TELECOM CHURN CASE STUDY

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PROBLEM STATEMENT

- To reduce customer churn, telecom companies need to predict which customers are at high risk of 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.
- Retaining high profitable customers is the main business goal here.
- Steps:- Reading, understanding and visualising the data Preparing the data for modelling Building the model Evaluate the model

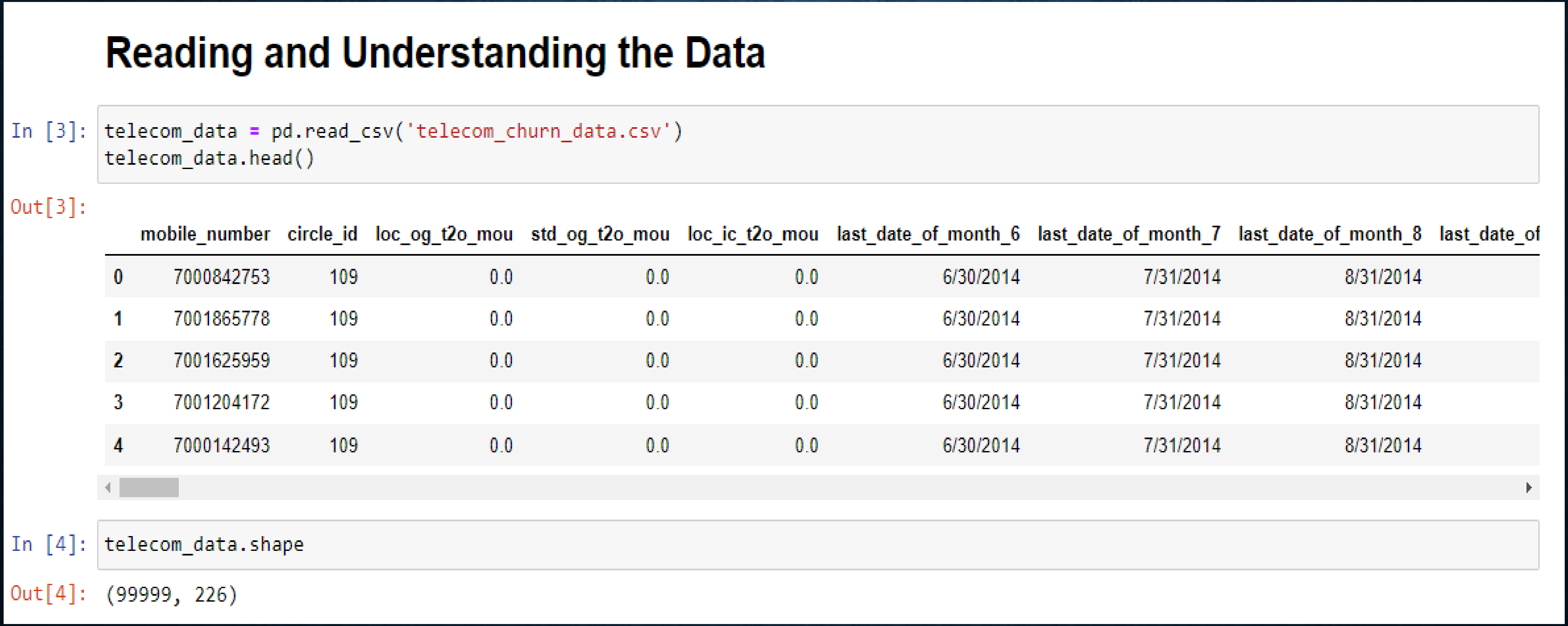
Steps:-

1. Reading, understanding and visualising the data
2. Preparing the data for modelling
3. Building the model
4. Evaluate the model

ANALYSIS APPROACH

- 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 become even more important than customer acquisition.
- Here we are given with 4 months of data related to customer usage. In this case study, we 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.
- Churn is predicted using two approaches. Usage based churn and Revenue based churn
- This case study only considers usage-based churn. Usage based churn is Customers who have zero usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time.
- In the Indian and the southeast Asian market, approximately 80% of revenue comes from the top 20% customers (called high-value customers). Thus, if we can reduce churn of the high-value customers, we will be able to reduce significant revenue leakage. Hence, this case study focuses on high value customers only.
- The dataset contains customer-level information for a span of four consecutive months - June, July, August and September. The months are encoded as 6, 7, 8 and 9, respectively.
- The business objective is to predict the churn in the last (i.e. the ninth) month using the data (features) from the first three months.

READING AND UNDERSTANDING THE DATA



Reading and Understanding the Data

```
In [3]: telecom_data = pd.read_csv('telecom_churn_data.csv')
        telecom_data.head()
```

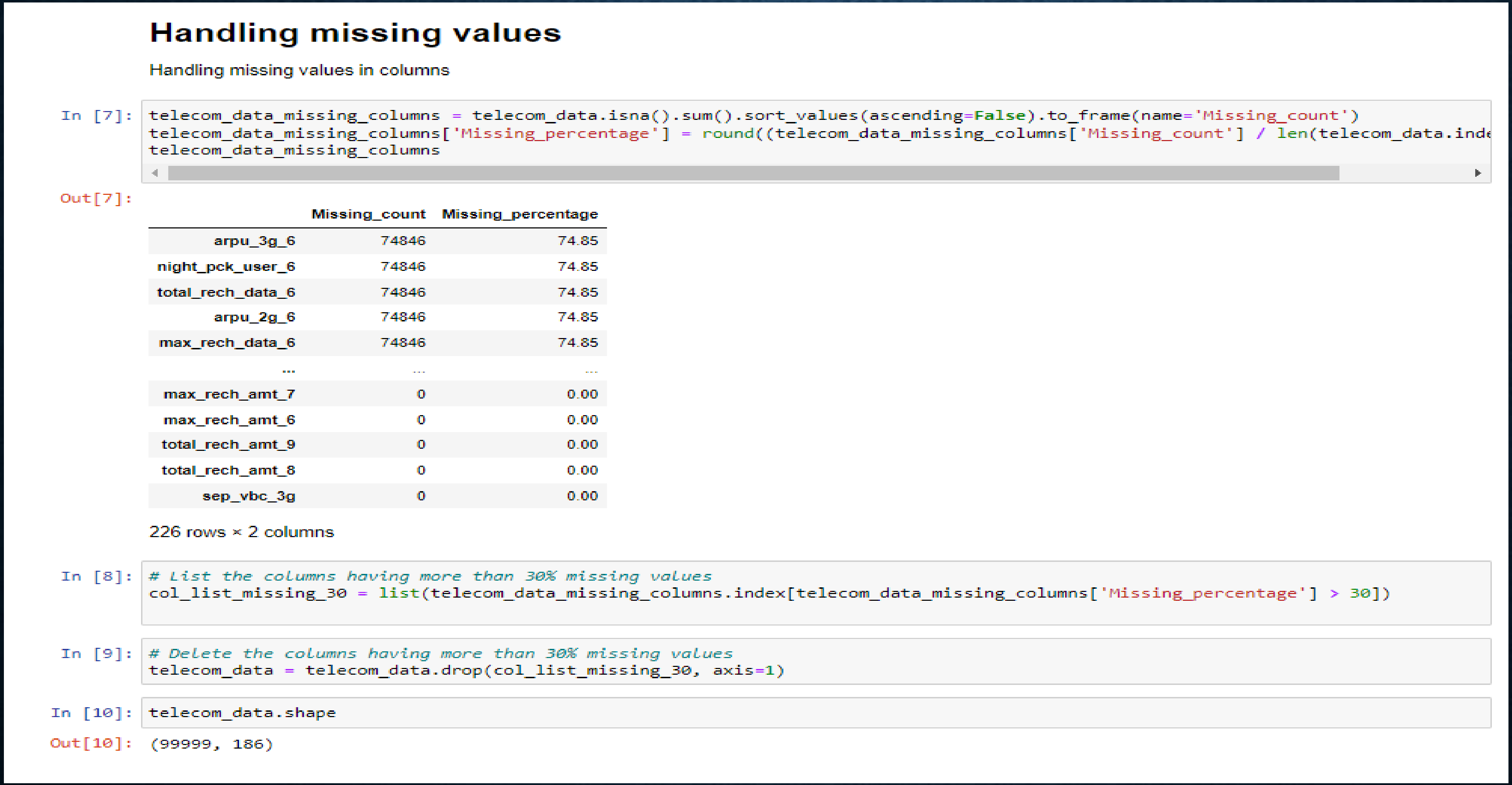
Out[3]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_of
0	7000842753	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
1	7001865778	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
2	7001625959	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
3	7001204172	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
4	7000142493	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	

```
In [4]: telecom_data.shape
```

```
Out[4]: (99999, 226)
```

