



Credit Card Customer Churn

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Introduction

It costs on average around 200 USD to acquire a credit card customer (up to and beyond 1,000 USD if they are affluent cards like “MasterCard World Elite” and “Visa Infinite”). The Apple Card doesn’t need any affiliates or marketing, yet analysts say that this new card has a customer acquisition cost of 350 USD and will take several years for Goldman Sachs to turn a profit on it.

That being said, it actually takes banks a few years to recover the acquisition investment of that customer and that's the main reason why they're motivated to predict which users are the most likely to churn, in order to proactively and not reactively retain the client.

Problem Statement

- Customer retention is critical for a good marketing and a customer relationship management strategy. The prevention of customer churn through customer retention is a core issue of Customer Relationship Management.
- Here, an analysis is done on purchasing behavior of bank customers.
- A detailed scheme is worked out to convert raw customer data into meaningful and useful data that suits the buying behavior, and in turn, converts this meaningful data into knowledge for which predictive data mining techniques are adopted.

Data Description

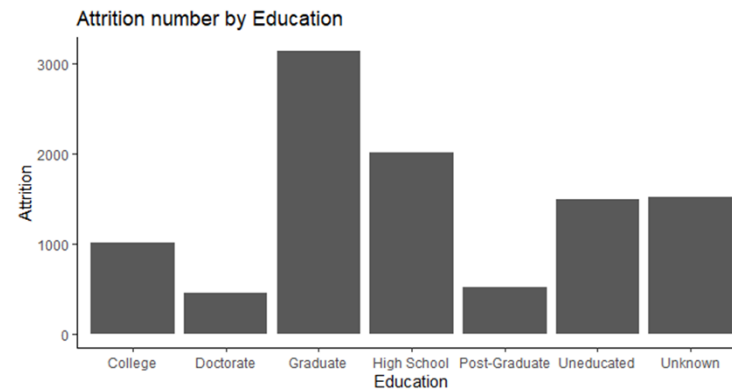
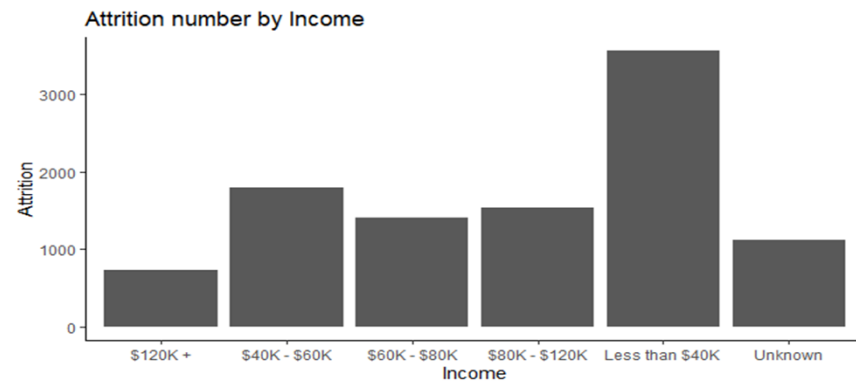
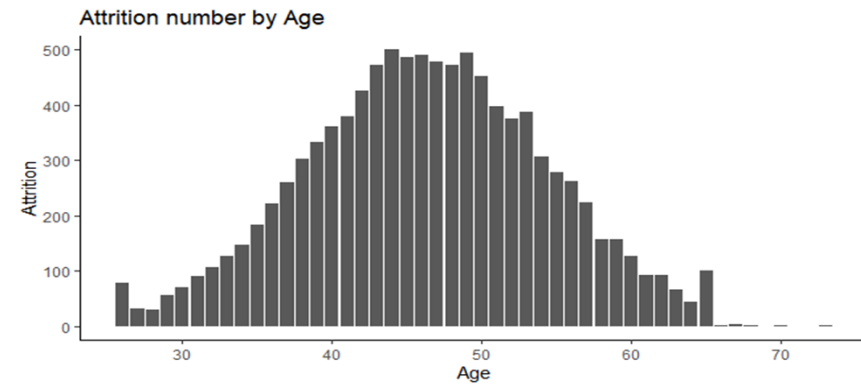
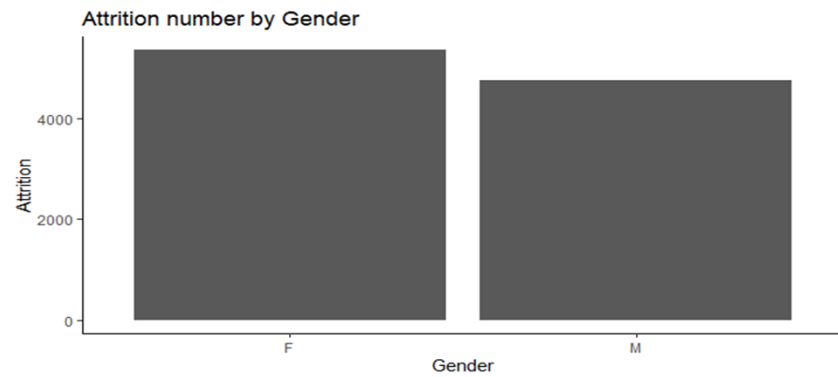
The dataset consists of records of 10,127 bank customers and 20 columns describing various features-

