

Telecom Churn Project

Domain Oriented Case Study



Shubham Apurwa

(GCP in Data Science and Artificial Intelligence)

Problem Statement

To 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.

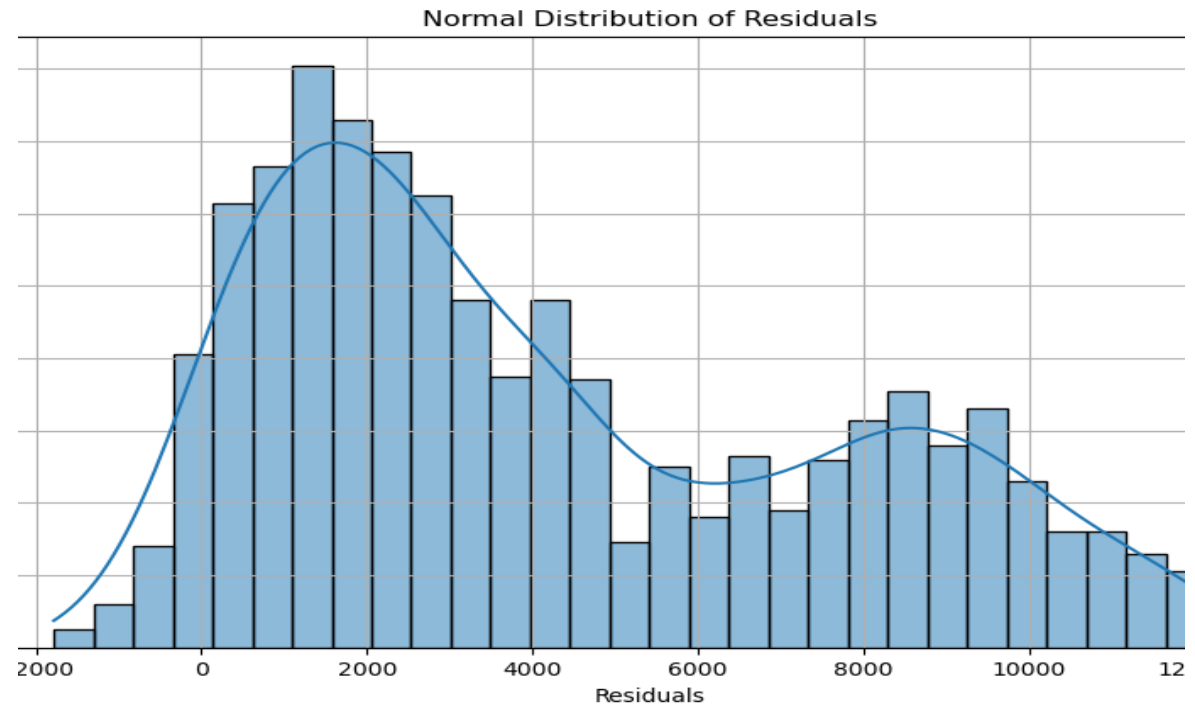
TECHNICAL ASPECT OF THE PROJECT

LINEAR REGRESSION : RIDGE AND LASSO

Non Normal Distribution of Residual Terms , We will consider
hyperparameter Tuning .

Technical Aspects

1. With respect to technical aspect , we found **errors** are **not normally distributed** in case of linear regression . It can be seen in figure given by side.
2. We use Lasso and Ridge Regression , to find out the value of **alpha** , which helps us to tune the parameters and make decision according to the parameter tuned.
3. As seen in table given , the r2 value for linear regression is not fit .
4. But after **hyperparameter tuning** , we get the best r2 score value for both Ridge and Lasso .
5. We see RSS(Test) and MSE(Test) values to choose between Ridge and Lasso
6. In the table given , low value of both gives us the best regression model
7. So , we consider **Lasso** in this case.



