

# TELECOM CHURN CASE STUDY

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## PROBLEM STATEMENT

The Indian and SEA market telecom market is highly competitive, where the industry's customer churn rate is on an average of 15%-25% annually. As the new customer acquisition is 5-10 times more costlier than customer retention, it is imperative that the organisation is focusing more upon the customer retention.

In this industry, retaining the high profitable customers is the primary business goal. To retain customer and reduce the churn, the companies need to predict which customers are at higher risk.

Here the organisation wants to identify the customers who are high value customers and have stopped using the services

# BUSINESS GOAL

- The company requires a model to be built for identifying the customers who are high value and have stopped using the services
- To identify the high value customers
- To predict the churn in the last month which is the 9<sup>th</sup> month.

# STRATEGY

Import Data.

Clean and prepare the acquired data for further analysis.

Filtering out the High Value Customers

Missing value Treatment

Exploratory data analysis for figuring out most helpful attributes for conversion.

Scaling features.

Handling data imbalance

Using PCA to reduce dimensionality.

Building Logistic Regression Model with PCA

Test the model on train set.

Evaluate model by different measures and metrics.

Test the model on test set.

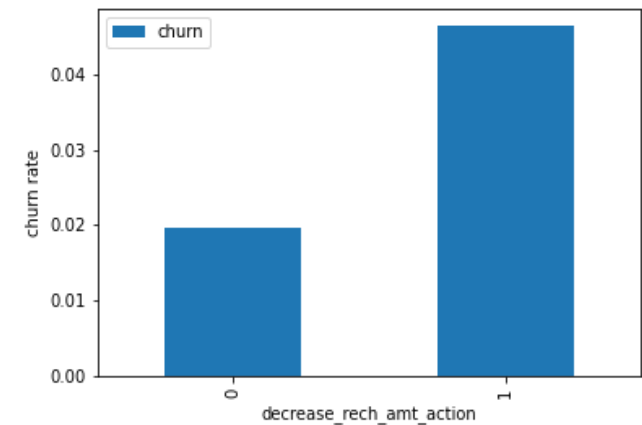
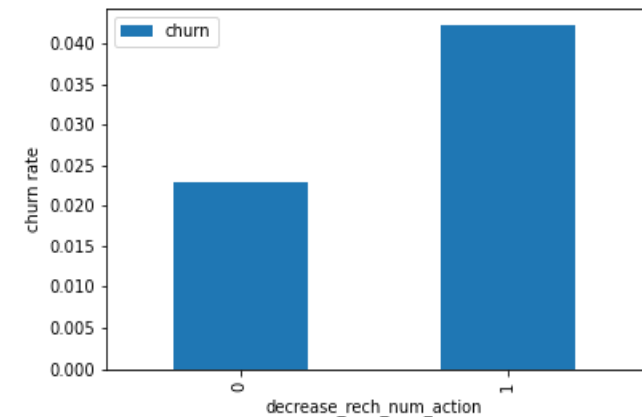
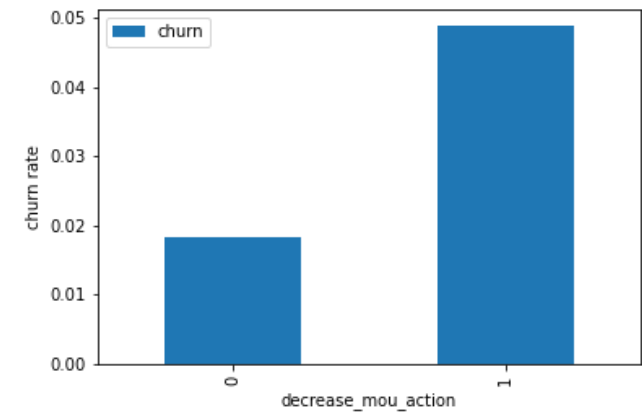
Measure the accuracy of the model and other metrics for evaluation.

