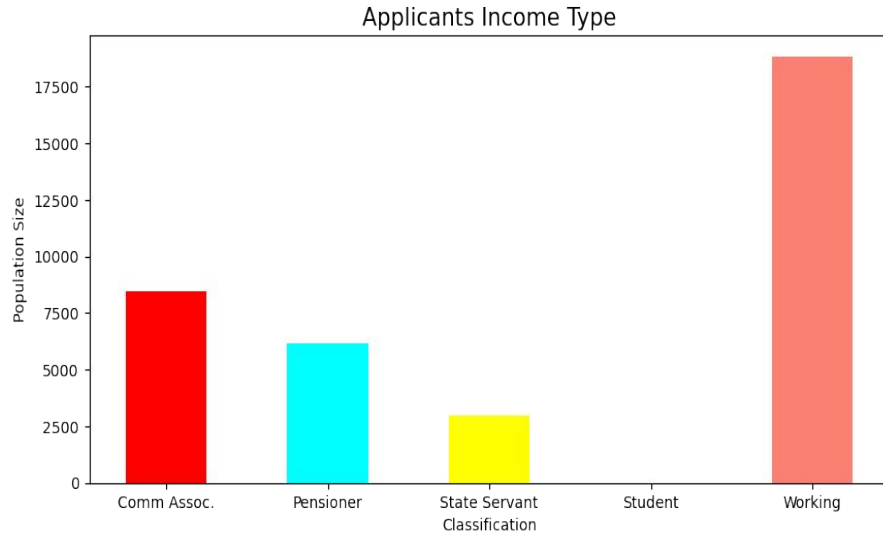


Realty Ownership



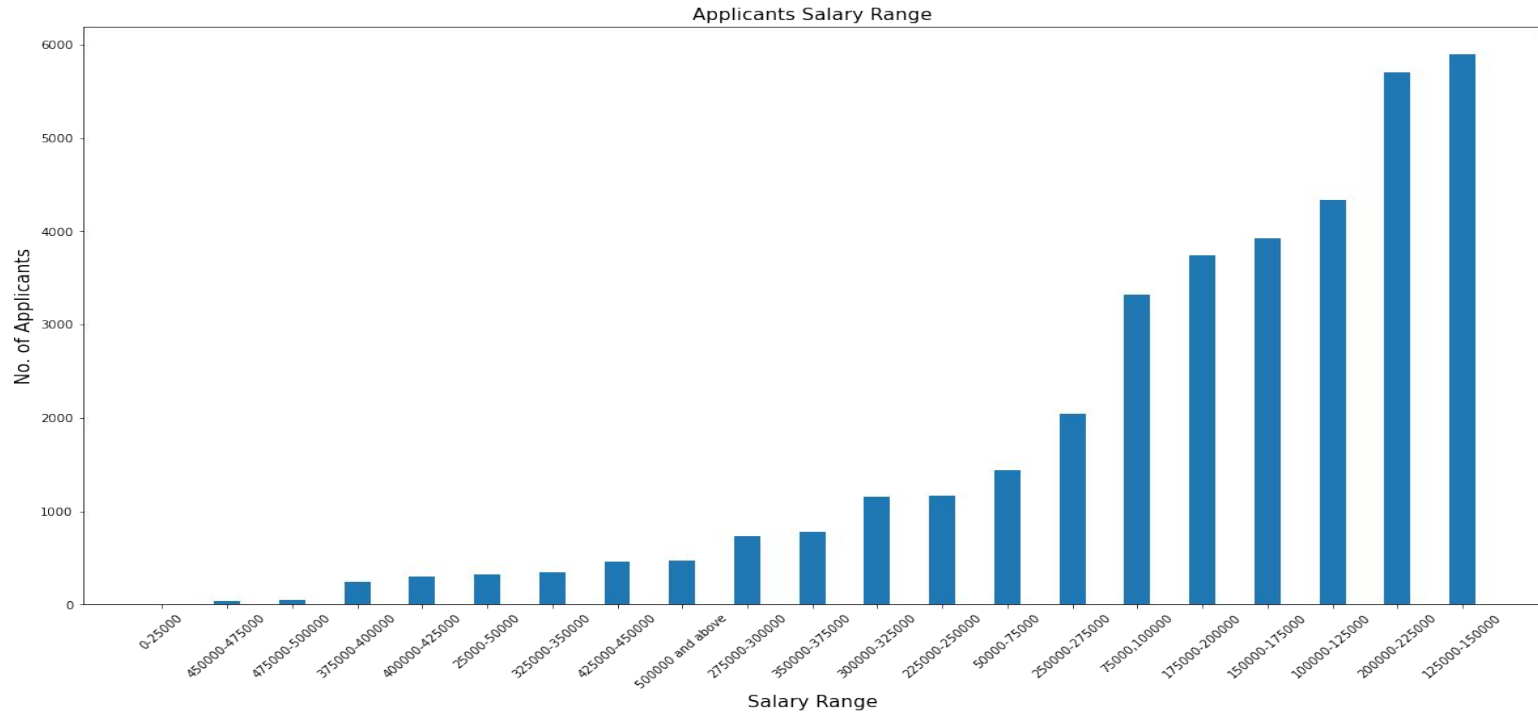
DATASET DEMOGRAPHICS

Applicants Income Type & Occupation



DATASET DEMOGRAPHICS

Applicants Salary Range



MACHINE LEARNING



Data Processing

Clean the data
Joins → pgAdmin
Merge → Pandas



Features

Random Oversampling
SVM
Decision Tree
Random Forest



Training & Testing Sets

Y value →
X value →



Model Choice

?



