DECODING DEPARTURES: A CLASSIFICATION JOURNEY INTO CUSTOMER CHURN

A MACHINE LEARNING PERSPECTIVE

Subhajyoti Maity

CONTENT

INTRODUCTION

Customer churn is a critical issue for telecom companies, as it can lead to significant revenue loss and damage to the company's reputation. ABC Voice, a telecom company that has been in operation since 1999, is no exception to this challenge. Customer churn can be defined as the rate at which customers stop using a company's services. For telecom companies, this typically means the number of customers who cancel their subscriptions or switch to another provider. There are many reasons like:

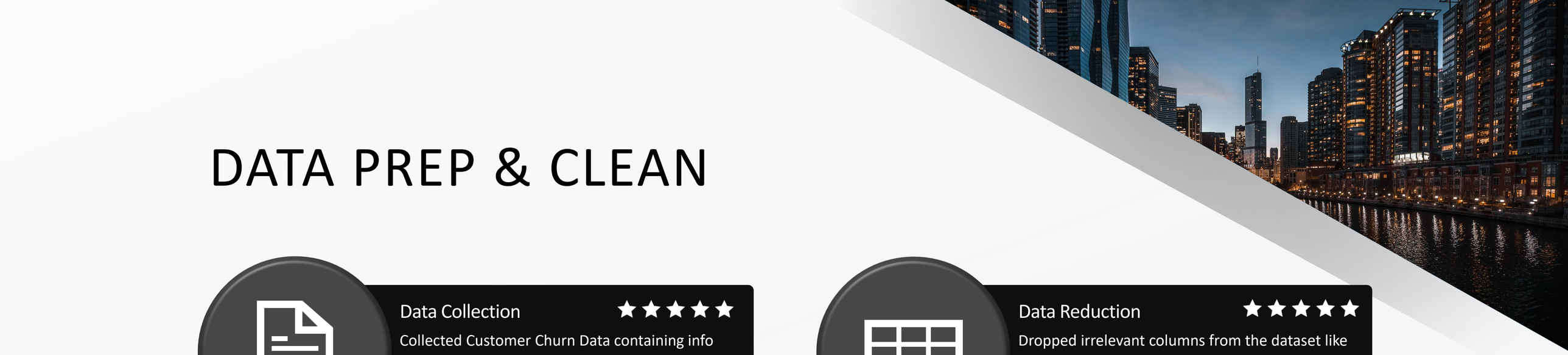
- Dissatisfaction with the service
- Better offers from competitors
- Life changes

PROBLEM STATEMENT

ABC Voice is facing a growing challenge in retaining its telecom customers. With increasing competition and changing customer preferences, the company is experiencing a high rate of customer churn. The objective of this project is to develop a predictive model that can accurately identify customers at risk of churning. By doing so, ABC Voice aims to proactively implement customer retention strategies and reduce churn rates, ultimately improving customer satisfaction and the company's profitability. This project will leverage machine learning techniques to analyze historical customer data and build a predictive model capable of identifying potential churners, enabling ABC Voice to take timely actions to retain these customers.

BENEFITS

- ENHANCED PROFITABILITY
- PROACTIVE CHURN MANAGEMENT
- COMPETITIVE ADVANTAGE
- ENHANCED SERVICE QUALITY



DATA PREP & CLEAN

Data Collection

Collected Customer Churn Data containing info on all 7,043 customers from a Telecom company (say, ABC Voice) in California in Quarter 2 of 2022

