Telecom Churn Case Study

Domain Case Study - BA

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PROBLEM STATEMENT

In the dynamic telecom landscape, characterized by intense competition and a substantial annual churn rate of 15-25%, retaining high-value customers has emerged as the foremost business objective for incumbent operators.

With the cost of customer acquisition significantly outweighing retention expenses, the focus has shifted towards predictive analytics to identify and mitigate churn risks effectively.

This project entails analyzing customer-level data from a prominent telecom firm to construct a machine learning model capable of accurately predicting churn. Leveraging advanced predictive modeling techniques, the goal is to develop a robust solution that empowers telecom companies to proactively retain valuable customers, thereby optimizing revenue streams and sustaining market competitiveness.

OVERALL OBJECTIVE TO ACHIEVE

- **Minimize Churn**: Significantly reduce the annual churn rate within the high-value customer segment, capitalizing on the disproportionate contribution of these customers to revenue.
- **Predictive Analytics Implementation**: Develop robust predictive models to identify customers at high risk of churn.
- **Customer Retention Enhancement**: Formulate and implement targeted customer retention strategies to proactively engage and retain high-value customers.
- **Cost Efficiency**: Ensure the cost of retention strategies is optimized, recognizing that it is substantially more cost-efficient to retain existing customers than to acquire new ones.
- **Data-Driven Decision Making**: Foster a culture of data-driven decision-making in customer retention strategies.
- **Operational Insight**: Gain deep operational insights into high-value customer behavior to inform future business strategies.
- **Actionable Intelligence**: Utilize predictive model insights to create actionable intelligence for frontline customer service teams.
- **Market Competitiveness**: Enhance the company's competitive edge in the Indian and Southeast Asian telecom markets through superior customer retention.

ANALYSIS APPROACH : A DATA-DRIVEN JOURNEY

The methodology revolves around developing a predictive model that anticipates high-value customer churn. This foresight enables us to proactively engage customers with tailored plans and incentives, thereby preempting their departure. Simultaneously, the model will uncover key churn predictors, offering us a window into the causative factors behind our customers' migration to competitors. This actionable intelligence is critical for crafting strategic measures that enhance customer loyalty and retention.

Data Preparation and Quality Assessment:

- Profiling high-value customers based on recharge amounts, using the 70th percentile as a threshold during the 'good' phase.
- Cleansing the dataset to ensure data integrity by removing duplicates and treating missing values.
- Encoding and standardizing categorical variables for analytical consistency.

Customer Behavior Analysis:

- Analyzing usage patterns over the four-month period to establish a baseline of normal customer activity.
- Identifying deviations from typical behavior in the 'action' phase indicative of potential churn risk.

Predictive Analytics:

- Deploying machine learning algorithms to model churn likelihood, with a focus on handling the imbalance in churn representation.
- Feature selection to pinpoint critical indicators of churn, employing models that offer interpretability such as decision trees or logistic regression.
- Validating model performance through metrics that account for the imbalance.

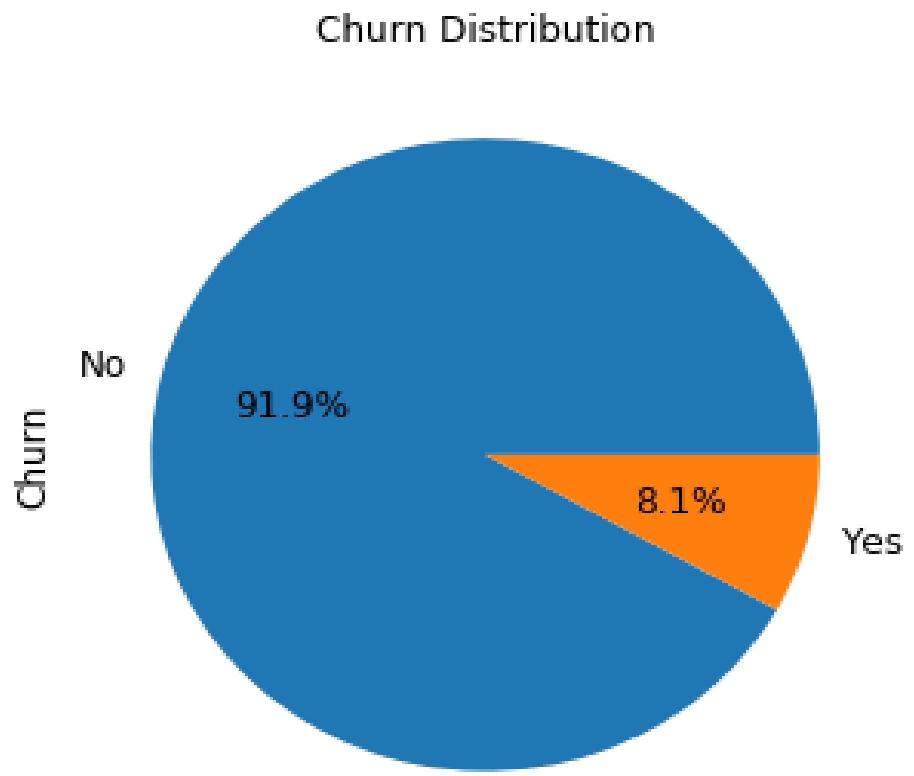
Churn Indicator Identification:

