Prediction of Customer Attrition in the   
Telecom Industry using Machine Learning

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Mid-Thesis Report  
**Master of Science in Data Science**  
Liverpool John Moores University

MARCH 2021

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# DEDICATION

This dissertation is dedicated to my family, whose unyielding love, support and encouragement have inspired me to pursue and complete this research.

# ACKNOWLEDGEMENTS

I would like to acknowledge Liverpool John Moores University for the opportunity to learn and obtain a renowned degree.

I want to express my heartfelt gratitude to my thesis supervisor, Karthick Kaliannan Neelamohan, for his invaluable guidance. He has guided and encouraged me to be professional even when the going gets tough, and I am fortunate to have him as a mentor.

I would like to thank my committee members and mentors from Liverpool John Moores University for their patient advice and guidance through the research process.

Finally, I thank my family, who supported me with love and understanding. Without you, I could have never reached this current level of success. Thank you all for your unwavering support.

# ABSTRACT

With the advent of increasing competition in various market segments, companies must retain customers to maximise profits. Customer retention policies can affect the annual turnover drastically depending on the rate of churn. The cost of customer churn to the Telecom industry is about $10 billion per year globally. Studies show that customer acquisition cost is 5-10 times higher than the price of customer retention. Companies, on average, can lose 10-30% of their customer annually. Developing processes and efficient consumer-centric policies can help reduce spend on customer relations. For this, one would need to understand and track customer behaviour to understand the indicators that make a customer likely to churn.

Datasets for customer churn are large and is saved in large data warehouses where many features are present. Not all attributes are significant for churn predictions. Hence, feature engineering requires not only excessive computation but a substantial amount of time as well.

This research intends to find the model that can predict churn most accurately and the behaviour patterns that can indicate customer churn. The aim is to predict churn accurately and showcase the variation in performance of various algorithms. The dataset to be used for this research paper is the IBM Watson Dataset on customer churn in the Telecom industry.

***Keywords***: Machine Learning, Churn, Telecom, Attrition, Classification, Data Science

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

|  |  |
| --- | --- |
| EDA | Exploratory Data Analysis |
| SVM | Support Vector Machine |
| KNN | K Nearest Neighbour |
| AUC | Area under ROC Curve |
| ROC | Receiver Operating Characteristics |
| XGBoost | Extreme Gradient Boosting |
| GSA | Gravitational Search Algorithm |
| CRM | Customer Relationship Management |
| AdaBoost | Adaptive Boosting |

# CHAPTER 1: INTRODUCTION

With the increase in the number of options consumers have in the Digital Age, for a company to be successful, it is vital to keep costs low and profits high. One of the most effective ways to do this is to retain the existing customer base and focus the remaining budget on acquiring new customers.

## 1.1 Background of the Study

With the increase in the number of options consumers have in the Digital Age, for a company to be successful, it is vital to keep costs low and profits high. One of the most effective ways to do this is to retain the existing customer base and focus the remaining budget on acquiring new customers.

The retention of the existing customer base in a focused and systemic manner is to be done, or its bottom line can be affected. A targeted way to approach the end goal of customer retention is to flag customers that have a high probability of churn. Based on customer behaviour and attributes, if we can flag the customers that are likely to churn, we can run targeted campaigns to retain customers.

### 1.1.1 The need for Customer Churn Analysis

The ability to retain customers showcases the company's ability to run the business. With the digital age, where everything is online, any business needs to virtually understand customer behaviour and mentality. The cost of customer churn in the Telecom Industry is approximately $10 billion annually (Castanedo et al., 2014). Customer acquisition costs are higher than customer retention by 700%; if we were to increase customer retention rates by just 5%, profits could see an increase from 25% to even 95% (Hadden et al., 2006). For a company to be profitable, it is thus essential to take pre-emptive action to retain customers that may churn. Churn is defined as customers who stop using their specific services and plans for long periods.