Data Reduction

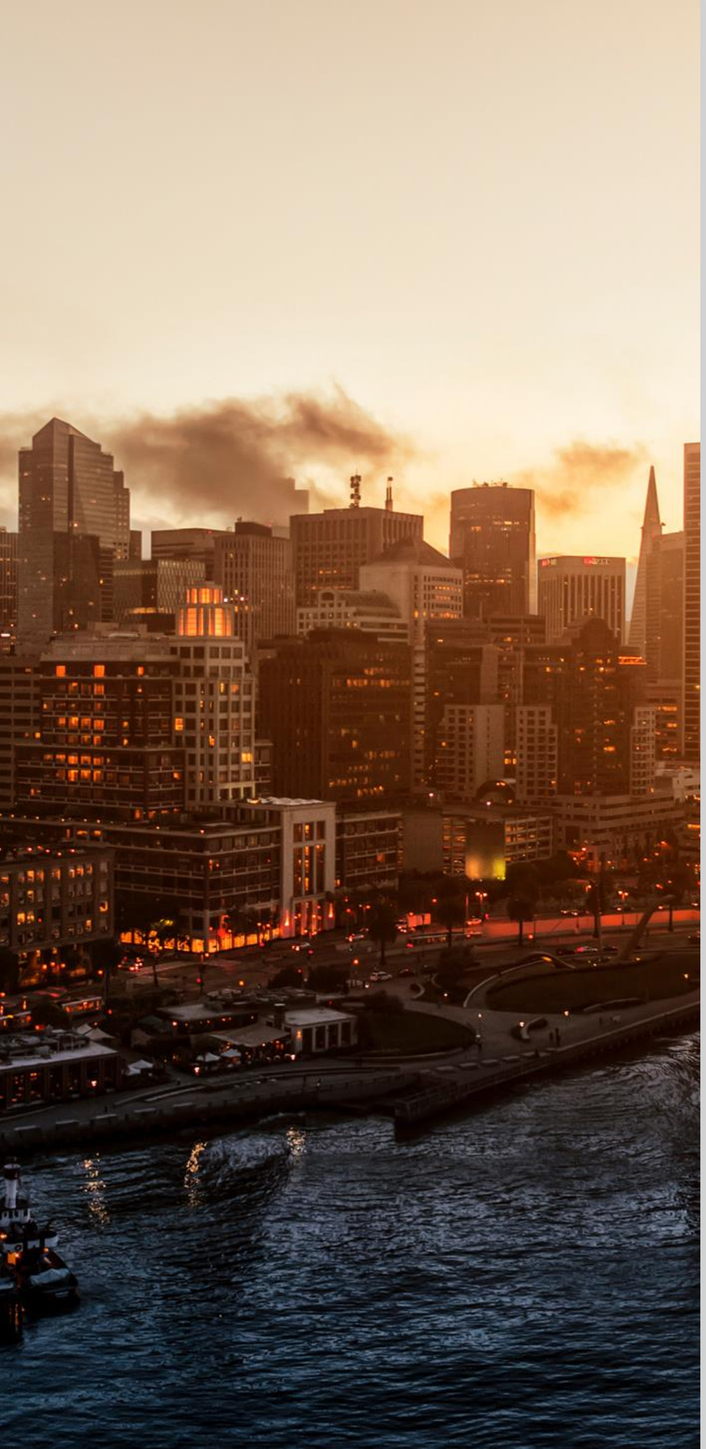
Dropped irrelevant columns from the dataset like Customer ID, Total Refunds, Zip Code, Latitude, Longitude, Churn Category & Churn Reason

Data Cleaning

Eliminated rows having Null Values for several columns. E.g., in 'Avg Monthly GB Download' column, 21.6% of the data instances contain NULL values

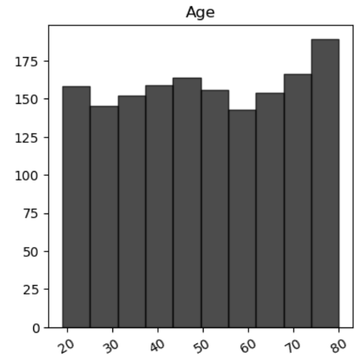
Data Categorization

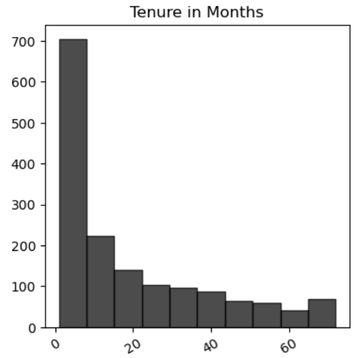
Categorized columns in Attributes, Discrete Variables & Continuous Variables for Analysis purpose

