

A close-up photograph of a wooden pencil with a sharpened lead tip, resting diagonally across a document. The document features a line graph with a dotted trend line and a solid line showing fluctuations. The y-axis has labels '100' and '50'. The x-axis has some numbers, including '1993' and '1998'. The background is blurred, showing more of the document and the pencil's body.

Telecom Churn – Case Study

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Telecom Churn – Case Study

Background:

In the telecom industry, customers can 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. It costs 5-10 times more to acquire a new customer than to retain an existing one, customer retention has now become more important than customer acquisition.

Problem Statement:

In the prepaid model, customers who want to switch to another network can simply stop using the services without any notice, and it is hard to know whether someone has actually churned or is simply not using the services temporarily. Thus, churn prediction is usually more critical (and non-trivial) for prepaid customers, and the term ‘churn’ should be defined carefully.

Goal:

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.

Understanding Data

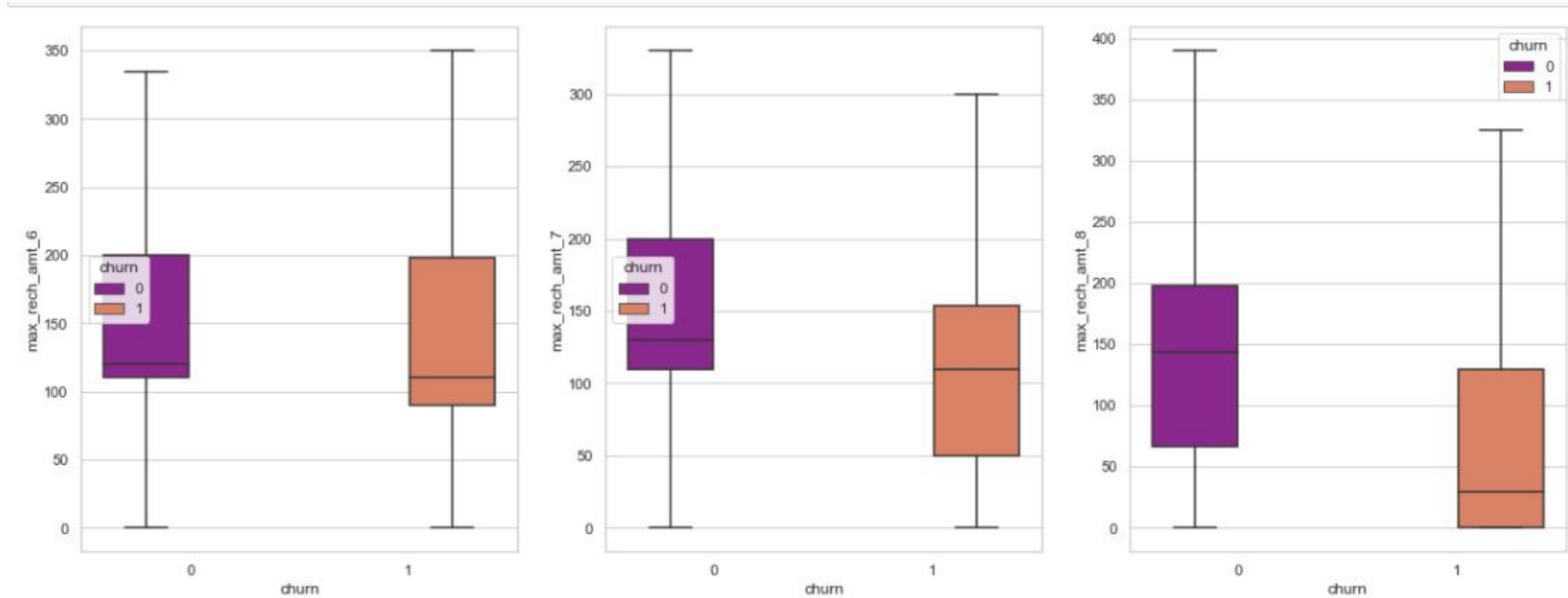
- The business objective is to predict the churn in the last (i.e., the ninth) month using the data (features) from the first three months. To do this task well, understanding the typical customer behavior during churn will be helpful.
- Data Cleansing
- Three Phases
 - The ‘good’ phase: In this phase, the customer is happy with the service and behaves as usual.
 - The ‘action’ phase: The customer experience starts to sore in this phase, for e.g. he/she gets a compelling offer from a competitor, faces unjust charges, becomes unhappy with service quality etc. In this phase, the customer usually shows different behavior than in the ‘good’ months. Also, it is crucial to identify high-churn-risk customers in this phase, since some corrective actions can be taken at this point (such as matching the competitor’s offer/improving the service quality etc.)
 - The ‘churn’ phase: In this phase, the customer is said to have churned