Accuracy Scores

Training →
Testing →

Data

Analysis

Logistic Regression

| | Predicted High Risk | Predicted Low Risk |
|------------------|---------------------|--------------------|
| Actual High Risk | 5068 | 2011 |
| Actual Low Risk | 1379 | 657 |

Accuracy Score : 0.5193059398963868

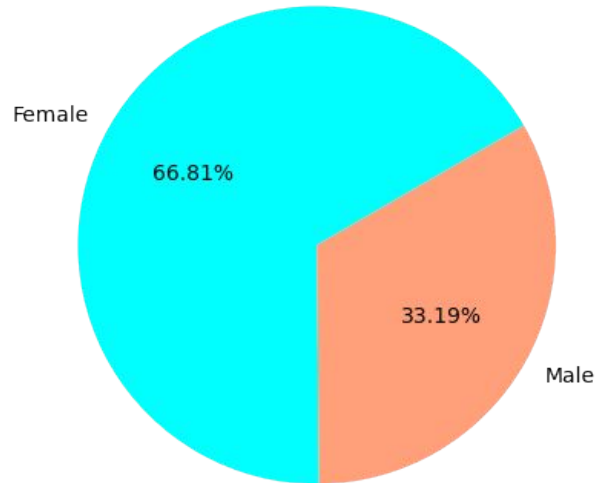
Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.78 | 0.52 | 0.63 | 7079 |
| 1 | 0.23 | 0.50 | 0.32 | 2036 |
| accuracy | | | 0.52 | 9115 |
| macro avg | 0.51 | 0.51 | 0.47 | 9115 |
| weighted avg | 0.66 | 0.52 | 0.56 | 9115 |

