

---

# **Capstone 2 Project : Credit Card Approval Prediction**

**Dev Joshi<sup>1</sup>**

(1) Spring Board Bootcamp

# Problem Statement

The personal information and data submitted by credit-card applicants can be used to decide creditworthiness of the applicants.



**The dataset source is :**

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

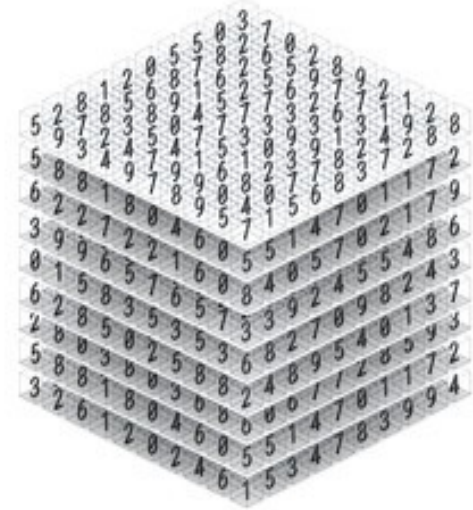
- Machine learning approaches can be applied to automate the approval of credit-card applications
- In this project, we build an automatic credit card approval predictor using machine learning techniques

# Datasets

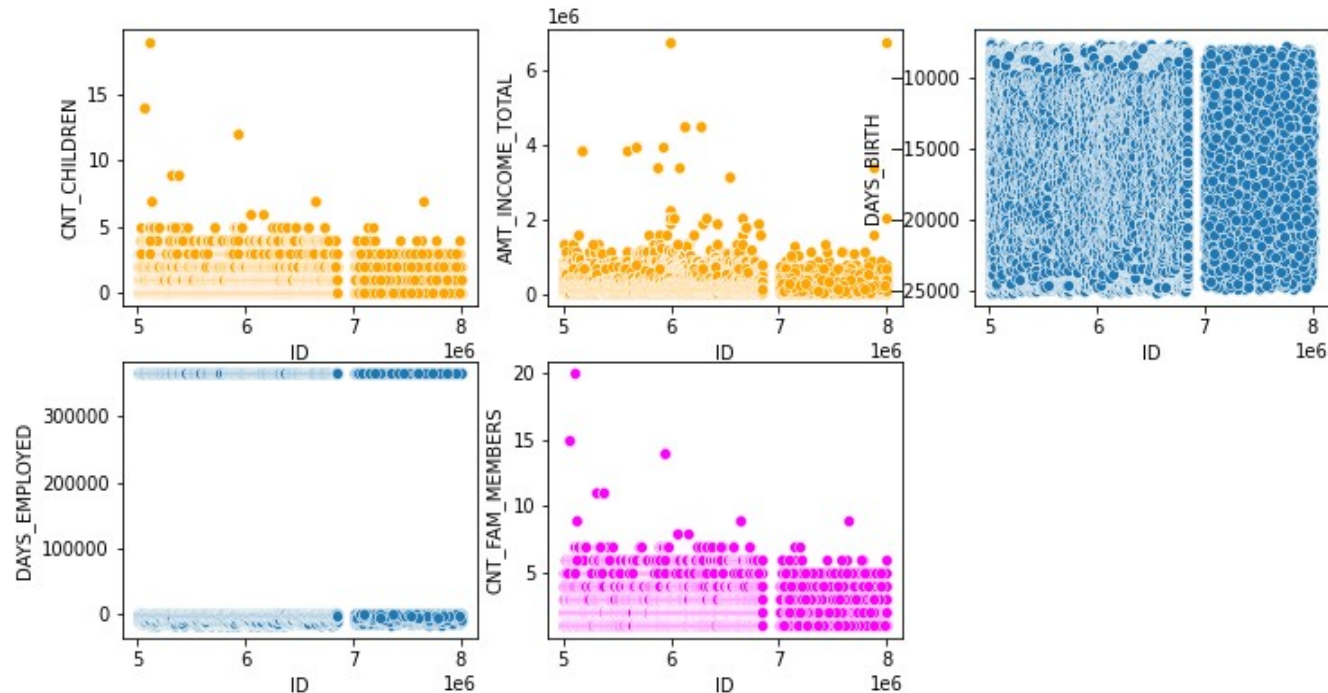
Two datasets :

- (i) one with the application records, and
- (ii) another with the credit-card records.