In this post-pandemic age, where virtual presence via calls and the internet is the top priority, customers are trying to reduce their monthly expenditure month to month. Competitors are employing low prices or value-add services to get consumers to switch telecom operators. After acquiring a significant customer base, the companies monetise their customer base and profit in the long-term. The companies that identify the segment of customers that are likely to leave and run targeted campaigns to showcase more value in their current offerings at a minimal budget are the ones that will be successful in the long run.

### 1.1.2 Flagging customers and retention policies

As service providers contend for a customer's rights, customers are free to choose a service- provider from an ever-increasing set of corporations. This increase in competition has led customers to expect tailor-made products at a fraction of the price (Kuo et al., 2009). Churned customers move from one service provider to another (Ahmad et al., n.d.) (Andrews, 2019). Customer churn can be due to the non-satisfaction of current services, better offerings from other service providers, new industry trends and lifestyle changes. Companies use retention strategies (Jahromi et al., 2014) to maximise customer lifetime value by increasing the associated tenure. For telecom companies to reduce churn, it is vital to analyse and predict key performance indicators to identify high-risk customers, estimated time to attrite and likelihood to churn.

The learnings from multiple such experiments have been introduced as deployable machine learning algorithms that have been iterated and refined based on the evolving need to flag prone patrons more accurately. The choice of the techniques to utilise will depend on the model's performance on the selected dataset, be it meta-heuristic, data mining, machine learning or even deep-learning techniques. In the customer's behaviour patterns, there is likely to be a few significant indicators as to why the customer is willing to take the active step of moving across service providers. We shall identify the attributes that can indicate if a customer is likely to churn in our methodology through this research.

## 1.2 Problem Statement

The reduction of attrition of customers from a company is vital to a company's bottom line. To be able to maintain a respectable market share in the competitive telecom industry, it is essential to understand and tackle the root cause as to why a customer might shift their service provider. This research will help telecom companies leverage their existing consumer database to predict and actively target campaigns to customers likely to churn. The machine learning methodology employed can be personalised to the use-case based on the operator. When a suitable set of machine learning algorithms run on a newer dataset, we can monitor the model's evaluation metrics, and high-risk customers can be appropriately targeted.

The recommended model's primary users will be telecom conglomerates that wish to reduce customer attrition and improve their profitability in the market. We will be able to predict customers that will churn accurately. This needs to be done, keeping in mind overhead costs. The set cadence and the hardware resources used for the same will be optimised to keep overhead costs nominal.

## 1.3 Aim and Objectives

The paper aims to develop a trustworthy and interpretable model that will predict the customers that will churn from a Telecom Company based on historical customer telecom data. The identification of the customers that churn will aid telecom companies in significantly reducing expenditure on customer relations.

The objectives of the research are based on the above aim and are as follows:

* To analyse the relationship and visualise patterns of customer behaviour to indicate to the telecom company if a customer is going to churn
* To suggest suitable feature engineering steps to extract the most value from the data, including picking the most significant features
* To find appropriate balancing techniques to enhance the model performance on the dataset
* To compare the classification or predictive models to identify the most accurate model to determine the customers that will churn
* To understand the factors and behaviour of consumers that leads to customer attrition in the telecom industry
* To evaluate the performance of the models to identify the appropriate models

## 1.4 Research Questions

The following research questions have been formulated based on the literature review done so far in the field of customer churn:

* Is there a clear conclusion regarding the best overall modelling approach, be it classical machine learning or more complicated algorithms?
* Does the presence of multicollinearity, outliers, or missing values in the training data impact customer churn prediction accuracy?
* Do techniques such as hyperparameter tuning result in significantly better models?
* Can we suggest balancing techniques for increasing the accuracy of the model?
* Can we trust the results obtained from interpretable models?
* Do statistically significant features mean that the business can take actionable insights directly?