	Metric	Linear Regression	Ridge Regression	Lasso Regression
0	R2 Score (Train)	3.780017e-02	0.004176	0.016662
1	R2 Score (Test)	-1.130888e+09	0.004040	0.021348
2	RSS (Train)	9.228711e+01	95.512095	94.314559
3	RSS (Test)	5.832701e+10	51.367931	50.475240
4	MSE (Train)	1.416265e-01	0.144080	0.143174
5	MSE (Test)	5.437150e+03	0.161355	0.159947

Technical Aspect

1. After **hyperparameter tuning**, we can see coefficients values of Ridge Regression has been made close to 0.
2. In case of Lasso Regression, we can see that some coefficients of parameters has been made to 0, so Lasso made important feature selection here.
3. The **features** selected by Lasso Regression are :
 - a) **avg_roaming_og_mou**
 - b) **spl_ic_mou_avg**
 - c) **monthly_2g_avg**
 - d) **monthly_3g_avg**
 - e) **sachet_3g_avg**

	Linear	Ridge	Lasso
aon	-3.139673	-3.348930e-09	-0.000000
aug_vbc_3g	-0.027506	-1.268490e-08	-0.000000
jul_vbc_3g	0.203508	-1.107186e-08	-0.000000
jun_vbc_3g	0.074775	-1.351520e-08	-0.000000
sep_vbc_3g	-0.004671	-1.825423e-07	-0.000000
avg_2g_usage	0.160540	-1.259699e-08	-0.000000
avg_3g_usage	0.400746	-8.609765e-09	-0.000000
avg_std_og_mou	1.610428	2.015837e-08	0.000000
avg_roaming_ic_mou	0.000057	4.715270e-05	0.000000
avg_roaming_og_mou	0.000688	1.064340e-04	0.000732
offnet_mou_avg	-2.000983	7.820644e-09	0.000000
loc_og_t2t_mou_avg	-0.441916	-5.182869e-08	-0.000000
loc_og_t2f_mou_avg	-0.006842	-4.450013e-07	-0.000000
loc_og_t2c_mou_avg	0.005617	6.500775e-07	0.000000
std_og_t2m_mou_avg	2.977416	2.583264e-08	0.000000
std_og_t2f_mou_avg	-0.000804	-9.166687e-07	-0.000000
isd_og_mou_avg	-0.000048	-1.415824e-06	-0.000000
spl_og_mou_avg	-0.006973	7.187172e-08	0.000000
loc_ic_t2t_mou_avg	0.128869	-5.499295e-08	-0.000000
loc_ic_t2f_mou_avg	-0.015307	-1.983241e-07	-0.000000
std_ic_t2t_mou_avg	-0.027650	6.469302e-08	0.000000
std_ic_t2f_mou_avg	-0.005621	-1.316362e-06	-0.000000
spl_ic_mou_avg	-0.000279	-1.481805e-05	-0.000173
isd_ic_mou_avg	-0.020542	-1.739297e-07	-0.000000
max_rech_amt_avg	-0.617211	-6.279696e-08	-0.000000
monthly_2g_avg	-0.001024	-8.996271e-06	-0.000968
sachet_2g_avg	-0.001912	-9.056875e-07	-0.000000
monthly_3g_avg	-0.000533	-6.905096e-06	-0.000597
sachet_3g_avg	-0.000554	-8.162506e-06	-0.000393
total_rech_num_avg	-0.031913	2.400647e-07	0.000000

LOGISTIC REGRESSION

We are considering building Logistic Regression Model , because we have binary classification . i.e. the customer will churn or not

Technical Aspect

1. While building the model with Logistic Regression , we used the **RFE (Recursive Feature Elimination)** method to select top predictor variable and then do manual elimination
2. After selecting **top 15 predictor variable** and removing the insignificant variable using p-values , we found out the following top 5 parameters :
 - a) **avg_std_og_mou**
 - b) **loc_og_t2t_mou_avg**
 - c) **loc_og_t2f_mou_avg**
 - d) **std_ic_t2f_mou_avg**
 - e) **max_rech_amt_avg**

