Telecom Churn Case Study

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PROBLEM STATEMENT OF TELECOM-CHURN

In the telecom industry, customers are able to choose from multiple service providers and actively switch from one operator to another. In this highly competitive market, the telecommunications industry experiences an average of 15-25% annual churn rate. Given the fact that it costs 5-10 times more to acquire a new customer than to retain an existing one, **customer retention** has now become even more important than customer acquisition.

- For many incumbent operators, *retaining high profitable customers is the number one business goal*.

- To reduce customer churn, telecom companies need to **predict which customers are at high risk of churn.**

OBJECTIVES OF TELECOM-CHURN

- In this project, we will analyse customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn and identify the main indicators of churn.
- After identifying important predictors, display them visually – we will use plots, summary tables etc. - whatever you think best conveys the importance of features.
- **recommend strategies to manage customer churn** based on your observations.

99999

#DATA OVERVIEW

- The provided *Telecom* dataset has around 9000 data points. This dataset consists of various attributes such as Churn, Age on Net,average revenue per user , service packs, etc. which may or may not be useful in ultimately deciding whether a lead will be converted or not.

- The target variable, in this case study, is the column ‘Churn’ which tells whether customer will leave this network.

CASE STUDY APPROACH

I. Data Preparation, Cleaning and EDA
II. Test-train Split and Scaling
III. Model Building
IV. Model Evaluation
V. Prediction on data sets
VI. Conclusion
VII. Recommendations

DATA PREPARATION.CLEANING & EXPLORATORY DATA ANALYSIS

Step 1: Importing Data

Step 2: Inspecting the Dataframe

Step 3: Data Cleaning

Step 4: EDA

Step 5: Data Preparation

IMPORTING & INSPECTING THE DATA

- There are 99999 rows and 226 columns in the dataframe.

- There are columns which give the details about the incoming call, On net usage , offnet usage, average recharge amount etc .

#NULL VALUES/MISSING VALUES

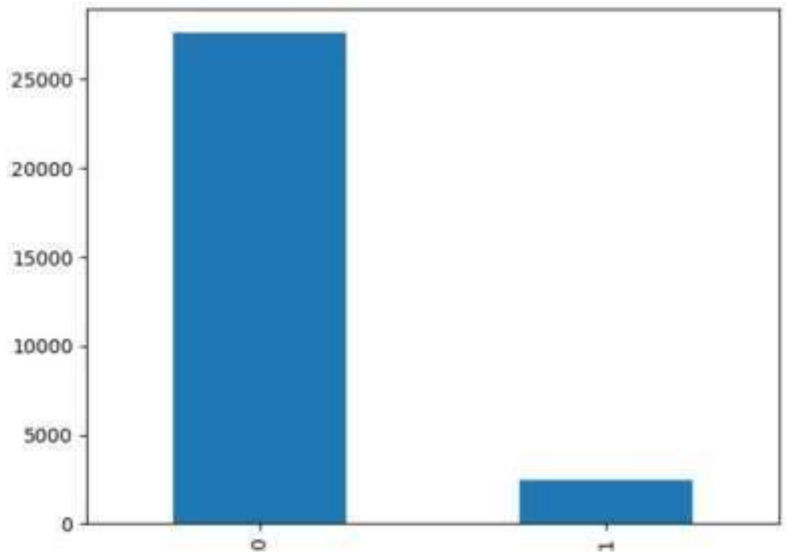
- Missing ValuesAnalysis (Percentage Wise)

arpu_3g_6	74.846748
arpu_3g_7	74.428744
arpu_3g_8	73.660737
arpu_3g_9	74.077741
arpu_2g_6	74.846748
arpu_2g_7	74.428744
arpu_2g_8	73.660737
arpu_2g_9	74.077741
night_pck_user_6	74.846748
night_pck_user_7	74.428744
night_pck_user_8	73.660737
night_pck_user_9	74.077741
fb_user_6	74.846748
fb_user_7	74.428744
fb_user_8	73.660737
fb_user_9	74.077741