Handling the missing values



Handling missing values

Handling missing values in columns

In [7]:
```
telecom_data_missing_columns = telecom_data.isna().sum().sort_values(ascending=False).to_frame(name='Missing_count')
telecom_data_missing_columns['Missing_percentage'] = round((telecom_data_missing_columns['Missing_count'] / len(telecom_data.inde
telecom_data_missing_columns
```

Out[7]:

	Missing_count	Missing_percentage
arpu_3g_6	74846	74.85
night_pck_user_6	74846	74.85
total_rech_data_6	74846	74.85
arpu_2g_6	74846	74.85
max_rech_data_6	74846	74.85
...	...	...
max_rech_amt_7	0	0.00
max_rech_amt_6	0	0.00
total_rech_amt_9	0	0.00
total_rech_amt_8	0	0.00
sep_vbc_3g	0	0.00

226 rows × 2 columns

In [8]:
```
# List the columns having more than 30% missing values
col_list_missing_30 = list(telecom_data_missing_columns.index[telecom_data_missing_columns['Missing_percentage'] > 30])
```

In [9]:
```
# Delete the columns having more than 30% missing values
telecom_data = telecom_data.drop(col_list_missing_30, axis=1)
```

In [10]:
```
telecom_data.shape
```

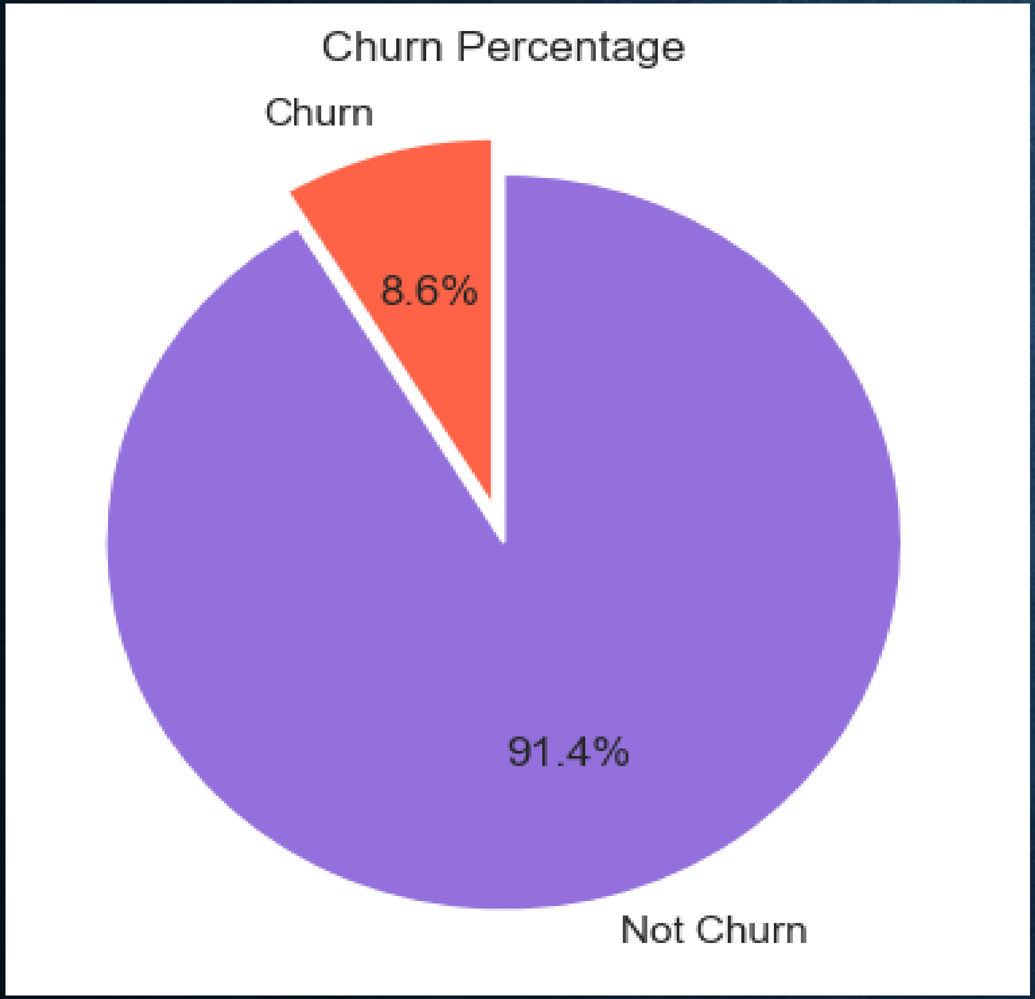
Out[10]:
```
(99999, 186)
```

DATA HANDLING

- Handling the Missing Value missing - Dropping the columns with more 30% missing values
- Deleting the date columns as the date columns are not required in our analysis
- Filter high-value customers
- Deleting all the attributes corresponding to the churn phase
- Churn percentage came as 8.6%.
- There is very little percentage of churn rate. We will take care of the class imbalance later.

OUTLIER TREATMENT

- In the filtered dataset except mobile_number and churn columns all the columns are numeric types. Hence, converting mobile_number and churn datatype to object.
- Drive new features
- Deriving new column decrease_arpu_action
- Deriving new column decrease_vbc_action