## 1.5 Scope of the Study

Due to the limitation of the time frame in this research, the scope of the study will be limited to the below points:

* The data for the study has directly been obtained from the authorised source, and data validation will not be part of this research
* The research will include the development and evaluation of various machine learning algorithms. The latest algorithms such as Neural Networks and Deep learning will not be considered as a part of this study due to a lack of resources and time
* The study will limit the use of classification algorithms such as logistic regression, decision tree, K-nearest Neighbour as a part of interpretable models, whereas random forest, support vector machine, gradient boosting, and XGBoost will be leveraged as black-box models for this study
* We will focus on interpretable models. If time permits, we will attempt to use other models to perform customer attrition analysis

## 1.6 Significance of the Study (Add on here)

The research contributes to explain and interpret various predictive models to support decision-making and increase the company's bottom line by flagging customers that are going to churn. This will help the telecom company allocate the optimal budget and effort directed at customers that are likely to churn by running targeted campaigns. The sales team will be able to offer value add-ons to high-risk and high-value customers. This can help the company recognise its customers' pain points and ultimately help in fundamental policy changes that can increase the overall profit.

## 1.7 Structure of Study

The structure of the study is as follows. Chapter 1 discusses the background of the Customer Churn Analysis in the Telecom Industry. The study's aim and objectives, along with the research questions, are discussed in Section 1.3 and Section 1.4. The study's significance to the Telecom Industry is discussed in Section 1.6, along with the contribution to the identification of churn as a driver for business growth.

Chapter 2 has been structured to state the telecom industry's theoretical understanding and highlights the work carried out to identify customer attrition. Analytics and visualisation play a pivotal role in performing predictive modelling on telecom data; this has been highlighted in Section 2.4 to understand how machine learning is being used to identify customers at a high risk of attrition. Feature engineering and visualisation techniques for exploratory data analysis have also been discussed in Section 2.5, followed by a detailed review of related Customer Churn and Telecom research papers in Section 2.6. Discussion on the literature survey carried out is done in Section 2.7, along with the summary of the work carried out in Chapter 2 is done in Section 2.8 to conclude.

Components of Chapter 3 discusses the research methodology and the proposed research framework for the dissertation. The study's framework is described under research design to present the approach for the proposed model through the steps of data selection, data pre-processing, data transformation, data visualisation, class balancing, model building, model evaluation and model deployment in the subsequent sub-sections under Section 3.2. Section 3.3 explains the proposed model to be employed based on the experiments carried out. Finally, the classification model to evaluate the customers at a high risk of churn in the telecom industry, along with the evaluation methods and next steps, is discussed in Section 3.4, the summary.

# CHAPTER 2: LITERATURE REVIEW

A thorough survey of the research and work done in the field of customer attrition, especially those involved in the space of the telecom industry will help us understand the advantages and disadvantages of a plethora of techniques. Through this literature review, we will set a baseline to understand the expected standard to implement a robust classification model to predict customers at a high risk of churn in the telecom industry. The approaches leveraged by the authors range from using algorithms such as ANN, SVM etc., using efficient pre-processing and feature engineering and some even included social (Oskarsdottir et al., 2016). Through this survey, we will also be able to understand the methods that other authors have used to solve traditional churn problems (Umayaparvathi and Iyakutti, 2016).

## 2.1 Introduction

In this chapter, we will provide a review of how data analytics is used in the telecom industry to identify customers that are at a high risk of attrition and the data driven processes followed to set the baseline of the techniques that have been carried out in the industry so far. In Section 2.2, we will review data driven techniques, how to implement them and the effect they can have on the customer base. Through Section 2.3 and Section 2.4, we will focus on feature engineering for the data and how we can handle class imbalance. Efficiently carrying out data preprocessing will help us obtain better results in the next stages of implementing machine learning and validation via k-fold cross validation in Section 2.5 and Section 2.6. Through the literature review, we will also understand the evaluation methods used to assess the performance of the models. In Section 2.7, we will review evaluation metrics that are used for classification. Finally, we will conclude the article by discussing our learning from the related research in Section 2.9 and summarize our learnings in Section 2.10. The algorithms and methods as implemented by the researchers has also been detailed out for reference.