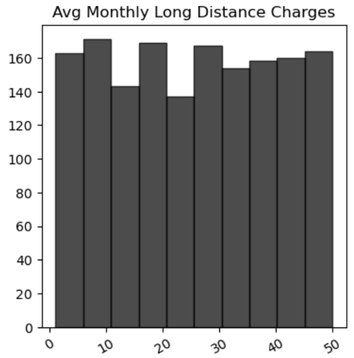


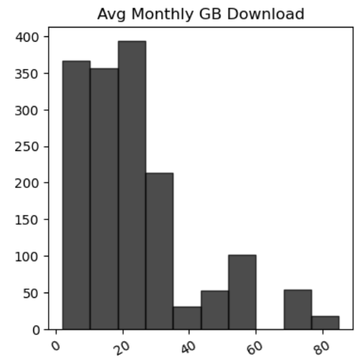
EXPLORATORY DATA ANALYSIS

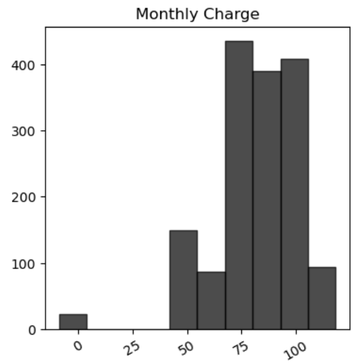
Exploratory Data Analysis (EDA) and data visualization provide a comprehensive understanding of the dataset by revealing hidden patterns and relationships. They aid in identifying factors contributing to customer churn and guide feature selection. Histograms and box plots for continuous variables highlight data differences between churned and non-churned customers. Bar plots for categorical variables offer insights into factors influencing churn, enabling targeted retention strategies. Additionally, data visualization simplifies complex information, facilitating data-driven decisions and improving customer satisfaction.