- The Application record dataset: 438557 rows and 18 columns.
- The credit record dataset: 1048575 rows and 3 columns.
- Both the datasets have a common column name ('ID') connecting both the datasets.
- The length of intersection of two datasets is found to be 36457.
- The data-types in the application record are converted from the non-numeric data (object data-type) to numeric data using labelencoder.

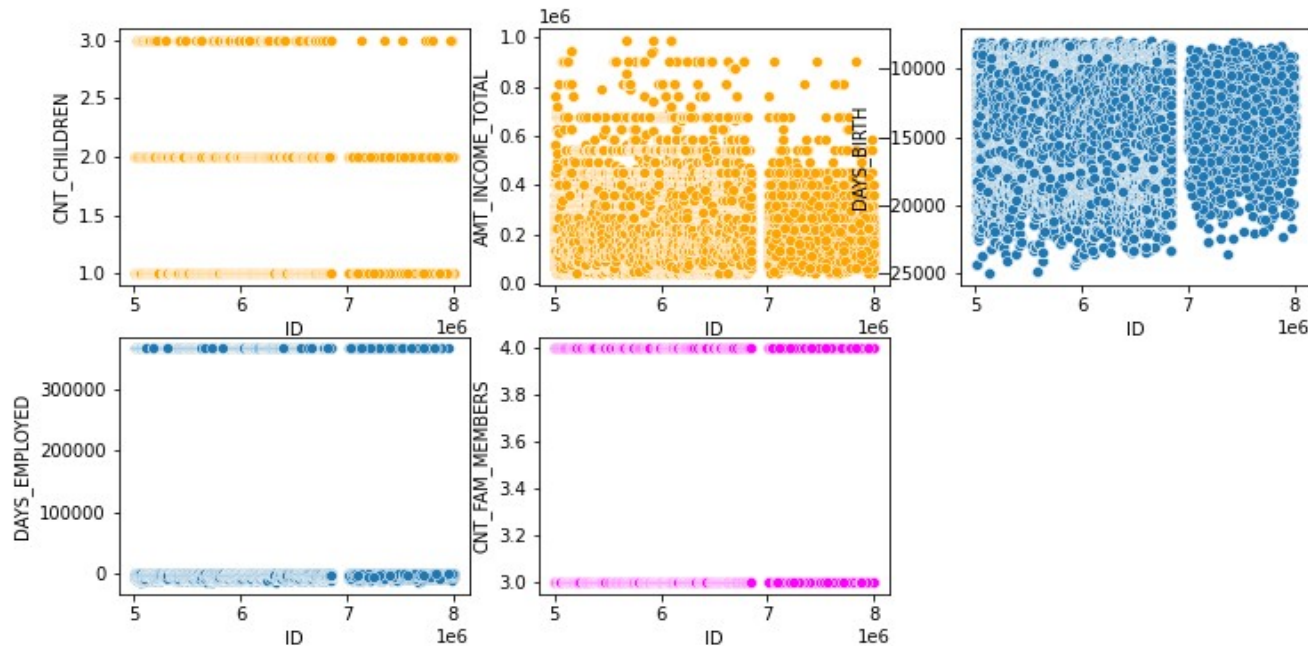


# Features



- Few variables in the application record data-set checked if there are outliers
- Plot shows outliers in 'cnt\_children', 'amt\_income\_total', 'cnt\_fam\_members'