- **Clientnum** - Client number. Unique identifier for the customer holding the account
- **Attrition_Flag** - Internal event (customer activity) variable
- **Customer_Age** - Customer's Age in Years
- **Gender** - M=Male, F=Female
- **Dependent_count** - Number of people dependents
- **Education_Level** - Educational Qualification of the account holder (example: high school, college graduate, etc.)
- **Marital_Status** - Married, Single, Unknown
- **Income_Category** - Annual Income Category of the account holder (< 40K, 40K - 60K, 60K - 80K, 80K-120K, > 120K, Unknown)
- **Card_Category** - Type of Card (Blue, Silver, Gold, Platinum)
- **Months_on_book** Months on book (Time of Relationship)

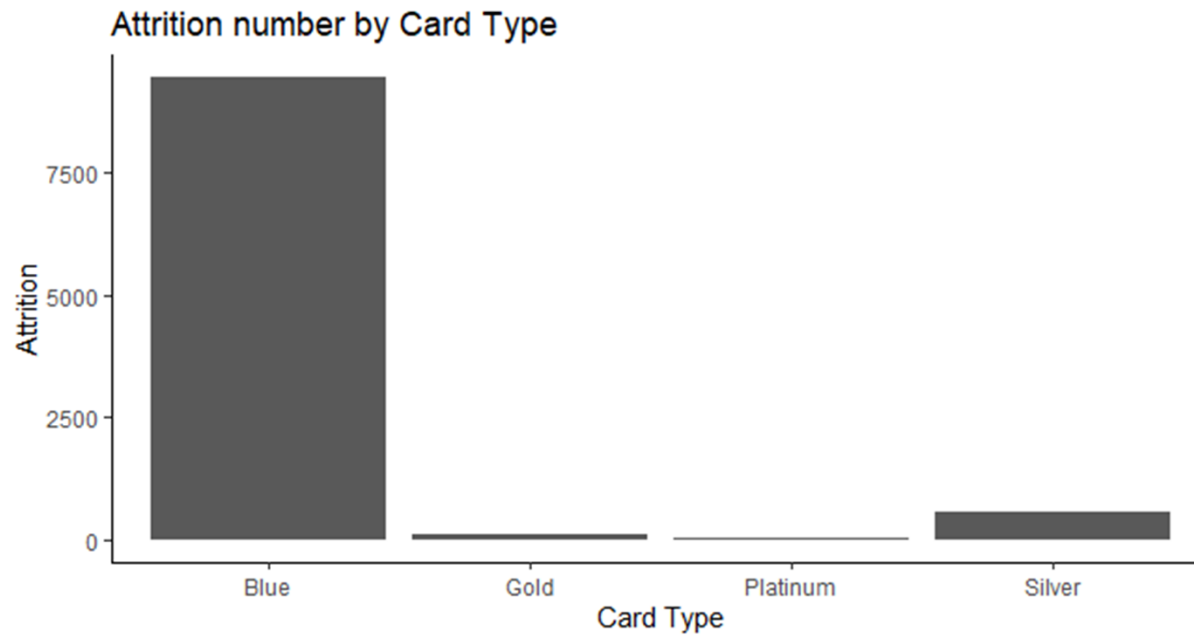
Data Description

- **Total_Relationship_Count** - Total no. of products held by the customer