#DATA CLEANING

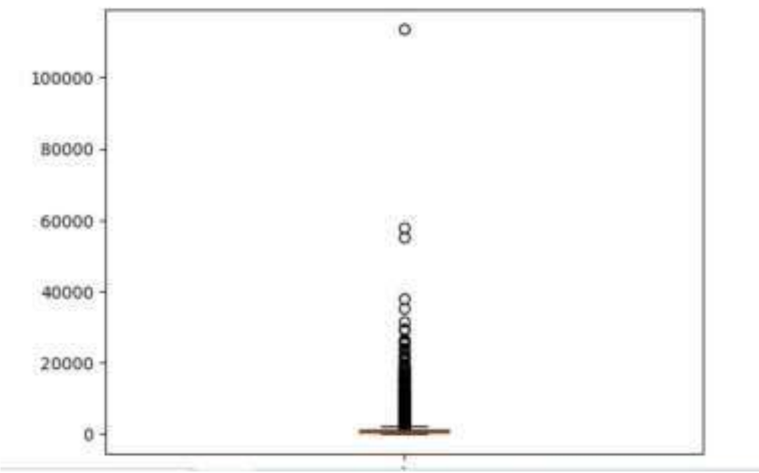
- After analyzing the null value percentage of all columns present in telecom Datasethave 75% of null values
- We have dropped the columns having Missing Values.
- We have imputted onnet, offnet, roam_og, loc_og, std_og, isd_og, spl_og, og_others as 0 as total_outgoing minutes of usage is 0 for customer
- Also, imputed the incoming calls columns like roam_ic, loc_ic, std_ic, spl_ic, isd_ic, ic_others as 0 as total_ic_mou is 0 for customer
- We have filtered out **high-value customers**
- Calculated the average recharges for 6 and 7th month.

