



TELECOM CHURN CASE STUDY

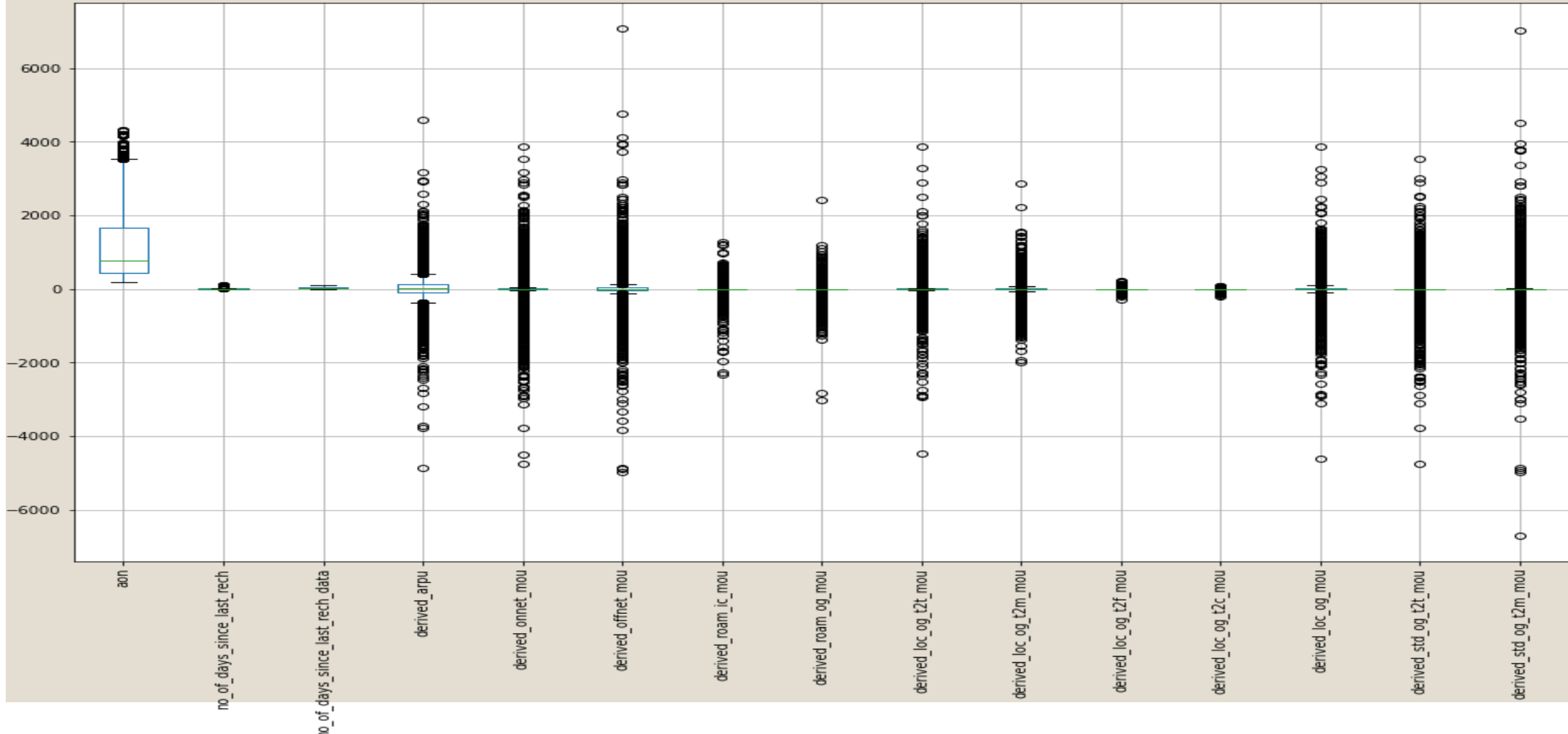
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Details

- 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.
- This project is based on the Indian and Southeast Asian market.
- 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. Understanding the typical customer behaviour during churn will be helpful to do this task well.