# Features



- Removed the outliers in the above columns of the application record data-set and remade the plot

# Credit-Record Dataset

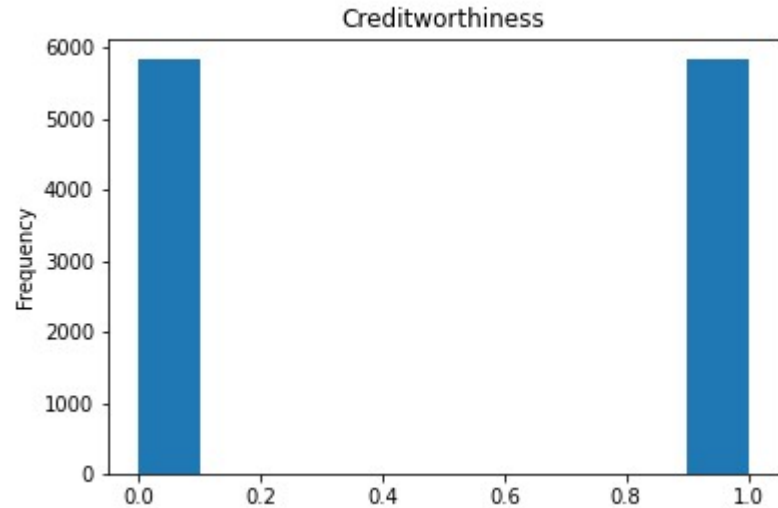
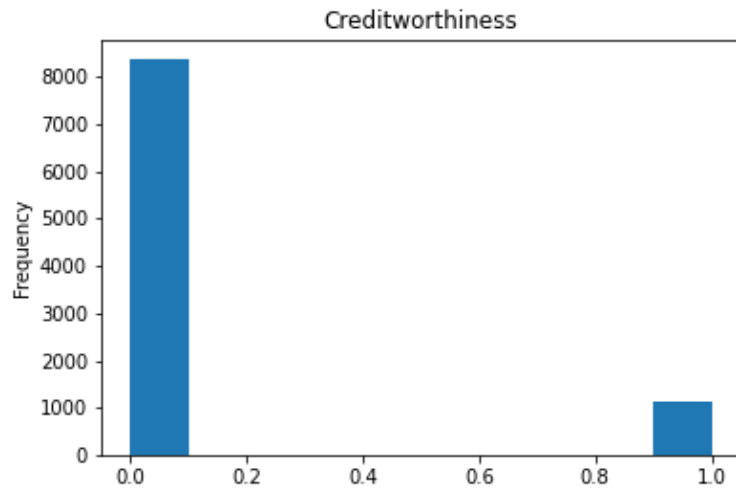
---

The credit-record dataset records the creditworthiness of a consumer into eight categories :

- 0 : 1 – 29 days past due
- 1 : 30 – 59 days past due
- 2 : 60 – 89 days over due
- 3 : 90 – 119 days over due
- 4 : 120 – 149 days over due
- 5 : Overdue or bad debts, write-offs for more than 150 days
- C : paid off that month
- X : no loan for the month