Approach

- Analyze the data provided.
- Data Cleansing
 - Check for missing values, incorrect data formats
 - For missing values, Impute the missing values or drop the rows/columns
 - Incorrect data types or data formats to be corrected
- Data Preparation
 - Filter high-value customers - Those who have recharged with an amount more than or equal to X, where X is the 70th percentile of the average recharge amount in the first two months (the good phase)
 - Tag churners and remove attributes of the churn phase: Those who have not made any calls (either incoming or outgoing) AND have not used mobile internet even once in the churn phase. The attributes you need to use to tag churners are total_ic_mou_9, total_og_mou_9, vol_2g_mb_9, vol_3g_mb_9
 - remove all the attributes corresponding to the churn phase
 - *H*andle class imbalance
- Build a regression Model
 - Build a Logistic model to predict Churn, Handle Multicollinearity
 - Identify important variables that are strong predictors of churn

Insights

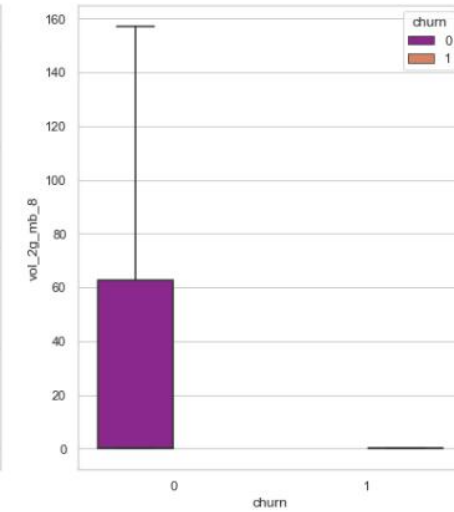
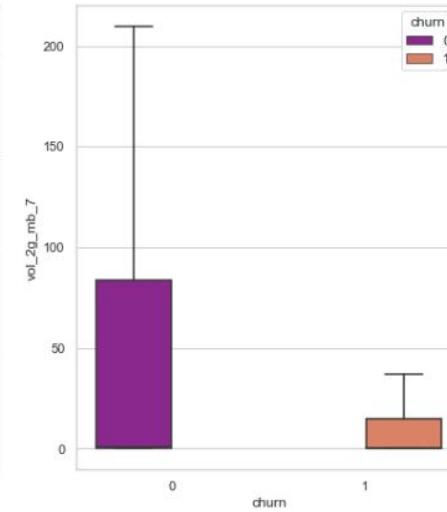
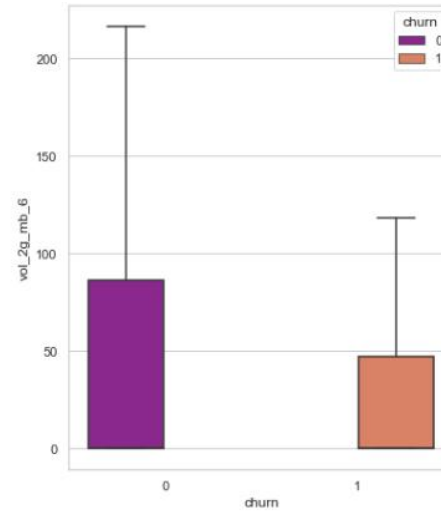
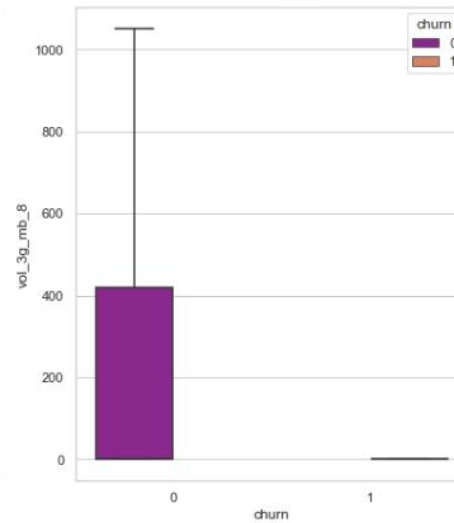
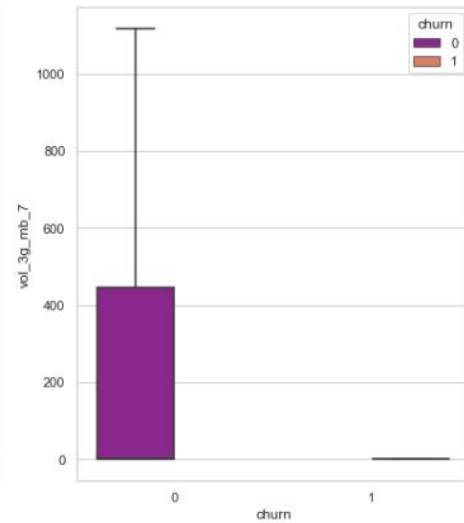
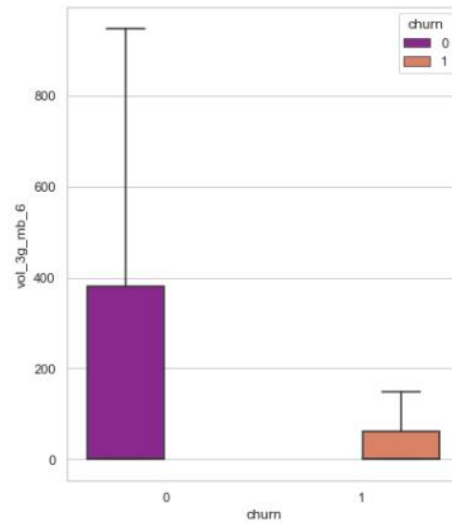
It can be observed that there is a drop in the max recharge amount for churned customers in the 8th Month (Action Phase)