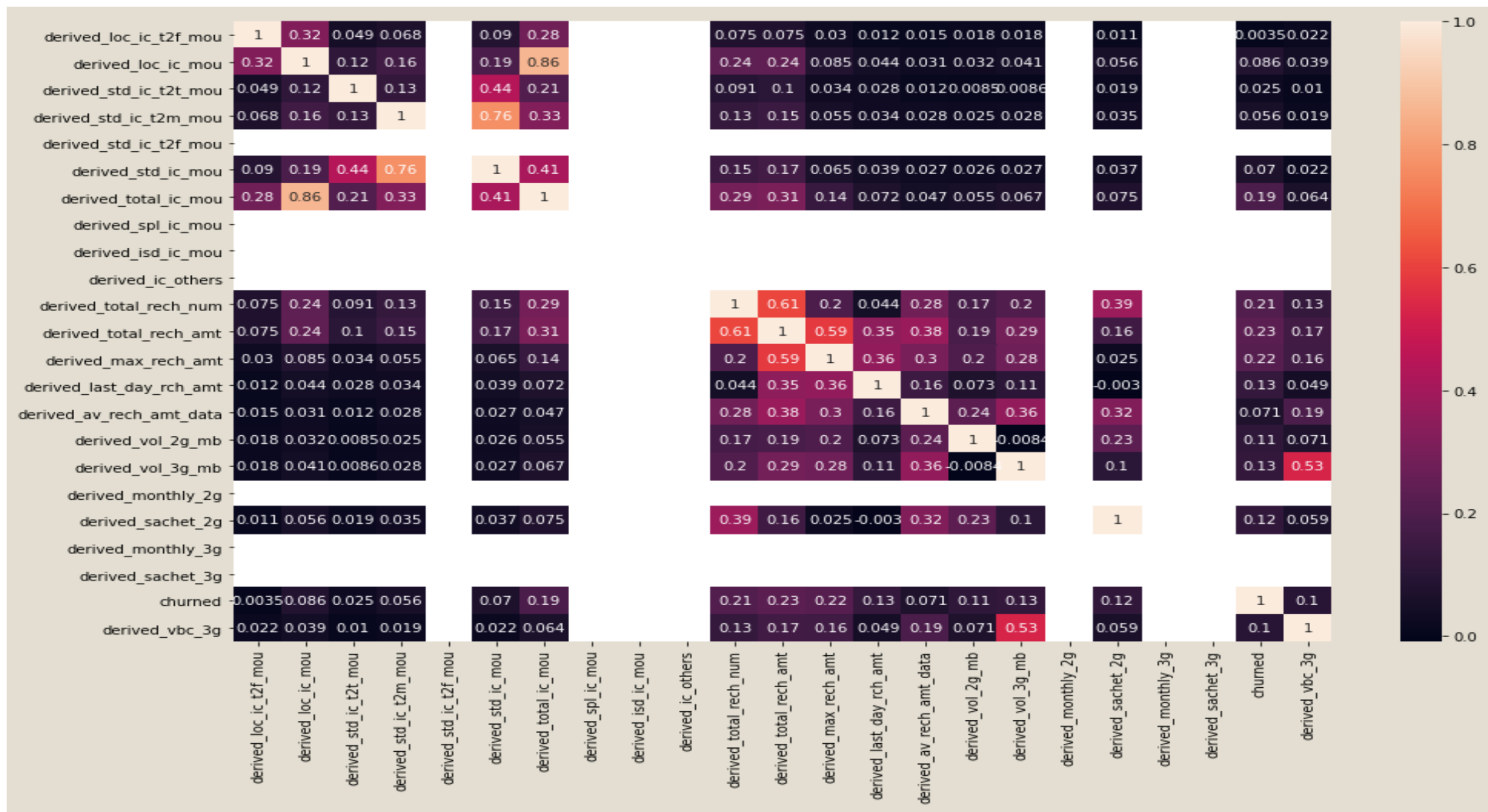
EDA

- **Outlier Treatment:** Most of the features have a high number of outliers, dropping the outliers will cause a loss of information. Hence capping and flooring the extreme values.