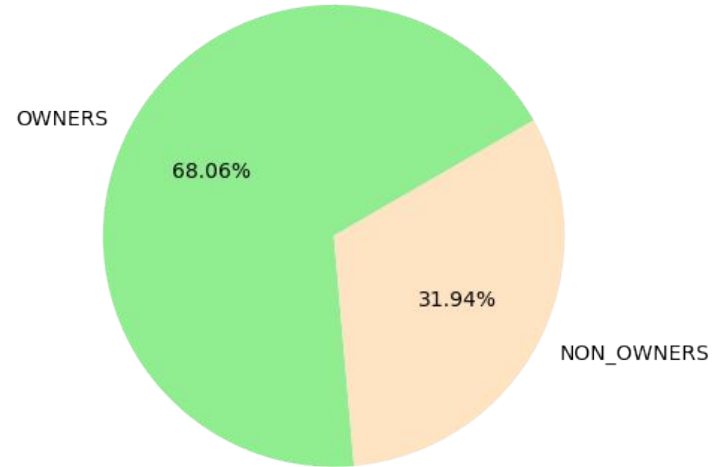
GOOD APPLICANTS DEMOGRAPHICS

Gender Distribution & Realty Ownership

Good Applicants Gender Distribution



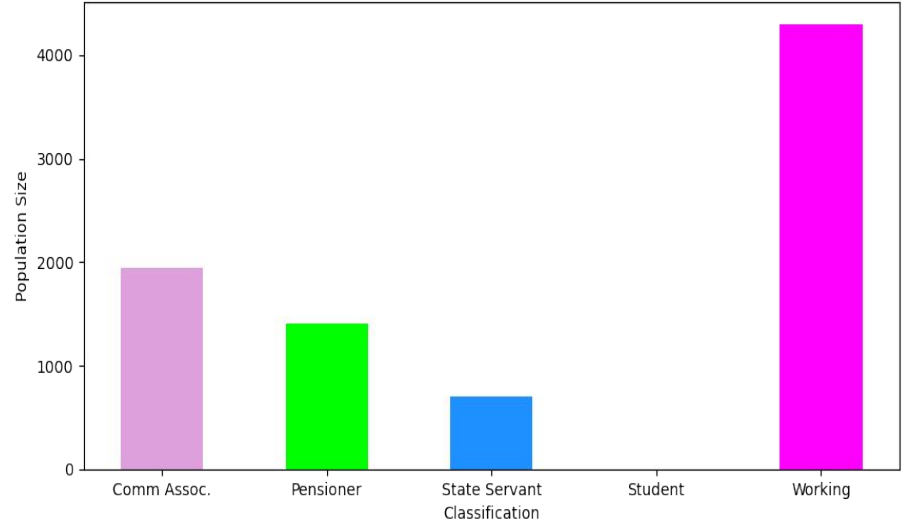
Good Applicants Realty Ownership



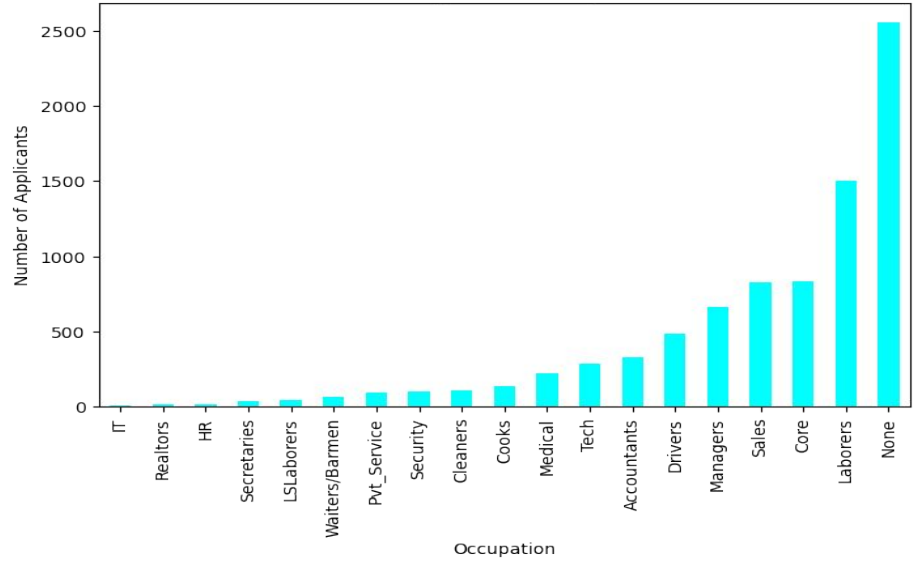
GOOD APPLICANTS DEMOGRAPHICS

Income Type & Occupation

Good Applicants Income Type



Good Applicants Occupation



DATABASE



Data Processing

Extract & Transform:
Jupyter Notebook, Python, Pandas



Database Setup

AWS RDS, PostgreSQL

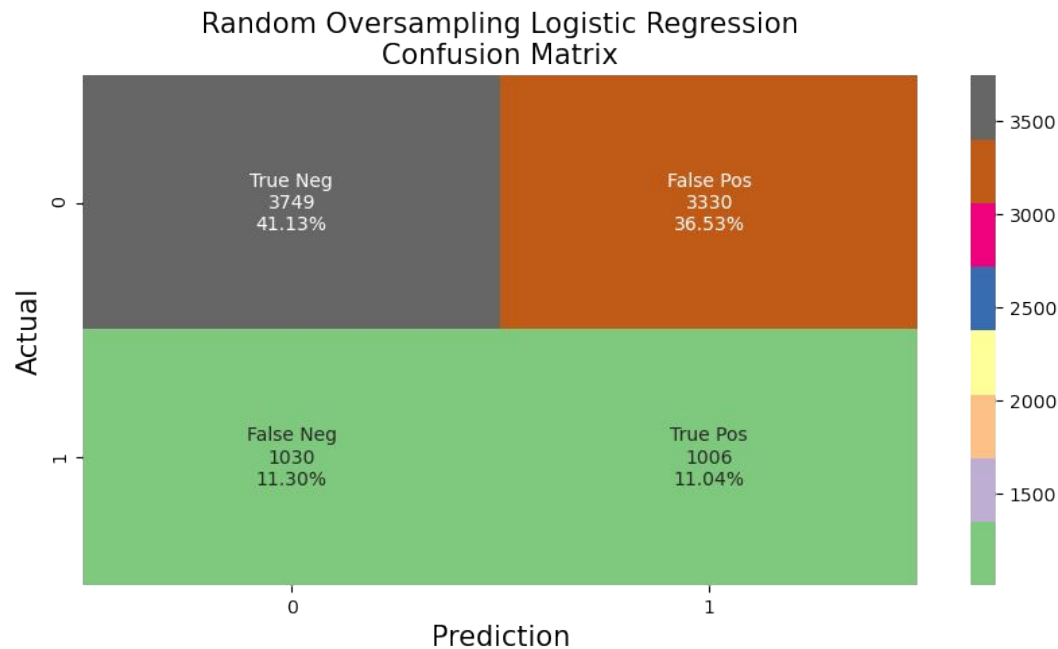


Table Joins

Database:
pgAdmin

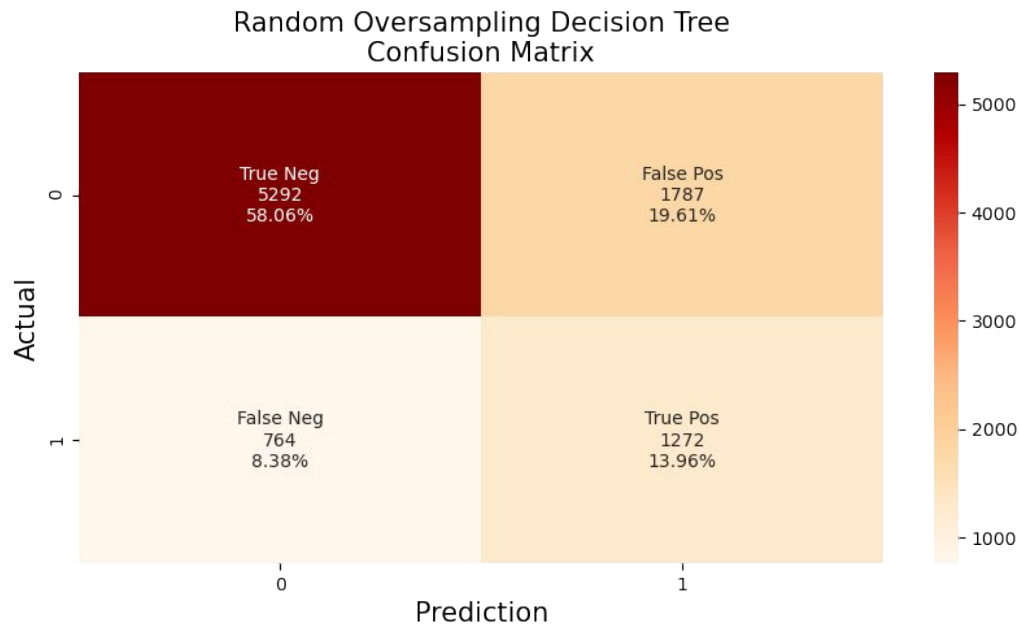
RANDOM OVERSAMPLING CONFUSION MATRIX

Logistic Regression



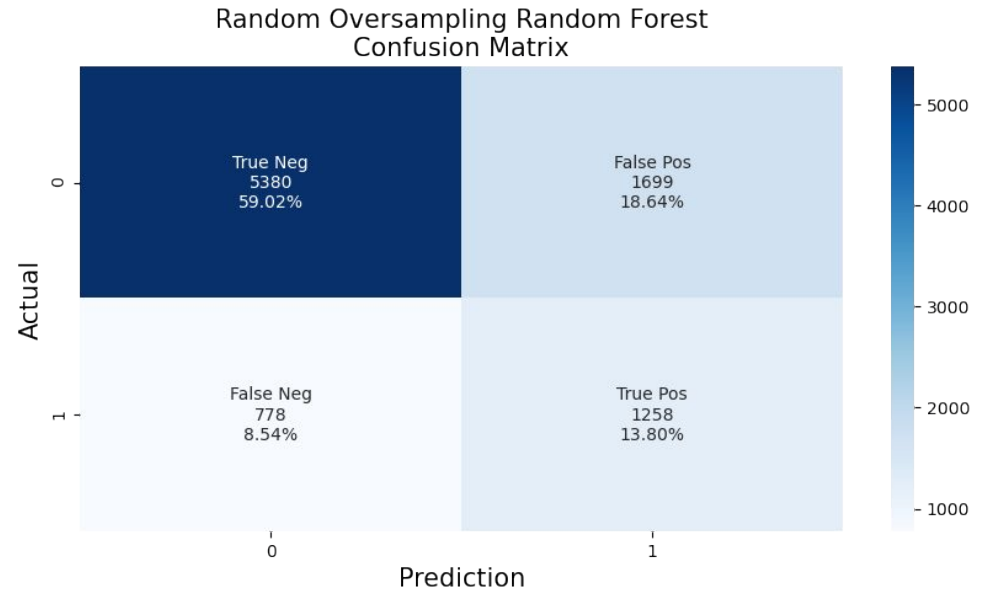
RANDOM OVERSAMPLING CONFUSION MATRIX

Decision Tree



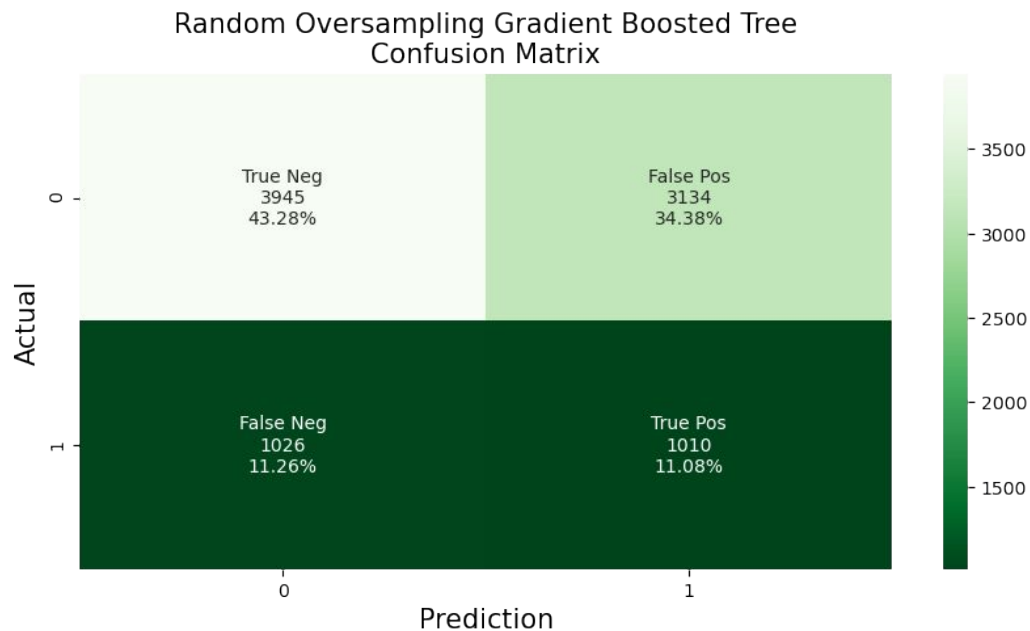
RANDOM OVERSAMPLING CONFUSION MATRIX

Random Forest