Insights

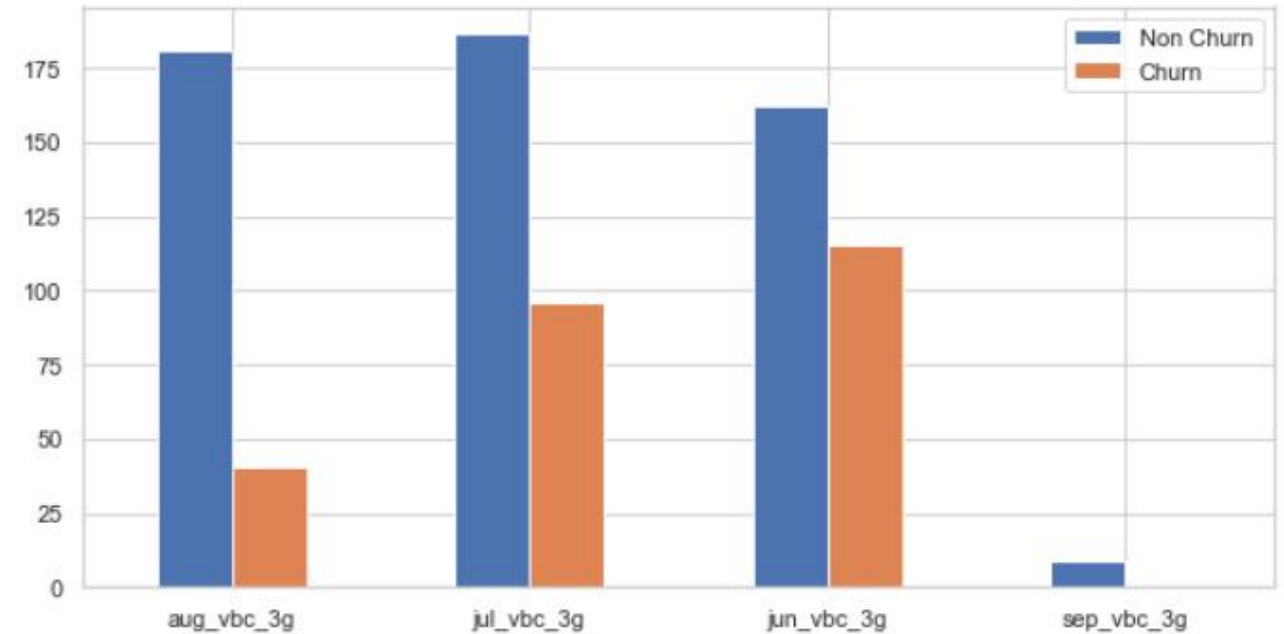
It can be observed that

- *2G and 3G usage for churned customers drops in 8th month*
- *It can be observed that 2G/3G usage is higher for non-churned customers indicating that churned customers might be from areas where 2G/3G service is not properly availal*