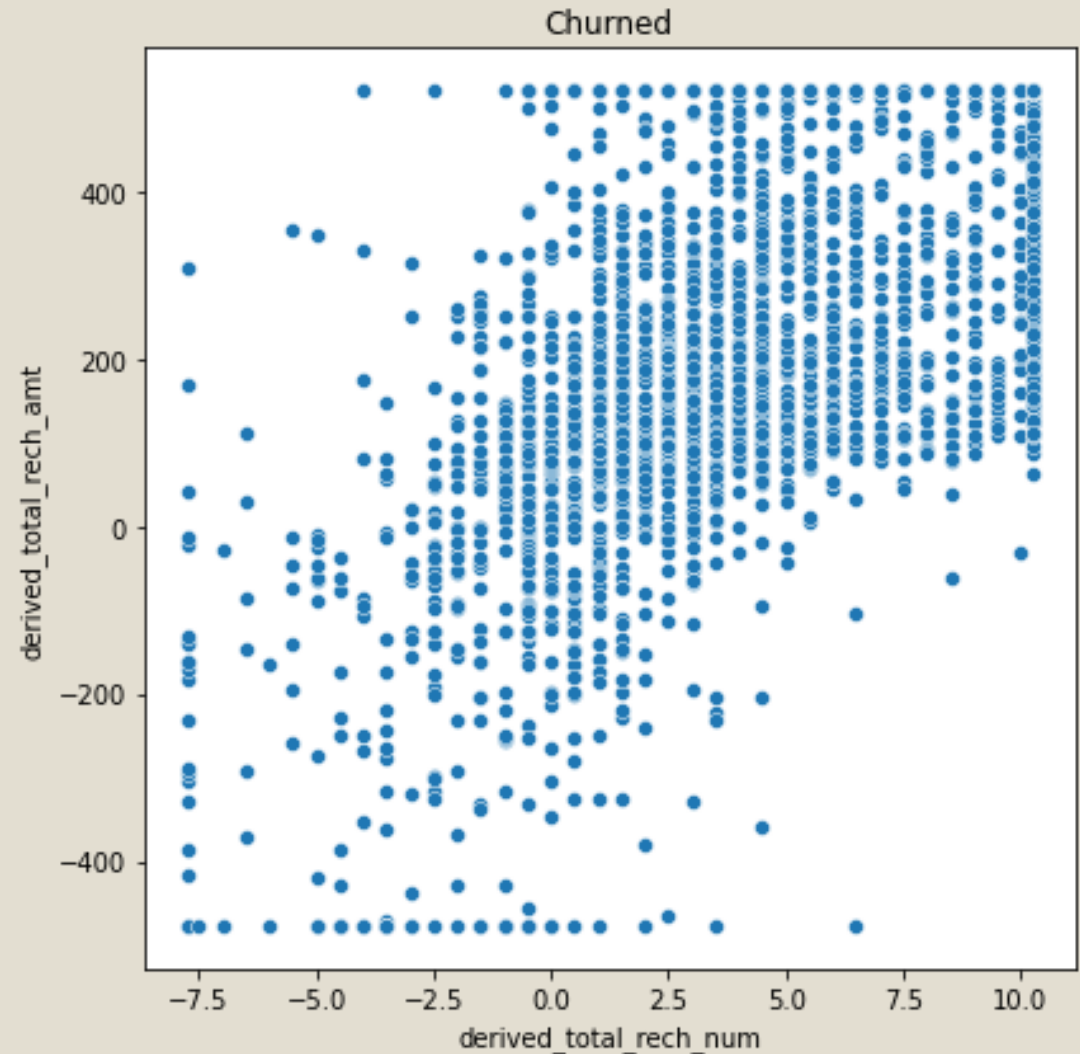
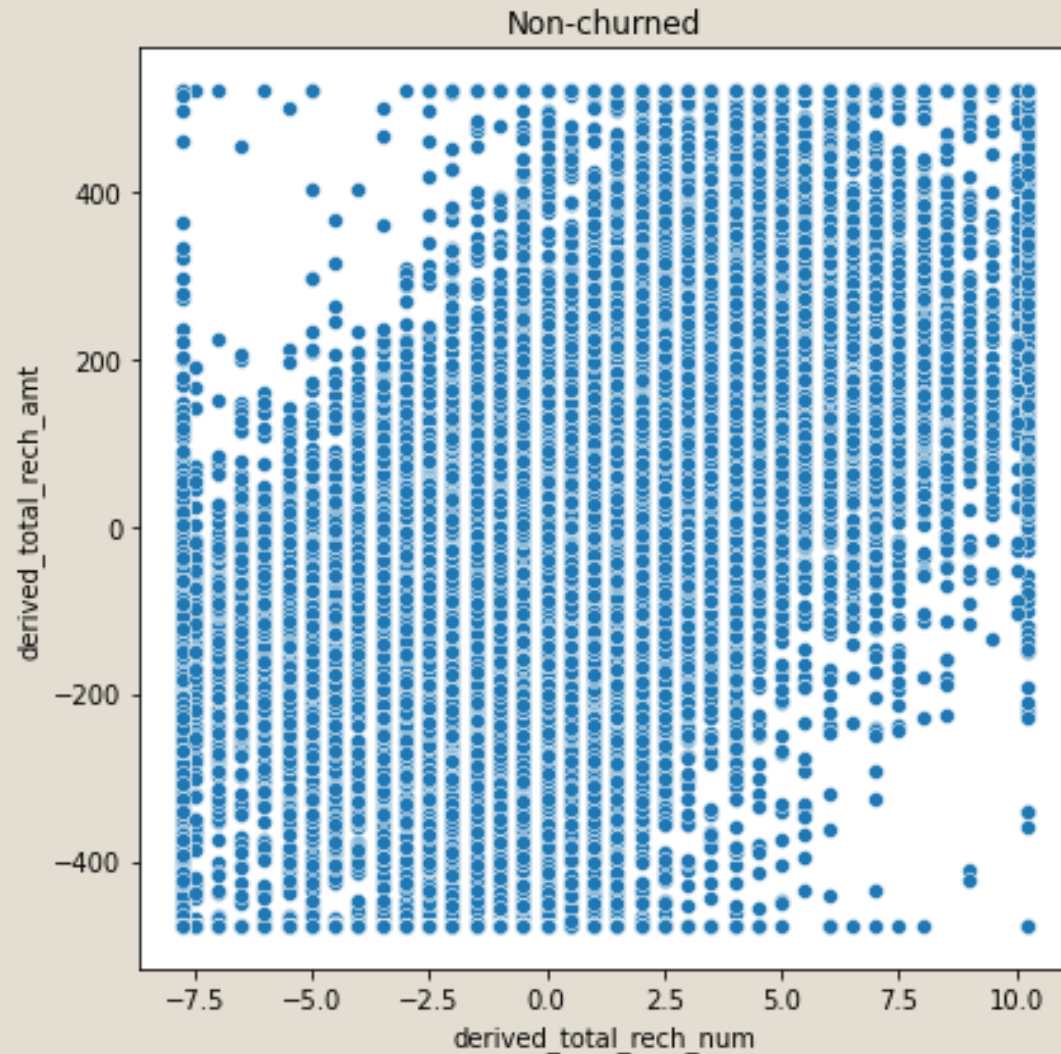