## 2.2 Data Analytics in the Telecom Industry

The telecom industry is the backbone of a nation. To have a higher stake in the Industrial Revolution 4.0, telecom operators need to focus on improving their CRM infrastructure to move from an internal support system to a strong value proposition for customers and other stakeholders (Li and Li, 2018). Attracting new customers may seem like a feasible way to grow market share, but the real growth and value drivers lie within the system; gaining new customers is 5 to 10 times more expensive than focusing on keeping existing customers loyal (Ebrah and Elnasir, 2019). Everyone is talking about data science changing the way industries work. Implementation is key here, with a variety of options of options that focus on the explainability and usage of models rather than a black box approach.

Tools such as RapidMiner that can leverage expalinable models that can be understood by senior management can be a good starting point (Halibas et al., 2019) for proof of conecpt implementations. Developing an in-house custom analytics solution seems to be the long-term aim with most companies requiring a custom setup for churn analysis on account of different datasets, technology stacks, databases and overall requirements. Understanding the requirement for the cadence of forcasting based on the model selected is also an important area of research to move from a batch-processing system to a more real-time system (Tamuka and Sibanda, 2021) depending on complexity of requirements and budget.

## 2.3 Feature Engineering for Telecom Datasets

Feature engineering is a critical step in the data science flow. Here, we analyze the existing techniques implemented by authors to be able to either pick the significant features from the dataset that can affect churn or generate new features from the existing set of attributes that can help us predict churn better. Another important task when we perform feature engineering on a dataset is to identify the attributes that have the highest impact on the target variable. This can be done leveraging rigorous algorithms or even tools such as RapidMiner and Azure ML Studio (Thontirawong and Chinchanachokchai, 2021).

The fusion of multilayer features using a framework of complementary fusion by employing feature construction and feature factiorization to improve the accuracy for churn prediction. This approach resolved the problem of high dimensionality and imbalance of data. Feature selection was also attempted and this led to the reappearence of imbalanced data (Ahmed and Linen, 2017).

Novel methods of engineering the data was also used in the research where tokenization was used for categorical attributes and standardization was used to standardize numerical attributes (Momin et al., 2020). Novel methods for feature selection such as gravitational search algorithm (Lalwani et al., 2017) have also been used. GSA helps reduce the dimensionality of the data and in turn, helps improve the accuracy of the data by optimizing the search for significant features (Lalwani et al., 2021).

Methods for data pre-processing tasks such as missiving value imputation have developed well over the last few years. A method used to explore and perform multiple missing value imputations to fill up quantitative variables that suffer from an uneven distribution is Predictive Mean Matching (Mahdi et al., 2020). While some methods used are agnostic to the type of the data, certain mathods assess the uneven distribution of numeric variables by using a logarithmic transformation (Tamuka and Sibanda, 2021). Categorical variables used in telecom datasets are also converted to numeric variables using techniques such as label encoding or one-hot encoding (Agrawal, 2018).

Feature selection is done using attribute scoring methods such as random forest, xgboost and advanced regression, based on which the less significant values are discarded and the effect on the accuracy of churn prediction is observed. Techniques that leverage the correlation with the target variable are also used; the correlation matrix operator (Halibas et al., 2019) is used to perform feature selection and less significant features were discarded.

