

Customer Connectivity

A Data-Driven Approach to Understanding Customer Churn

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Marketing Purpose

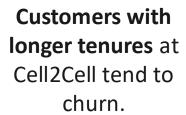
Develop a **proactive churn management program** to be recommended to the Customer Base Management (CBM) Group.

We will do this by **analyzing customer data** to identify at-risk customers and devising targeted incentives to reduce churn.



What makes customers leave?







Customers paying less tend to churn.

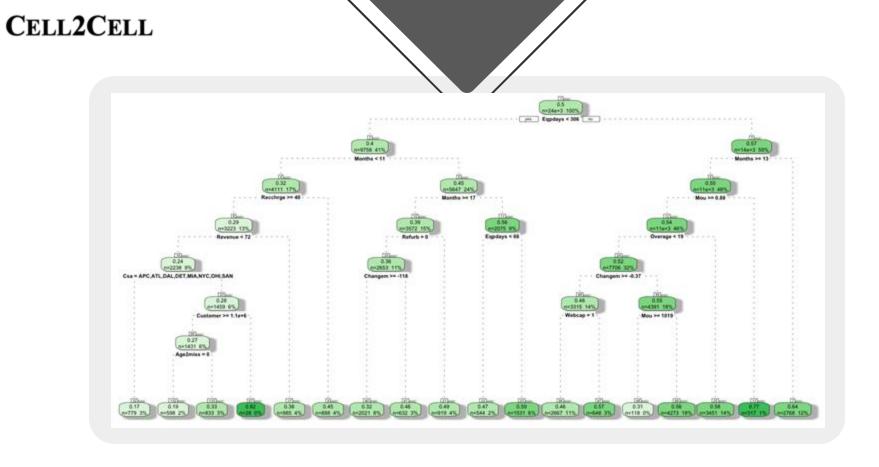


Higher number of
Customer Care calls
and the number of
retention calls
suggests potential
churn.



O2. Churn Prediction

Decision Tree



Decision Tree Helps Us Predict Churn Based on Customer Data



Most Important Factors



Equipment Use

<306 days



Months in Service

> or < 1 year



O3. Churn Prediction

Logistic Regression

LOGISTIC REGRESSION

VARIABLE	PARAMETER ESTIMATE	IMPORTANCE (Pr > (z))	MEANIN G	
Eqpdays	0.0026	4.32 E-51 ***	For every extra day that a customer uses current equipment, odds of chuming versus not chuming go up by 0.26%.	
Retcall	0.75	9.89 E-26 ***	Customers who have made a call to the retention team have approximately 2.11 times higher odds of the outcome compared to those who haven't.	
Months	-0.0016	0.63	For every extra month in service, odds of chuming versus not chuming decrease by 0.16%.	
Refurb	0.29	1.63 E-13 ***	For every extra handset refurbished, odds of chuming versus not chuming increase by 34.18%.	
Uniqsubs	0.20	4.37 E-15 ***	For every extra unique subscriber, odds of churning versus not churning go up by 21.87%.	
Mailres	-0.21	3.20 E-14 ***	Customers who respond to mail offers have approximately 80.97% of the odds of churning versus not churning compared to those who don't respond.	
Overage	0.0018	2.04 E-22 ***	For each additional mean overage minute of use, the odds of churning versus not churning increase by approximately 0.18%.	
Mou	-2.17 E-5	0.72	For each additional mean monthly minute of use, the odds of churning versus not churning decrease by approximately 0.002%.	

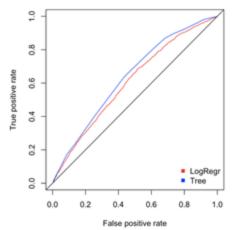
LOGISTIC REGRESSION

VARIABLE	PARAMETER ESTIMATE	IMPORTANCE (Pr > (z))	MEANING	
Setprcm	-0.25	1.77 E-09 ***	Instances with missing data on handset price have approximately 77.89% of the odds of chuming versus not chuming compared to instances with available data.	
Creditde	-0.24	9.08 E-09 ***	Instances with a low credit rating have approximately 78.47% of the odds of churning versus not churning compared to instances without a low credit rating.	
Actvsubs	-0.18	1.35 E-07 ***	For each additional active subscriber, the odds of churning versus not churning decrease by approximately 16.80%.	
Roam	0.011	1.77 E-05 ***	For each additional mean number of roaming calls, the odds of churning versus not churning increase by approximately 1.06%.	
Changem	-0.00024	2.57 E-06 ***	For each percentage change in minutes of use, the odds of churning versus not churning decrease by approximately 0.024%.	
Eqpdays: Months	-3.97 E-05	5.12 E-16 ***	For each unit increase in the product of "Eqpdays" and "Months," the odds of decrease by approximately 0.004%. The joint effect of the number of days of the current equipment and the months in service on the outcome is very close to 1, indicating minimal impact on the odds of chuming versus not chuming.	
Months: Mou	-1.42 E-05	6.19 E-07 ***	For each unit increase in the product of "Months" and "Mou," the odds of decrease by approximately 0.001%. The joint effect of the number of months in service and the mean monthly minutes of use on the outcome is very close to 1, indicating minimal impact on the odds of chuming versus not chuming.	