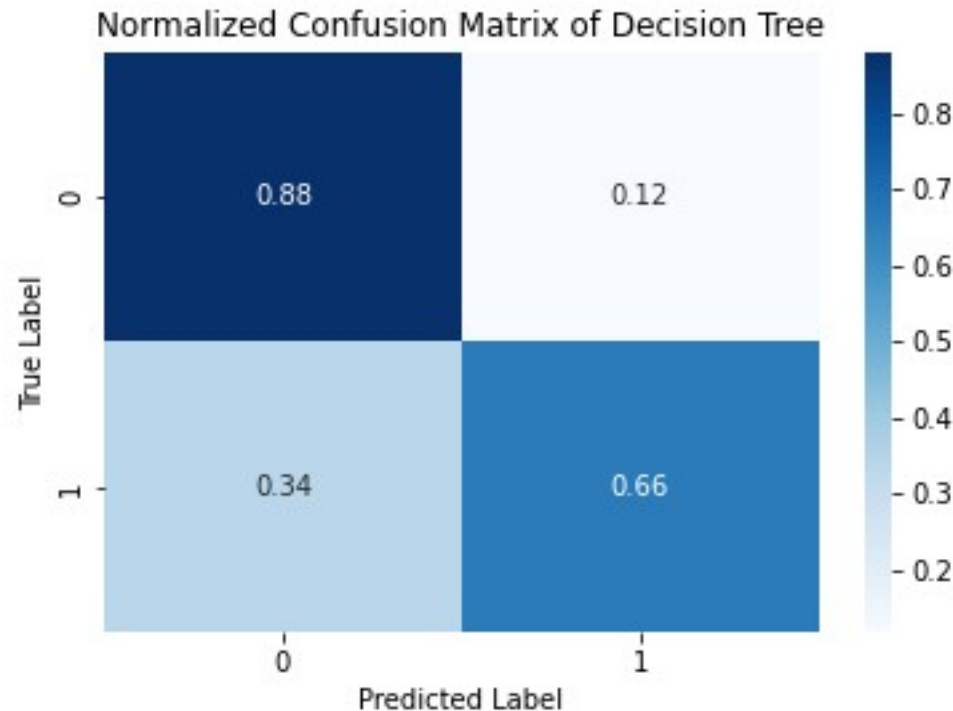
We regrouped these categories in only two : 0 (creditworthiness – 0, C, X) and 1 (no creditworthiness ( 1, 2, 3, 4 , 5)).

# SMOTE Algorithm



- The 'status' - which is the target 'variable' - has 87.97 % as 0 (creditworthiness) and 12.03 % as 1 (no credit-worthiness) (image in the left)
- The creditworthy category has larger population than the non-creditworthy. It suffers oversampling.
- We divided the data into those that will be used to train the model and those that will be used to predict the approval : 70 % for training and 30 % testing.
- To correct the over-sampling, we applied SMOTE (Synthetic Minority Over-sampling Technique) algorithm to generate the second category of data (non-creditworthiness) (image in the right)

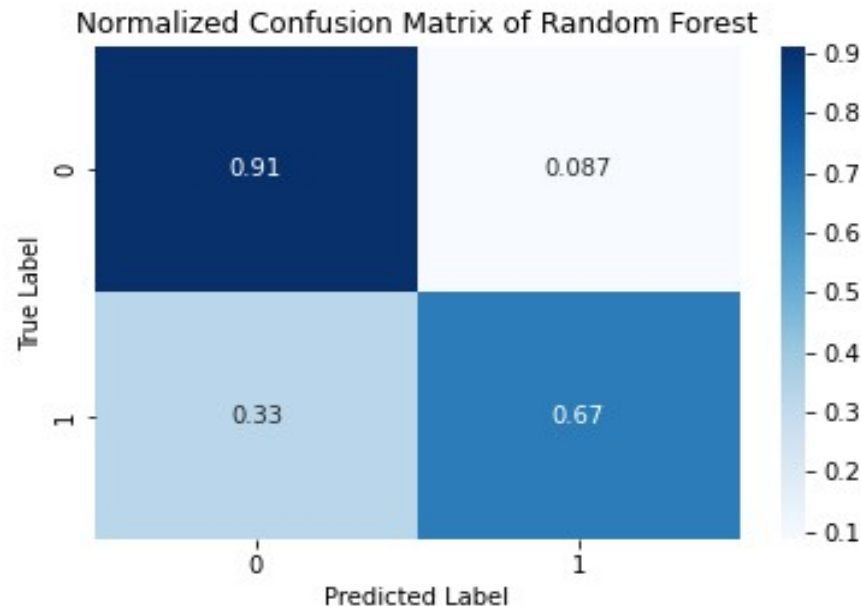
# CONFUSION Matrix



- We applied machine-learning models to the processed data.
- We began with the Decision Tree Classifier.
- The confusion matrix above shows it has high True Negative and True Positive.
- The accuracy score from this confusion matrix is 0.77.