Dep. Variable:	Churn	No. Observations:	4601
Model:	GLM	Df Residuals:	4595
Model Family:	Binomial	Df Model:	5
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-412.69
Date:	Sat, 14 Sep 2024	Deviance:	825.39
Time:	20:43:31	Pearson chi2:	4.12e+03
No. Iterations:	10	Pseudo R-squ. (CS):	0.02636
Covariance Type:	nonrobust		

	coef	std err	z	P> z	[0.025	0.975]
const	-33.6757	42.513	-0.792	0.428	-116.999	49.648
avg_std_og_mou	91.5155	32.687	2.800	0.005	27.450	155.581
loc_og_t2t_mou_avg	-55.5194	20.066	-2.767	0.006	-94.849	-16.190
loc_og_t2f_mou_avg	-9.9304	3.880	-2.559	0.010	-17.535	-2.326
std_ic_t2f_mou_avg	-3.3461	1.493	-2.242	0.025	-6.271	-0.421
max_rech_amt_avg	-26.3822	10.324	-2.555	0.011	-46.617	-6.147

Technical Aspect

1. While selecting the 5 parameters during RFE method , we saw only the significance of the parameters
2. After considering the VIF values and **elimination** of the **high VIF valued parameters** , we get the following two variables
3. The two variables are :
 - a) **avg_std_og_mou**
 - b) **std_ic_t2f_mou_avg**

Dep. Variable:	Churn	No. Observations:	4601
Model:	GLM	Df Residuals:	4598
Model Family:	Binomial	Df Model:	2
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-434.26
Date:	Sat, 14 Sep 2024	Deviance:	868.52
Time:	20:44:26	Pearson chi2:	3.97e+03
No. Iterations:	10	Pseudo R-squ. (CS):	0.01719
Covariance Type:	nonrobust		

	coef	std err	z	P> z	[0.025	0.975]
const	152.9720	26.075	5.867	0.000	101.866	204.078
avg_std_og_mou	173.9858	28.314	6.145	0.000	118.490	229.481
std_ic_t2f_mou_avg	-4.6128	1.622	-2.844	0.004	-7.792	-1.434

