Telecom Churn Case Study

Submitted by,

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Problem Statement

- In highly competitive telecom industry, customers are able to choose from multiple service providers and actively switch from one operator to another. Due to which 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 even more important than customer acquisition. So the business goal is to retain high value customers by developing suitable model for prediction based on given data.

Objective

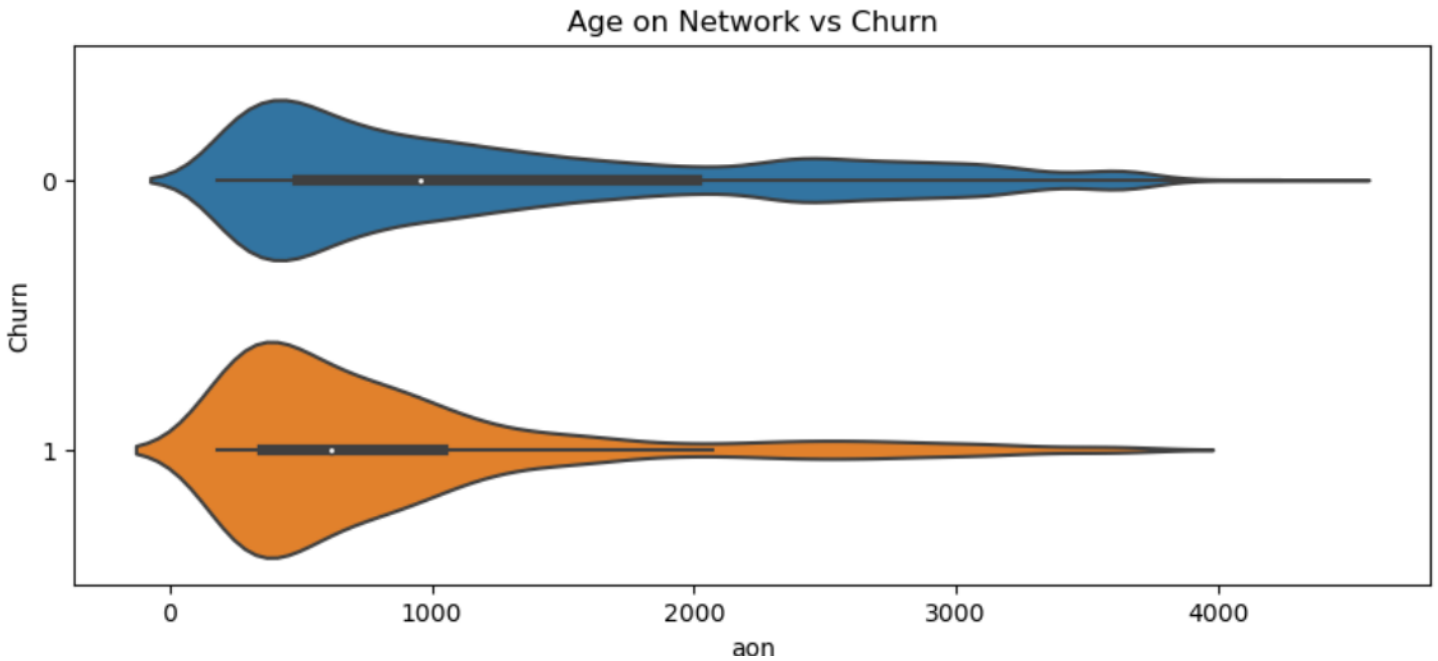
The objectives of this case study can be bifurcated as follows:

- To identify high value customers for customer retention.
- To understand customer behaviour.
- To build predictive model using advance ML algorithms in order to predict which customers are at high risk of churn.
- To to predict the churn in 9^{th} month using the data from the first three months.