#UNIVARIATE ANALYSIS



- As seen in the graph maximum is for 0 and less is for 1

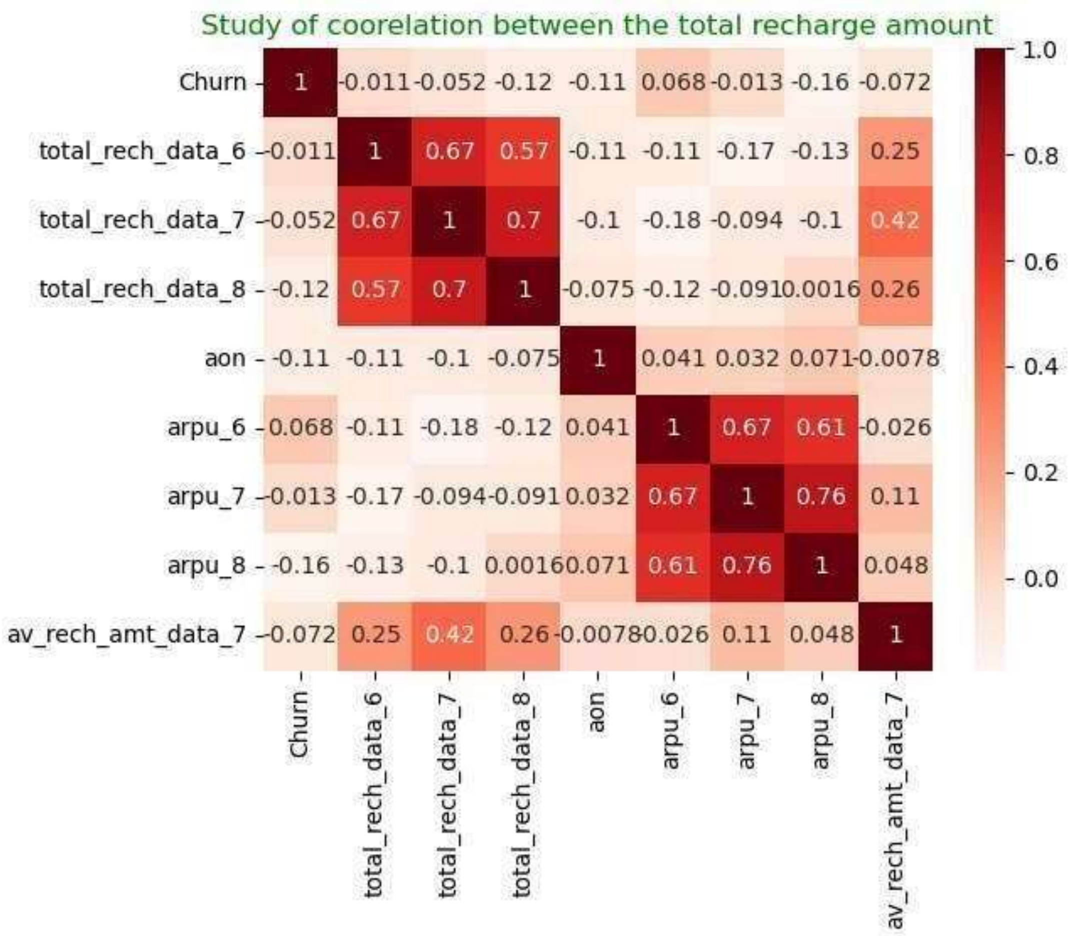
#UNIVARIATE ANALYSIS



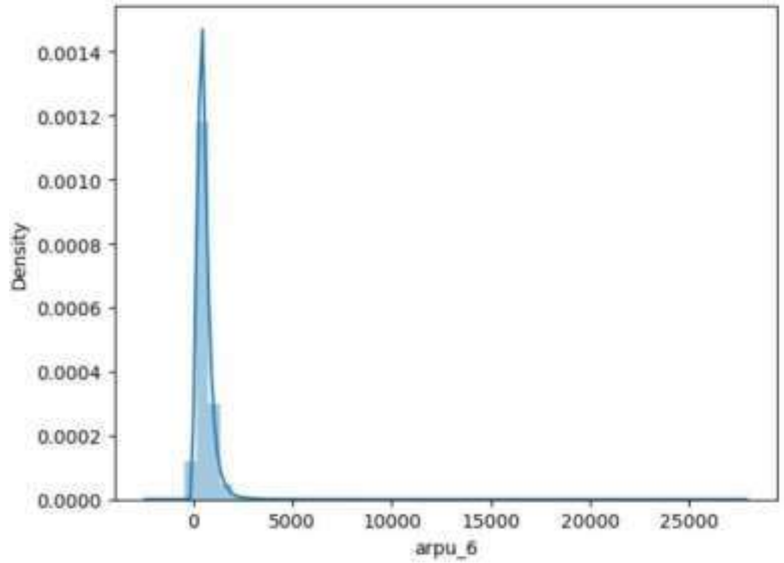
- This graph was plotted for the total rech amount for 6th month
- As seen in the graph there are many outliers

#MULTIVARIATE ANALYSIS

- There is a positive correlation with Average unit per user and average amount recharge
- -Churn has a positive correlation with average revenue per user for 6th month.

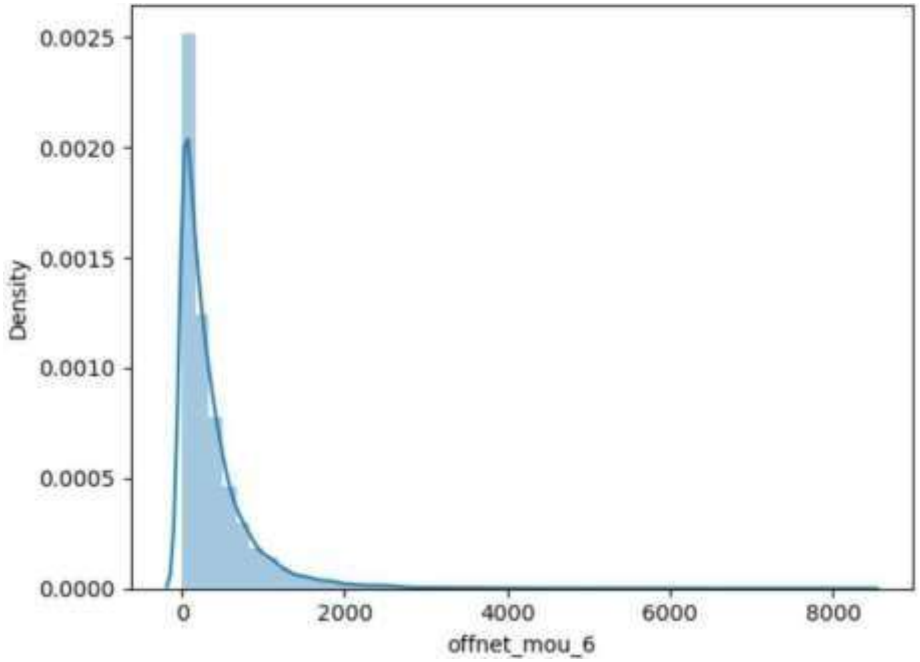


AVERAGE REVENUE PER USER



- As seen in the graph the maximum average revenue per user is 27731.