Checking Correlation





Bivariate and Multivariate Analysis

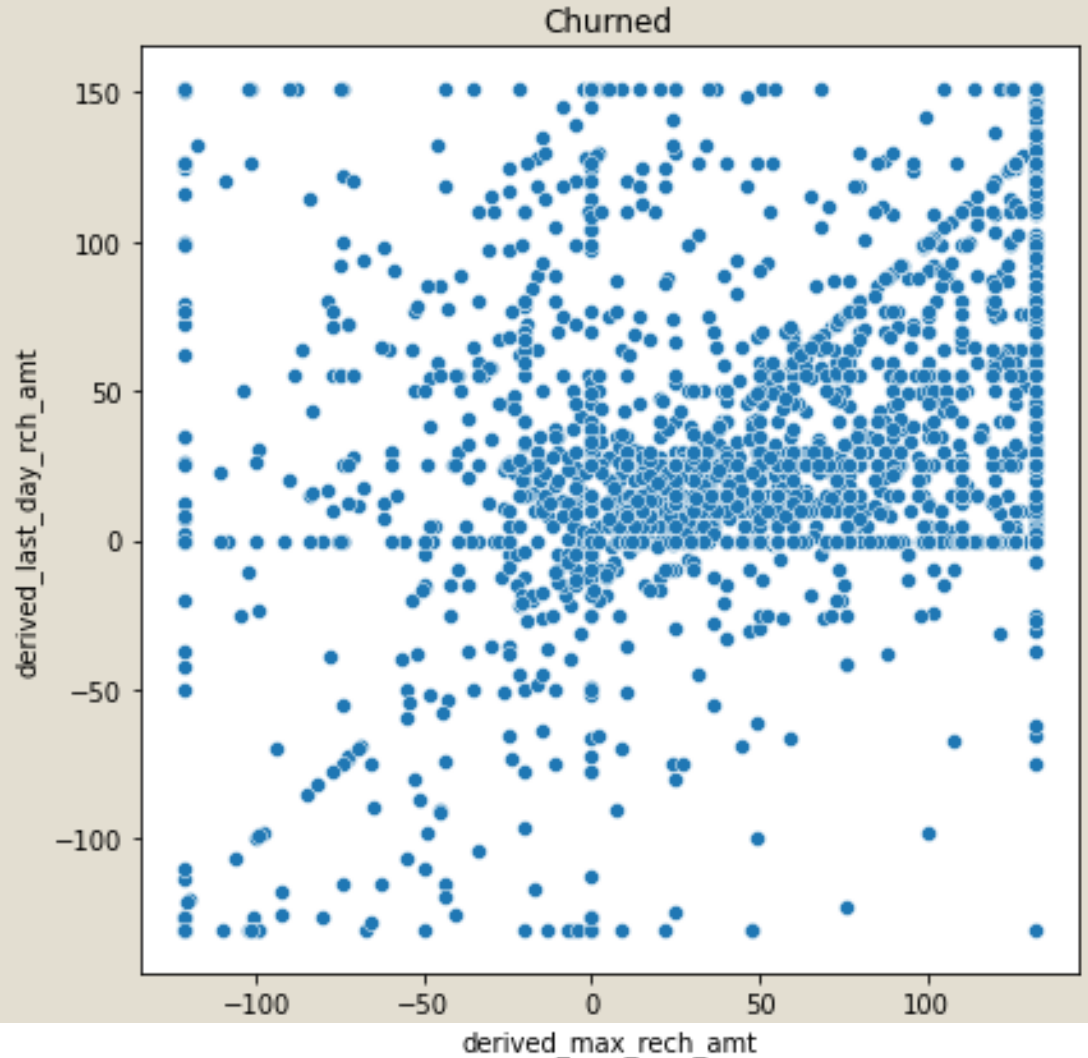
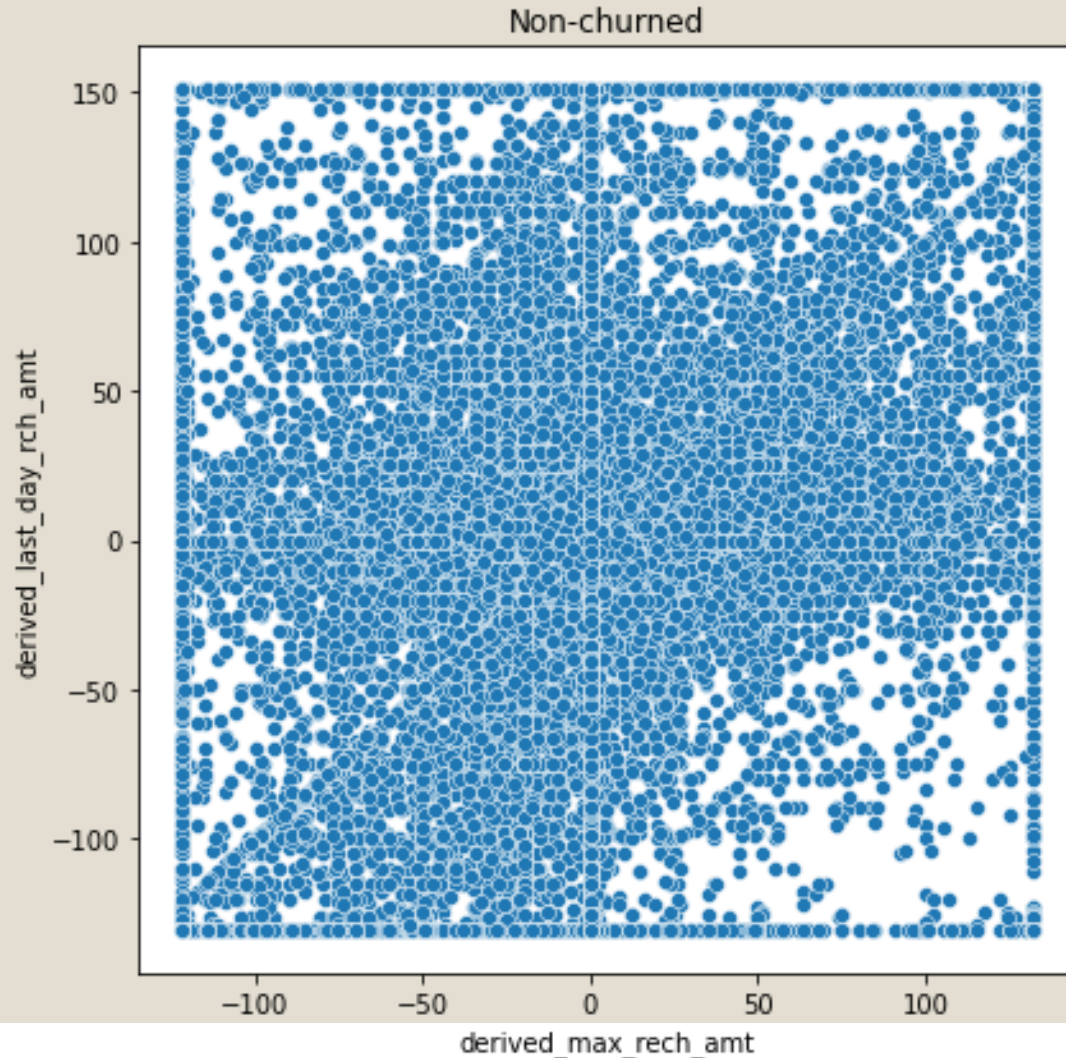