Checking the performance metrics by using Decision Tree, Random Forest with PCA and Logistic Regression without PCA

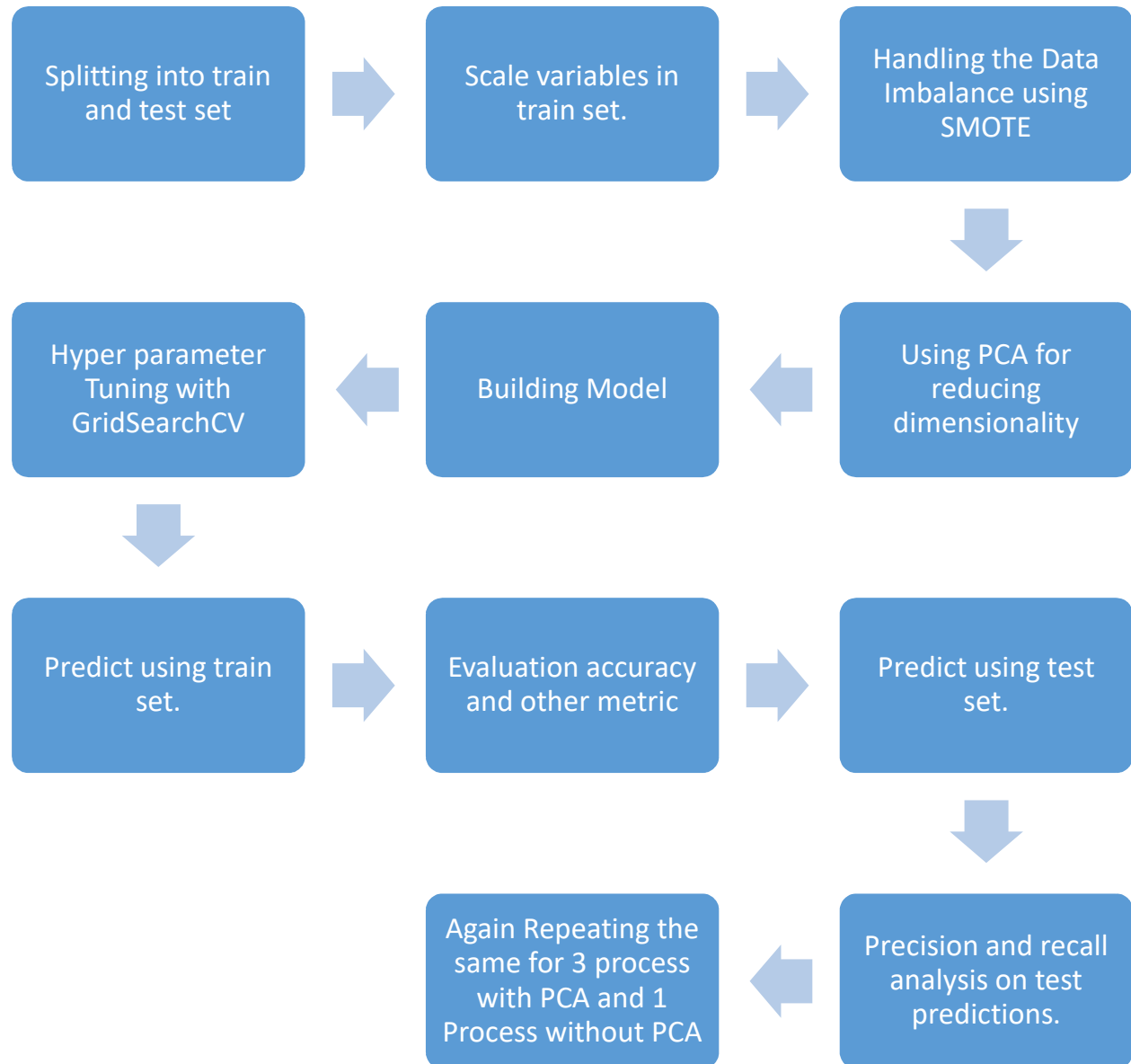
# EXPLORATORY DATA ANALYSIS

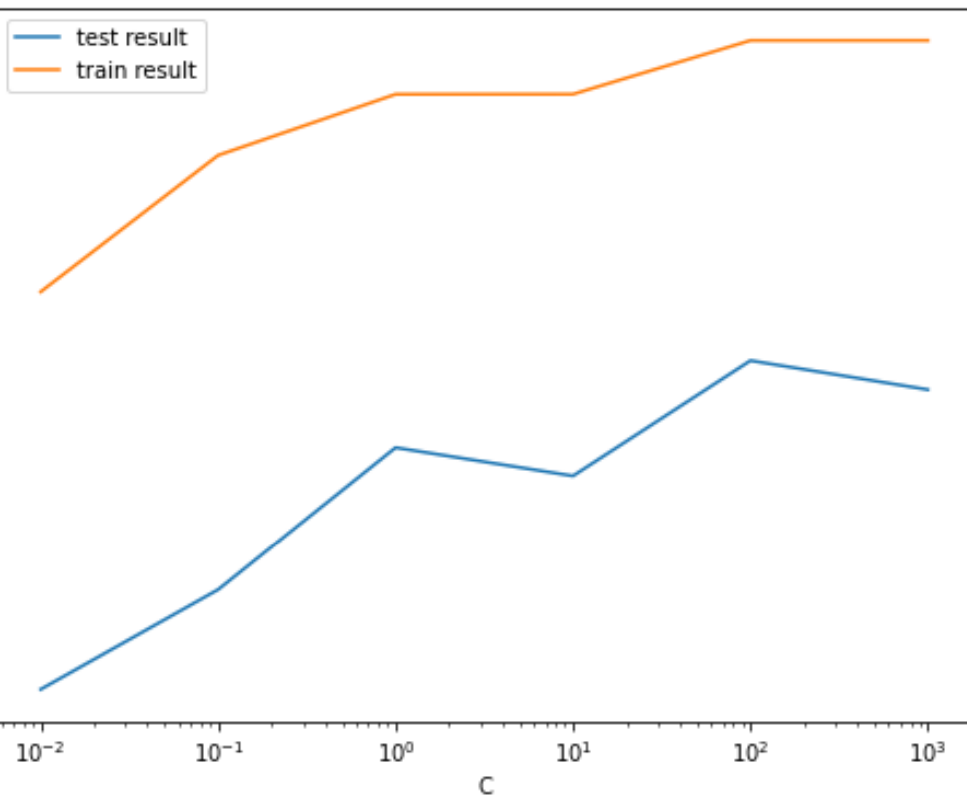
Behaviour of Churn Customer in Action Phase

Early depicting that the churn customers have  
their average usage time, count of recharge,  
of recharge in the third month