#OFF-NET MINUTES OF USAGES



- As seen in the graph the offnet minutes of usage for 6^{th} month is 8362

TEST-TRAIN SPLIT & SCALING

- Step 1: Test-Train Split

  The dataset is split into Training and Testing Data in the ratio of 70:30 .

- Step 2: Feature Scaling
  - The Feature Scaling is done by using *StandardScalar* function.
  - For training data, *fit_transform* function is used.
  - For testing data, *transform* function is used.
  - This will be different for different models.

PREPARED VARIOUS MODEL'S BASED ON FOLLOWING ALGORTHIMS.

Model Building

- Principle component Analysis and Regression
- Logistic Regression with RFE and VIF
- Decision Tree
- ADA Boosting with Decision Tree
- Random Forest

MODEL EVALUATION PARAMETERS

Step 1: Accuracy

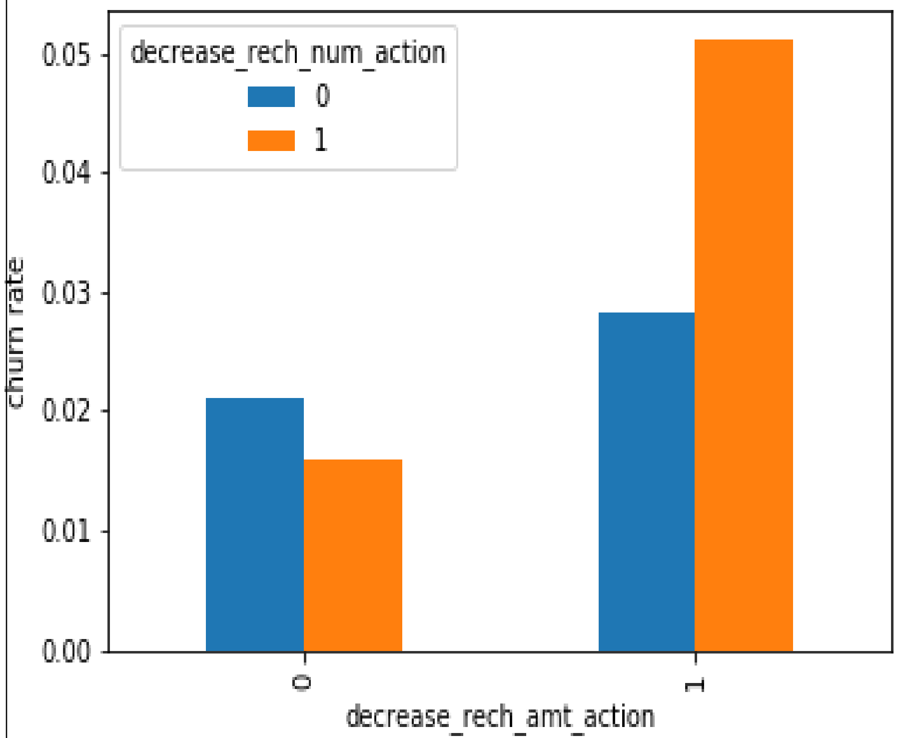
Step 2: Sensitivity and Specificity

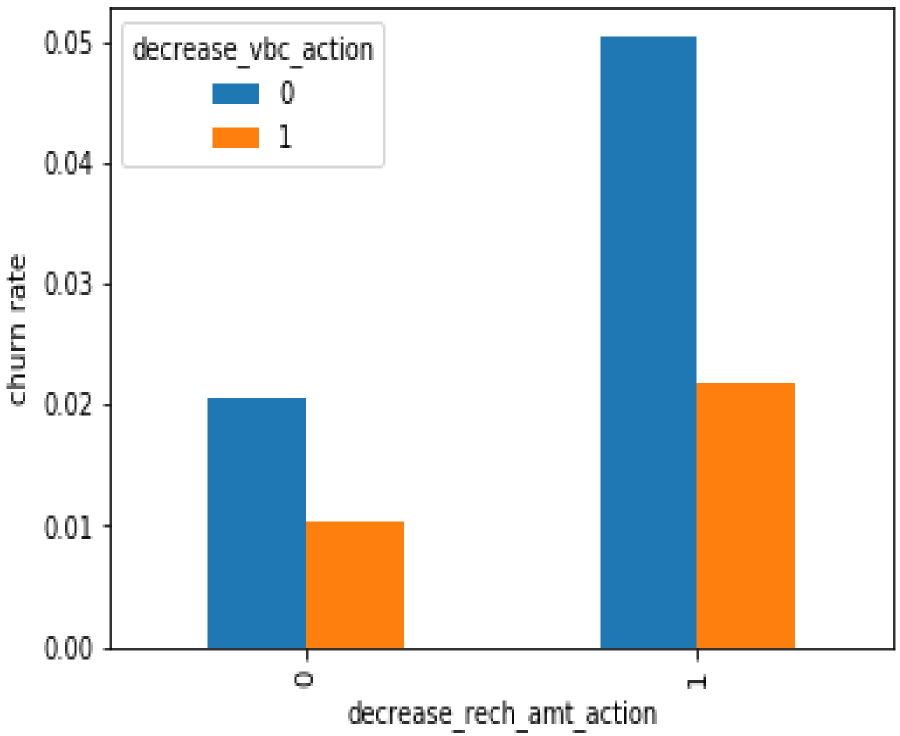
Step 3: Precision and Recall

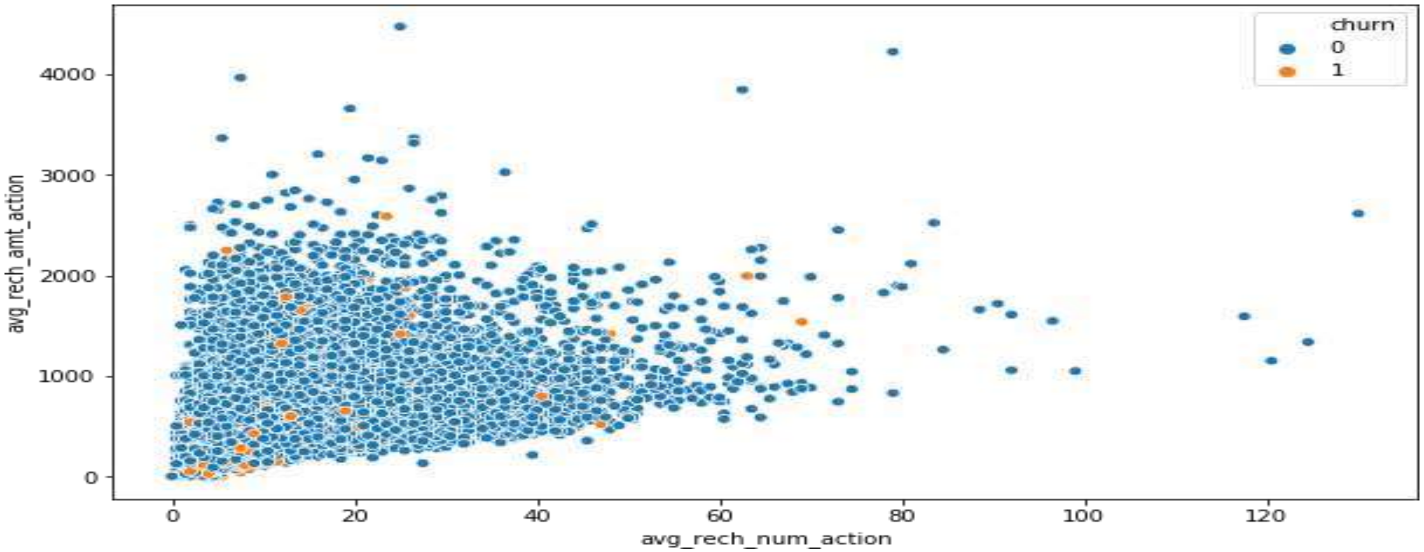
DETERMINING THE PRECISION &RECALL FOR VARIOUS MODEL'S TEST DATA SETS

MethodologyTest -	Precision	Test - Recall
--PCA with regression	37	71.33
--Logistic Regression	40.7	71.33
--Decision Tree	73	46
--ADA Boosting with DT	69.1	52.3
--Random Forests	74	50.0

