Telecom Churn Case Study

Srinidhi Ramesh
Shagun Sharma
Mohit Dubey

Churn in Telecom Sector

1. Telecommunications industry experiences an average of 15-25% annual churn rate
2. To reduce customer churn, telecom companies need to predict which customers are at high risk of churn
3. In the Indian and Southeast Asian markets, approximately 80% of revenue comes from the top 20% of customers (called high-value customers).
4. Thus, reducing churn of high-value customers, will help in reducing significant revenue leakage
5. **<u>OBJECTIVE</u>: To define high-value customers based on a certain metric and predict churn only on high-value customers**

Business Objective

Predict Churn

To predict the churn in the last (i.e. the ninth) month using the data (features) from the first three months

Filtering customers

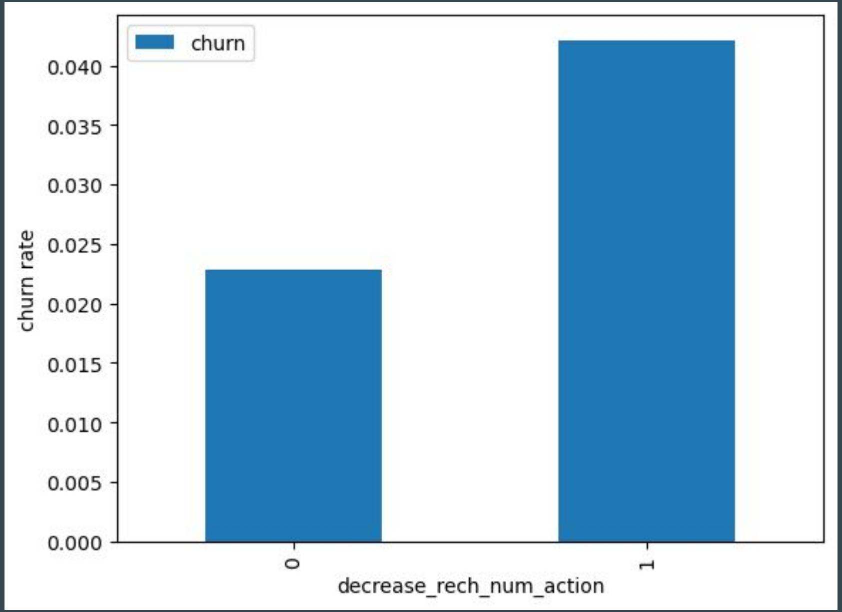
Filtering dataset for “High-value customers” by calculating average recharge amounts for months 6 and 7

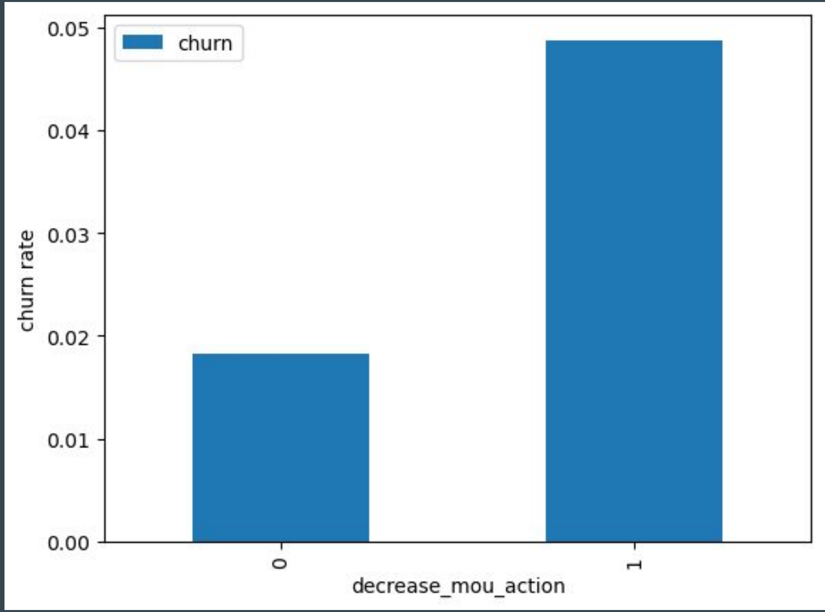
Recommendations

Recommendations on offers and policies based on Churn predictive exercise.