Insights

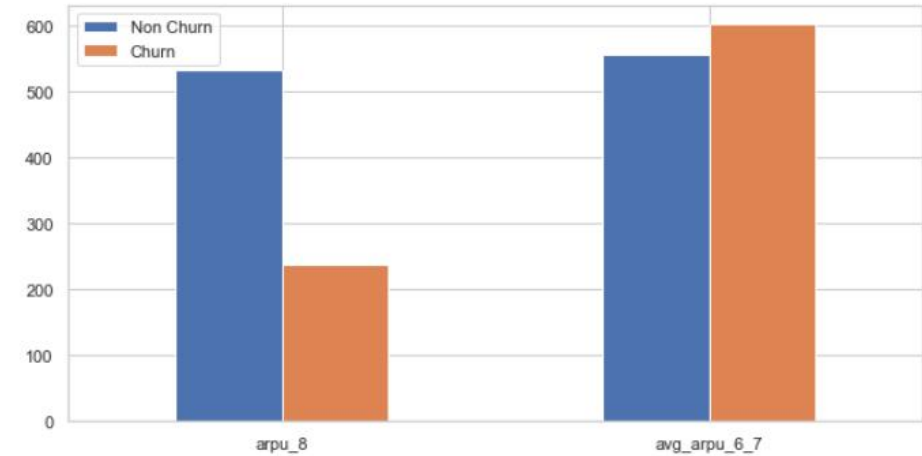
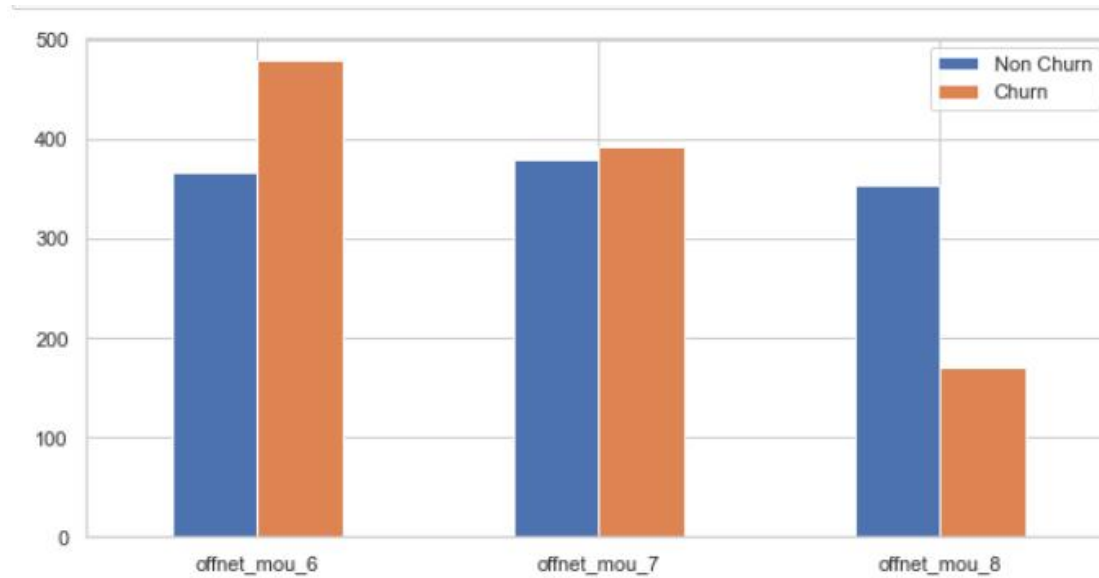
It can be observed that volume-based cost for 3G is much lower for Churned customers as compared to Non-Churned Customers and there is a drop in vbc in 8th month also.