## 2.4 Handling Class Imbalance in Machine Learning

Class imbalance in the dataset exists as we go through

## 2.5 Supervised Machine Learning

## 2.6 K-Fold Cross Validation

## 2.7 Review of Evaluation Metrics for Classification

## 2.8 Related Research on Customer Churn Prediction

|  |  |  |  |
| --- | --- | --- | --- |
| Authors | Year | Feature Engineering | Model |
| (Tamuka and Sibanda, 2021) | 2021 | Feature Importance, Logarithmic Transformation | Accuracy:  Logistic Regression - 97.8% Decision Tree - 78.3% Random Forest - 79.2%  F1 Measure:  Logistic Regression - 97.8 Decision Tree - 77.9 Random Forest - 77.8 |
| (Lalwani et al., 2021) | 2021 | Phase 1:  Variance Analysis,  Correlation Matrix,  Outliers Removed Phase 2:  Cleaning & Filtering Phase 3:  Feature Selection using Gravitational Search Algorithm  Feature Importance | AUC: Logistic regression - 0.82, Logistic Regression (AdaBoost) - 0.78, Decision Tree - 0.83,  Adaboost classifier - 0.84,  Adaboost Classifier (Extra Tree) - 0.72  KNN classifier - 0.80,  Random Forest - 0.82, Random Forest (AdaBoost) - 0.82,  Naive Bayes (Gaussian) - 0.80,  SVM Classifier Linear - 0.79, SVM Classifier Poly - 0.80, SVM (Adaboost) - 0.80, XGBoost - 0.84, CatBoost - 0.82 |
| (Momin et al., 2020) | 2020 | Tokenization,  Standardization | Accuracy: Logistic Regression - 78.87% Naïve Bayes - 76.45% Random Forest - 77.87% Decision Trees - 73.05% K-Nearest Neighbor - 79.86% Artificial Neural Network - 82.83% |
| (Oka and Arifin, 2020) | 2020 | Label Encoding Binary Columns, Scaling Numerical Columns,   Feature Importance result: Contract month-to-month, tenure,  Internet Service Fiber Optic | Accuracy: Random Forest - 77.87%,  XGBoost - 76.45%,  Deep Neural Network - 80.62%  AUC: Random Forest 0.83,  XGBoost 0.84,  Deep Neural Network - 0.84 |
| (Mahdi et al., 2020) | 2020 | PMM - Predictive Mean Matching | Accuracy: PPForest with LDA - 72% PPForest with SVM - 75%  AUC: PPForest with LDA - 0.67 PPForest with SVM - 0.73 |
| (Ebrah and Elnasir, 2019) | 2019 | K-Cross Validation with hold-out (30%) method (k=10) | Accuracy: Naïve Bayes - 76% SVM - 80% Decision Tree - 76.3%  AUC: Naïve Bayes - 0.82 SVM - 0.83 Decision Trees - 0.76 |
| (Havrylovych and Nataliia Kuznietsova, 2019) | 2019 |  | Semiparametric Cox Proportional Model, Parametric Weibull, Log-normal survival model  Best model: log-normal model |
| (Halibas et al., 2019) | 2019 | Feature Selection using  Correlation Matrix Operator  Total Charges is discarded  RapidMiner is used to perform feature selection: Contract, Online Security,  Tech Support, Tenure &  Device Protection | AUC: Gradient Boosted Trees  (*before oversampling*) - 0.834 Gradient Boosted Trees  (*after oversampling*) - 0.865 Generalized Linear Model - 0.841 Logistic Regression - 0.841 |
| (Kriti, 2019) | 2019 | Feature Selection using XGBoost | AUC: XGBoost - 0.85 Random forest - 0.84 Decision Tree - 0.81  SHAP, LIME is used for Local interpretable model agnostic explanations |
| (Hargreaves, 2019) | 2019 | Top 5 Significant features using Feature Selection: Fiber Optic,  Month To Month Contract, DSL, One Year Contract, Streaming Movies | Logistic Regression: Accuracy - 76.7% AUC - 0.767 |
| (Pamina et al., 2019) | 2019 | Feature Selection -  XGBoost Classifier | Accuracy: K-Nearest Neighbour - 0.754 Random Forest - 0.775  XGBoost - 0.798 |
| (Induja and Eswaramurthy, 2015) | 2019 | Feature Selection: total charges, monthly contract and fiber optic Internet service, senior citizen | AUC: Random Forest *with RFE* - 0.96  ANN *with RFE* - 0.77 |
| (Agrawal, 2018) | 2018 | One Hot Encoding | Accuracy: ANN - 80.03% |