- **Months_Inactive_12_mon** - No. of months inactive in the last 12 months
- **Contacts_Count_12_mon** - No. of Contacts in the last 12 months
- **Credit_Limit** - Credit Limit on the Credit Card
- **Total_Revolving_Bal** - Total Revolving Balance on the Credit Card
- **Avg_Open_To_Buy** - Open to Buy Credit Line (Average of last 12 months)
- **Total_Amt_Chng_Q4_Q1** - Change in Transaction Amount (Q4 over Q1)
- **Total_Trans_Amt Num** - Total Transaction Amount (Last 12 months)
- **Total_Trans_Ct Num** - Total Transaction Count (Last 12 months)
- **Total_Ct_Chng_Q4_Q1** - Change in Transaction Count (Q4 over Q1)
- **Avg_Utilization_Ratio** - Average Card Utilization Ratio

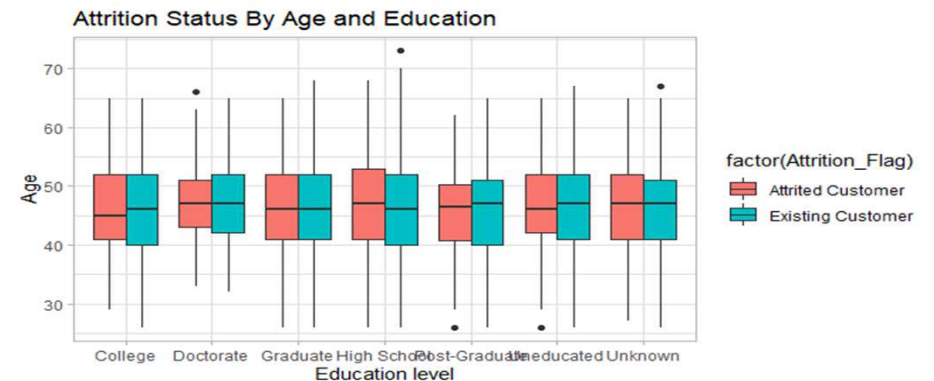
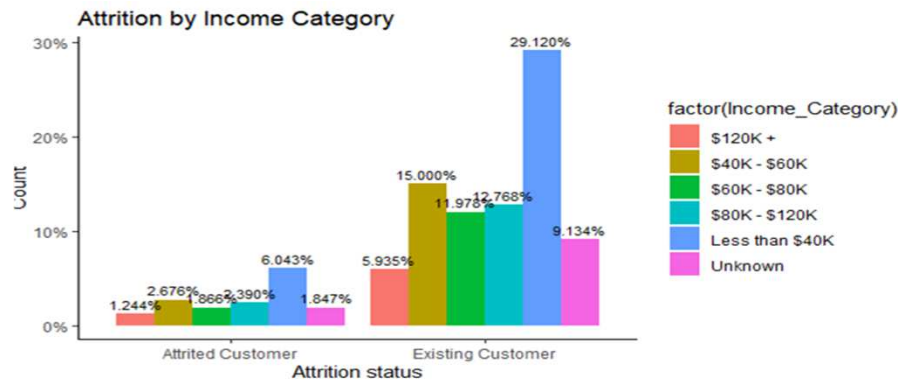
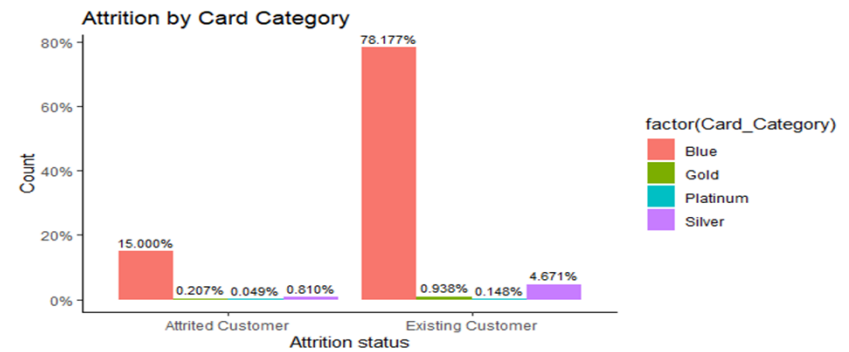
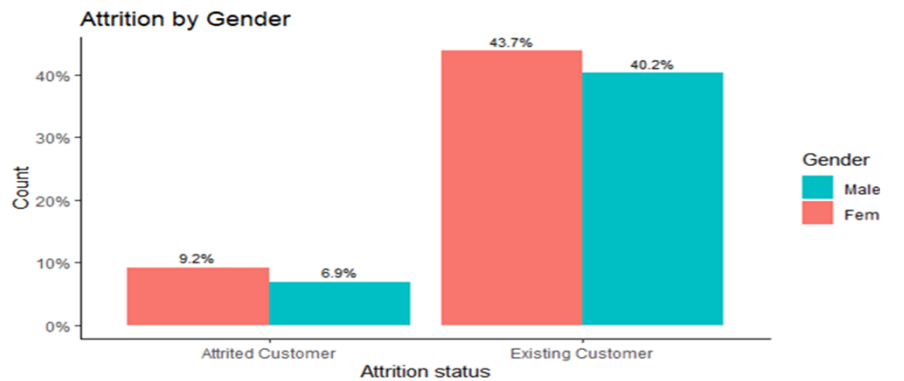
Exploratory Data Analysis