COMPARING MODELS

AUC



Comparing the AUC scores of the decision tree and logistic regression,

Decision Tree. seems to perform better

Lift in the 10th Decile

Decision Tree: 1.3245

Logistic Regression: 1.3360

The lift signifies the true churn rate for the group. Basically, how many people in the 10th decile churned divided by the total number of customers in the 10th decile (customers having

0.9 < churn probability < 1). The higher the lift, the better the model is, so **logistic regression** model seems to be slightly better than the DT.

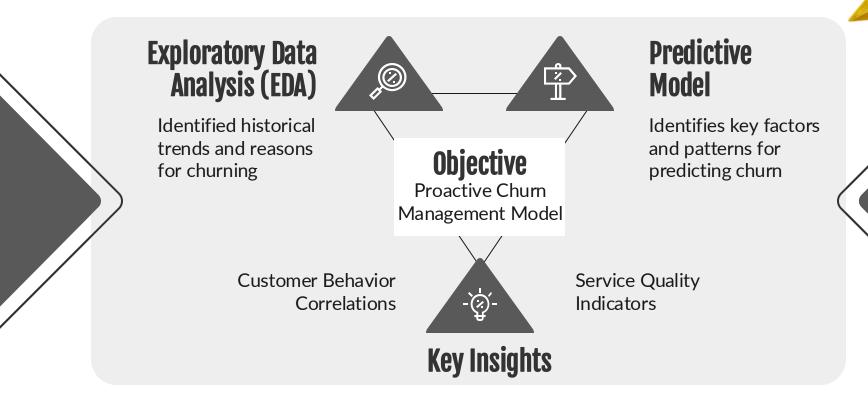
False Negatives

Decision Tree: 1480

Logistic Regression: 1723

False Negatives signify how many customers were predicted to not churn but ended up being churned. We want to minimize the FNs, since we do not want to miss the opportunity of offering promotions to them. FNs are significantly low in **Decision Tree** when compared with logistic regression, it performs better wrt this parameter.

Winner Model: Decision Tree

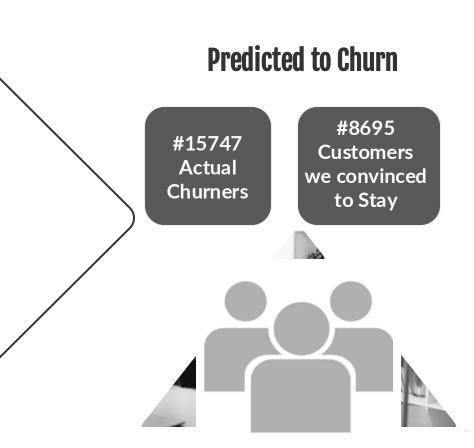


Accurate churn prediction and pinpointing the drivers empower proactive customer targeted strategies



Predicted Results of the four customers

	X15747	X29301	X8695	X34573
Customer	1039199	1073314	1021961	1086325
Revenue	60.325	53.715	5	34.99
Churn	1	1	0	0
pchurn.lr	0.79514	0.276412	0.732123	0.262196
pchurn.tree	0.772871	0.170732	0.772871	0.170732





Predicted to Stay

#29301 Unpredicted Churners #34573 Loyal Customers

Predicted to Churn

1. Enhancing Loyalty

- a. Personalized Promotion Offers flexible payment options
- b. Priority Customer Service
- c. Free Equipment Upgrade
- d. Bonus data or minutes
- 2. Proactive Communication
- 3. Incentives for re-joining



Predicted to Stay

1. Loyalty Awards

- a. Bonus data or minutes
- b. Early or bonus access to premium features
- c. Annual discount for staying with us for another year
- 2. Feedback Sollicitation





Thank you!

Any Questions?