

Telecom Churn:

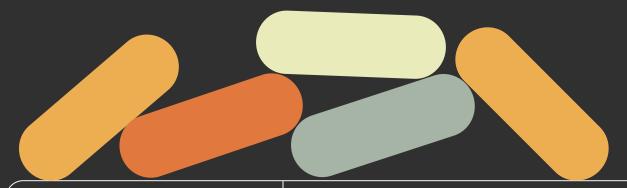
Case Study

Business Problem

- Industry Context: The telecom industry faces an annual churn rate of 15-25% due to multiple service provider options.
- Business Impact: Acquiring a new customer costs 5-10 times more than retaining an existing one.
- **Key Challenge:** Identifying and retaining **high-value customers** who contribute **most revenue.**
- Project Objective: Analyze customer data, build predictive models, and identify key churn indicators to help telecom firms take proactive action.
- Market Focus: This study is based on the Indian and Southeast Asian markets, where prepaid customers dominate.
- Churn Definition:
 - Usage-based churn: Customers who have zero usage (calls, data, SMS, etc.) over a period.
 - High-Value Churn: Focusing on the customers who generate the majority of revenue.



Dataset Overview



- **Source:** Telecom customer dataset (99,999 records, 226 features).
- Data Span: Customer data collected over four consecutive months June,
 July, August, and September (encoded as months 6, 7, 8, and 9).
- Business Objective: Predict churn in the last (9th) month using data from the first three months.
- Customer Lifecycle Phases:
 - Good Phase (Months 6 & 7):
 Regular customer behavior.
 - Action Phase (Month 8):
 Changes in behavior indicate possible churn.
 - Churn Phase (Month 9):
 Customer either churns or stays.
- Key Features: Recharge history, usage patterns, roaming behavior, data consumption.
- Target Variable: Churn (Yes/No).

Telecom Churn Dataset Overview 3

Data Dictionary

(For Reference)

- MOBILE NUMBER: Customer phone number
- **CIRCLE_ID**: Telecom circle area to which the customer belongs
- LOC: Local calls within the same telecom circle
- **STD**: STD calls outside the calling circle
- IC: Incoming calls, OG: Outgoing calls
- **T2T**: Operator T to T (within same operator)
- **T2M**: Operator T to other operator mobile
- **T20:** Operator T to other operator fixed line
- **T2F:** Operator T to fixed lines of T
- **T2C:** Operator T to its own call center
- **ARPU:** Average revenue per user
- MOU: Minutes of usage voice calls
- AON: Age on network number of days on operator T's network
 - **ONNET:** All calls within the same operator network
- **OFFNET:** All calls outside operator T's network
- **ROAM:** Indicates customer is in a roaming zone
- SPL: Special calls, ISD: ISD calls
- RECH: Recharge, NUM: Number, AMT: Amount in local currency
- MAX: Maximum, DATA: Mobile internet
- VOL: Mobile internet usage volume (in MB)
- **2G**: 2G network, **3G**: 3G network
- **AV:** Average, **PCK:** Prepaid service schemes
- NIGHT: Night-hour schemes, MONTHLY: Monthly service schemes
- **SACHET:** Short-term service schemes
- FB_USER: Social media data pack user
- **VBC**: Volume-based cost (pay-per-use data charges)
- ***.6, *.7, .8, .9: KPI for June, July, August, and September respectively

Process/Flow

Exploratory Data Analysis (EDA)

Data Preprocessing & Model Building

Model Selection

Model Performance & Metrics

Deriving Business Insights & Recommendations

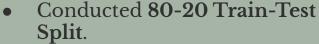
Top EDA Takeaways

- Churn Rate is higher for customers who registered a decrease in minutes of usage (mou) during the 'action' phase. (fig. 1)
- Churn Rate is higher for customers who registered a decrease in number of recharges during the 'action' phase. (fig. 2)
- Churn Rate is higher for customers who registered a decrease in recharge amount during the 'action' phase. (fig. 3)
- Churn Rate is higher for customers who registered a decrease in arpu during the 'action' phase. (fig. 4)
- Churn Rate is much lesser for customers who have actually seen an increase in volume based cost. (fig. 5)



Data Preprocessing

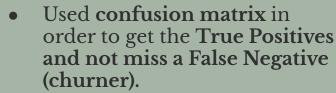
& Model Building



- Since rate of churn was low, around 5-10%, we used SMOTE technique to deal with data imbalance.
- Standardized numerical features using StandardScaler.
- To extract the most important features to reduce dimensionality, we created a model with Principal Component Analysis (PCA).