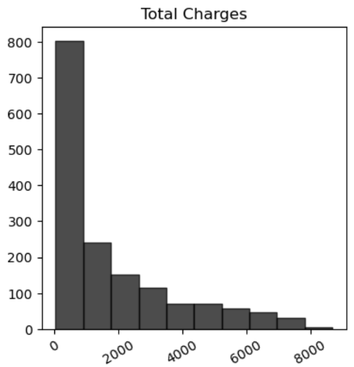


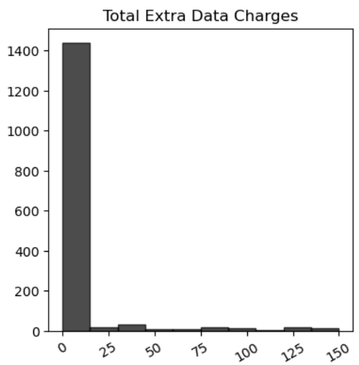


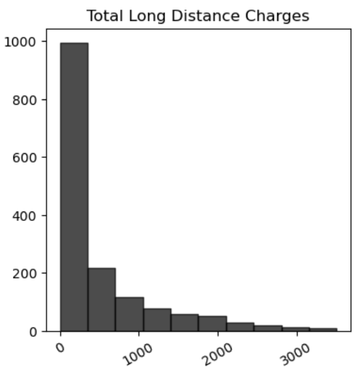


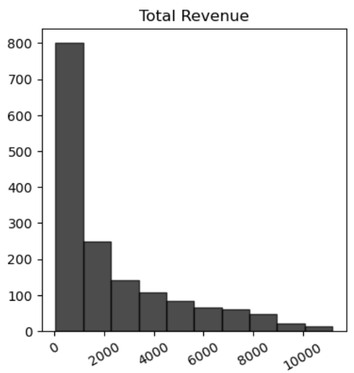










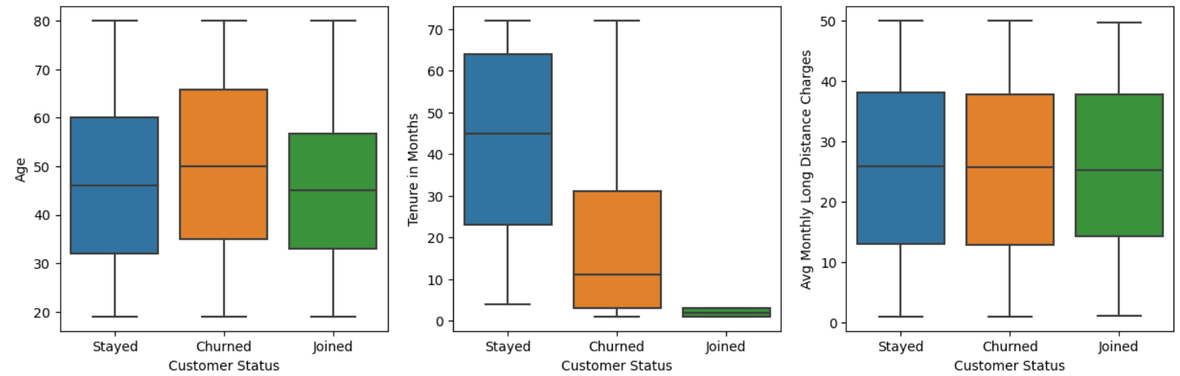


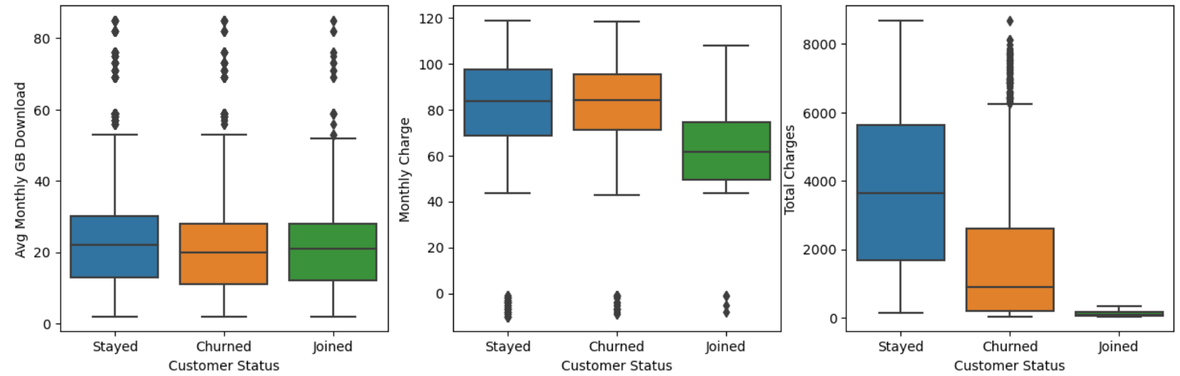
HISTOGRAM OF DISTRIBUTION OF CHURNED CUSTOMERS

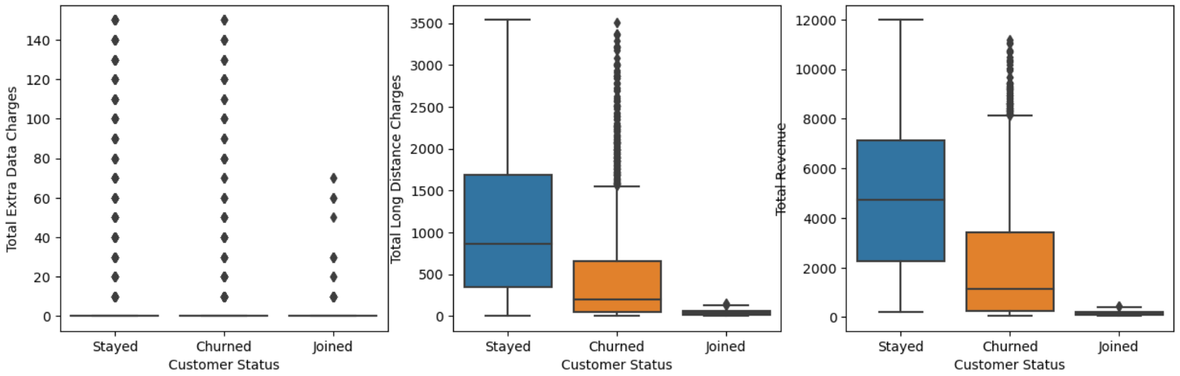
Customers in their late 80s & customers with shorter tenure have high churn; But different levels of avg monthly long distance charges has no effect on churn.

The customers with lower data usage, higher monthly charges & lower total charges have a higher churn rate.

The customers with lower extra data charges, lower long distance charges & lower revenue are more likely to churn