## 2.9 Discussion

## 2.10 Summary

# CHAPTER 3: RESEARCH METHODOLOGY

## 3.1 Introduction

Write something here

### 3.1.1 Business Understanding

The telecom industry is a highly competitive industry where customers can choose to move across operators if they believe they are getting more value with another service provider. We also noted that based on the customer's behaviour patterns, we would have indicators to report if a customer might churn or not. Since the cost of retention is much higher than customer acquisition, it is vital to the company's survival to identify the customers likely to churn and run targeted campaigns to retain the existing customer base. It was also observed that a reduction of customer attrition of 5% could lead to profit margins increasing from 25% to 95% (Hadden et al., 2006). In the telecom industry, where the approximated annual cost of customer attrition is $ 10 billion annually (Castanedo et al., 2014), and 30% of customers churn on average, there is a substantial need to perform active targeting to retain the customer base.

### 3.1.2 Data Understanding

There are various data sources used to predict customer churn in the telecom industry through the literature survey. This research shall be using the IBM Watson Telecom churn data found on the Kaggle website derived from the IBM Cognos Analytics Community (Cognos Analytics - IBM Business Analytics Community, 2021). The telecom churn data consists of 7043 rows and 21 attributes at a customer-id level. The data combines numerical and categorical variables that can be used as feature variables to predict the target variable churn. Churn is indicated within the dataset as a "Yes" or a "No", indicating if a customer has churned or not churned respectively. This data presented is for the last month based on which predictions are to be made.

The information obtained from the data can be broken down into four broad categories and is as follows (Ebrah and Elnasir, 2019):

* Services that the customer may be using such as streaming movies and tv, technical support, device protection, online backup and service, broadband services
* Account Information of the customer such as customer tenure, total costing, monthly charges, paperless billing, payment method
* Demographic information such as age, gender, information about dependents and partners
* The given data consists of multiple factors about the customers regarding lifestyle, behaviour in a Yes or No format that can be leveraged post-processing. It is presented in a .csv format with customer attributes information as metadata

Each row in the telecom churn represents customer attributes used to describe the customer's behaviour. The data is unique at a Customer ID level with a high cardinality of 7043. We also note that the Total Charges column is uniquely distributed. There is an equal 50-50 distribution of male and female customers. As one would expect in the Churn column, there is an imbalance, with 27% of customers churning and 73% retention. This dataset has been collected over a month with a Kaggle Usability Score of 8.8 based on the provided metadata and various other factors, as mentioned in the website (Kaggle, 2018).

Let us understand the descriptive dataset statistics in detail. Here, we will analyse and understand the dataset better by deep driving into the statistics of each column:

* Customer ID: Unique Customer Id assigned to each customer (7043 unique values)
* Gender: Indicative of whether a customer is male or female
* Senior Citizen: Binary of whether the customer is a senior citizen or not
* Partner: Information on whether the customer has a partner or not
* Dependents: Indicative of whether the customer has dependents or not
* Tenure: Number of months the customer has stayed with the company
* Phone Service: Indicative of whether the customer uses the phone service or not
* Multiple Lines: Whether the customer has multiple lines or not
* Internet Service: Information regarding the internet service provider (DSL, Fiber optic, No)
* Online Security: Whether the customer has online security or not
* Online Backup: Whether the customer has opted in for Online Backup
* Device Protection: Whether the customer has open in for Device Protection Plan
* Technical Support: Whether the customer has requested Technical Support
* Streaming TV: Whether the customer has opted in for TV Streaming services
* Streaming Movies: Whether the customer has opted in for Streaming Movies services
* Contract: Whether the customer has opted for a monthly, annual or two-year plan
* Paperless Billing: Whether the customer has opted in for paperless billing
* Payment Method: Method of payment of the customer: Electronic check, Mailed check, Bank Transfer or Credit Card
* Monthly Charges: Monthly Charges of the customer
* Total Charges: The total charges of the customer
* Churn: Whether the customer has churned or not

From the above description, we have now understood the descriptive statistics of the IBM Telecom Churn dataset that is going to be used in this study. We have 18 features that are categorical, two integer features and one feature of type float. The dataset has 7043 rows and 21 columns that describe customer behaviour. The dataset is taken over one month and will be used for analysis and predictive modelling in this study.