# MODEL BUILDING





Best test sensitivity is 0.8974883072810858 at C = 100

# MODEL EVALUATION

## TRAIN with Optimal C

### Confusion Matrix

15580

3170

1902

16848

- Accuracy : 86.47%
- Sensitivity : 89.85%
- Specificity : 83.09%

DEL  
UATION-TEST  
Optimal C

- Confusion Matrix

6634

1389

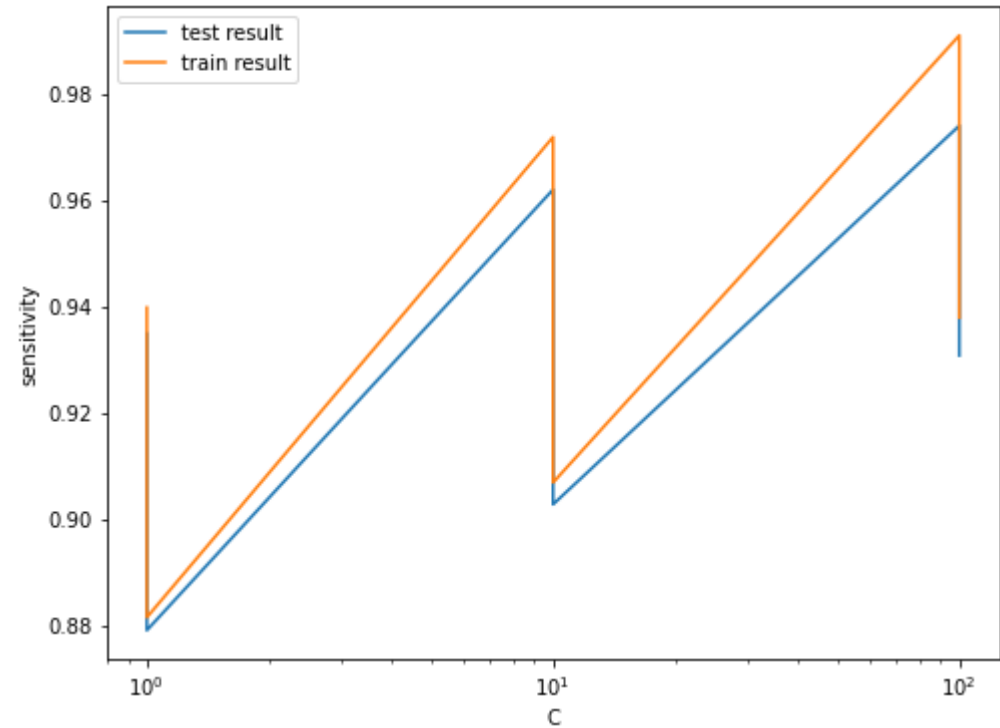
54

235

- Accuracy : 82.63%
- Sensitivity : 81.31%
- Specificity : 82.68%



# MODEL EVALUATION-TEST (with PCA Minimal C and Score)



- The highest test sensitivity is 0.9740533333333334 at C = 100

# MODEL EVALUATION-TRAIN by Decision

## e

Confusion Matrix

649

2101

324

17426

Accuracy : 90.86%

Sensitivity : 92.93%

Specificity : 88.79%

# MODEL EVALUATION-TEST Decision Tree

- Confusion Matrix

6977	1046
94	195

- Accuracy : 86.28%
- Sensitivity : 67.47%
- Specificity : 86.96%

# MODEL EVALUATION-TRAIN by Random Forest

Confusion Matrix

649	2101
324	17426

Accuracy : 90.86%

Sensitivity : 92.93%

Specificity : 88.79%

# MODEL EVALUATION-TEST Random Forest

- Confusion Matrix

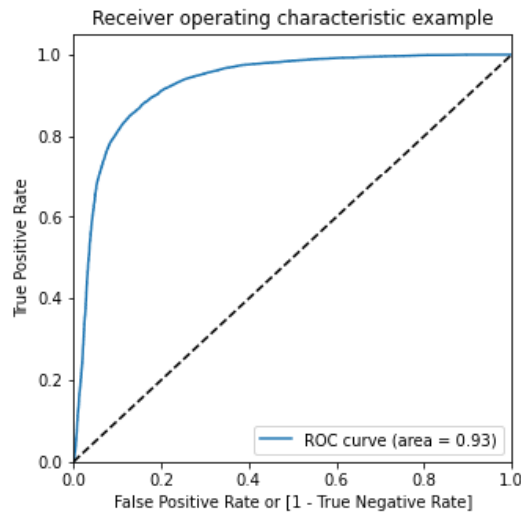
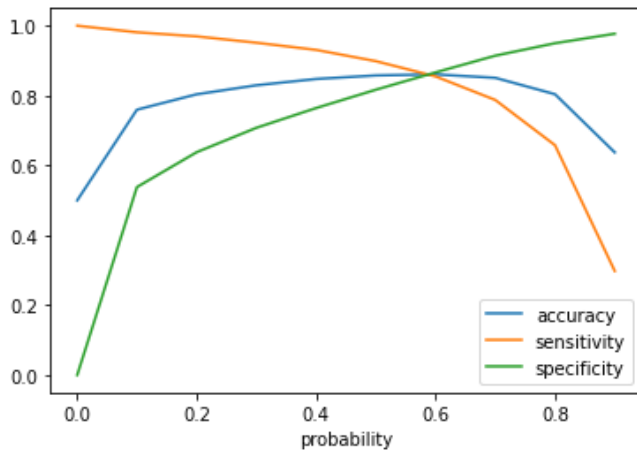
6977	1046
94	195

- Accuracy : 86.28%
- Sensitivity : 67.47%
- Specificity : 86.96%

## CONCLUSION-Model Building with PCA

After trying several models we can see that for achieving the best sensitivity, which was our ultimate goal, the classic Logistic regression or the SVM models preforms well. For both the models the sensitivity was approx. 85%. Also we have good accuracy of approx. 80%.

# MODEL EVALUATION- TRAIN with Logistic Regression



st test sensitivity is 0.8974883072810858 at C = 100

## Confusion Matrix

15314

3436

1903

16847

- Accuracy : 85.76%
- Sensitivity : 89.85%