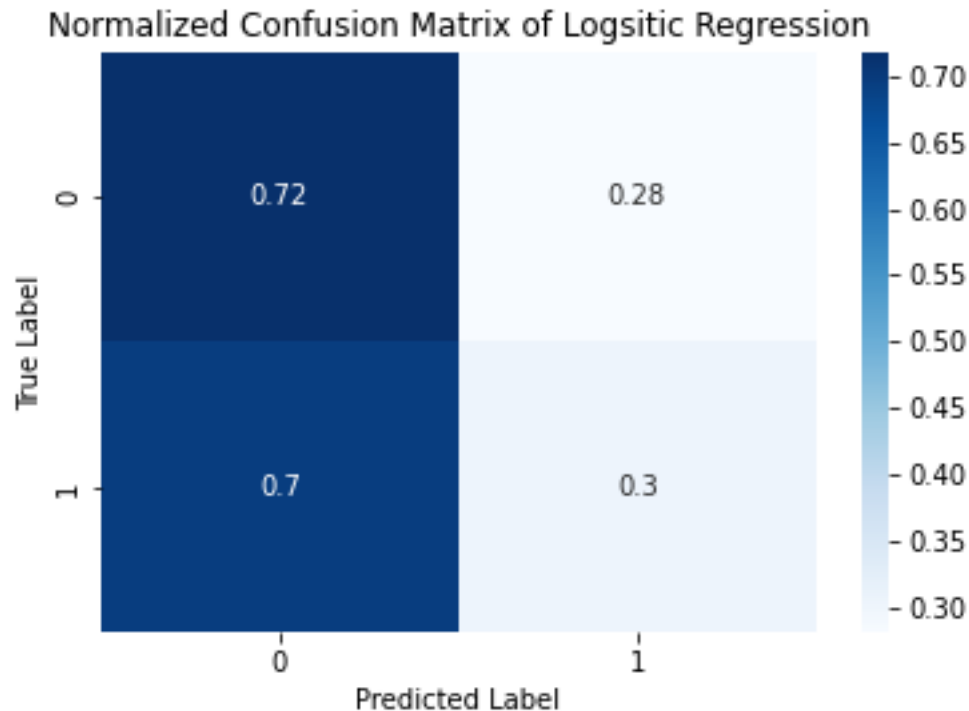


# CONFUSION Matrix



- Next, we fitted the Random Forest model on the training set of the data and use the model to make prediction using the test data.
- The accuracy score from this confusion matrix is 0.79.
- The Random Forest model was run with three variables : `n_estimators = 150`, `max_depth = 16` and `min_samples_lead = 12`.
- We employed GridSearchCV to get the optimum values of these parameters and found `n_estimators = 300`, `max_depth = 20` and `min_samples_leaf = 9`.
- We refitted the model using these parameters and got the accuracy to be 0.80 - similar to previous value.

# CONFUSION Matrix



- We then repeated the process of plotting the confusion matrix with the Logistic Regression model.
- We got the accuracy of this model to be 0.511.

# Conclusions

- We built a machine learning-based classifier that predicts if a credit card application will get approved or not, based on the information provided in the application.
- While building this credit card approval predictor, we learned about common preprocessing steps such as label encoding, and handling outliers.
- We implemented three different machine learning models, optimized the hyper-parameters for one, and evaluated the performance using the accuracy score.
- Based on the accuracy score, we found the Random Forest Model to be most accurate.
- We have used python's machine learning libraries to implement machine learning algorithms. In the future, we can investigate to estimate the tangible benefits of the predictions of these machine learning models.

---

**Thank You !**