

DOMAIN CASE STUDY = TELECOM

CHURN

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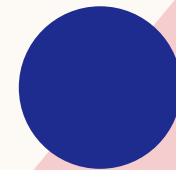
AGENDA

Introduction

Primary goals

Steps to Follow

Summary



INTRODUCTION

Problem statement:-

To reduce customer churn, telecom companies need to predict which customers are at high risk of churn. In this project, we will analyze 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.



PRIMARY GOALS

Retaining High profitable customers

STEPS TO FOLLOW

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

SUMMARY

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 on 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.

SUMMARY

Recommendations

9. Top Predictor variables

Business recomendation

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 probability.

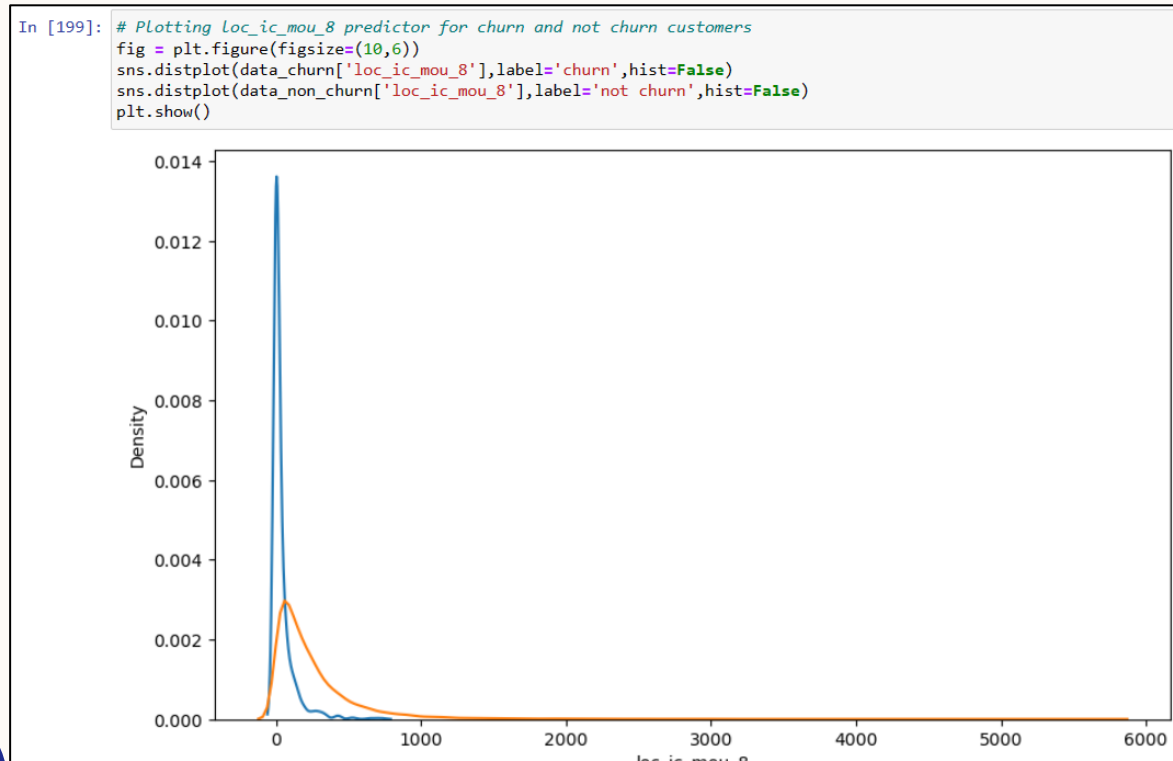
E.g.:-

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.

SUMMARY

Recommendations

10. We can see that for the churn customers the minutes of usage for the month of August is mostly populated on the lower side than the non churn customers.