- Leveraging the models to identify key predictors of churn, including service usage decline, customer service interactions, and changes in recharge patterns.
- Utilizing techniques like recursive feature elimination and model coefficient analysis to solidify the selection of churn indicators..

Insights / Impact Analysis:

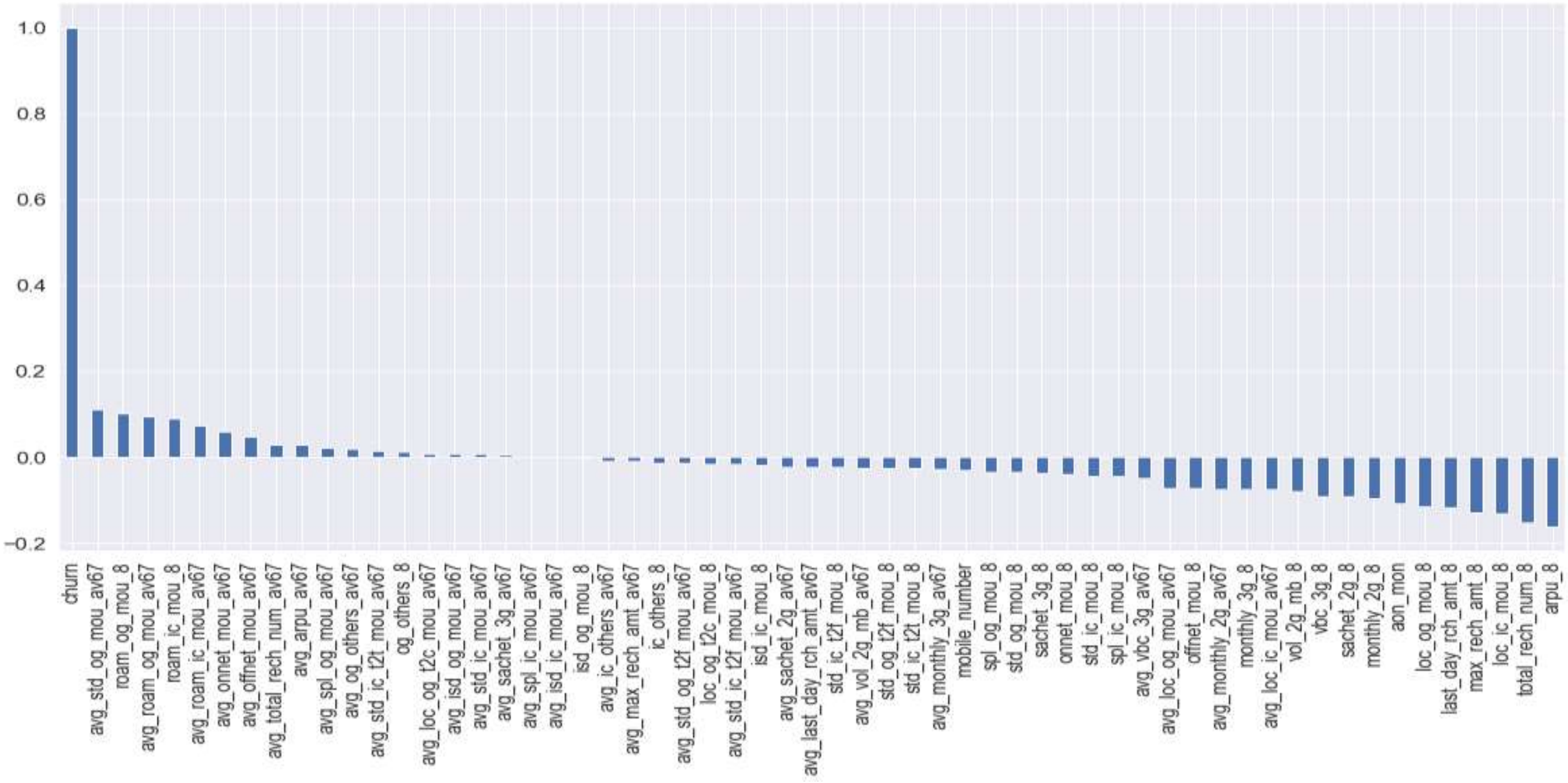
- Translating analytical findings into business insights, delineating clear patterns and trends that signal churn risk.
- Conducting scenario analysis to forecast potential churn under varying conditions and service usage behaviors.
- Developing a framework for deploying insights into operational systems, enabling real-time identification of at-risk customers.