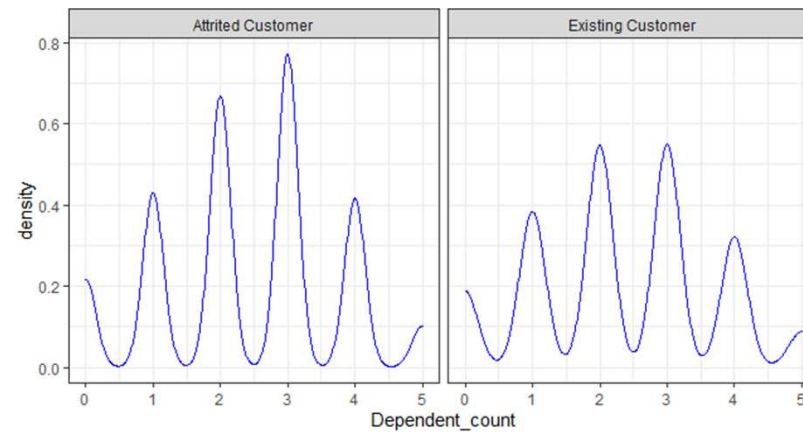
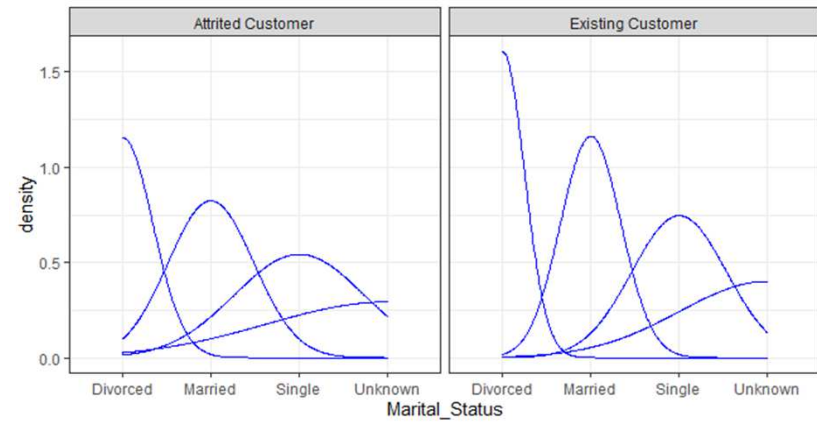
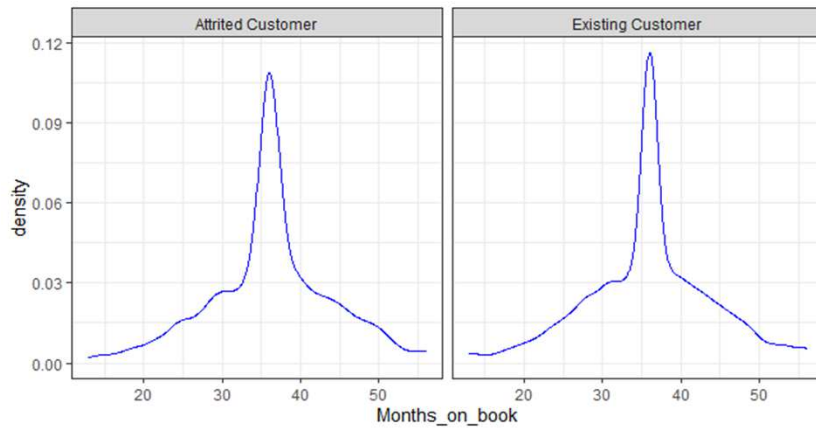
Exploratory Data Analysis