- Specificity : 81.67%

# MODEL EVALUATION-TEST Using Logistic Regression

- Confusion Matrix

6549	1474
47	242

- Accuracy : 81.70%
- Sensitivity : 83.73%
- Specificity : 81.62%



## CONCLUSION-Model Building without PCA

We can see that the logistic model with no PCA has good sensitivity and accuracy, which are comparable to the models with PCA. So, we can go for the more simplistic model such as logistic regression with PCA as it explains the important predictor variables as well as the significance of each variable. The model also helps us to identify the variables which should be acted upon for making the decision of the to be churned customers. Hence, the model is more relevant in terms of explaining to the business.

# CONCLUSION- Business Recommendation

The customers, whose MoU of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in the month of August) are to be targeted.

Target the customers, whose outgoing others charge in July and incoming others on August are less. Also, the customers having value based cost in the action phase increased are more likely to churn than the other customers.

So, these customers may be a good target to provide offers.

Customers, whose monthly 3G recharge in August is more, are likely to be churned.

Customers having decreasing STD incoming MoU for operators T to fixed lines of T for the month of August are more likely to churn. Customers decreasing monthly 2G usage for August are most probable to churn.

Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.

onnnet\_mou\_8 variables have positive coefficients (4.59). That means for the customers, whose all kinds of calls within the same operator are likely to churn.

THANK YOU