# Credit Rating using Random Forest Report



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28.01.2018
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# **Problem Description**

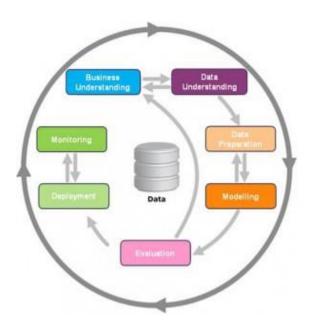
Bank ABC wants to predict app score for current credit card customers. The app score will denote a customer's credit worthiness and help the bank in reducing credit default risk.

The target variable denoted as Bad\_flag\_worst6.

If value is 0 – it means customer has good credit history

If value is 1 – it means customer has falls into 30 DPD + bucket

# Methodology



Crisp DM methodology is followed to build and evaluate the model.

## **Data Preparation**

- 1. Data Imputation
- 2. Data Balancing
- 3. Feature Extraction

### **Data Imputation**

- 1. Cashlimit and cur\_balance\_amt are imputed using zeros.
- 2. Cur\_balance\_amt with negative values are replaced with 1.
- 3. Sed diam nonummy nibh euismod

## **Data Balancing**

#### **Synthetic Minority Over-sampling Technique**

#### **Advantages**

- Mitigates the problem of overfitting caused by random oversampling as synthetic examples are generated rather than replication of instances
- No loss of useful information

#### **Before SMOTE**

Total Observations = 34,111

Fraudulent Observations = 1464

Non Fraudulent Observations = 32647

Event Rate = 4 %

#### **After SMOTE**

Total Observations = 40104

Fraudulent Observations = 7457

#### Non Fraudulent Observations = 32647

Event Rate = 18.5 %

#### **Feature Extraction**

Payment\_history\_avg\_dpd\_0\_29\_bucket, total\_diff\_lastpaymt\_opened\_dt, min\_months\_last\_30\_plus, utilisation\_trend, Ratio\_currbalance\_creditlimit, mean\_diff\_lastpaymt\_opened\_dt, mean\_diff\_open\_enquiry\_dt, payment\_history\_mean\_length, max\_freq\_enquiry, perc\_unsecured\_others.

The above columns are extracted using the formula given in the questionnaire.

# **Insights**

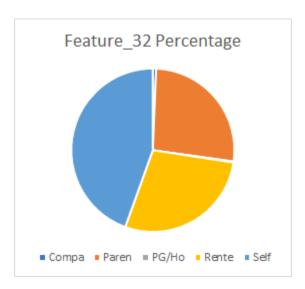
| Rule Number | Rule   | Cover     | Output |
|-------------|--|-----------|--------|
| 1           | feature_1=Golf<br>Card,Insignia  | 2657 (6%) | 1      |
| 2           | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh dpd_29=12,13,21,30,33                            | 794 (2%)  | 1      |
| 3           | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh feature_51=,American Express Banking Corporation | 942 (2%)  | 1      |

|   | e_total_diff_lastpaymt_<br>opened_dt>=7173<br>feature_36=,Governme<br>nt<br>Organisation,MNC,Priva<br>te Ltd.<br>Co.,Proprietorship  |           |   |
|---|--|-----------|---|
| 4 | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh  dpd_29=?,1,10,11,14,1 5,16,17,18,19,2,20,22,2 3,24,25,26,27,28,29,3,3 1,32,37,38,39,4,40,42,4 5,5,6,69,7,8,9 feature_27=  feature_51=,American Express Banking Corporation  e_total_diff_lastpaymt_ opened_dt>=7173 feature_36=Public Ltd Co. | 398 (1%)  | 0 |
| 5 | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh  dpd_29=?,1,10,11,14,1 5,16,17,18,19,2,20,22,2 3,24,25,26,27,28,29,3,3 1,32,37,38,39,4,40,42,4 5,5,6,69,7,8,9 feature_27=  feature_51=,American  | 1786 (4%) | 0 |

|   | Express Banking Corporation  e_total_diff_lastpaymt_ opened_dt< 7173  |             |   |
|---|---|-------------|---|
| 6 | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh  dpd_29=?,1,10,11,14,1 5,16,17,18,19,2,20,22,2 3,24,25,26,27,28,29,3,3 1,32,37,38,39,4,40,42,4 5,5,6,69,7,8,9 feature_27= feature_51=AXIS Bank,Citibank N.A.,HDFC Bank,HSBC Bank,ICICI Bank,IndusInd Bank Ltd.,Kotak Mahindra Bank Ltd.,Standard Chartered Bank,State Bank of India | 3364 (8%)   | 0 |
| 7 | feature_1=Platinum Cricke,Platinum Deligh,Platinum Maxima,RBL Bank Fun+,Titanium Deligh  dpd_29=?,1,10,11,14,1 5,16,17,18,19,2,20,22,2 3,24,25,26,27,28,29,3,3 1,32,37,38,39,4,40,42,4 5,5,6,69,7,8,9  feature_27=Architect,C A,Diploma,Doctor,Engin eer,Graduate,MBA/MM S,Others,Post- Graduate,Professional   | 32405 (77%) | 0 |