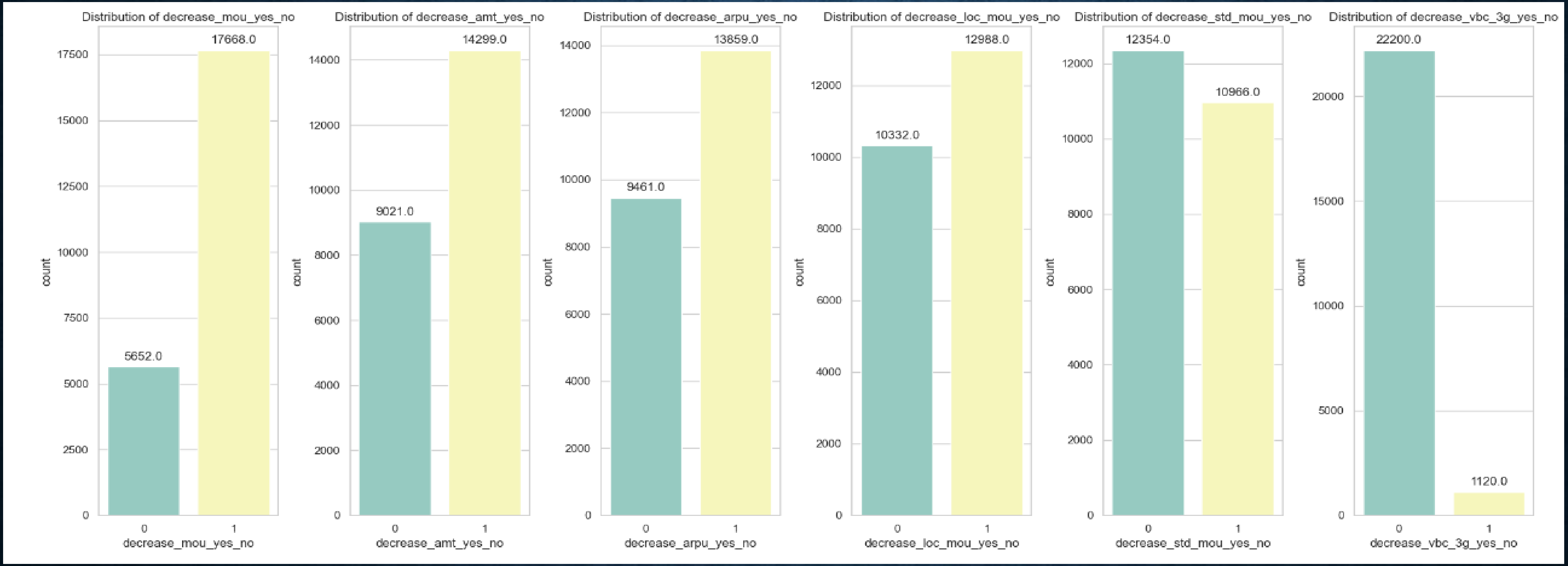


Analysis:

The Pie-chart illustrates a low churn rate of 8.6%, with a majority (91.4%) not churning.

EDA

Univariate analysis:



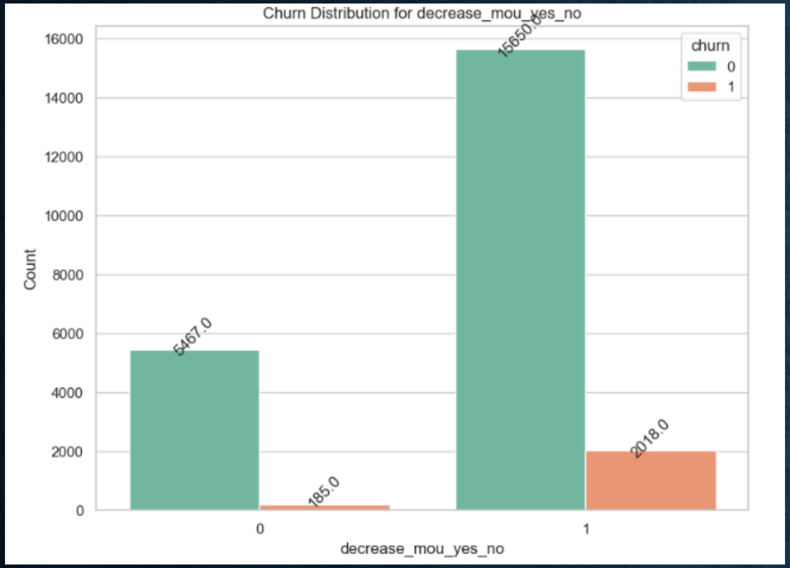
Analysis:

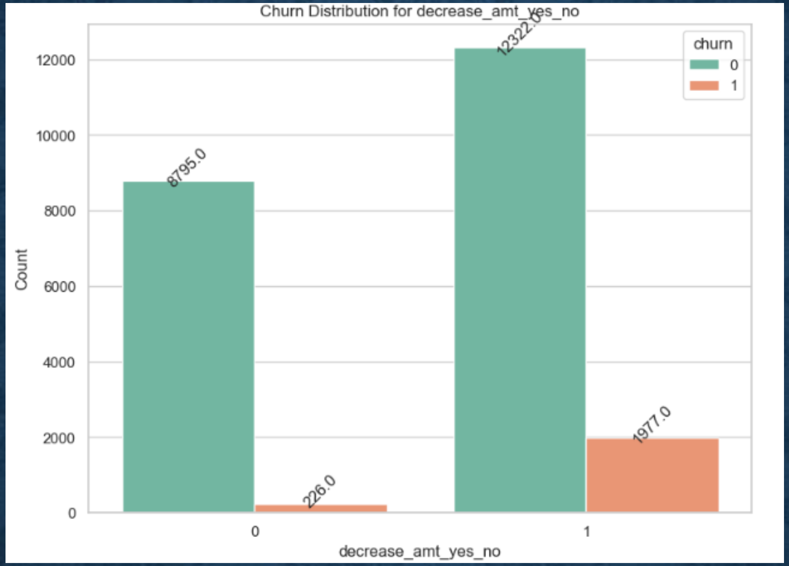
Customers with lower minutes of usage (MOU) during the action phase, reduced recharge frequency, or higher volume-based costs exhibit higher churn rates. Churned customers typically have an average revenue per user (ARPU) in the 0 to 900 range, while non-churned clients range from 0 to 1000 ARPU. Stronger MOU correlates with lower turnover, emphasizing the impact of usage patterns on customer retention.

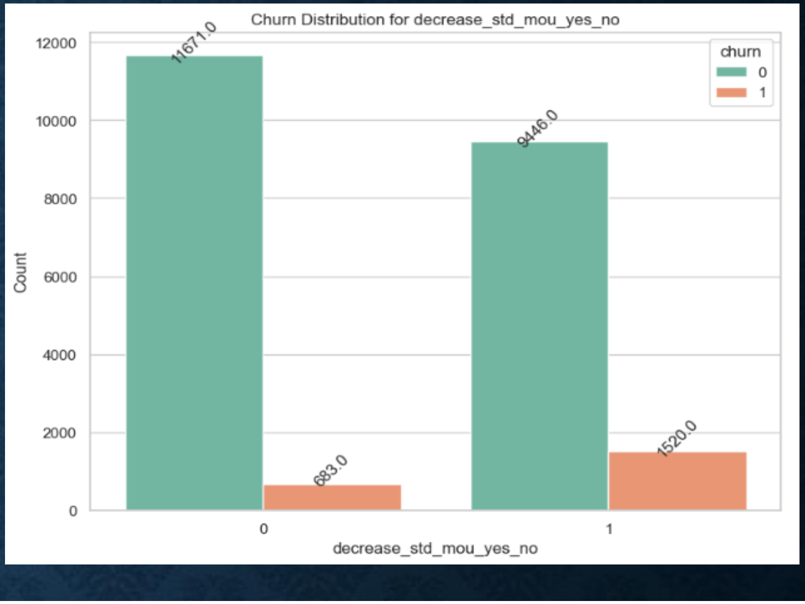
BIVARIATE ANALYSIS :

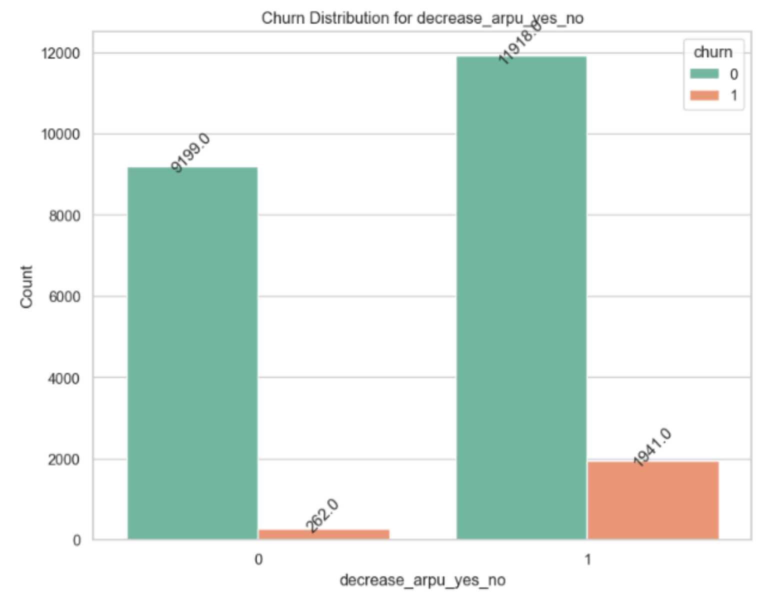
Analysis:

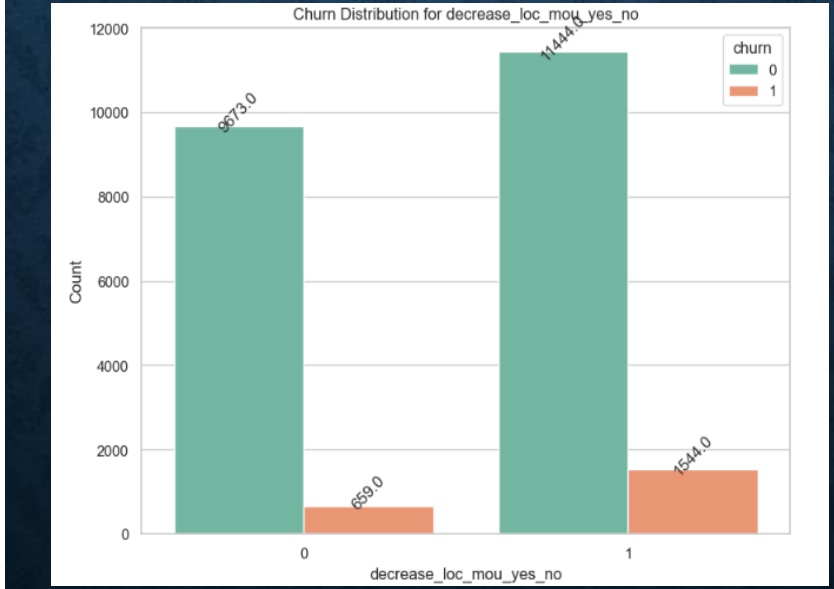
Decreasing recharge amounts and fewer recharges in the action phase correlate with higher churn rates. Higher volume-based costs exacerbate this trend. Proportional relationship observed between recharge quantity and number.