## 3.2 Research Methodology

### 3.2.1 Data Selection

### 3.2.2 Data Pre-Processing

Now that we have selected the dataset, we would like to proceed within this domain. We shall now discuss the Data Pre-processing steps we will be implementing to ensure that the data is standardised as we use it in our next steps. We will perform a sense check of the telecom churn dataset to understand if the import of the data and the dataset's encoding are per expectations. Once we view the data types of the features, we will check on the shape of the data to ensure the number of rows and columns is consistent per expectations. We will then focus on the columns that have at least one missing value. Once we understand the attributes to consider, we will understand the percentage of missing values column-wise. This will help us to decide the strategies to take for the next steps. Post missing value analysis, we will determine if we can proceed with all the columns to the next step if we must drop columns based on absent value percentage or employ methods such as mean imputation, mode imputation, deletion of rows and iterative imputation.

Looking at the percentage of missing values for each attribute after the missing-value analysis will help us understand the base dataset that we will be using when we go to the next step of feature engineering.

We will also perform outlier analysis and understand the skewness of the data to understand the feature's impact on customer churn. After understanding each features' distribution, we will proceed to perform a univariate analysis. This will help us understand and map out the inherent properties and distributions of each attribute. The bivariate analysis will then be performed on the data, ultimately followed by multivariate analysis to understand the features' direct and latent impact on the customer churn's target variable.

### 3.2.3 Data Transformation (Feature Engineering)

Based on the cleaned dataset, we will now decide the following steps to extract the most value from the dataset. We can perform steps such as one-hot encoding on the categorical features. Besides this, we shall also derive features from the existing dataset and feature engineer newer attributes. Based on the understanding of telecom's business, we will also apply business rules that make sense to the business and derive new features. Performing efficient feature engineering will save us the hassle of running complicated models to get an accurate prediction. This will make the machine learning pipeline easier to deploy, thus reducing the business expenditure on hardware.

Data visualisation here will play a crucial part here to be able to draw insights that might help to be able to derive more from the data. We will use advanced Exploratory Data Analysis packages such as pandas profiling, Sweetviz and data prep to perform visualisation of the data; this will give us a complete overview of the data. Mapping out and understanding the relationship of each numerical and categorical variable with churn will help us start identifying the attributes that might have a direct or latent impact on customer churn. We shall perform multicollinearity and variance inflation factor tests to understand the data's inherent properties to understand the significant features to select for modelling. We will also look at the correlation scores for the numerical variables to identify the features with a high positive or negative correlation with the target variable. We will also perform a categorical analysis of type object variables to deep-drive into implicit and latent connections within the data.

### 3.2.4 Data Visualization

### 3.2.5 Class Balancing

### 3.2.6 Model Building

Model Building is one of the more crucial components of this study. The following steps will help us identify the right set of models and appropriate techniques we can leverage to get optimal results. We shall now choose the models we would implement after the data cleaning, feature engineering, and data formatting steps.

#### 3.2.6.1 Model Selection Techniques

We shall now select the models we will be working with to predict customer churn efficiently and accurately for the model selection. From the literature review, it has been observed that the supervised classifier models have given us good results. We shall use logistic regression, decision trees, Naïve Bayes, random forest, support vector machine and understand how the algorithms perform. Post analysis of the individual algorithms, we shall also attempt ensemble models with boosting, such as XGBoost and Light GBM.

#### 3.2.6.2 Test Designing

Another vital step to model building is to decide the train and test split strategically. If there were a larger dataset, we could have opted to go for a validation dataset as well. We will go for an 80-20 train-test split for the models. For the top-performing models with this design, we shall also attempt a 90-10 split, as this was recommended in the literature review for a few research papers. This aspect of model building is also vital as having the right split will result in better results when cross-validation is carried out in the model validation phase for the models that are performing well.