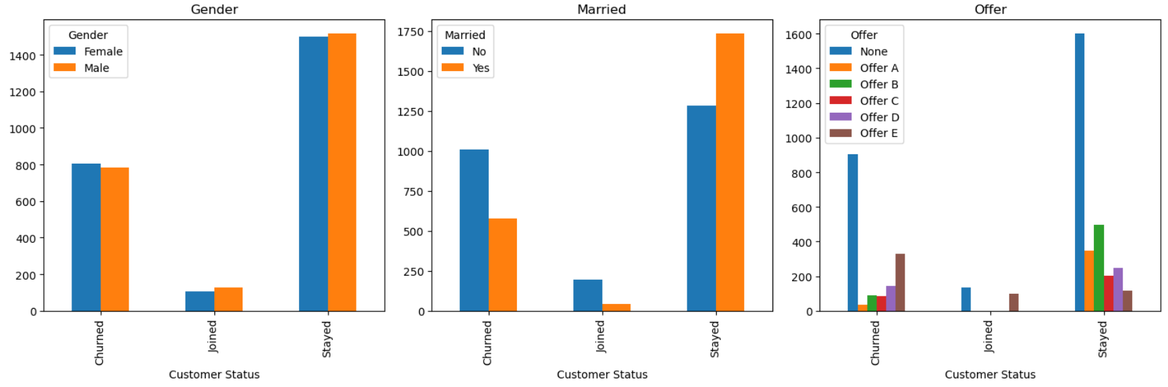


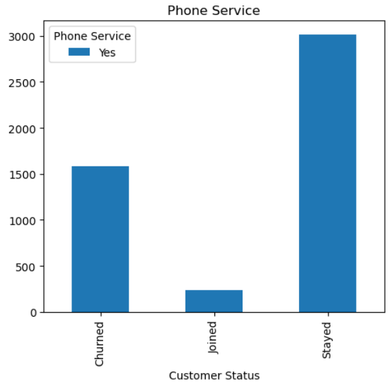
BOX PLOT OF CUSTOMER DISTRIBUTION

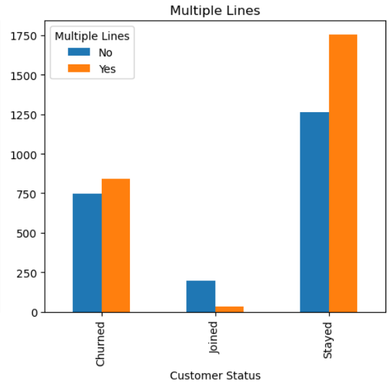
Joined customers are generally younger than others; the stayed ones have a longer tenure; But the distribution of average monthly long distance charges has no effect on churn

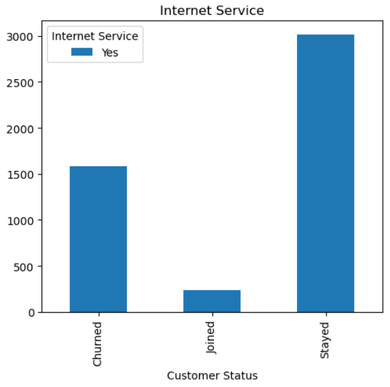
All types of customers have same data usage; joined customers have lower monthly charges; and for the churned customers, the overall total charges are less but some of them have unusual high charges.

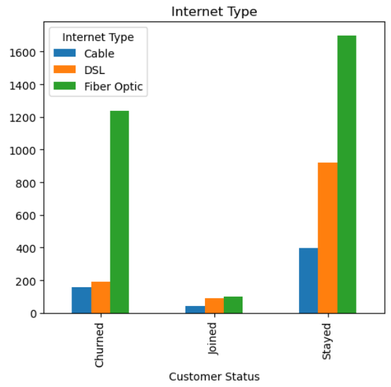
All customers tend to have unusual observations for extra data charges; many of the churned customers have unusually high long distance charges; and stayed customers generate higher revenue.