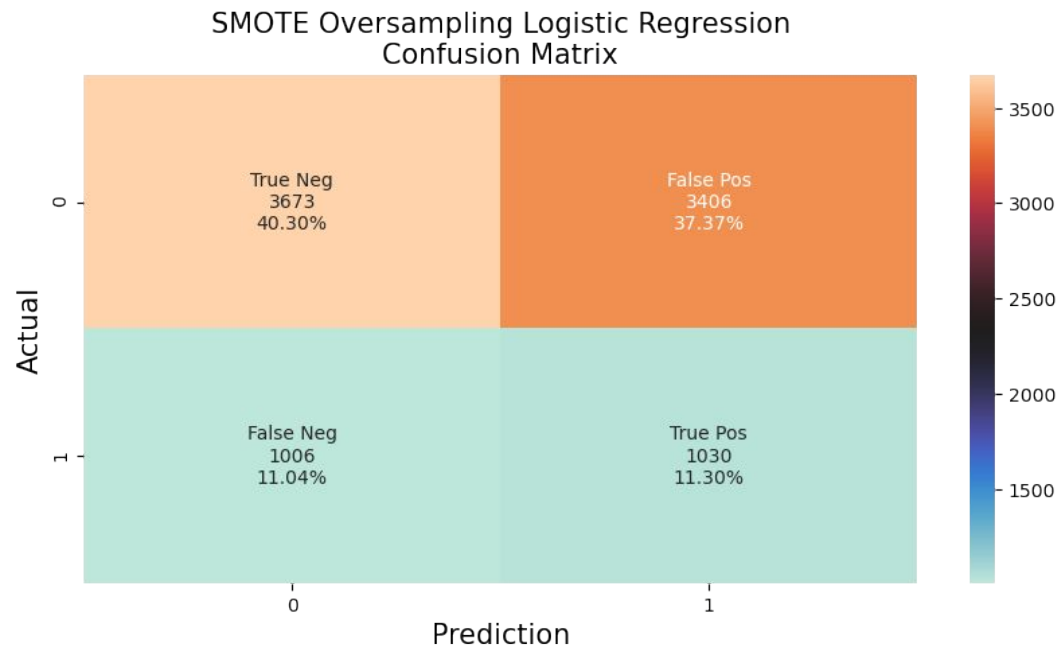
RANDOM OVERSAMPLING CONFUSION MATRIX

Random Forest



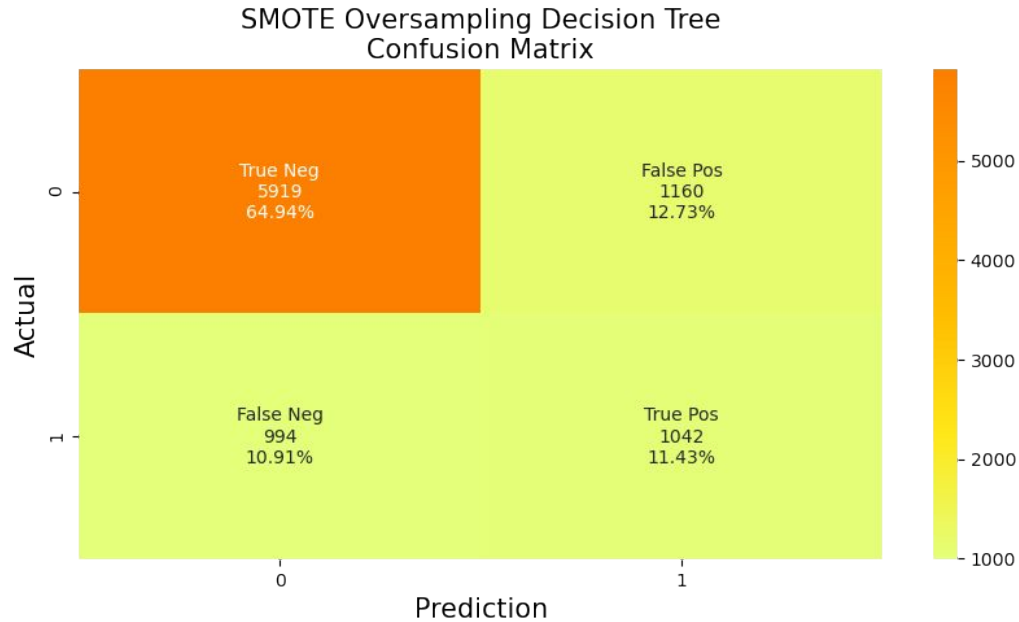
SMOTE OVERSAMPLING CONFUSION MATRIX

Logistic Regression



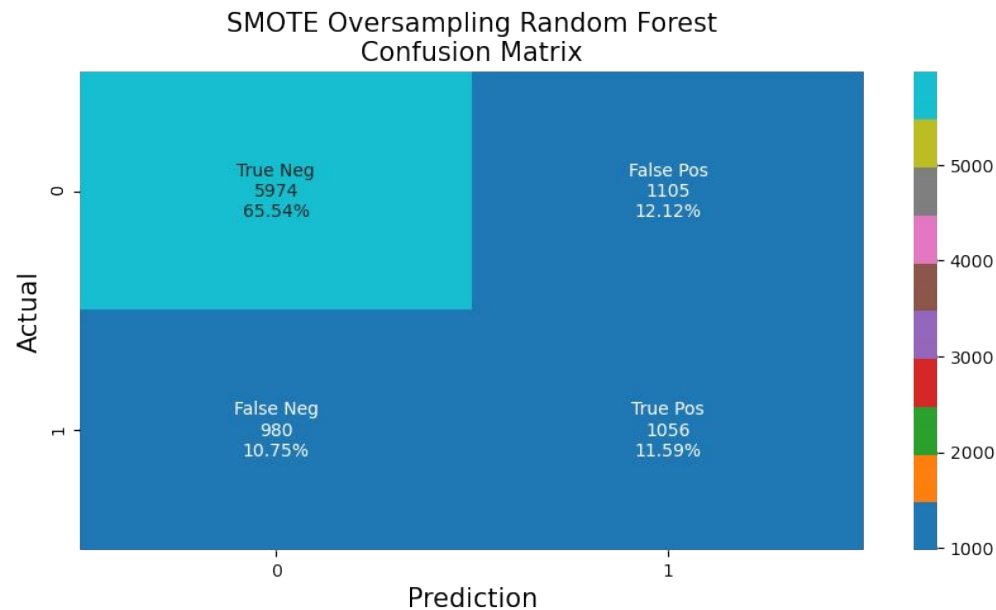
SMOTE OVERSAMPLING CONFUSION MATRIX

Decision Tree



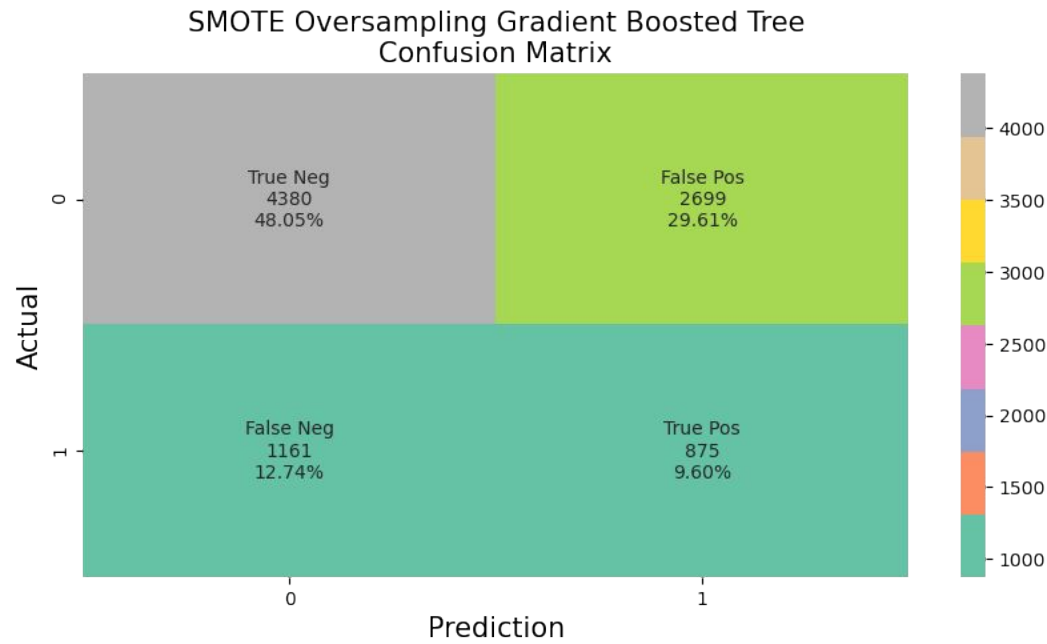
SMOTE OVERSAMPLING CONFUSION MATRIX

Random Forest



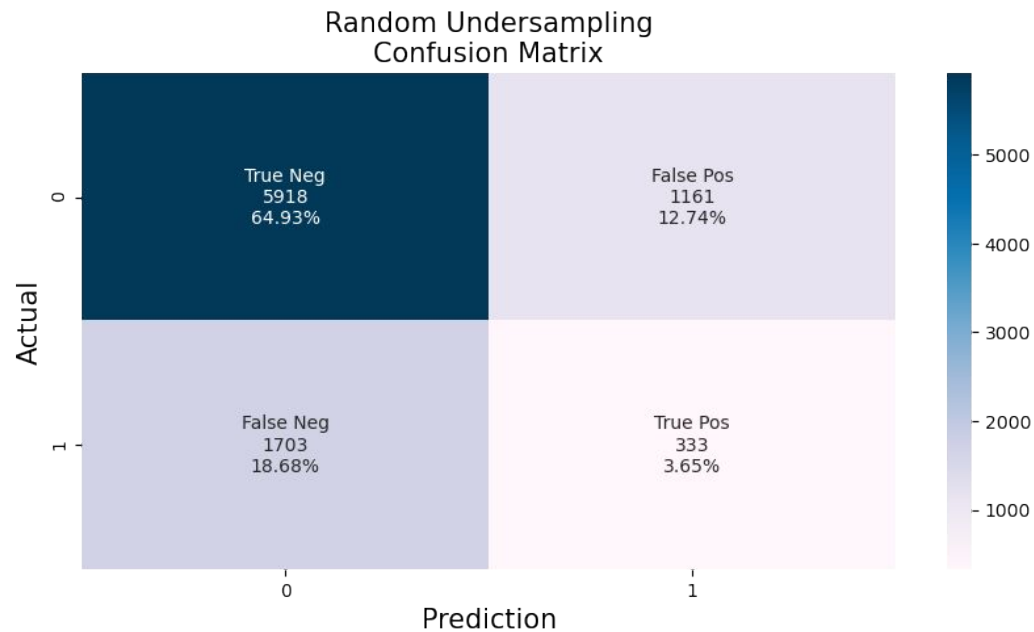
SMOTE OVERSAMPLING CONFUSION MATRIX

Gradient Boosted Tree



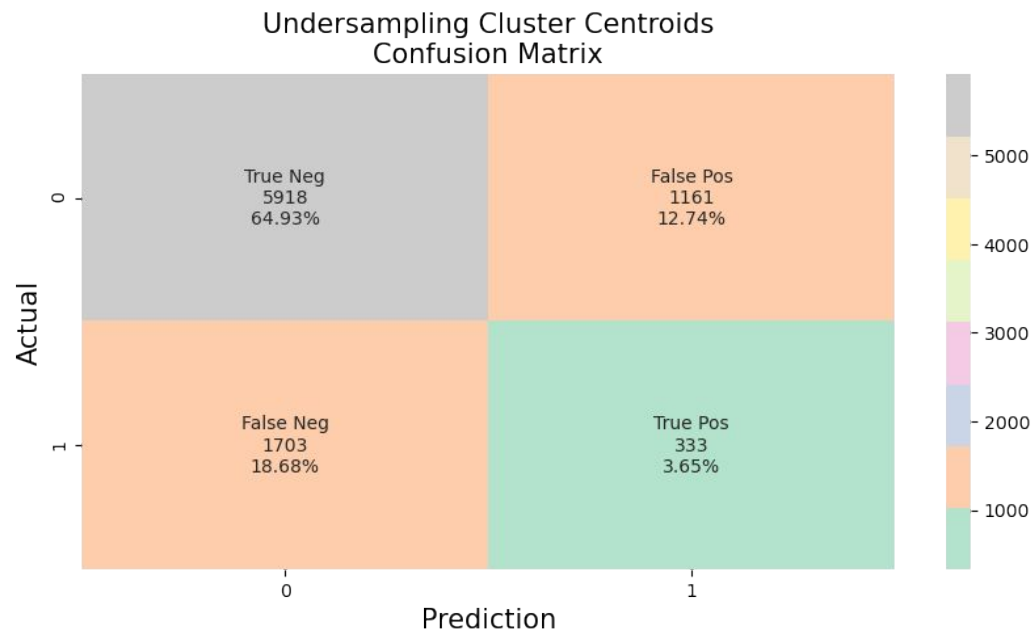
UNDERSAMPLING CONFUSION MATRIX

Random



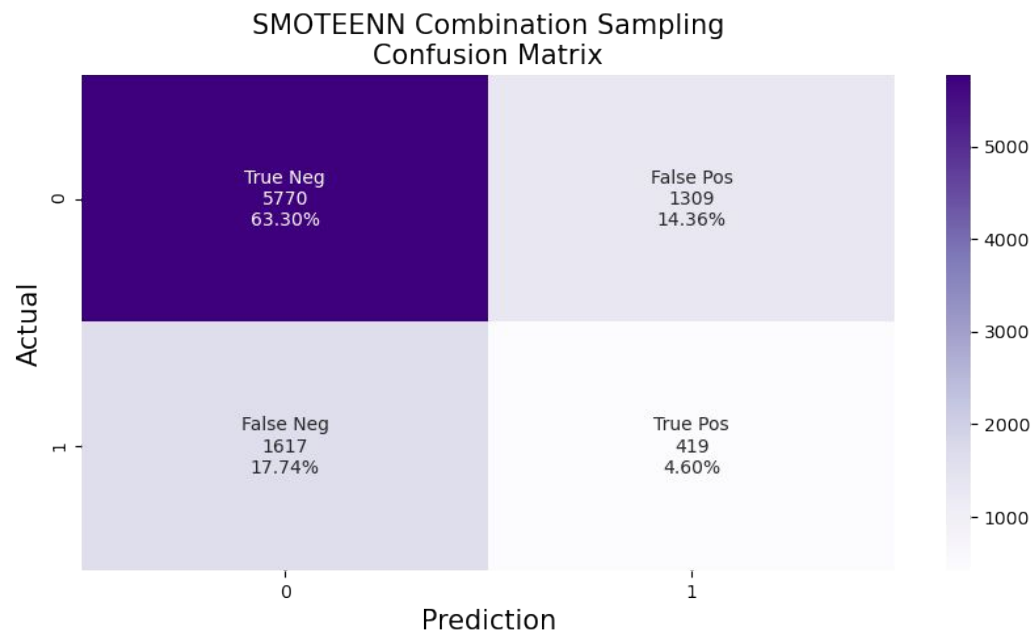
UNDERSAMPLING CONFUSION MATRIX

Cluster Centroids



COMBINATION SAMPLING CONFUSION MATRIX

SMOTEENN

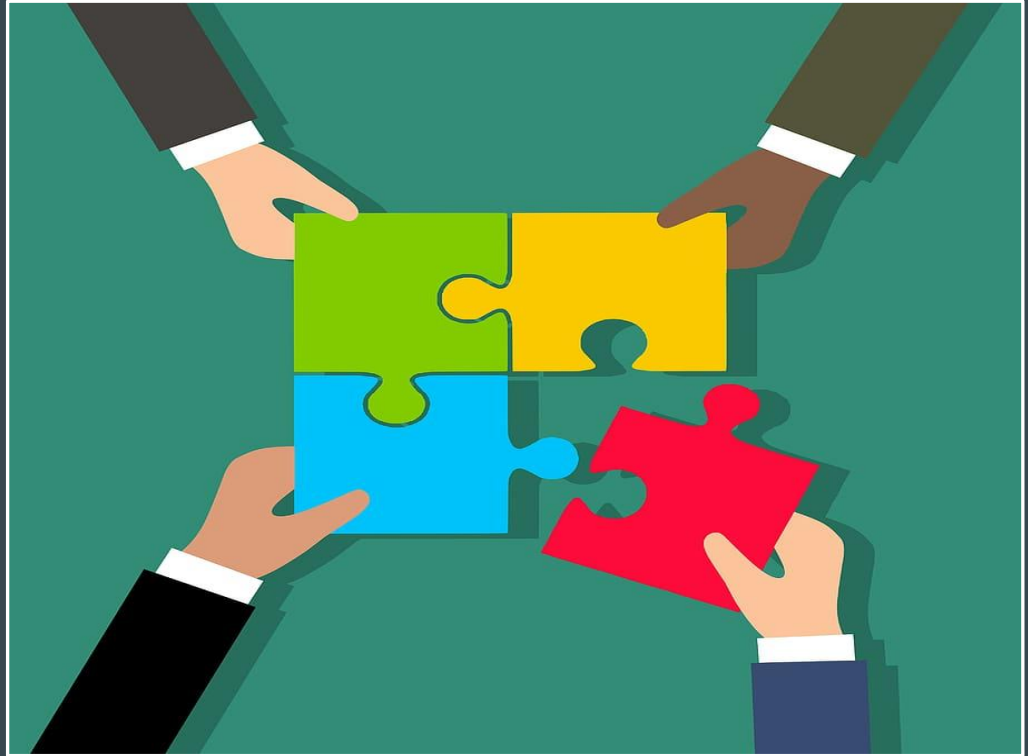


Dashboard Description

Tools: JavaScript, HTML

Interactive element(s)Features :

- Age
- Education
- Occupation
- Net income