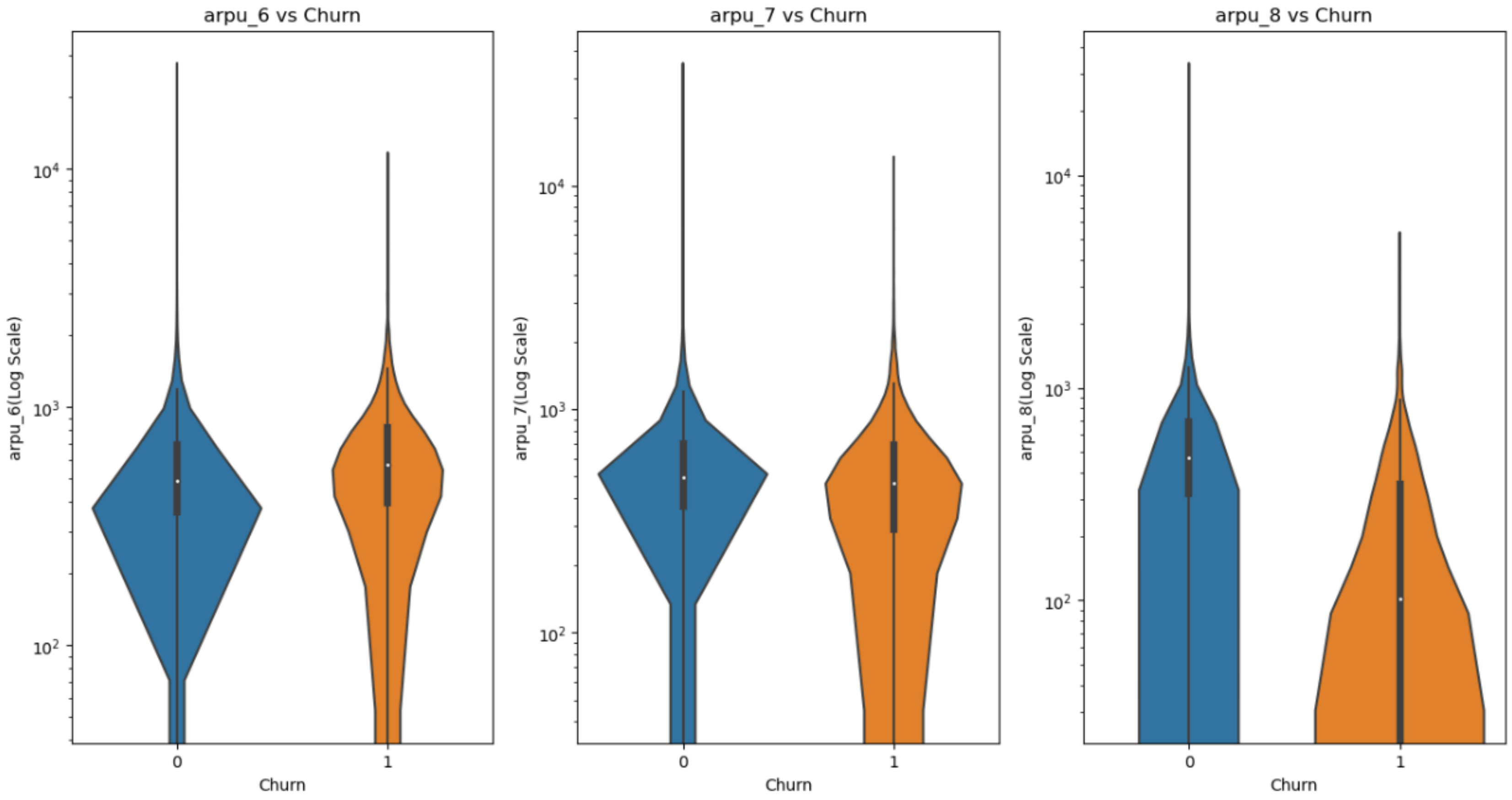
Steps involved

- **Data Understanding and reading**
  - *Customer behaviour:*
    - The "good" phase: During this time, the client is satisfied with the assistance and acts normally.
    - The "action" phase is when the customer's experience starts to go south. The client typically behaves differently during this time than during the "good" months.
    - The "churn" phase is when the customer is considered to have left. This stage is the basis for defining churn.
- **Preprocessing**
  - Aligning data in required format
  - Handling missing values
- **Perform EDA**
- **Train and evaluate models**
- **Choose the best suitable one**