	aug_vbc_3g	jul_vbc_3g	jun_vbc_3g	sep_vbc_3g
Non Churn	180.50	186.21	162.37	8.71
Churn	40.85	96.08	115.10	0.32

Insights

It can be observed that there is drop for Arpu in 8th month for churned customers

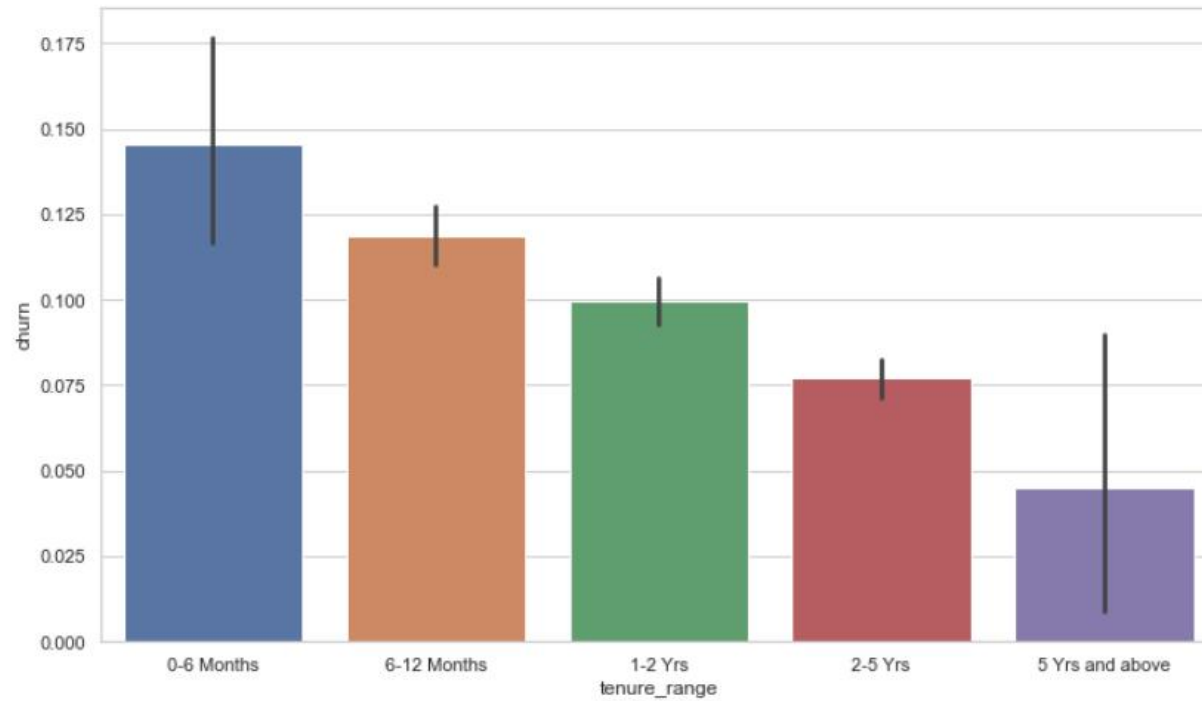


	arpu_8	avg_arpu_6_7
Non Churn	532.64	555.91
Churn	237.20	601.66

It can be observed that there is drop in offnet mou services in the 8th month

Insights

❖ *It can be observed that Most Churn happens during the first 6 months. As a customer stays longer with the network, Churn decreases*