KEY “Data-Driven” INSIGHTS

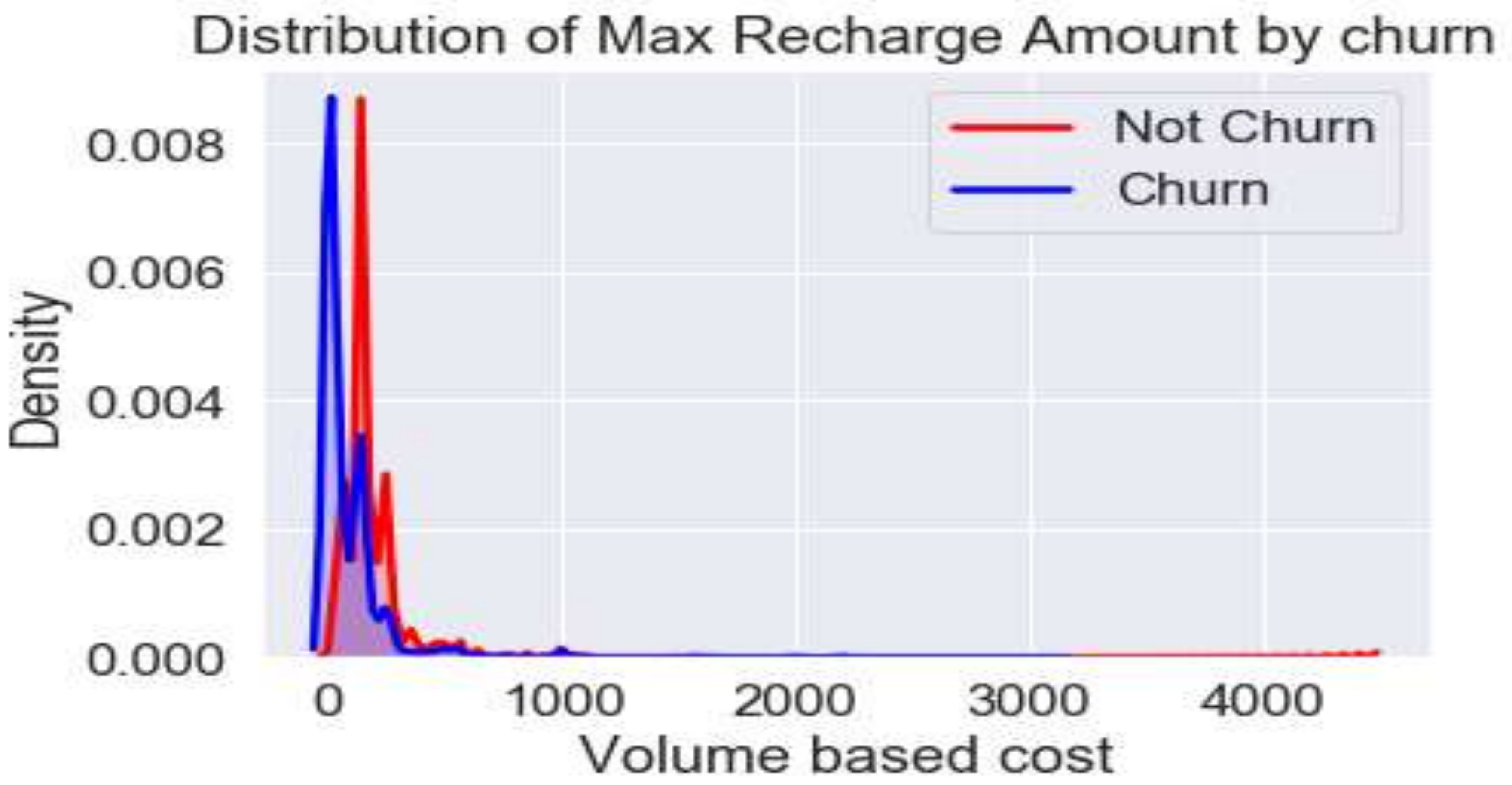


- In our data, 91% of the customers do not churn. Clearly the data is skewed as we would expect a large majority of the customers to not churn. This is important to keep in mind for our modelling as skeweness could lead to a lot of false negatives. We will see in the modelling section on how to avoid skewness in the data.

KEY “Data-Driven” INSIGHTS… *contd*



Avg STD Outgoing Calls for Month 6 & 7, Outgoing calls in Roaming seems to be positively correlated with Churn while Avg Revenue, No Of Recharge for 8th Month seems negatively correlated.



- People Who Recharge with less Amount are more likely to Churn

Random forest Observations

- From random forest algorithm, Local Incoming for Month 8, Average Revenue Per Customer for Month 8 and Max Recharge Amount for Month 8 are the most important predictor variables to predict churn.
- The results from random forest are very similar to that of the logistic regression and in line to what we had expected from our EDA

Summary : Telecom Churn

- Very Less Amount of High Value customers are churning which is a good service indicator
- Large no of Customers are new to Telecom Company and fall under < 5 Yr Tenure
- Std Outgoing Calls and Revenue Per Customer are strong indicators of Churn
- People with less than 4 Yrs of Tenure are more likely to Churn
- Behaviour of Volume Based Cost is not a strong indicator of Churn
- Max Recharge Amount could be a good Churn Indicator
- Random Forest is the best method to Predict Churn followed by SVM, other models too do a fair job
- Behaviour is 8 Month can be the base of Churn Analysis
- Local Incoming and Outgoing Calls for 8th Month and Average Revenue in 8th Month are strong indicators of Churn Behaviour