Exploratory Data Analysis

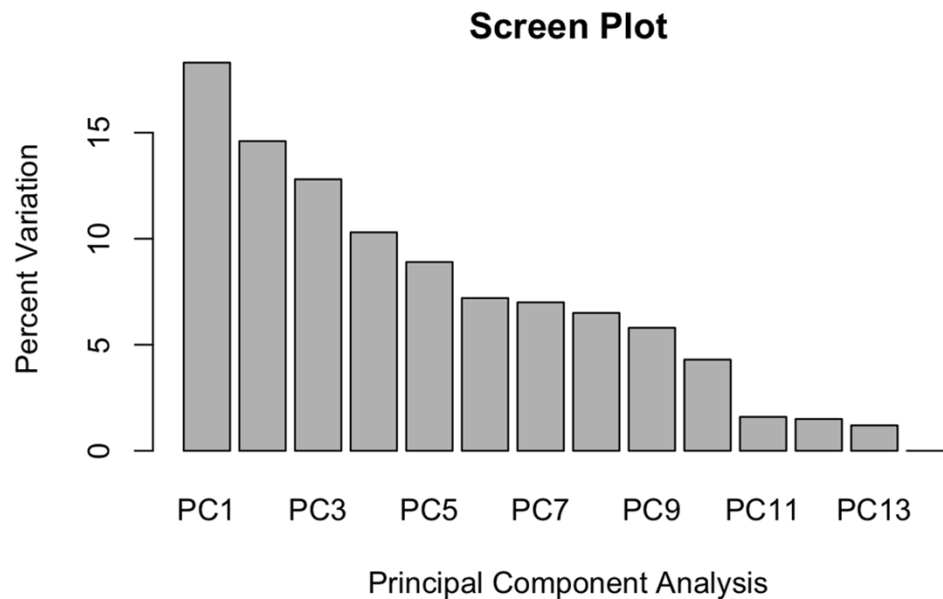


Exploratory Data Analysis



Principal Component Analysis

To extract the principal components (that can be used to train the models), we perform Principal Component Analysis on the dataset containing 14 feature data in which 7 features came out to account for most variation in data.



ML Models

Random Forest

Confusion matrix:

	Attrited Customer	Existing Customer	class.error
Attrited Customer	1086	216	0.16589862
Existing Customer	82	6718	0.01205882

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	265	20
Existing Customer	60	1680

Accuracy : 0.9605
95% CI : (0.9511, 0.9686)
No Information Rate : 0.8395
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.8457

Mcnemar's Test P-Value : 1.299e-05

Sensitivity : 0.8154
Specificity : 0.9882
Pos Pred Value : 0.9298
Neg Pred Value : 0.9655
Prevalence : 0.1605
Detection Rate : 0.1309
Detection Prevalence : 0.1407
Balanced Accuracy : 0.9018

'Positive' Class : Attrited Customer

Model with Non-PCA data

Confusion matrix:

	Attrited Customer	Existing Customer	class.error
Attrited Customer	675	627	0.48156682
Existing Customer	109	6691	0.01602941

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	166	18
Existing Customer	159	1682

Accuracy : 0.9126
95% CI : (0.8994, 0.9245)
No Information Rate : 0.8395
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.6066

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.51077
Specificity : 0.98941
Pos Pred Value : 0.90217
Neg Pred Value : 0.91363
Prevalence : 0.16049
Detection Rate : 0.08198
Detection Prevalence : 0.09086
Balanced Accuracy : 0.75009