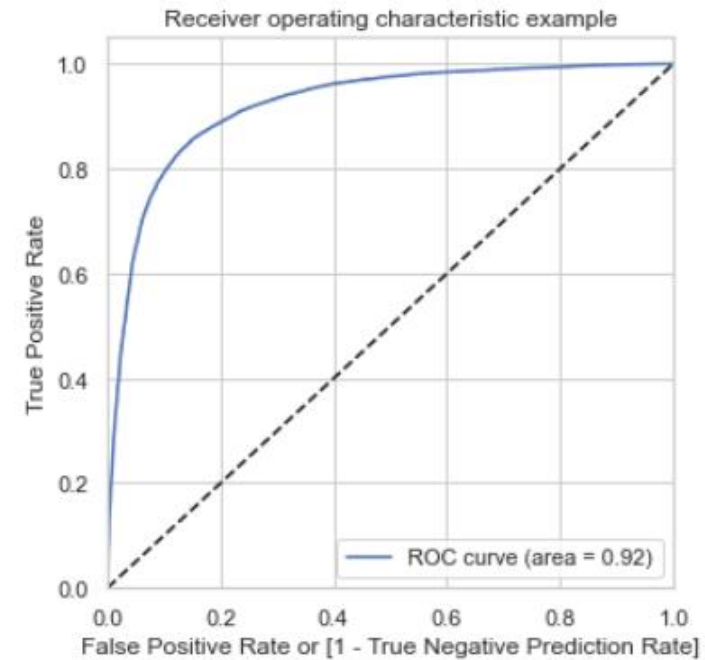
Training Results

Sensitivity: 85

Specificity: 85

Precision: 85.2

*Roc Curve of training
data*



Test Results

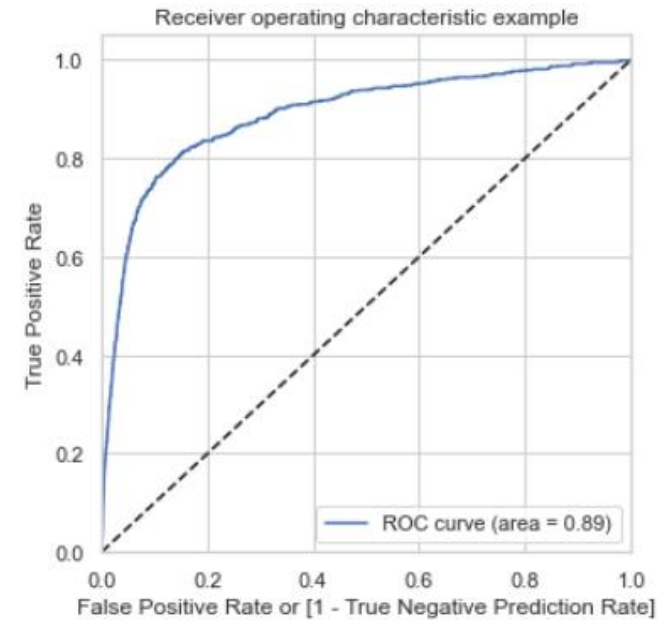
Accuracy : 85

Sensitivity: 80

Specificity: 85.7

We built a model with 85 % accuracy

Roc Curve of test data



Recommendations

- ✓ *Based on tenure, Customers who are with less than 4 years are more likely to churn. So, company should concentrate more on that segment by rolling out new schemes to that group.*
- ✓ *Company must provide better 2G/3G area coverage where 2G/3G services are not good, it is a strong indicator of churn.*
- ✓ *It is observed that the recharge amount, volume-based cost drop for 8th month indicates Churn*
- ✓ *Incoming and Outgoing Calls on roaming for 8th month are strong indicators of churn*
- ✓ *Average revenue per user seems to be most important feature in determining churn prediction.*