#### 3.2.6.3 Model Iterations

After the above model building steps, as mentioned earlier, are performed, we shall perform more iterations, correspondingly assessing model performance with each iteration. This can include monitoring p-values, the number of features, model performance, variance inflation factor scores which would differ across models. The top selected models will now be the challenger models based on which the best model will be decided. We will perform hyperparameter tuning on the given models using previous learnings and methods such as Grid Search, Random Search, and Bayesian optimisation depending on the model considered.

#### 3.2.6.4 Model Assessment

For any models to be used by the business, model assessment is a critical part of the process. As we develop models from a Data Scientist's eyes up until this point, we will need to take steps to ensure that the predictions are as expected for the company to leverage the model. There are multiple metrics one can use to perform the model assessment in this stage. We have noticed that accuracy and AUC were used to assess models across the board from our literature review. We will also focus on model sensitivity and specificity curves to make a generalised model that can be leveraged.

  
Figure 1: Model Building Process by Author via [draw.io](https://app.diagrams.net/)

Model interpretability is vital to the business's functioning as they would like to understand the customers that are likely to churn and gain insights as to why. Therefore, we are in the model assessment stage; we will need to focus on actionable insights and provide the business with the customer behaviour patterns linked with the high likelihood of churn.

### 3.2.7 Model Evaluation

We have now settled on the best model that we would like to showcase. This is the model on which extensive feature engineering has been carried out, and from a wide range of models, we have chosen the best. We will follow the below-mentioned steps to perform the model evaluation.

#### 3.2.7.1 Metrics for Evaluation

We will now proceed to compare the model results obtained with the other literature we have previously surveyed. Using the same metrics of accuracy, F-Score, the area under the curve, we will compare the new ensemble or individual models' performance to the models' performance in the field's reviewed literature. Once we evaluate the results and see if they are satisfactory, we will proceed to the next steps. Else, if they are not adequate, we will move to re-evaluate our approach to improve iteratively.

#### 3.2.7.2 Process Review

We will list the final process post the different iterations we have carried out and carefully review the process. As compared to the other research done in this field, we will analyse if there are any potential misses, flaws in approaches an address them.

#### 3.2.7.3 Determine Next Steps

Based on the process review carried out in the above step, we will decide if we would like to finish our research project and move on to the next steps. If not, we shall initiate further iterations and refine the model. This is an essential step and will be based on the comparative analysis we will perform to benchmark our model.

### 3.2.8 Model Deployment

We will now decide the next steps for the business use that our model evaluation is satisfactorily completed.

#### 3.2.8.1 Plan for Deployment

The model is to be utilised by telecom companies to reduce the churn rate by targeting customers at a high likelihood of churn. There are certain factors to consider here based on which the company's return on investment can be maximised. 80% of revenue is generated by 20% of the customer base (Rajagopal, 2011). Based on the allocated budget for customer retention, we should filter out high-value customers with a high customer lifetime value and target those most likely to churn. Allocating too much time to customers who are not generating as much revenue can be prioritised lower.

#### 3.2.8.2 Monitoring and Maintenance

A cost-benefit analysis will be carried out to understand the actual cost of running the model in real-time. There might be potential data anomalies while new data comes in. Robust machine learning pipelines along with teams to monitor the same will be deployed. This will help us monitor the results and understand how we can make the deployment more efficient.

#### 3.2.8.3 Reporting Results

For a machine learning model to improve with time, it is essential to create a feedback loop. Documentation of the research carried out, the results, and loopholes must be carefully documented to improve the model in the next iteration. If a similar accuracy can be obtained with lesser processing, this will also help the company save operationalisation expenditure costs.

#### 3.2.8.4 Final Review

We will contemplate in the final review what are the things done right and what went wrong. There will be learnings from the entire process that we shall document and use in our next steps. We should also learn what was done well and what could have been avoided.

## 3.3 Proposed Model

## 3.4 Summary

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# APPENDIX A: RESEARCH PLAN

# APPENDIX B: RESEARCH PROPOSAL

# APPENDIX C: ETHICS FORMS

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