Logistic Regression

Using PCA



- Focussed on 'Recall' more than Accuracy, as it helped us understand how our model actually identifies churners.
- Performance:

Train set:

1. Accuracy: 86.01%

2. Sensitivity: 89.09%

3. **Specificity** 82.94%

Test set:

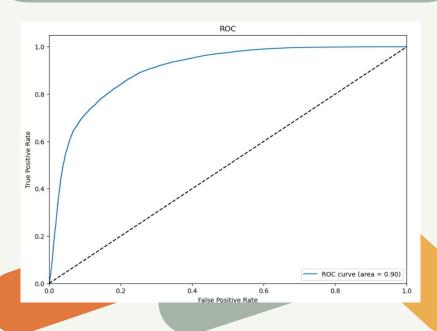
1. Accuracy: 82.84%

2. Sensitivity: 81.87%

3. Specificity 82.87%

Logistic Regression

Without PCA



- Used **Coarse Tuning** to deal with unwanted features.
- First used RFE and then manually removed features based on VIFs.
- Created a total of 5 models.

Train set:

- 1. Accuracy: 81.99%
- 2. Sensitivity: 87.47%
- 3. Specificity 76.52%

Test set:

- 1. Accuracy: 75.87%
- 2. Sensitivity: 80.83%
- 3. Specificity 75.69%

Model Selection

To recall, our model with PCA generated these results:

Train set:

1. Accuracy: 86.01%

2. Sensitivity: 89.09%

3. Specificity 82.94%

Test set:

1. Accuracy: 82.84%

2. Sensitivity: 81.87%

3. Specificity 82.87%

Conclusion on model choice:

As we can see, based on performance on test set, the sensitivity of the PCA model is slightly better than model without PCA (81.87% vs. 80.83%).

Since sensitivity (recall) is our priority, we should choose Logistic Regression with PCA, as it captures more churn cases both in training and testing.

Top Features

These are the top features:

- 1. Number of recharges in August (total_rech_num_8)
- 2. Number of recharges in July (total_rech_num_7)
- 3. Difference in recharge count over months (difference_rech_num)
- 4. Total recharge amount in June (total_rech_amt_6)
- 5. Total recharge amount in July (total_rech_amt_7)
- 6. Local incoming call minutes in August (loc_ic_mou_8)
- 7. Local incoming calls to fixed lines in August (loc_ic_t2f_mou_8)
- 8. Monthly 3G usage in August (monthly_3G_8)
- Decrease in volume-based data charges (vbc_action_decrease)
- 10. Incoming calls from other operators in August (ic_others_8)
- 11. Outgoing calls to other operators in July (og_others_7)

Top Recommendations

Personalized Retention Offers: Customers reducing recharges may be churning. Offer them discounts or bonus data for continued engagement.

Recharge Consistency Plans: Encourage customers to maintain regular recharges by offering loyalty points or free add-ons.

Early Warning System: Flag customers whose recharge numbers are dropping sharply for proactive retention efforts.

High-Value Customer Retention: If high-spending customers are reducing recharge amounts, offer exclusive discounts or premium customer service.

Price Sensitivity Analysis: Test new pricing structures or promotions to prevent further decline in spending.

Call Usage Trends: Customers with decreasing incoming calls might be shifting to other networks. Offer better call quality or free incoming call packs.

Enterprise & Business Solutions: If business users are reducing calls to fixed lines, promote VoIP solutions or bundled corporate plans.

Data Upsell Campaigns: Encourage customers with declining 3G usage to switch to 4G with discounts or better plans.

Push Data Packs: If customers are moving away from pay-per-use data, upsell unlimited data packs.

Competitor Influence Check: If more calls are from other networks, competitors might be attracting customers. Counter this with competitive offers.

Inter-Operator Retention Strategy: Offer better call rates for cross-network calls to reduce churn risk.

Top 5 Business Actions

- 1. Develop a churn prevention model based on declining recharge frequency, recharge amount, and data usage patterns.
- 2. Launch proactive retention offers for customers showing early signs of churn.
- 3. Analyze competitor influence based on incoming/outgoing call trends to other operators.
- 4. Segment high-value customers (based on recharge amount) and provide personalized incentives.
- Encourage prepaid customers to switch to postpaid plans for better customer stickiness.



Thank You