Observation:

- There is a positive correlation between total recharge amount and total number of recharges.
- 'derived_total_rech_amt' is derived by taking average of total recharge done in good phase (i.e. month 6 and 7) and deducting recharge of action phase (month 8) from it.
- A positive value of this feature means, recharge amount value dropped from good phase to action phase. The same applies for 'derived_total_rech_num' as well.
- A negative value of this feature means, recharge amount value increased from good phase to action phase. The same applies for 'derived_total_rech_num' as well.
- By comparing churned and non-churned customer we can see that, for churned customers both recharge number and recharge amount have dropped in action phase.

Observation:

- `derived_max_rech_amt` and `derived_last_day_rch_amt` are most likely to be positive for churned customers. This means, drop in maximum recharge amount and last day recharge amount in action phase can signify customer churn.



VIF data frame for all the variables

	Features	VIF
3	derived_arpu	2.47
8	derived_total_rech_num	1.98
5	derived_loc_og_mou	1.60
9	derived_max_rech_amt	1.55
11	derived_av_rech_amt_data	1.46
14	derived_sachet_2g	1.40
2	no_of_days_since_last_rech_data	1.34
7	derived_loc_ic_t2m_mou	1.28
13	derived_vol_3g_mb	1.28
1	no_of_days_since_last_rech	1.19
10	derived_last_day_rch_amt	1.18
12	derived_vol_2g_mb	1.17
6	derived_loc_ic_t2t_mou	1.15
4	derived_loc_og_t2f_mou	1.06
0	aon	1.02

VIF and p-value of the remaining features are in acceptable range. p-value < 0.05 (significance level)

Conclusion

- **Predictor Model**
- Since reducing customer churns with attractive offers is less expensive than making new customers, sensitivity score is considered for the building the final predictor model.
- Logistic Regression trained with 15 principal components has accuracy score of 0.74 and sensitivity score of 0.82 for Probability Cutoff = 0.42
- **The final model could predict 82% of the churned customers correctly out of all the churned customers. (sensitivity)**
- **Accuracy score 0.74 means 74% of the predictions made by the final model are correct out of all the predictions.**