To identify most effective target set of customers and aim to increase customer retention

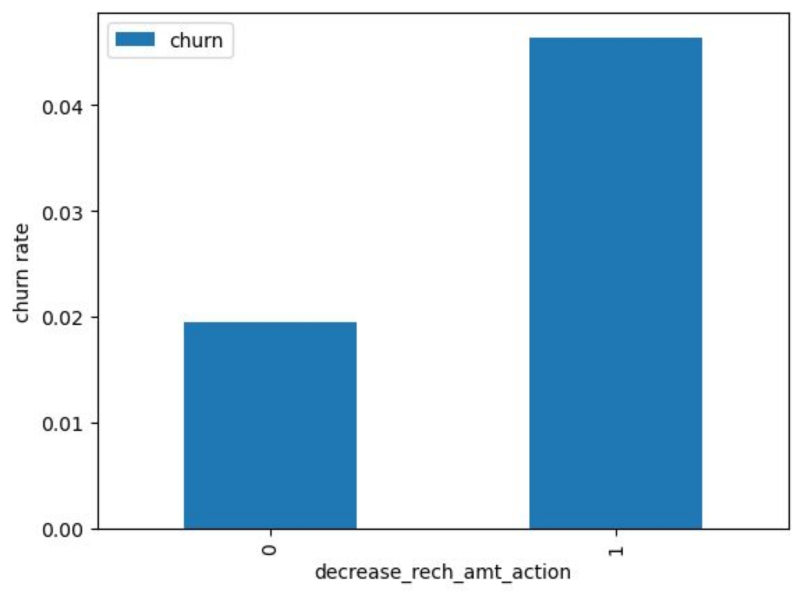
Churn - Exploratory Data Analysis

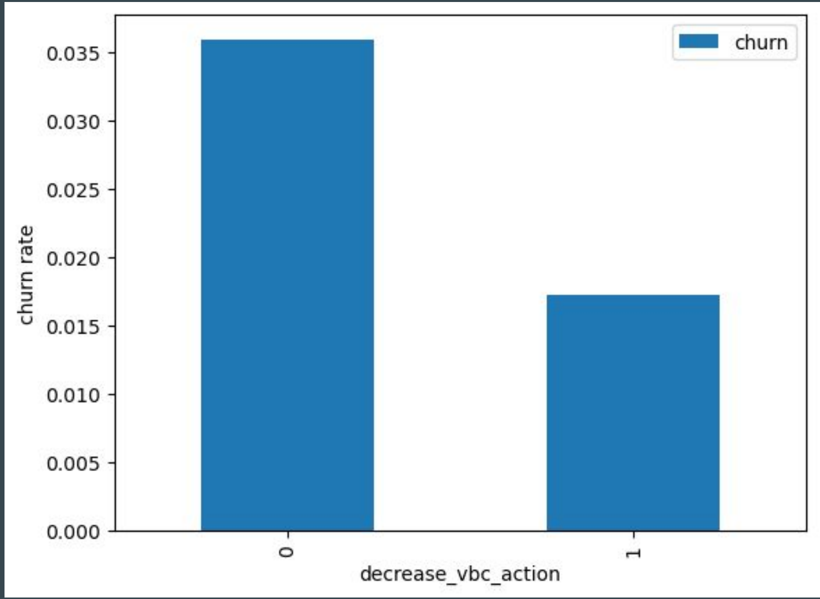




Customers with decreasing minutes and recharges calling are more likely to churn

