TELECOM CHURN CASE STUDY

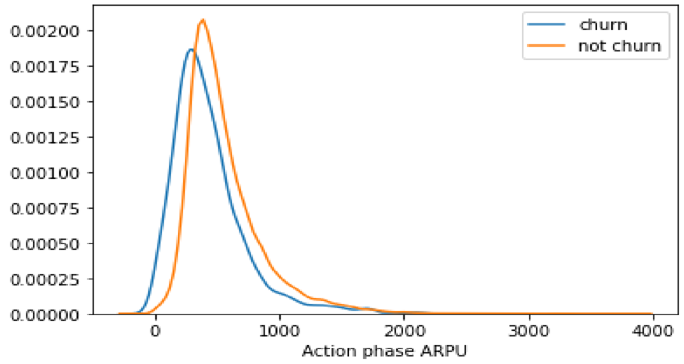
PROBLEM STATEMENT

- 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

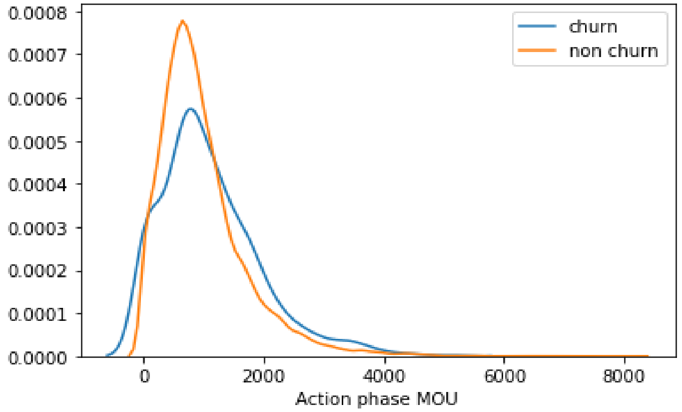
1. Reading, understanding and visualizing the data
2. Preparing the data for modelling
3. Building the model
4. Evaluate the model

UNIVARIATE ANALYSIS



Average revenue per user (ARPU) for the churned customers is mostly densed on the 0 to 900. The higher ARPU customers are less likely to be churned.

ARPU for the not churned customers is mostly densed on the 0 to 1000.

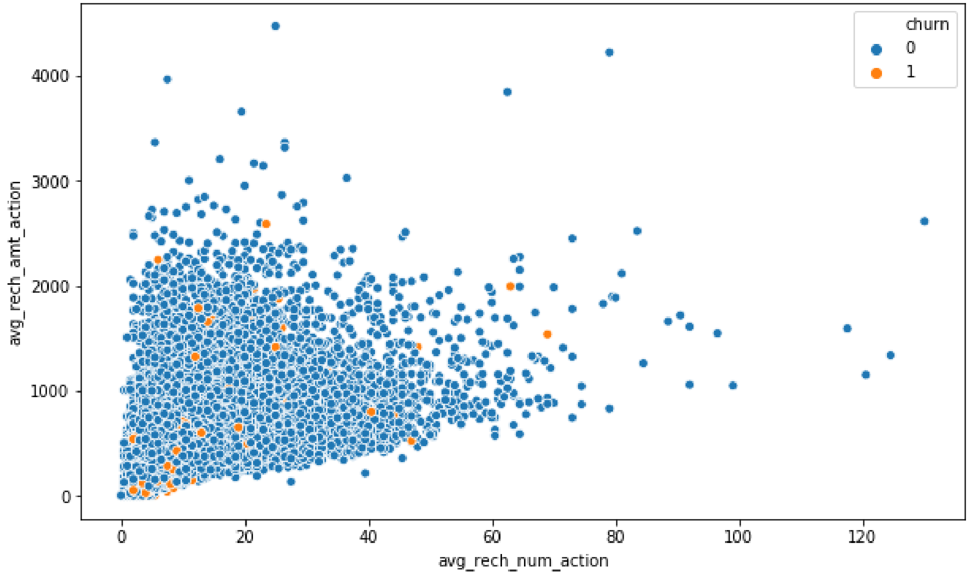


Minutes of usage(MOU) of the churn customers is mostly populated on the 0 to 2500 range. Higher the MOU, lesser the churn probability.

BIVARIATE ANALYSIS

Analysis of recharge amount and number of recharge in action month

In [85]:
```
plt.figure(figsize=(10,6))
ax = sns.scatterplot('avg_rech_num_action','avg_rech_amt_action', hue='churn', data=data)
```



__Analysis__

We can see from the above pattern that the recharge number and the recharge amount are mostly propotional. More the number of recharge, more the amount of the recharge.

PCA

Conclusion with PCA:

After trying several models, we can see that for achieving the best sensitivity, which was our ultimate goal, the classic Logistic regression or the SVM models preforms well. For both the models the sensitivity was approx 81%. Also, we have good accuracy of approx. 85%.

Conclusion without 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 explains the important predictor variables as well as the significance of each variable. The model also helps 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.

TOP PREDICTORS

Below are few top variables selected in the logistic regression model.

Variables	Coefficients
loc_ic_mou_8	-3.3287
og_others_7	-2.4711
ic_others_8	-1.5131
isd_og_mou_8	-1.3811
decrease_vbc_action	-1.3293
monthly_3g_8	-1.0943
std_ic_t2f_mou_8	-0.9503
monthly_2g_8	-0.9279
loc_ic_t2f_mou_8	-0.7102
roam_og_mou_8	0.7135

We can see most of the top variables have negative coefficients. That means, the variables are inversely correlated with the churn probablity.

E.g.:-

If the local incoming minutes of usage (loc_ic_mou_8) is lesser in the month of August than any other month, then there is a higher chance that the customer is likely to churn.

RECOMMENDATIONS

1.Target the customers, whose minutes of usage of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in the month of August).

2.Target the customers, whose outgoing others charge in July and incoming others in August are less.

3.Also, the customers having value based cost in the action phase increased are more likely to churn than the other customers. Hence, these customers may be a good target to provide offer.

4.Customers, whose monthly 3G recharge in August is more, are likely to be churned.

5.Customers having decreasing STD incoming minutes of usage for operators T to fixed lines of T for the month of August are more likely to churn.

6.Customers decreasing monthly 2g usage for August are most probable to churn.

7.Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.

8.roam_og_mou_8 variables have positive coefficients (0.7135). That means for the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.