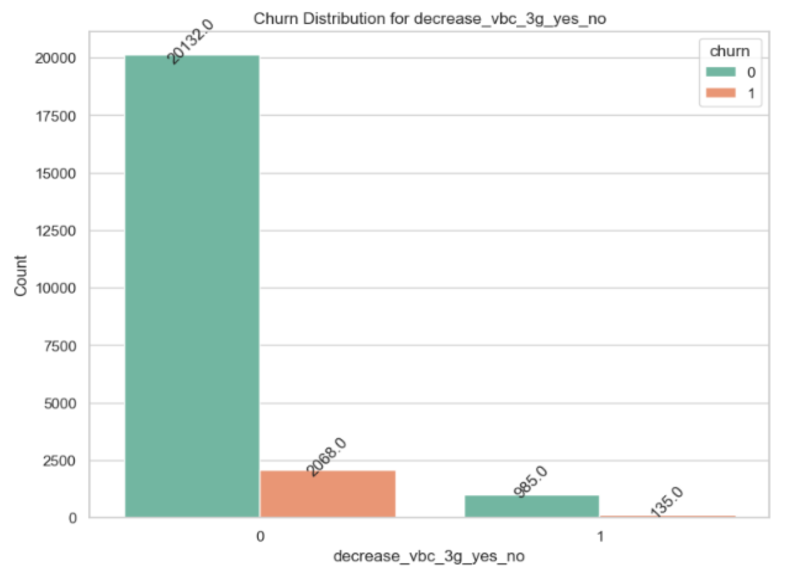

Churn Distribution for decrease_mou_yes_no


Churn Distribution for decrease_amt_yes_no


Churn Distribution for decrease_std_mou_yes_no


Churn Distribution for decrease_arpu_yes_no

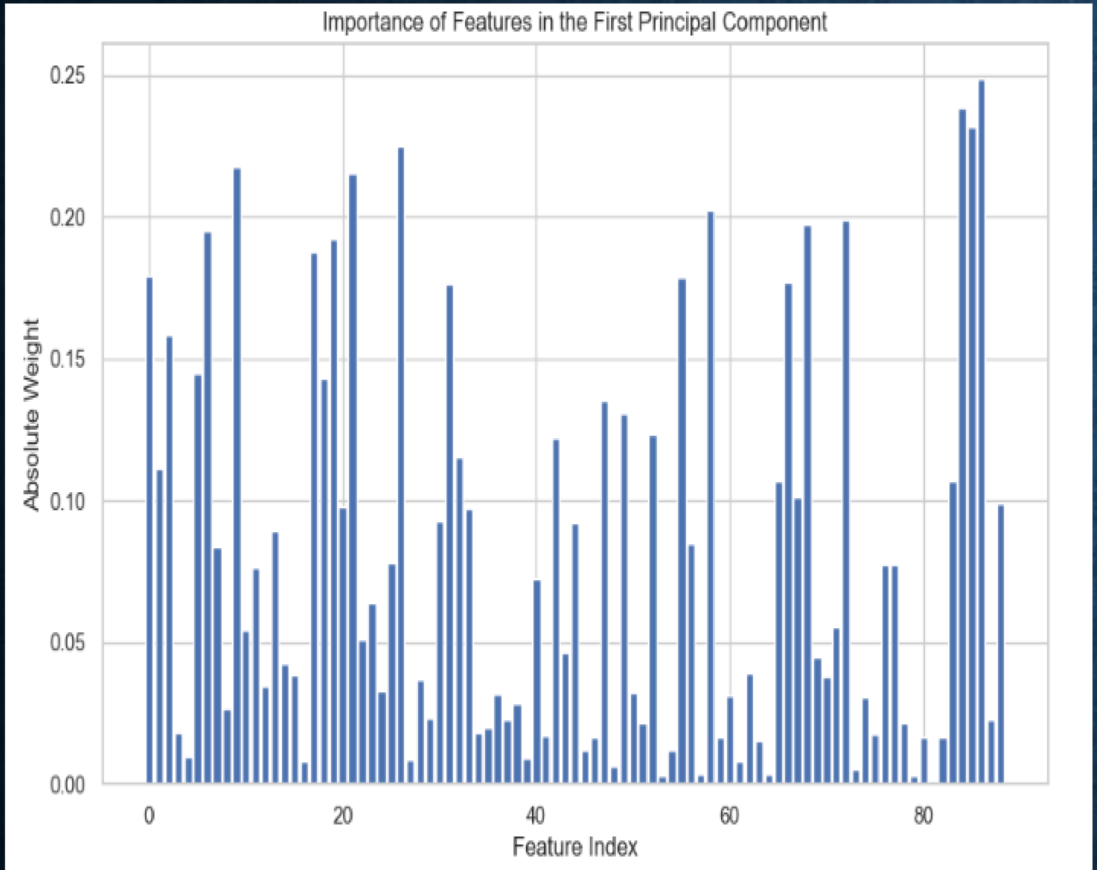

Churn Distribution for decrease_loc_mou_yes_no

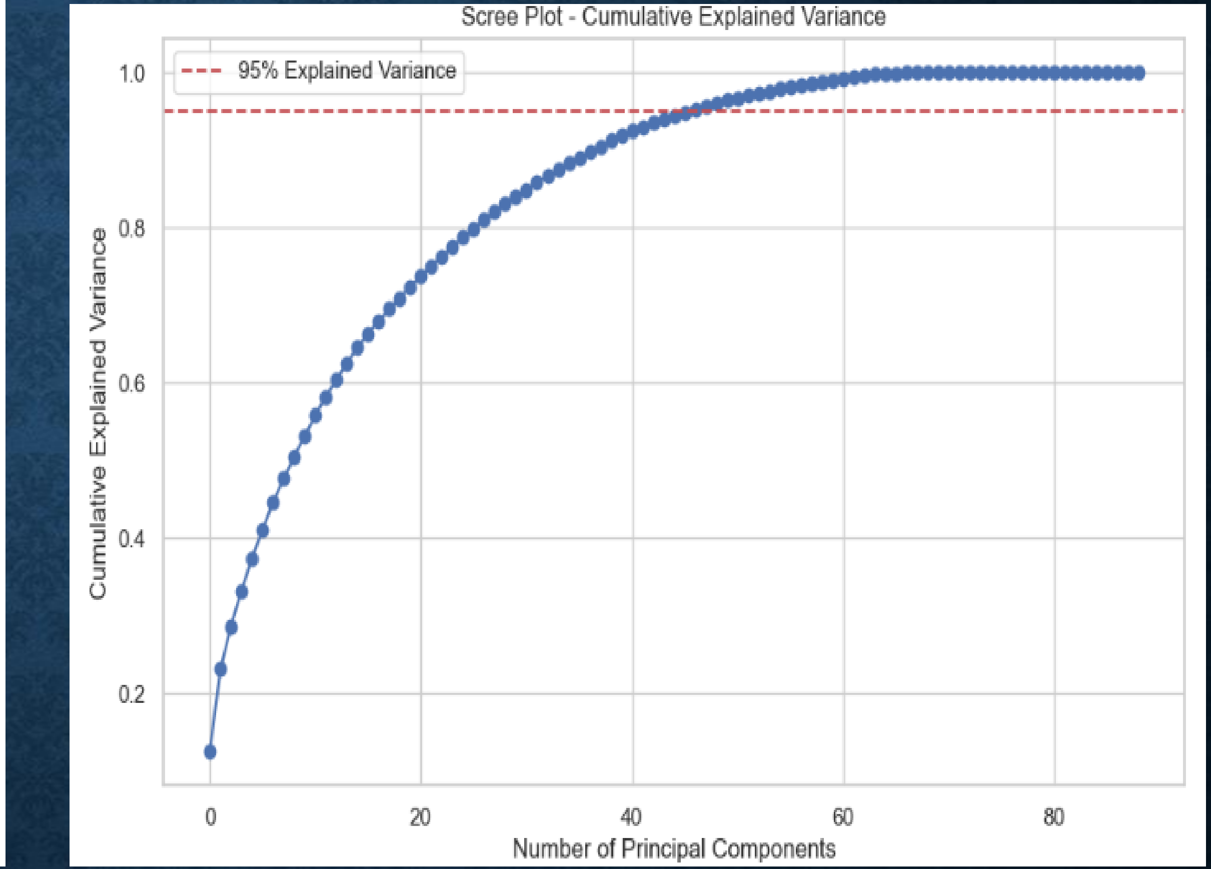

Churn Distribution for decrease_vbc_3g_yes_no

DATA Preparation

- Train –Test Split with 80 : 20
- Dealing with Data Imbalance with SMOTE
- Feature Scaling done with Standard Scaler Technique
- Model with Principal component analysis and Performing PCA with 46 components
- Logistic regression with PCA
- Decision Tree PCA
- Random forest
- Logistic regression with No PCA

MODEL WITH PCA

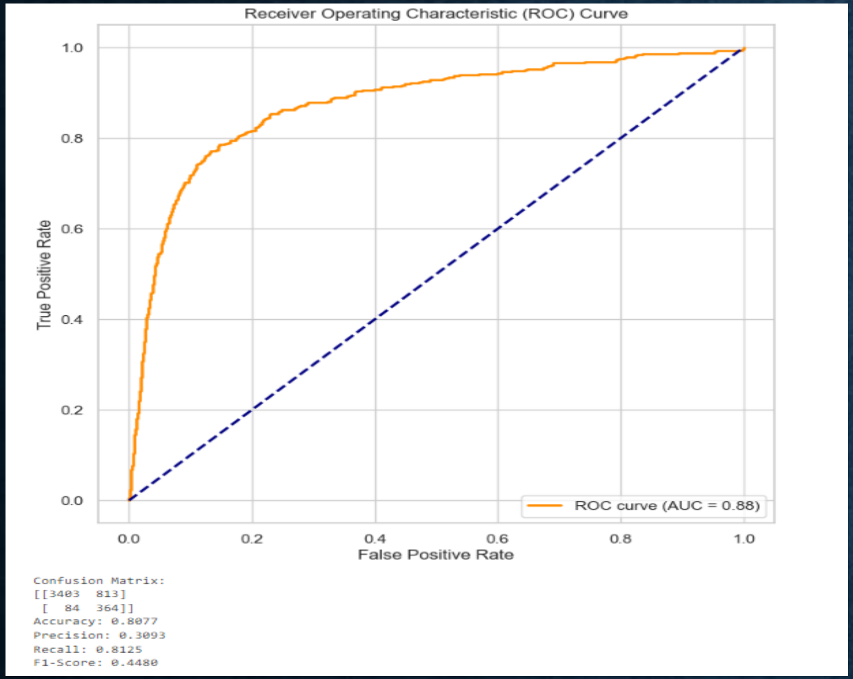




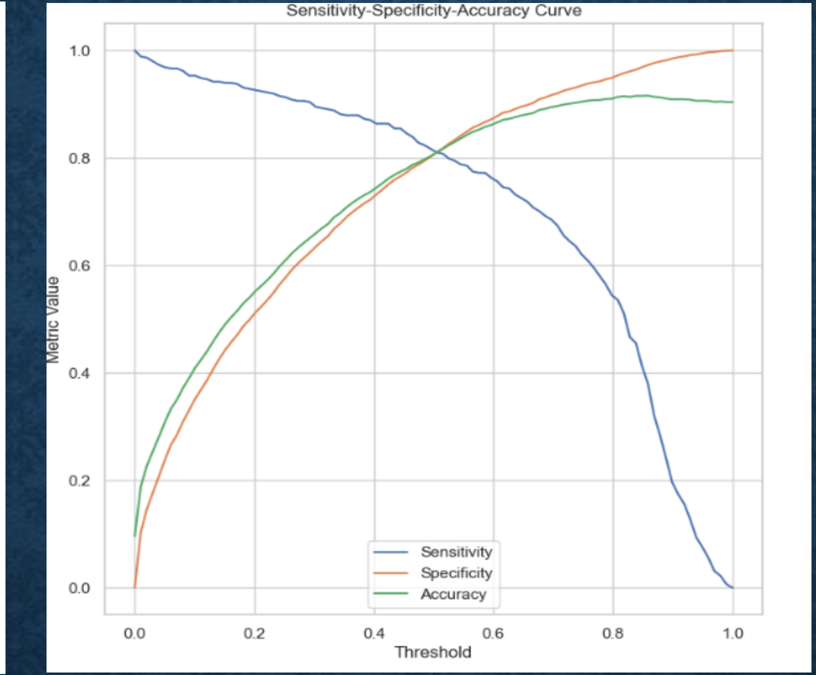
Analysis:

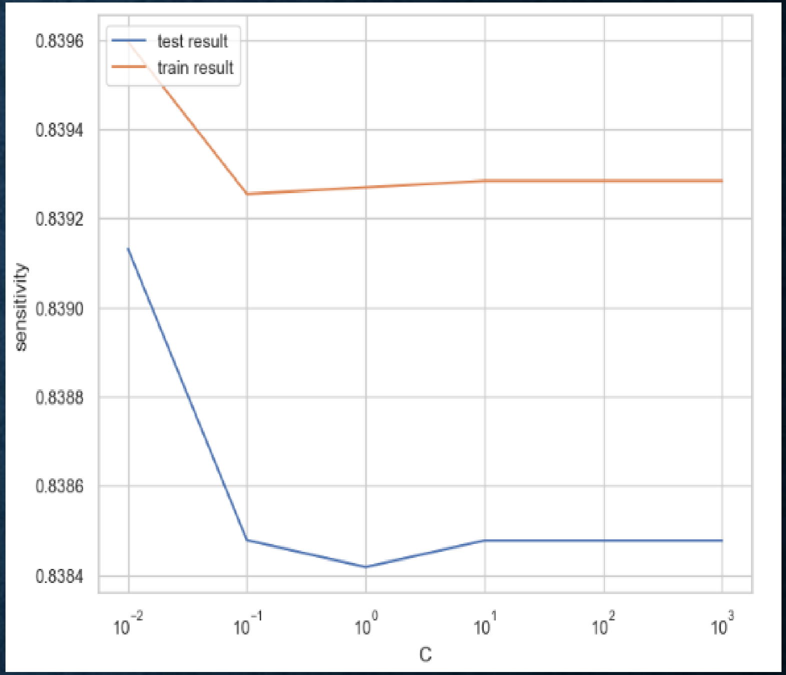
46 Principal components represents the point where you have 95% of the total variance explained.

Logistic regression with PCA



```
Confusion Matrix:
[[3403  813]
 [  84  364]]
Accuracy: 0.8077
Precision: 0.3093
Recall: 0.8125
F1-Score: 0.4480
```





Training Data:

- **Cross-Validation Scores (Train):**
  - **[0.8206, 0.8277, 0.8291, 0.8272, 0.8231]**
- **Mean Cross-Validation Score (Train):**
  - **0.8255**

Test Data:

- **Cross-Validation Scores (Test):**
  - **[0.9153, 0.9025, 0.9228, 0.9164, 0.9195]**
- **Mean Cross-Validation Score (Test):**
  - **0.9153**

The cross-validation scores on the training data are consistently around 82.55%, indicating that the model performs well on the training set.

The cross-validation scores on the test data are slightly higher, around 91.53%, suggesting that the model generalizes well to unseen data.

The mean cross-validation score is a good indicator of the overall performance of the model.

DECISION TREE PCA

Model summary

- Train set

Accuracy = 0.90 Sensitivity = 0.91 Specificity = 0.88

- Test set

Accuracy = 0.86 Sensitivity = 0.70 Specificity = 0.87

Training Data:

- **Cross-Validation Scores (Train):**
  - [0.8636, 0.9102, 0.9031, 0.9070, 0.9070]
- **Mean Cross-Validation Score (Train):**
  - 0.8982

Test Data:

- **Cross-Validation Scores (Test):**
  - [0.9250, 0.9218, 0.9250, 0.9293, 0.9260]
- **Mean Cross-Validation Score (Test):**
  - 0.9254

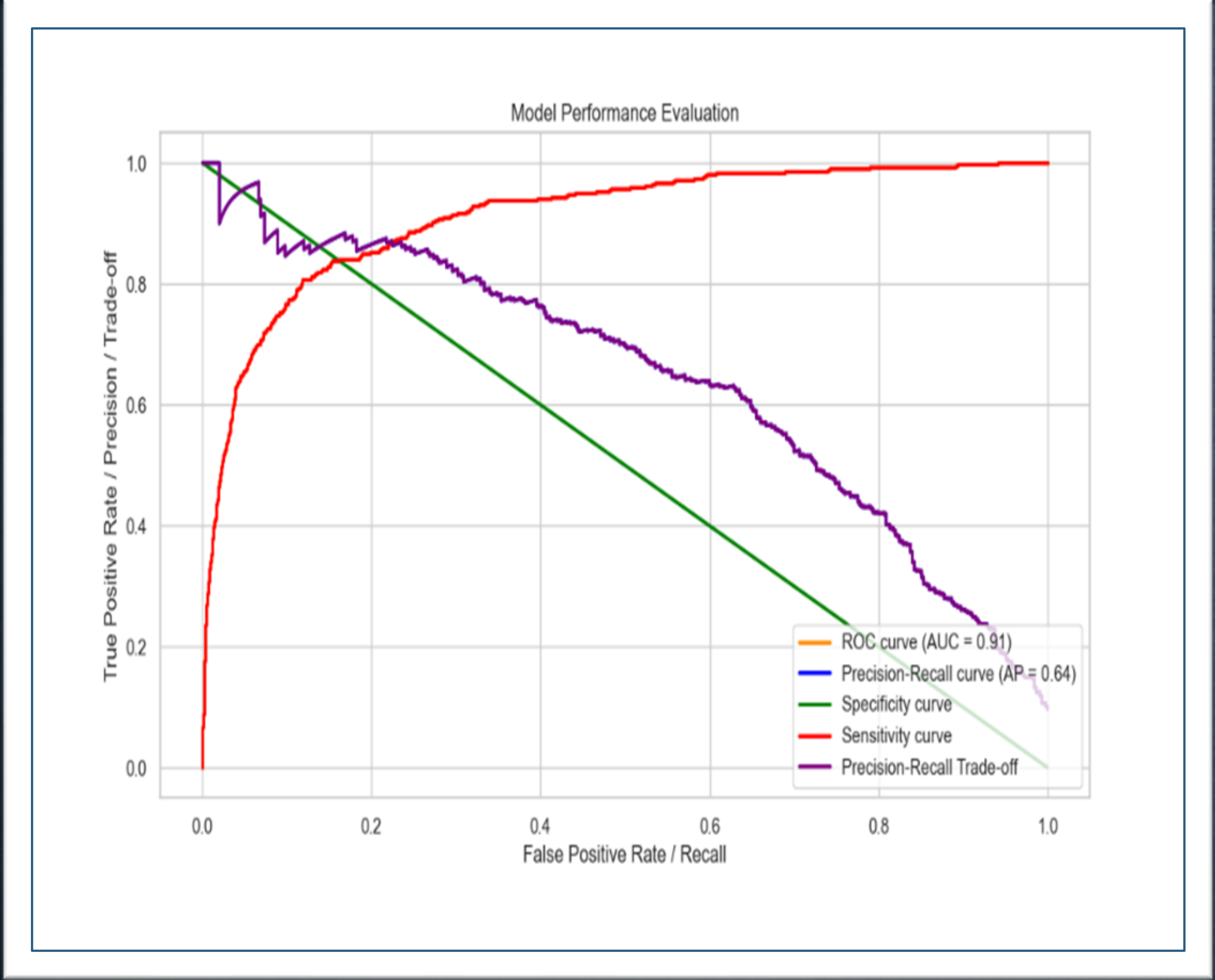
Insights:

- The model demonstrates good performance on the training data, with cross-validation scores ranging from 86.36% to 91.02%.
- The mean cross-validation score for the training data is approximately 89.82%, indicating overall strong performance on the training set.