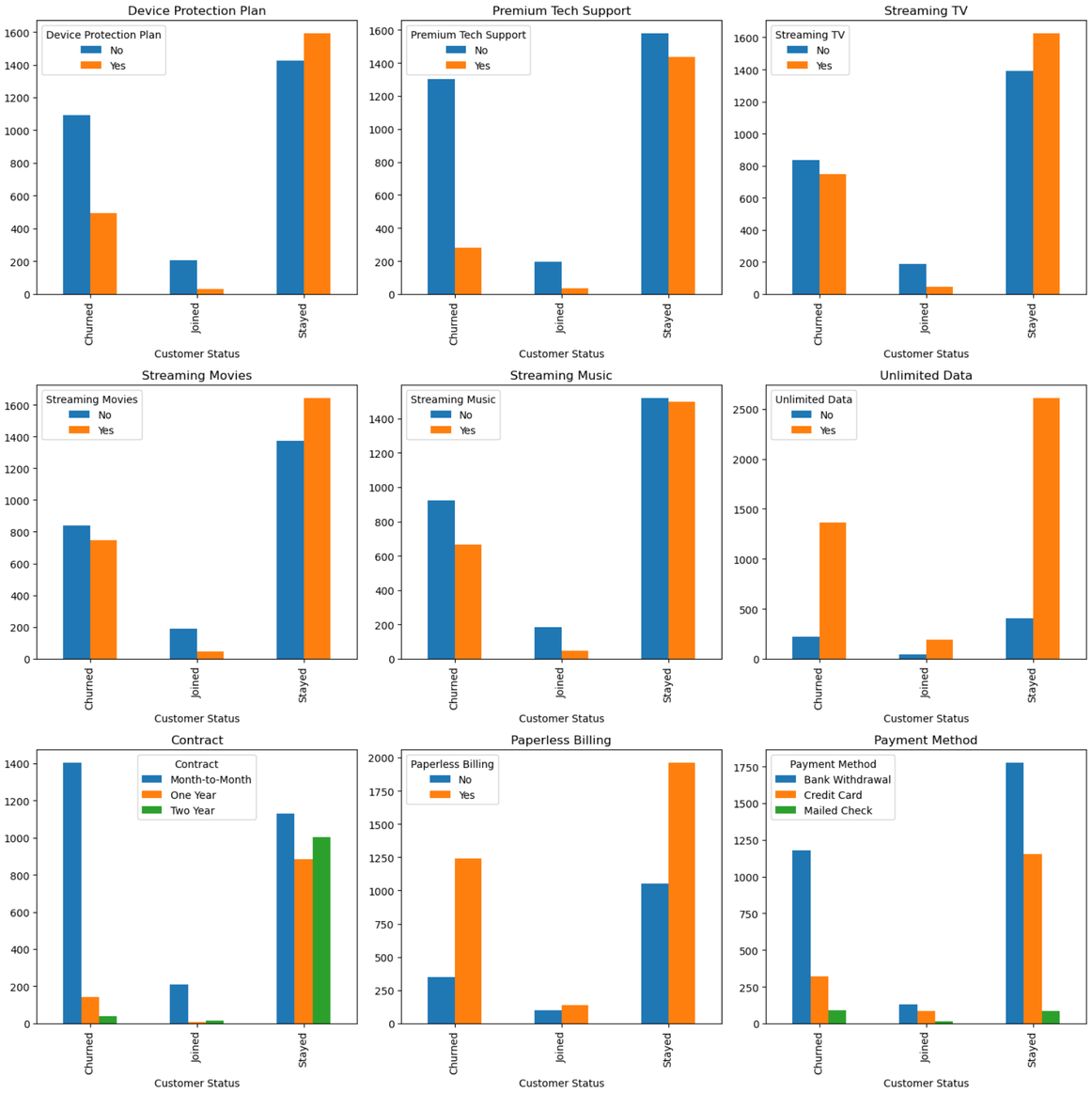


BAR PLOT OF CUSOMER DISTRIBUTION ON DIFFERENT ATTRIBUTES

Gender distribution for all are almost same; married customers are more likely to stay; and certain offers might be more associated with churned or joined customers.

All types of customers have same phone service & same internet service; but a single line have a higher join rate.

Certain statuses are more likely to churn or join; but customers not getting online security & online backup has high churn rate.



BAR PLOT OF CUSOMER DISTRIBUTION ON DIFFERENT ATTRIBUTES

Customers without a device protection plan and without premium tech support are more likely to churn

Customers who have streaming TV, Movies, Music & unlimited data are more likely to stay.

Customers with a yearly contract have less churn rate; paperless billings have no effects on churn rate; and customers using credit card & mailed cheques are rare to churn.

FEATURE ENGINEERING

Key steps include feature encoding for categorical variables, label encoding to convert labels to numerical format, dummy variable introduction for binary representation, feature scaling for magnitude uniformity and train-test splitting for model evaluation on unseen data.

Feature Encoding

Gender values, Paperless Billing, Unlimited Data Usage, Movies-Music- TV Streaming, Premium Tech Support, Device Protection Plan, Online Backup & Security, Multiple Lines, Marital Status are converted into numerical representations

Label Encoding

Customer statuses (Churned, Joined & Stayed) are encoded into numerical representations, (0,1,2) facilitating the incorporation of this information into machine learning models.