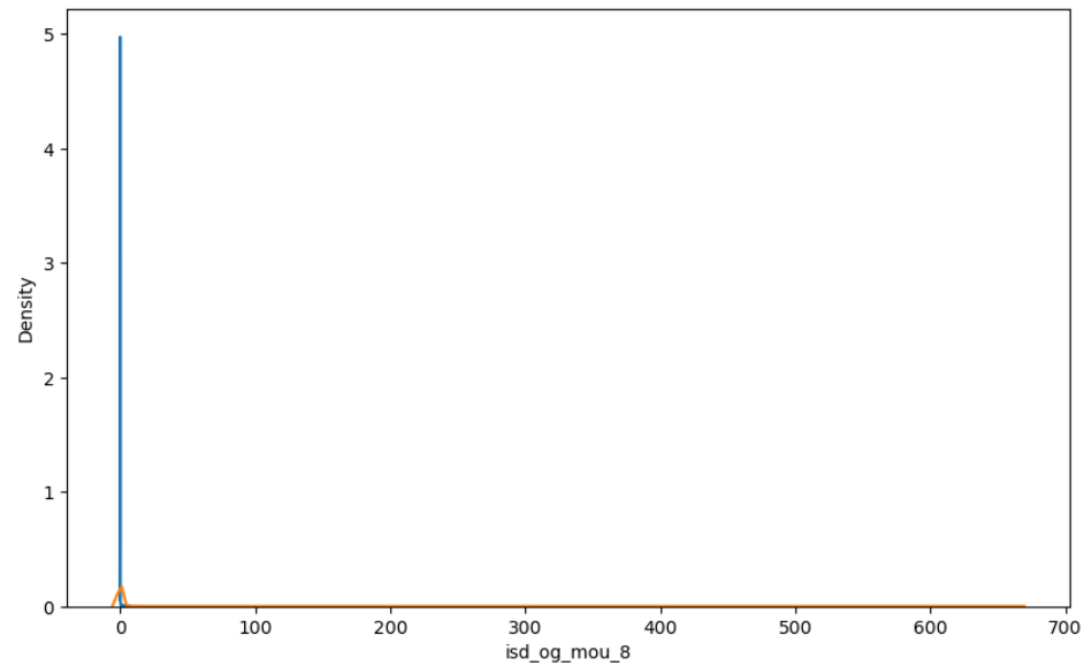


SUMMARY

Recommendations

11. We can see that the ISD outgoing minutes of usage for the month of August for churn customers is dense approximately to zero. On the other hand for the non churn customers it is little more than the churn customers.

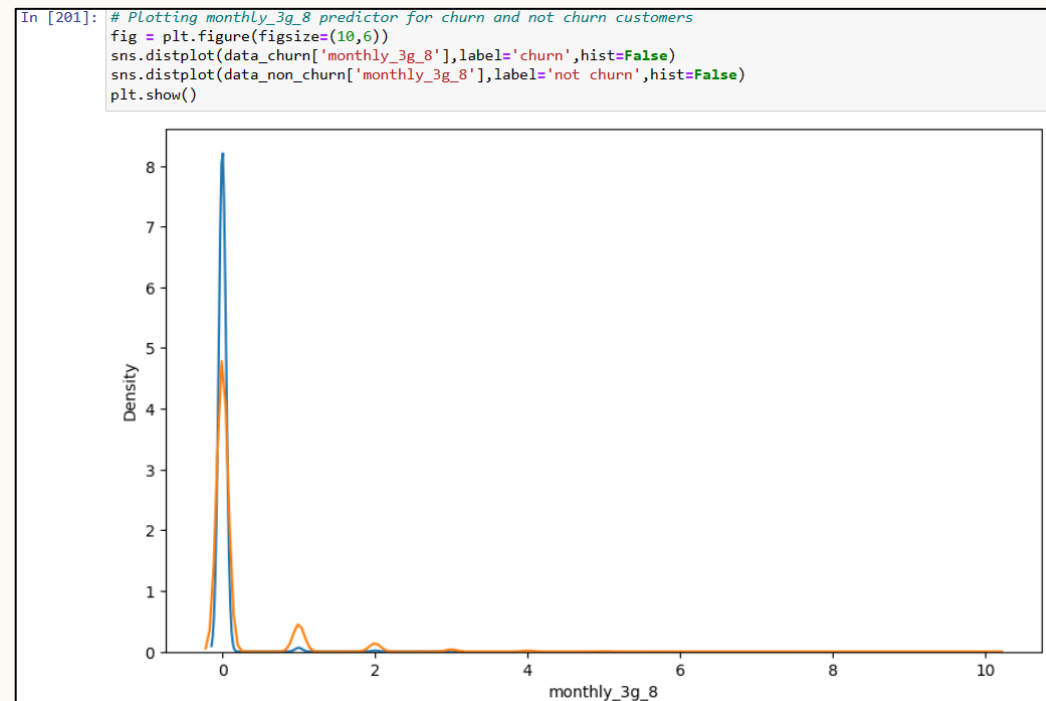
```
In [200]: # Plotting isd_og_mou_8 predictor for churn and not churn customers
fig = plt.figure(figsize=(10,6))
sns.distplot(data_churn['isd_og_mou_8'],label='churn',hist=False)
sns.distplot(data_non_churn['isd_og_mou_8'],label='not churn',hist=False)
plt.show()
```



SUMMARY

Recommendations

12. The number of monthly 3g data for August for the churn customers are very much populated around 1, whereas of non churn customers it spread across various numbers.





THANK YOU

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