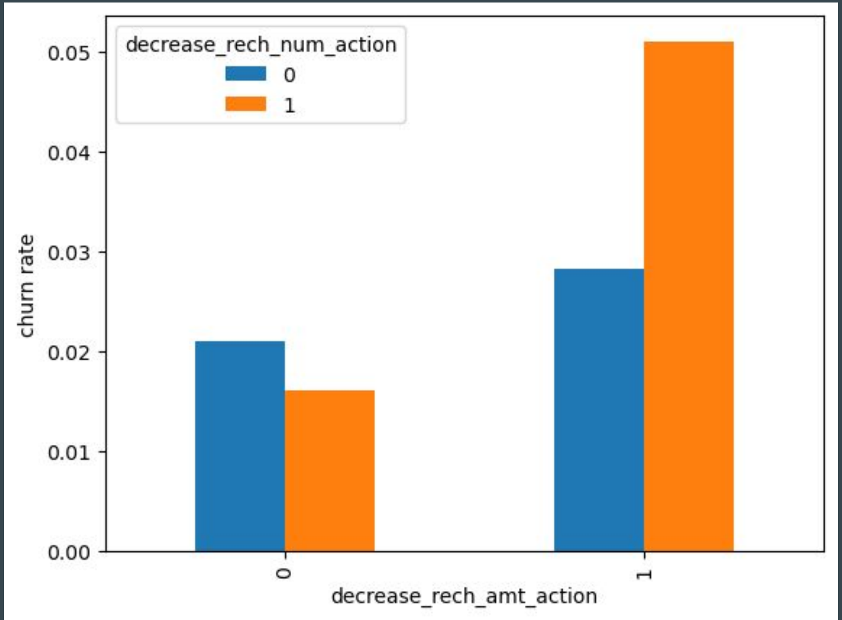
Churn - Exploratory Data Analysis

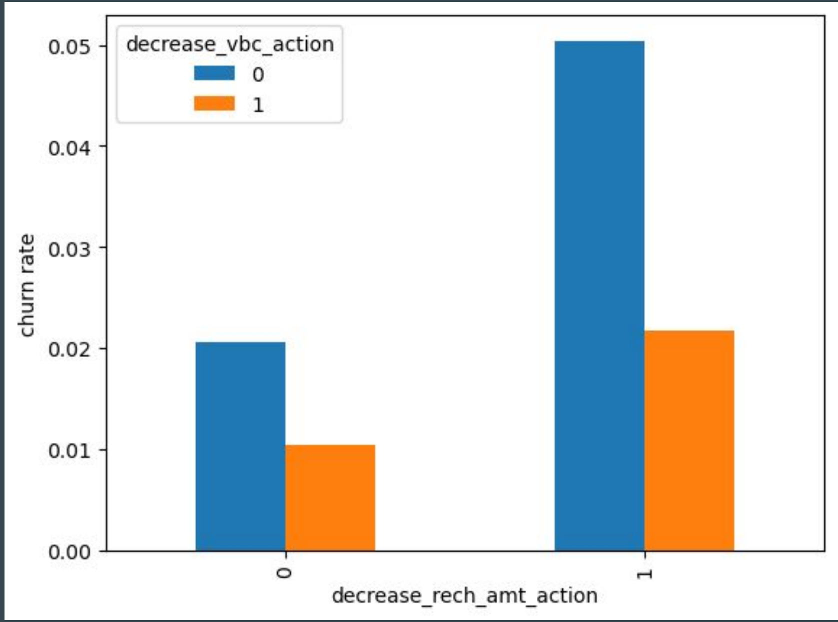




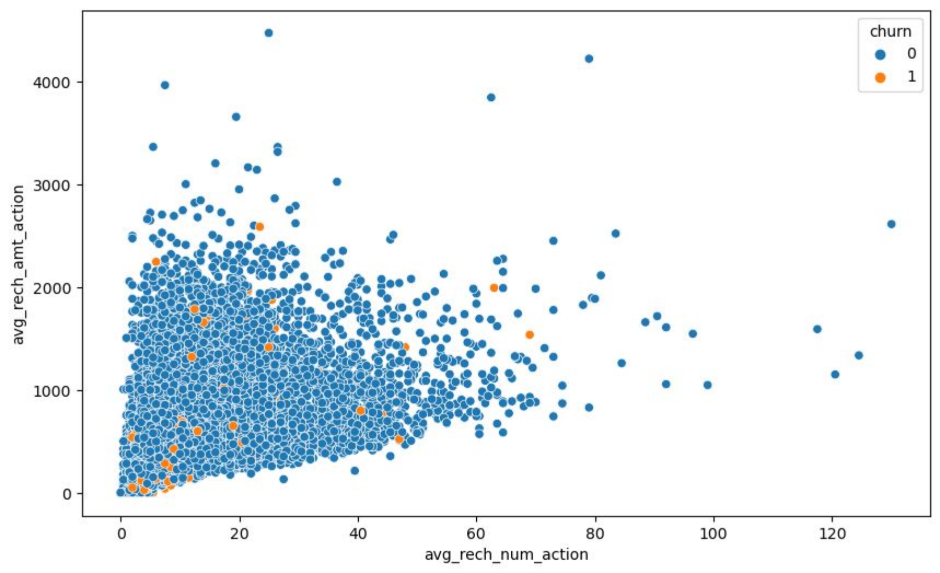
Customers with decreasing recharge amount and data usage are more likely to churn