Actionable Recommendations

- **Incentivized Usage Program**: We should implement a strategic initiative to provide complimentary local voice call minutes during the 'action' phase to those customers identified by our Machine Learning Model I as potential churners. This will not only encourage continued utilization of our network's voice services but is also anticipated to contribute to a reduction in the churn rate.

- **Enhanced Value Proposition**: For customers exhibiting a decrease in Average Revenue Per User (ARPU) during the 'action' phase relative to the 'good' phase, it would be prudent to offer additional benefits. This targeted approach is designed to realign their perceived value of our services with the investment they make.

- **Data Usage Incentive**: In response to customers with diminished 2G data usage in the 'action' phase, providing complimentary data enhancements–subject to regulatory compliance–could prevent them from transitioning to alternative providers. This offering should not only encompass additional data but also an improved data speed, thereby enhancing their overall experience.

- **Recharge Validation Extension**: For those customers who have not undertaken any recharge activity during the 'action' phase, an extension of network validity along with complimentary talk time may be extended. This gesture is intended to sustain their connectivity and demonstrate our commitment to their satisfaction.

- **Communication Credits for At-Risk Customers**: Customers who show a significant reduction in Minutes of Usage (MOU) from the 'good' phase to the 'action' phase should be considered high-risk for churn. Proactively offering them select complimentary services could serve as a tangible incentive to remain within our network ecosystem.


THANK
YOU