'Positive' Class : Attrited Customer

Model with PCA data

ML Models

(SVM) Support
Vector Machine

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	62	5
Existing Customer	263	1695

Accuracy : 0.8677
95% CI : (0.8521, 0.8821)
No Information Rate : 0.8395
P-Value [Acc > NIR] : 0.0002322

Kappa : 0.2766

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.19077
Specificity : 0.99706
Pos Pred Value : 0.92537
Neg Pred Value : 0.86568
Prevalence : 0.16049
Detection Rate : 0.03062
Detection Prevalence : 0.03309
Balanced Accuracy : 0.59391

'Positive' Class : Attrited Customer

Model with Non-PCA data

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	94	12
Existing Customer	231	1688

Accuracy : 0.88
95% CI : (0.865, 0.8938)
No Information Rate : 0.8395
P-Value [Acc > NIR] : 1.563e-07

Kappa : 0.3879

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.28923
Specificity : 0.99294
Pos Pred Value : 0.88679
Neg Pred Value : 0.87962
Prevalence : 0.16049
Detection Rate : 0.04642
Detection Prevalence : 0.05235
Balanced Accuracy : 0.64109

'Positive' Class : Attrited Customer

Model with PCA data

ML Models

Naive Bayes

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	203	127
Existing Customer	122	1573

Accuracy : 0.877

95% CI : (0.8619, 0.891)

No Information Rate : 0.8395

P-Value [Acc > NIR] : 1.156e-06

Kappa : 0.5465

McNemar's Test P-Value : 0.7999

Sensitivity : 0.6246

Specificity : 0.9253

Pos Pred Value : 0.6152

Neg Pred Value : 0.9280

Prevalence : 0.1605

Detection Rate : 0.1002

Detection Prevalence : 0.1630

Balanced Accuracy : 0.7750

'Positive' Class : Attrited Customer

Model with Non-PCA data

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	146	28
Existing Customer	179	1672

Accuracy : 0.8978

95% CI : (0.8838, 0.9106)

No Information Rate : 0.8395

P-Value [Acc > NIR] : 2.646e-14

Kappa : 0.5329

McNemar's Test P-Value : < 2.2e-16

Sensitivity : 0.44923

Specificity : 0.98353

Pos Pred Value : 0.83908

Neg Pred Value : 0.90330

Prevalence : 0.16049

Detection Rate : 0.07210

Detection Prevalence : 0.08593

Balanced Accuracy : 0.71638

'Positive' Class : Attrited Customer

Model with PCA data

ML Models

Decision Tree

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	246	59
Existing Customer	79	1641

Accuracy : 0.9319

95% CI : (0.92, 0.9424)

No Information Rate : 0.8395

P-Value [Acc > NIR] : <2e-16

Kappa : 0.7406

McNemar's Test P-Value : 0.1058

Sensitivity : 0.7569

Specificity : 0.9653

Pos Pred Value : 0.8066

Neg Pred Value : 0.9541

Prevalence : 0.1605

Detection Rate : 0.1215

Detection Prevalence : 0.1506

Balanced Accuracy : 0.8611

'Positive' Class : Attrited Customer

Model with Non-PCA data

Confusion Matrix and Statistics

Prediction	Reference	
	Attrited Customer	Existing Customer
Attrited Customer	171	74
Existing Customer	154	1626

Accuracy : 0.8874

95% CI : (0.8728, 0.9009)

No Information Rate : 0.8395

P-Value [Acc > NIR] : 5.090e-10

Kappa : 0.536

McNemar's Test P-Value : 1.678e-07

Sensitivity : 0.52615

Specificity : 0.95647

Pos Pred Value : 0.69796

Neg Pred Value : 0.91348

Prevalence : 0.16049

Detection Rate : 0.08444

Detection Prevalence : 0.12099

Balanced Accuracy : 0.74131

'Positive' Class : Attrited Customer

Model with PCA data

ML Models

Logistic Regression

```

target
y_pred  1    2
1      44  204
2     281 1496

```

Accuracy : 0.7605
95% CI : (0.7413, 0.7789)
No Information Rate : 0.8395
P-Value [Acc > NIR] : 1.0000000