- Rent

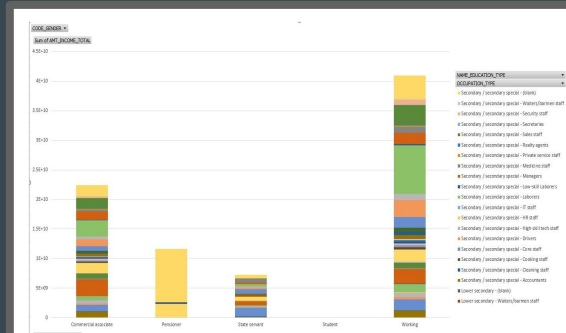


Credit Card Approval Prediction Dashboard

Using personal information and data submitted by credit card applicants, the model will predict the probability of future defaults and credit card borrowings.

Approve or not?

The objective of this project is to help a financial institution to decide whether to issue a credit card to an applicant. Using personal information and data submitted by credit card applicants, the model will predict the probability of future defaults and credit card borrowings.



| id | code_gender | flag_own_car | flag_own_realty | cnt_children | amt_income_total | name_income_type | name_education_type | name_family_status |
|-----------------------------|-----------------------|-----------------------|-----------------------|--------------|------------------|------------------------|-------------------------------|------------------------|
| [PK] character varying (10) | character varying (2) | character varying (2) | character varying (2) | integer | real | character varying (40) | character varying (40) | character varying (40) |
| 5008805 | M | Y | Y | 0 | 4.275 | Working | Higher education | Civil marriage |
| 5008806 | M | Y | Y | 0 | 1.125 | Working | Secondary / secondary spec... | Married |
| 5008808 | F | N | Y | 0 | 2.7 | Commercial associate | Secondary / secondary spec... | Single / not married |
| 5008809 | F | N | Y | 0 | 2.7 | Commercial associate | Secondary / secondary spec... | Single / not married |
| 5008810 | F | N | Y | 0 | 2.7 | Commercial associate | Secondary / secondary spec... | Single / not married |
| 5008811 | F | N | Y | 0 | 2.7 | Commercial associate | Secondary / secondary spec... | Single / not married |