Insights:

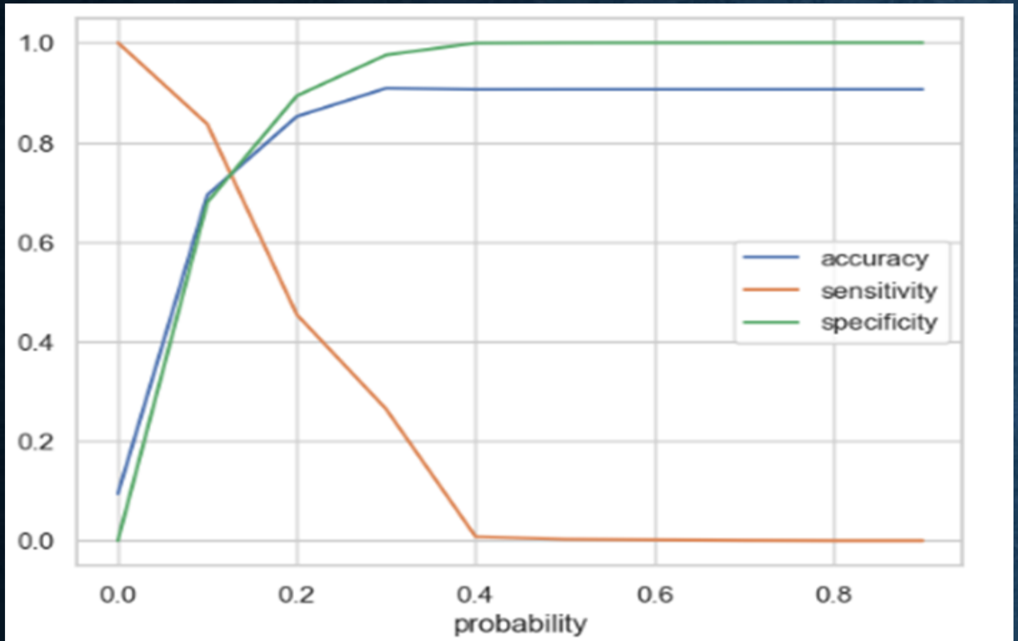
- The model's performance on the test data is also quite impressive, with cross-validation scores ranging from 92.50% to 92.93%.
- The mean cross-validation score for the test data is approximately 92.54%, suggesting that the model generalizes well to unseen data.

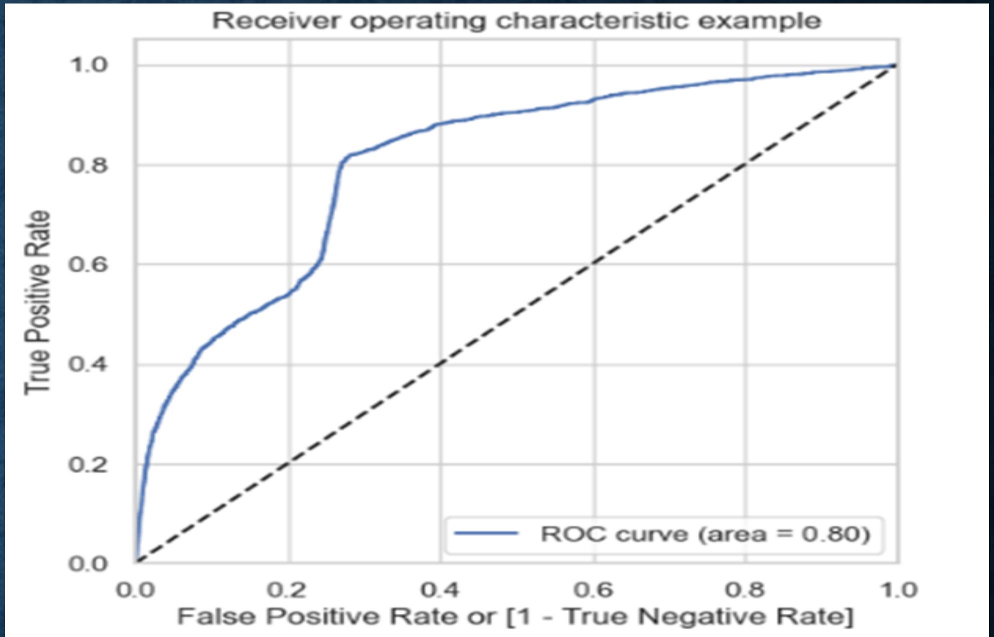
RANDOM FOREST

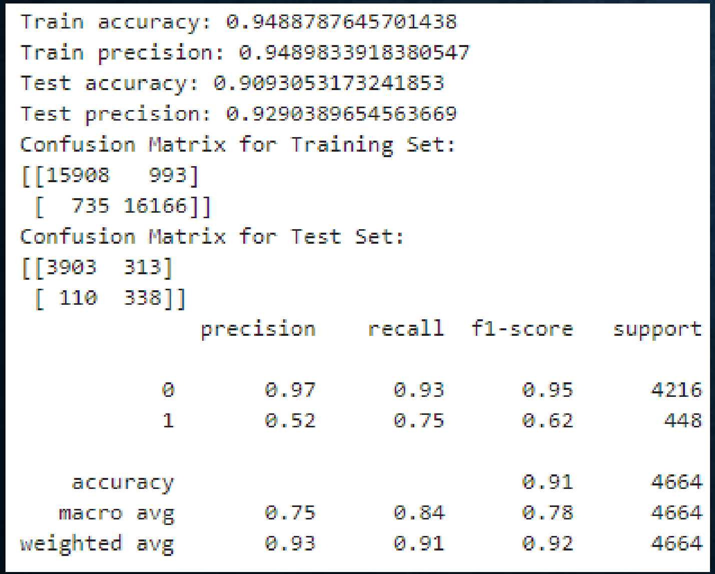


```
Train accuracy: 0.9488787645701438

Train precision: 0.9489833918380547

Test accuracy: 0.9093053173241853

Test precision: 0.9290389654563669

Confusion Matrix for Training Set:
[[15908   993]
 [  735 16166]]

Confusion Matrix for Test Set:
[[3903  313]
 [ 110  338]]
              precision    recall  f1-score   support

           0       0.97      0.93      0.95      4216
           1       0.52      0.75      0.62       448

    accuracy                           0.91      4664
   macro avg       0.75      0.84      0.78      4664
weighted avg       0.93      0.91      0.92      4664

Cross-Validation Scores: [0.90119805 0.93285017
0.93180473 0.93032544 0.93461538]

Mean Cross-Validation Score: 0.92615875596989

Cross-Validation Scores (Test): [0.92604502
0.93676313 0.9249732  0.93140407 0.92811159]

Mean Cross-Validation Score (Test):
0.9294594022696641
```

LOGISTIC REGRESSION WITHOUT PCA







```
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Train precision: 0.9489833918380547
Test accuracy: 0.9093053173241853
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Confusion Matrix for Training Set:
[[15908   993]
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Confusion Matrix for Test Set:
[[3903  313]
 [ 110  338]]
              precision    recall  f1-score   support

           0       0.97      0.93      0.95      4216
           1       0.52      0.75      0.62       448

    accuracy                           0.91      4664
   macro avg       0.75      0.84      0.78      4664
weighted avg       0.93      0.91      0.92      4664
```

Training Data:

•Cross-Validation Scores (Train):

- [0.8636, 0.9102, 0.9031, 0.9070, 0.9070]

•Mean Cross-Validation Score (Train):

- 0.8982

Test Data:

Cross-Validation Scores (Test):

- [0.9250, 0.9218, 0.9250, 0.9293, 0.9260]

Mean Cross-Validation Score (Test):

- 0.9254

Insights:

•The model demonstrates good performance on the training data, with cross-validation scores ranging from 86.36% to 91.02%.

•The mean cross-validation score for the training data is approximately 89.82%, indicating overall strong performance on the training set.

Test Data:

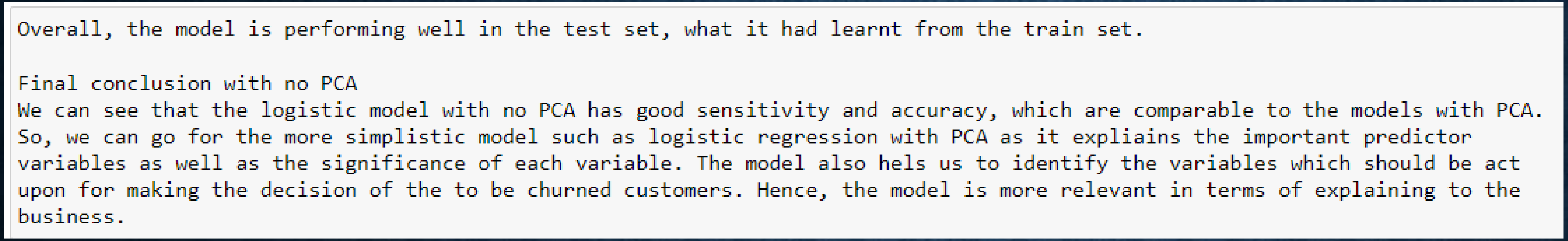
Insights:

•The model's performance on the test data is also quite impressive, with cross-validation scores ranging from 92.50% to 92.93%.