Kappa : 0.017

Mcnemar's Test P-Value : 0.0005586

Sensitivity : 0.13538
Specificity : 0.88000
Pos Pred Value : 0.17742
Neg Pred Value : 0.84187
Prevalence : 0.16049
Detection Rate : 0.02173
Detection Prevalence : 0.12247
Balanced Accuracy : 0.50769

'Positive' Class : 1

Model with Non-PCA data

Confusion Matrix and Statistics

```

target
y_pred  1    2
1     165   41
2     160 1659

```

Accuracy : 0.9007
95% CI : (0.8869, 0.9134)
No Information Rate : 0.8395
P-Value [Acc > NIR] : 1.038e-15

Kappa : 0.5676

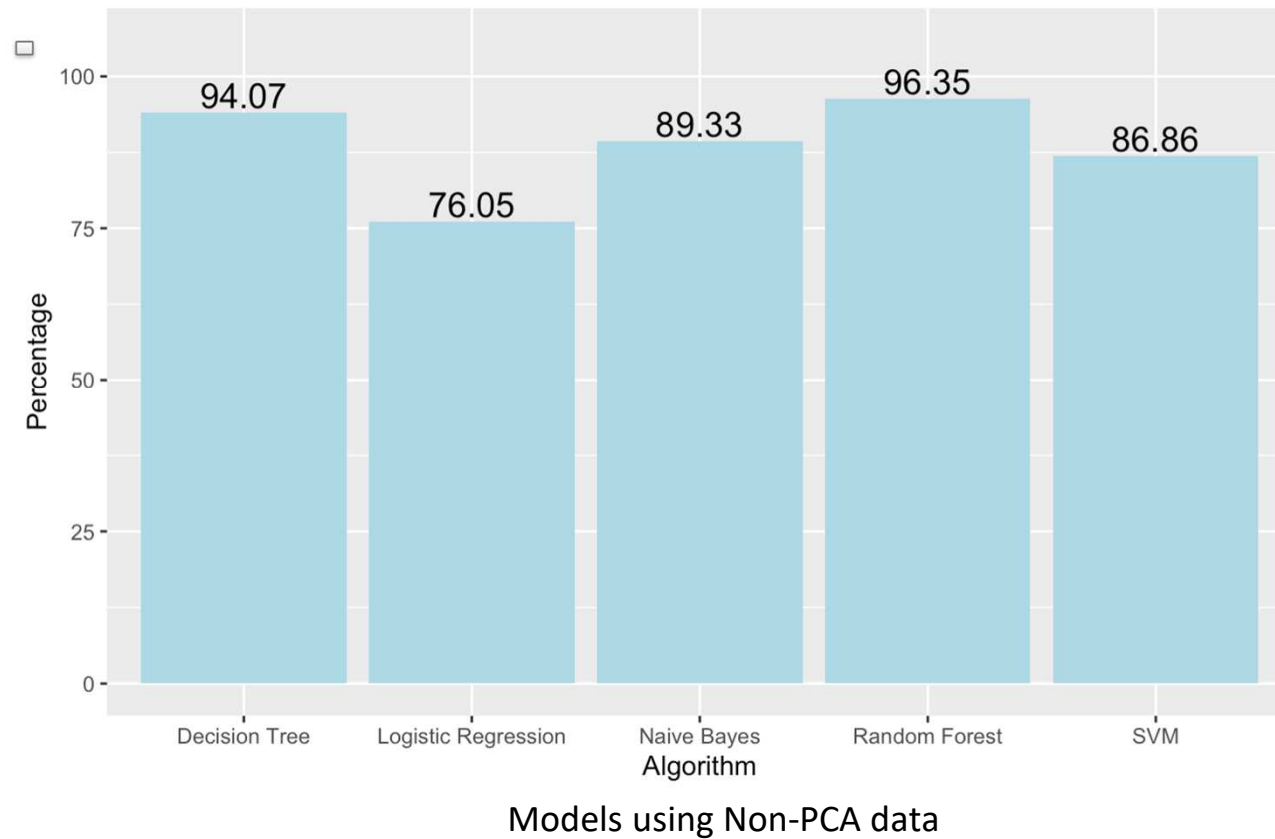
Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.50769
Specificity : 0.97588
Pos Pred Value : 0.80097
Neg Pred Value : 0.91204
Prevalence : 0.16049
Detection Rate : 0.08148
Detection Prevalence : 0.10173
Balanced Accuracy : 0.74179