| 5008812 | F | N | Y | 0 | 2.835 | Pensioner | Higher education | Separated |
| 5008813 | F | N | Y | 0 | 2.835 | Pensioner | Higher education | Separated |
| 5008814 | F | N | Y | 0 | 2.835 | Pensioner | Higher education | Separated |
| 5008815 | M | Y | Y | 0 | 2.7 | Working | Higher education | Married |
| 5112956 | M | Y | Y | 0 | 2.7 | Working | Higher education | Married |
| 5008819 | M | Y | Y | 0 | 1.35 | Commercial associate | Secondary / secondary spec... | Married |
| 5008820 | M | Y | Y | 0 | 1.35 | Commercial associate | Secondary / secondary spec... | Married |
| 5008821 | M | Y | Y | 0 | 1.35 | Commercial associate | Secondary / secondary spec... | Married |
| 5008822 | M | Y | Y | 0 | 1.35 | Commercial associate | Secondary / secondary spec... | Married |
| 5008823 | M | Y | Y | 0 | 1.35 | Commercial associate | Secondary / secondary spec... | Married |

Filter Search

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WHAT WOULD
WE DO
DIFFERENTLY?



The Team



Binoy Luckoo

Lorem ipsum dolor sit amet,
consectetur adipiscing elit,
sed do eiusmod tempor



Samir Rifi

Ut enim ad minim veniam,
quis nostrud exercitation
ullamco laboris nisi ut
aliquip ex ea commodo
consequat



Jane Huang

Duis aute irure dolor in
reprehenderit in voluptate
velit esse cillum dolore eu
fugiat nulla pariatur



Lucas Chandra

Excepteur sint occaecat
cupidatat non proident, sunt
in culpa qui officia deserunt
mollit anim id est laborum

QUESTIONS



CITATIONS

Slide 1 Background picture:

<https://wowplus.net/these-are-the-new-upcoming-changes-to-your-credit-score-and-credit-cards/> (sept,2021)

Slide 2 pictures:

<https://godmen.org/2021/02/20/best-credit-card-offers-what-are-the-best-offers/> (sept,2021)

Data:

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