•The mean cross-validation score for the test data is approximately 92.54%, suggesting that the model generalizes well to unseen data.

PREDICATIONS ON FINAL MODEL

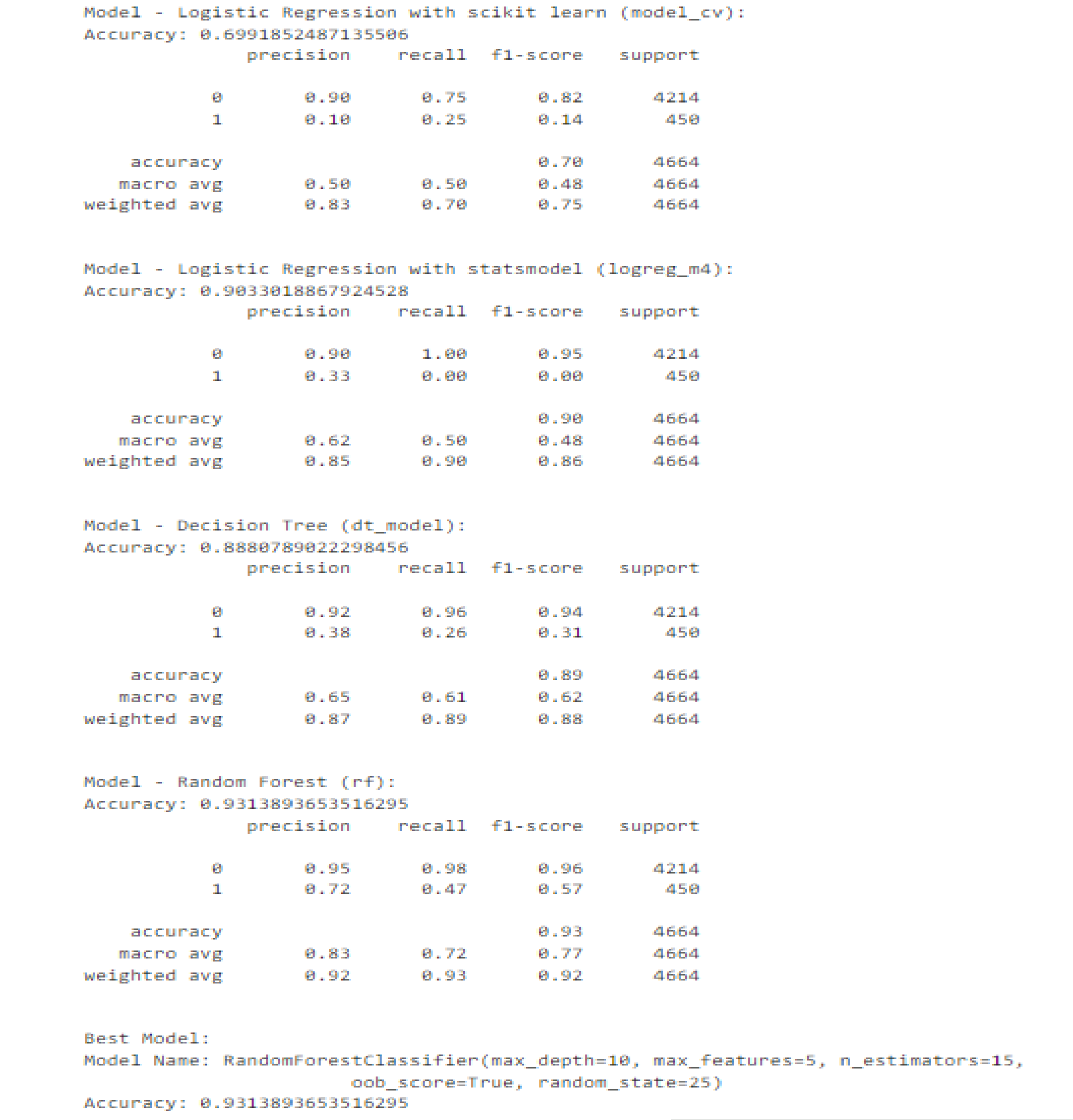
```
Accuracy:- 0.78487637610539 62
Sensitivity:- 0.8238341968911918
Specificity:- 0.7834704562453254
```



Overall, the model is performing well in the test set, what it had learnt from the train set.

Final conclusion with no 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 expliains the important predictor variables as well as the significance of each variable. The model also hels us to identify the variables which should be act upon for making the decision of the to be churned customers. Hence, the model is more relevant in terms of explaining to the business.

ANALYSIS ON MODEL



```
Model - Logistic Regression with scikit learn (model_cv):
Accuracy: 0.6991852487135506
              precision    recall  f1-score   support

           0       0.90      0.75      0.82      4214
           1       0.10      0.25      0.14       450

    accuracy                           0.70      4664
   macro avg       0.50      0.50      0.48      4664
weighted avg       0.83      0.70      0.75      4664


Model - Logistic Regression with statsmodel (logreg_m4):
Accuracy: 0.9033018867924528
              precision    recall  f1-score   support

           0       0.90      1.00      0.95      4214
           1       0.33      0.00      0.00       450

    accuracy                           0.90      4664
   macro avg       0.62      0.50      0.48      4664
weighted avg       0.85      0.90      0.86      4664


Model - Decision Tree (dt_model):
Accuracy: 0.8880789022298456
              precision    recall  f1-score   support

           0       0.92      0.96      0.94      4214
           1       0.38      0.26      0.31       450

    accuracy                           0.89      4664
   macro avg       0.65      0.61      0.62      4664
weighted avg       0.87      0.89      0.88      4664


Model - Random Forest (rf):
Accuracy: 0.9313893653516295
              precision    recall  f1-score   support

           0       0.95      0.98      0.96      4214
           1       0.72      0.47      0.57       450

    accuracy                           0.93      4664
   macro avg       0.83      0.72      0.77      4664
weighted avg       0.92      0.93      0.92      4664


Best Model:
Model Name: RandomForestClassifier(max_depth=10, max_features=5, n_estimators=15,
                       oob_score=True, random_state=25)
Accuracy: 0.9313893653516295
```

Analysis:

- **Logistic Regression with scikit-learn (model_cv): Accuracy: 0.6992 Key Insight: This model has a relatively lower accuracy compared to the other models. It struggles with both precision and recall for class 1.**

- **Logistic Regression with statsmodels (logreg_m4): Accuracy: 0.9033 Key Insight: This model shows high accuracy but has issues with recall for class 1. It seems to have a challenge correctly identifying instances of class 1.**

- **Decision Tree (dt_model): Accuracy: 0.8881 Key Insight: This model performs reasonably well but has lower precision, recall, and F1-score for class 1 compared to class 0. It might be sensitive to imbalances in the data.**

- **Random Forest (rf): Accuracy: 0.9314 Key Insight: The Random Forest model outperforms the other models in terms of accuracy. It provides a good balance between precision and recall for both classes. This model seems promising.**

- **Best Model (Random Forest): Model Name: RandomForestClassifier(max_depth=10, max_features=5, n_estimators=15, oob_score=True, random_state=25) Accuracy: 0.9314 Key Insight: This model is identified as the best-performing one. It achieves a high accuracy, and its precision, recall, and F1-scores for both classes are relatively well-balanced.**