Important graphs



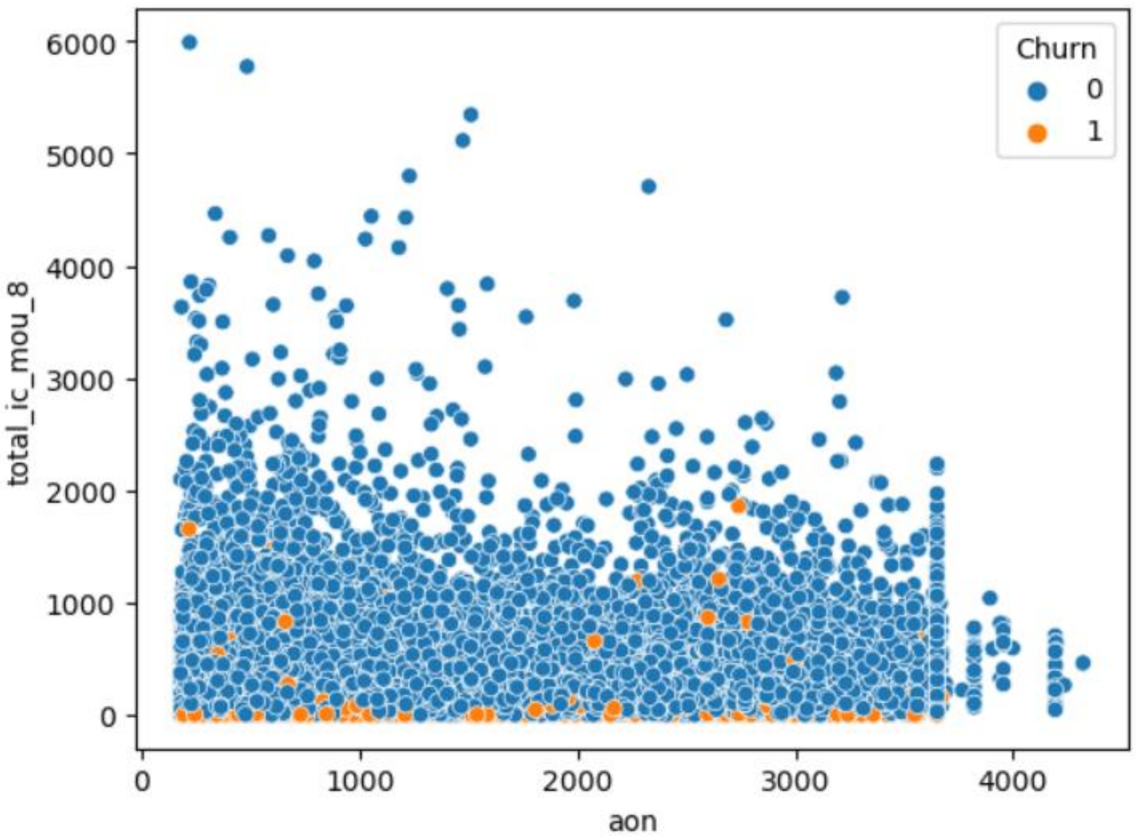
Analysis: The customers with lesser 'aon' are more likely to Churn when compared to the Customers with higer 'aon'



Analysis: Above graphs shows revenue and churn relationship of 6th, 7th and 8th month

1.We can understand from the above plots that revenue generated by the Customers who are about to churn is very unstable.

2.The Customers whose arpu decreases in 7th month are more likely to churn when compared to ones with increase in arpu.



Analysis:

1.The customers with less total_ic_mou_8 are more likely to churn irrespective of aon.

2.The customers with total_ic_mou_8 > 2000 are very less likely to churn.

Model evaluation:

- Overall accuracy of Model 2

1. Accuracy: 91.88 %
2. Specificity: 99.37 %
3. Sensitivity: 12.91 %

Conclusion

- Following are the most important predictors of churns with reference to the model that we built:

1. mothly_2g_8
2. const
3. monthly_2g_7
4. total_rech_num_8
5. sachet_3g_7_0
6. total_rech_num_7
7. total_rech_num_6
8. std_og_t2f_mou_8
9. std_ic_t2f_mou_8
10. loc_ic_t2f_mou_8
11. spl_og_mou_8
12. Isd_og_mou_6
13. loc_ic_t2n_mou_8

Recommendations

- Focus on the customers who are more likely to be using monthly 2g/3g package in action period.
- Concentrate on customers who recharge less number of times.

References:

- Upgrad’s in module case study and examples
- Kaggle