Dummy Introducing

Dummy variable is introduced for some columns like Payment Method, Contract, Internet Type, Offer & City

Feature Scaling

Dependents, age, referrals, tenure, monthly charges etc. columns are scaled by normalization

Data Splitting

80-20 Split for Train & Test

MODELLING

Naïve Bayes

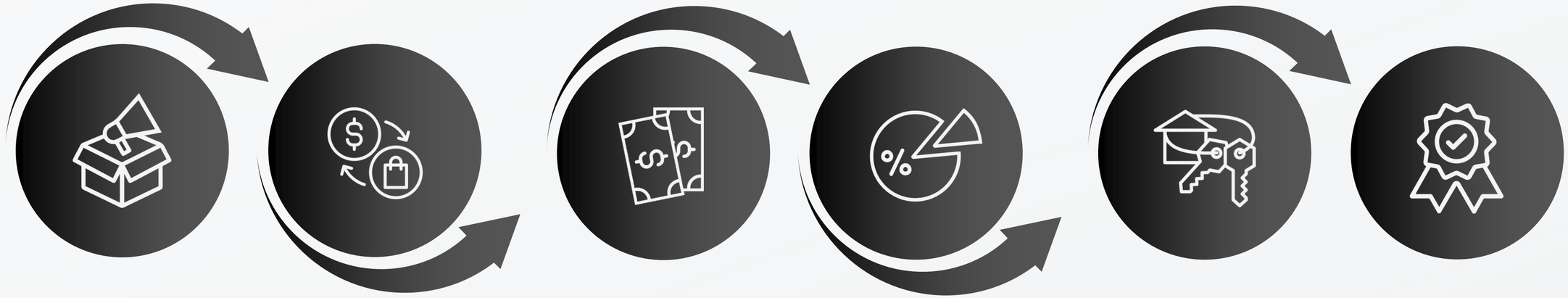
The Naive Bayes algorithm employs Bayes' theorem and assumes feature independence given the churn status. It calculates the probability of a customer churning based on observed features, considering the prior probability of churn and individual feature probabilities.

Random Forest

Random Forest for a three-class churn classification involves using an ensemble of decision trees to predict whether customers will Stay, Churn or Join. Features like usage patterns, complaints, and customer behavior are considered in the training process.

SVM

SVM for three-class churn classification uses "one-vs-one" or "one-vs-the-rest," creating binary classifiers for class pairs or treating each class individually. Trained on labeled data with features reflecting customer behavior, SVM seeks decision boundaries maximizing class separation.



Logistic Regression

Logistic regression is employed by assembling a dataset with numerically encoded labels and utilizing the 'multinomial' option for multiclass classification. The interpretability of logistic regression allows for understanding the impact of individual features on the likelihood of churn, as indicated by the model's coefficients.

Decision Tree

Decision Tree recursively splits the dataset based on features to create a tree-like structure. Each leaf node represents a class .Decision Tree, the algorithm recursively splits the dataset into Stayed, Churned or Joined based on features to create a tree-like structure. Each leaf node represents a class.

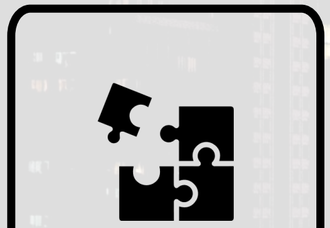
XGBoost

XGBoost is applied to a three-class churn classification by first preparing a dataset with relevant features and numerically encoding the class labels. The XGBoost algorithm, known for its ensemble of decision trees, is then employed to learn the patterns in the data.