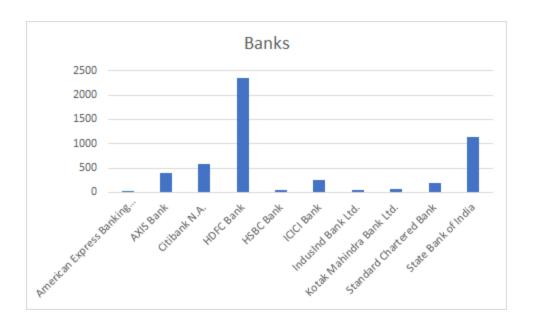
## Feature 32

If a customer is not a credit defaulter then he is likely to stay with Companion 44%, Parents 27%, Rent 28%.



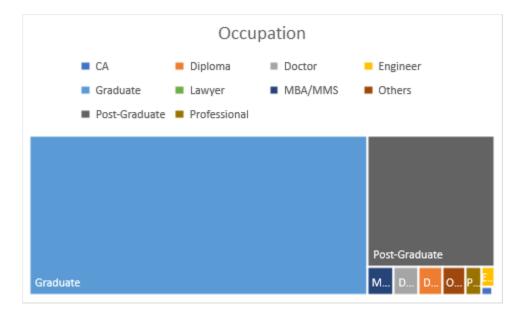
# **Customers Bank**

Customers having account in HDFC and State Bank of India are safe(loans can be given) and less likely to default.



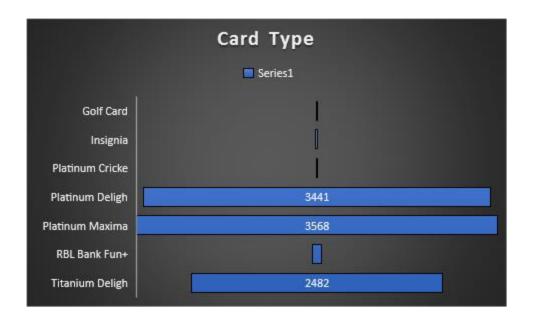
# **Occupation**

Graduates and Post Graduates are the majority who apply for loan.



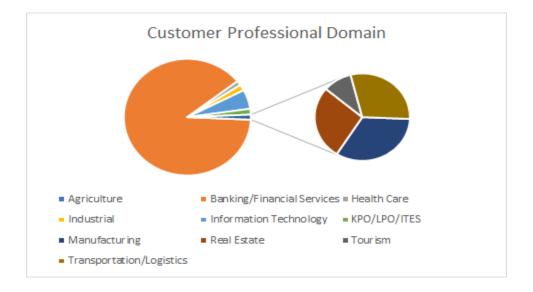
# **Card Type**

Platinum Maxima, Platinum Deligh and Titanium Deligh card holders are reliable borrowers.



## **Customer Professional Domain**

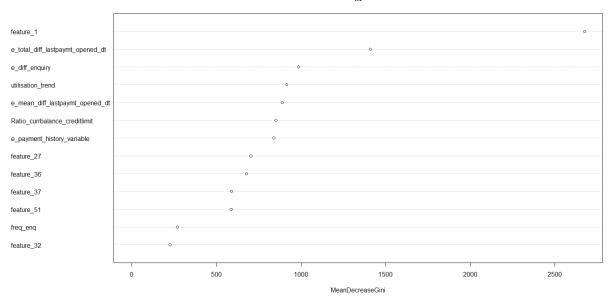
Customer from Banking are topping the charts in applying loan and followed by Information Technology.



## **RESULTS**

## Variable Importance

fit



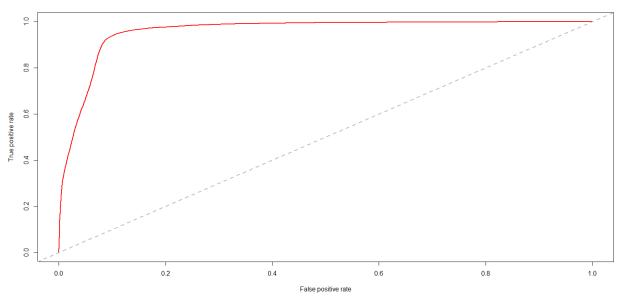
## **Confusion Matrix**

# **Accuracy**

```
> accuracy
[1] 0.9393999
```

## ROC





#### **CONCLUSION**

The Model is able to capture major part of the borrowers who could repay the loan but performs poorly in capturing the defaulters. So better to give loans to borrowers who comes under True positive category.

#### **REFERENCES**

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