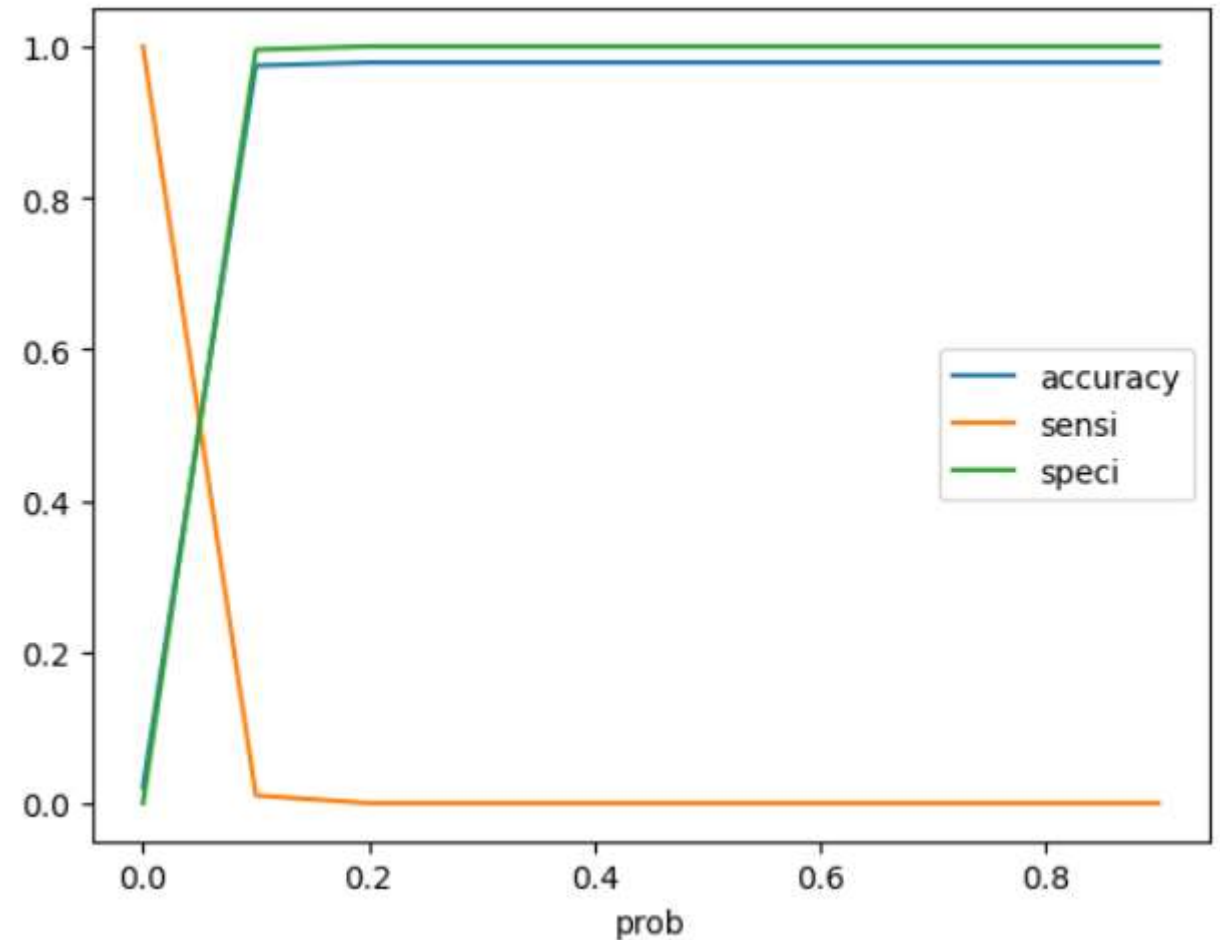
	Features	VIF
0	avg_std_og_mou	1.74
1	std_ic_t2f_mou_avg	1.74

FINDING OPTIMAL CUT-OFF

Technical Aspect

1. As in previous models , we considered probability of a customer to be churn as greater than 0.5 .
2. Due to which , we have **overfitting** of the model .
3. To **make fit model** and **more predictable** , we will find **optimal cut off** .
4. After plotting the **graph** , we found that cut off where , **accuracy** , **sensitivity** and **specificity** of the model makes fit .
5. The **cut off** is **0.06**

Note : Here the cut off is low because we have data imbalance .



BUSINESS ASPECT OF THE PROJECT

Business Aspect

1. With respect to the Business Aspect , if a customer will churn or not churn , we can consider parameters containing :

INCOMING (LOCAL & ROAMING)

OUTGOING (LOCAL & ROAMING)

2G USAGE

3G USAGE

TOTAL NUMBER OF RECHARGE DONE IN A MONTH

MAXIMUM AMOUNT OF RECHARGE

Business Aspect

- The telecom company must see whether the customer is using **Offnet Services** like Calls , Messages more OR **Onnet Services** Like Whatsapp , Instagram , Facebook etc.
- This can be identified by seeing the **Recharge history** of the **customer** mobile number , which Package he is selecting , whether it is call and messages pack OR Data pack .
- The telecom company must see his **number of recharges** and **amount of recharge** he/she is doing in a month
- Based on above criteria , the telecom company must **launch** effective **Calling package** or **Data package** based on customer **consumption history** .
- The telecom company must also take into consideration whether the competitor telecom company tariff plans , to make customer to not to switch to other network services by doing **surveys** and **feedback** and **suggestions** .
- The above **consideration** and **action plan** by the telecom company will make customer **not to churn**.