CONFUSION MATRIX

Logistic Reg

244	4	100
18	13	19
73	0	496

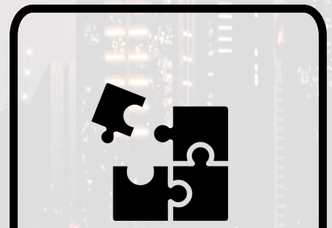


Naïve Bayes

169	92	87
18	15	17
359	64	146

Decision Tree

214	22	112
30	20	0
71	0	498



Random Forest

219	0	129
40	9	1
28	0	541

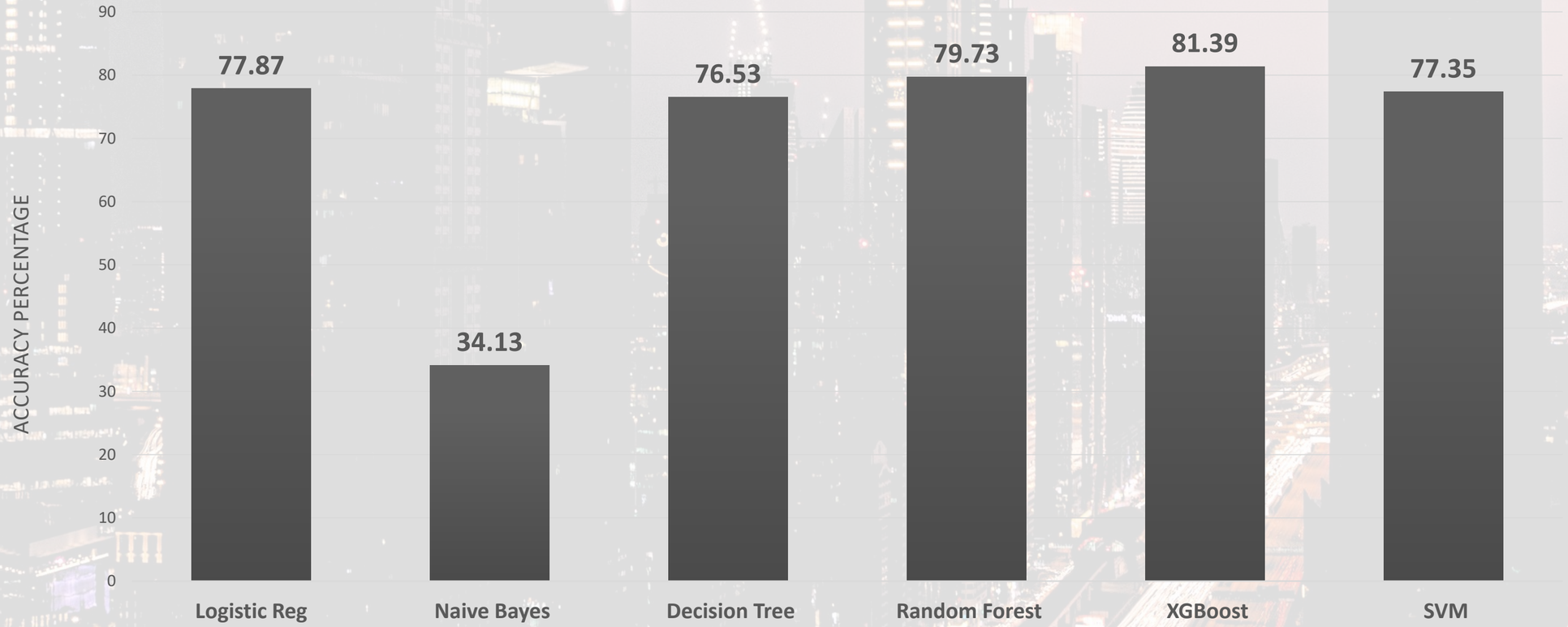
XGBoost

231	0	107
25	25	0
38	0	531

SVM

241	0	107
32	0	18
62	0	507

ACCURACY EVALUATION



CHALLENGES

Inaccuracies, missing values or outdated information can compromise the model's accuracy and reliability. Also, no real life data follows any particular distribution; so modelling on that dataset may violate model assumptions.

Selecting relevant features is crucial for accurate predictions. Understanding the business domain and identifying meaningful features can be highly challenging.

Striking the right balance to prevent overfitting or underfitting of models is challenging. Proper model tuning and regularization techniques are necessary to achieve optimal performance on unseen data.

Interpreting complex models for stakeholders can be challenging. In industries where decisions impact customer relationships, explaining predictions is crucial for gaining trust and acceptance.

FUTURE WORK

Future works involve refining feature engineering, optimizing model hyperparameters, exploring advanced techniques like ensemble methods & deep learning and fostering collaboration with business stakeholders for continuous model improvement aligned with strategic goals. Ethical considerations, bias assessment and user-friendly interfaces are also essential aspects to address in the evolving landscape of customer behavior prediction.

Handling Imbalanced Data

Implement techniques to address class imbalance in the dataset, especially if the occurrence of churn is significantly lower than retention.

Business Strategy Integration

Collaborate closely with business stakeholders to align the model's predictions with actionable strategies for customer retention and engagement.

Cost Benefit Analysis

Conduct a thorough cost-benefit analysis to understand the economic impact of implementing churn prevention strategies based on the model's predictions.

CONCLUSION

The work conclusively empowers businesses with actionable insights, derived from machine learning models, to strategically mitigate customer churn and foster sustained growth.

Actionable Insights

Business Impact

Empowering Decision-Making

RKMVERI