Churn - Bivariate Analysis



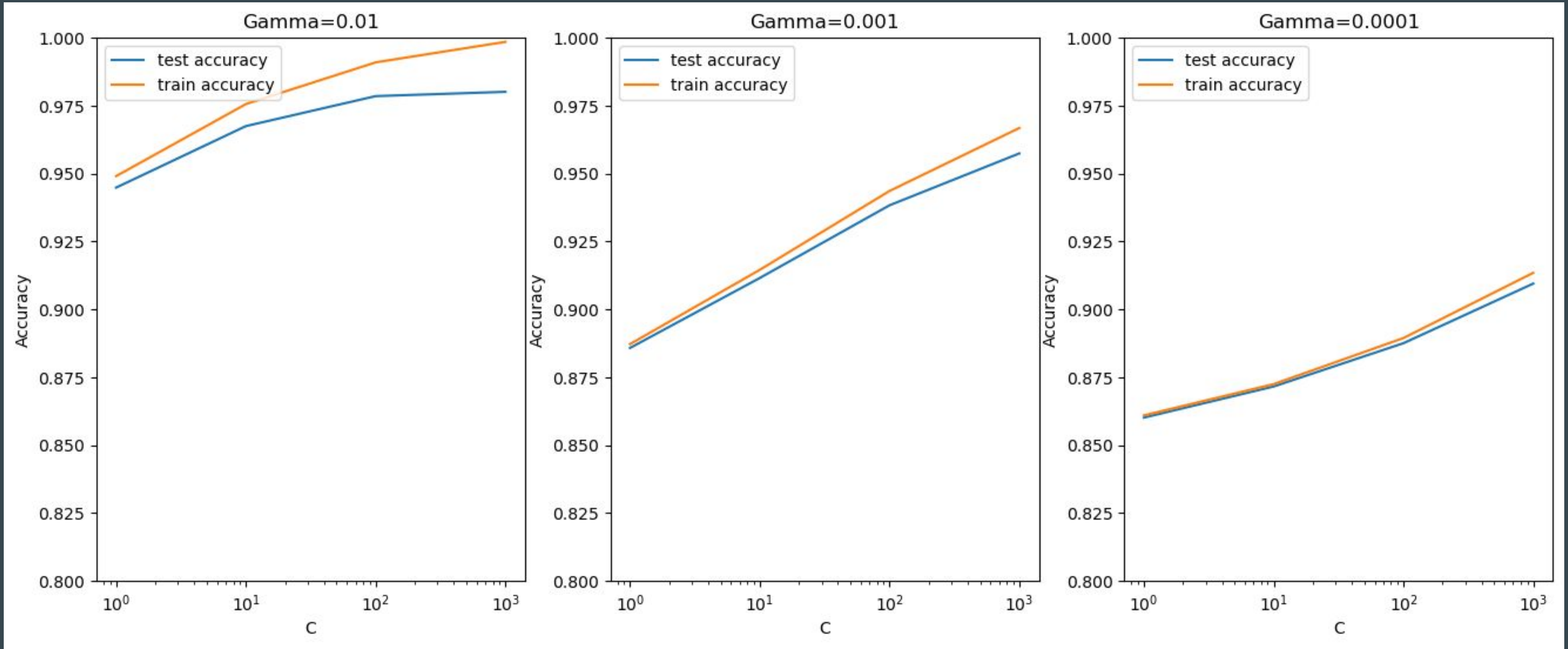


Churn - Scatter Plot



Average recharge number and recharge amounts follow the same pattern in both kinds of customers

Churn - Train and Testing



Confusion matrix and Metrics Evaluation

In [198]:
```
# Confusion matrix
confusion = metrics.confusion_matrix(y_test_pred_final['churn'], y_test_pred_final['test_predicted'])
print(confusion)
```

```
[[4540  808]
 [  46  147]]
```

In [199]:
```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
```

In [200]:
```
# Accuracy
print("Accuracy:-",metrics.accuracy_score(y_test_pred_final['churn'], y_test_pred_final['test_predicted']))

# Sensitivity
print("Sensitivity:-",TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

```
Accuracy:- 0.8458761956325573
Sensitivity:- 0.7616580310880829
Specificity:- 0.8489154824233358
```

Key Factors

ARPU	• Average revenue per user is an important variable for Churn prediction
Incoming / Outgoing minutes of usage	• Incoming and Outgoing Calls on roaming are strong indicators of churn behaviour
Tenure	• Tenure of Customer at the company is key to predicting churn/creating offers catered to them
Network Connectivity	• 2G/3G network network is important in predicting Customer churn

Observations on Churn

Decreasing Data Usage	• Customers decreasing monthly 2g usage for August are most probable to churn.
Decreasing Incoming	• Customers having decreasing incoming minutes of usage in August
Decreasing Recharge amounts	• Customers with decreasing recharge amounts are more likely to discontinue

Churn Observations/Predictors

- Customers decreasing monthly 2g usage for August are most probable to churn.
- Customers having decreasing incoming minutes of usage in August are likely to Churn
- To target customers where minutes of usage of the incoming local calls and outgoing ISD calls are less as they maybe be likely to churn

Recommendations

- Focus on “high value customers” as they are less likely to churn
    - Efforts must be taken to convert more customers into “high value”
- Offers can be catered to customers with the below patterns in an effort to increase customer retention
    - Target customers with decreasing incoming/outgoing calls
    - Target customers with decreasing 2G/3G data usage
    - Target customers with erratic recharge patterns
    - Target customers with

Thank You