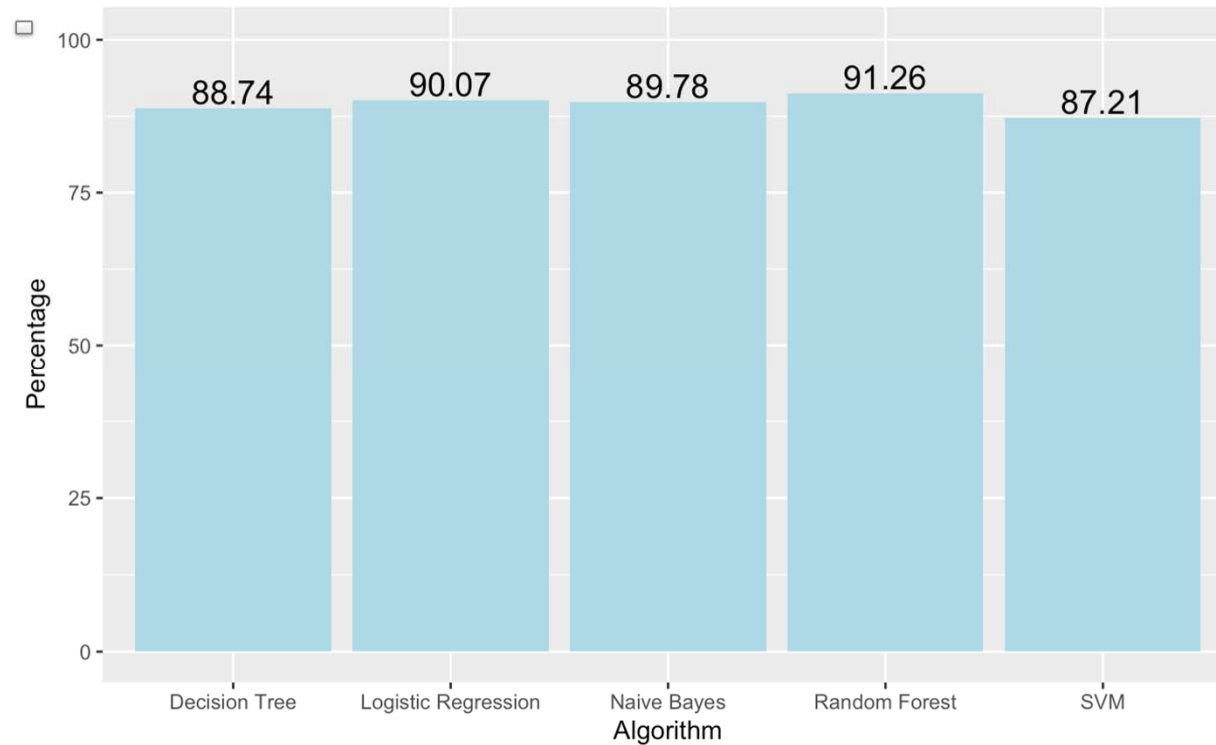
'Positive' Class : 1

Model with PCA data

Comparison of ML Models



Comparison of ML Models



Models using PCA data

Conclusion

- From the previous graphs, we can clearly conclude that the Random Forest Model have outperformed the remaining models, let it be in the regular data or the transformed data with reduced dimensions and principal components.
- Also, as we observe the graphs, we can see few models performed a bit better with the transformed PCA data instead of the regular ones and vice versa. Dataset is of 20 dimensions (features), which might not be considered large enough to perform dimensionality reduction or even PCA, but performing PCA altered the model accuracy to an extent. Accuracy of all the models before PCA differed a lot from each other, but after PCA all the models gave the same accuracy in the range of 90%. This shows that all the models were able to train and fit the data correctly and capture the variability of the features, which was not the case when we considered all the features from the dataset.

Future Scope

- The data set is minimal, hence more data can be included.
- The machine learning model that are built, can be used in real life web applications.
- More complex algorithms like the deep learning models can be trained and used for the prediction.
- In few cases, the models can be fine-tuned according to the bank's requirement.

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THANK YOU