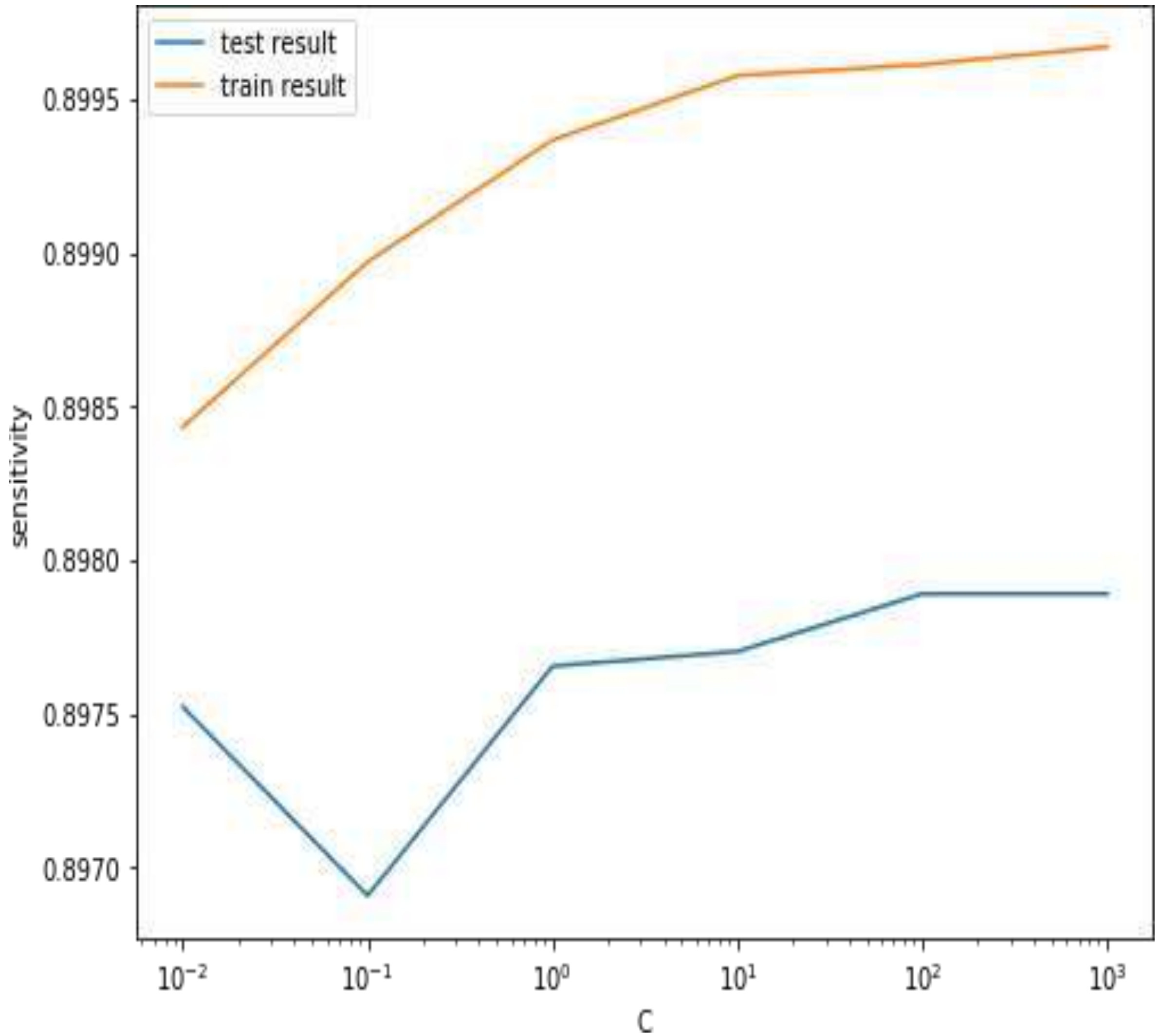
BIVARIATE ANALYSIS







Logistic regression with PCA

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The highest test sensitivity is 0.8978916608693863 at C
= 100
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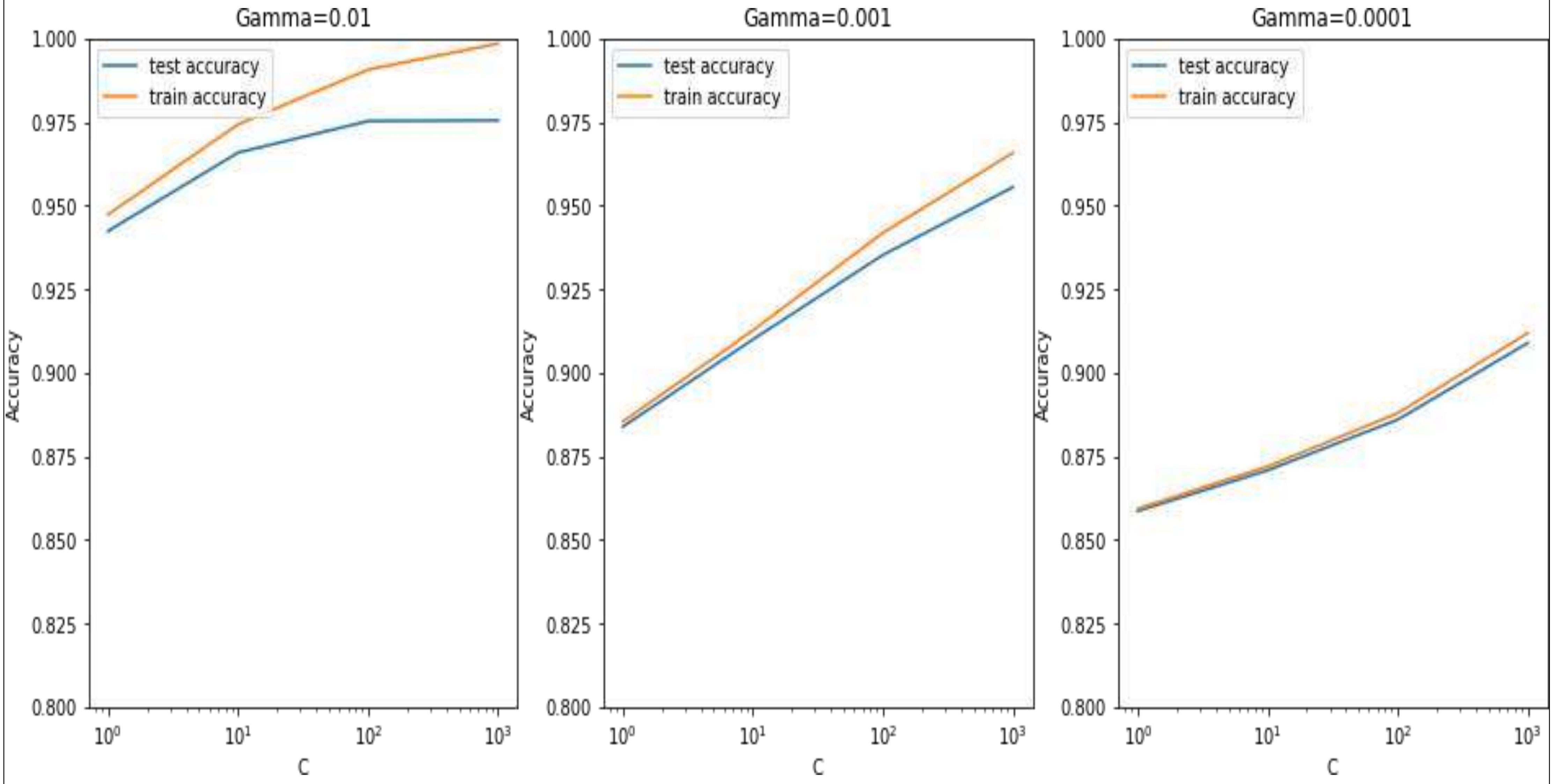
Support Vector Machine(SVM) with PCA



RECOMMENDATION

1.Target the customers, whose minutes of usage of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in the month of August).

2. Target the customers, whose outgoing others charge in July and incoming others on August are less.

3.Also, the customers having value based cost in the action phase increased are more likely to churn than the other customers. Hence, these customers may be a good target to provide offer.

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

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

6. Cutomers decreasing monthly 2g usage for August are most probable to churn.

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

8.roam_og_mou_8 variables have positive coefficients (0.7135). That means for the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.

THANKYOU