# Capstone Project 2 - Final Report

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**PRJ3213: Capstone Project 2**

**Final Report**

# Analysing the Factors Affecting Customer Churn and Predicting Customer Churn for a Telecommunication Industry


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## Abstract

Customer attrition or churn is a major challenge faced by companies across industries, incurring substantial revenue losses and costs of acquiring new customers. For telecommunications firms competing in saturated markets, minimizing subscriber defections is imperative but analytically challenging. This capstone report aims to develop an accurate, interpretable churn prediction model and actionable insights tailored to a major telecom provider's 3000+ customer dataset.

The Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology structured the analytical approach across business understanding, data pre-processing, modelling, and evaluation phases. The project utilized both statistical techniques including logistic regression, multiple regression, ANOVA, factor analysis, and principal component analysis alongside machine learning algorithms such as neural networks, decision trees, and clustering.

By fusing multiple modelling paradigms, the project aimed to balance predictive accuracy through advanced machine learning with interpretability regarding churn drivers and customer segmentation provided by statistical methods. Rigorous evaluation methodology based on metrics like AUC, accuracy, precision, recall, F1-score, and qualitative criteria guided model selection and optimization.

Key outcomes encompassed an operationalized Docker container to predict customer churn risks, a standalone interface to demonstrate functionality, intuitively visualized results, and actionable insights into churn predictor importance. The findings revealed service usage, demographics, billing amounts, contract types, and satisfaction metrics as salient drivers of churn for the telecom provider. Recommendations focused on targeted retention campaigns for high-risk segments.

In conclusion, this project applied a synthesis of data mining techniques tailored to the telecommunications sector to uncover predictive signals and behavioural insights on customer churn. The churn modelling system prototyped, and insights gained aim to equip firms with a competitive capability to reduce subscriber loss through data-driven optimization of customer experiences and retention initiatives. With both technical deliverables and business recommendations, this project endeavoured to bridge the gap from data analytics to operational impact.

## Table of Content

## List of Abbreviations

| Abbreviations | Full Form |
|---|---|
| AUC | Area Under the ROC Curve |
| ANN | Artificial Neural Networks |
| ANOVA | Analysis of Variance |
| CART | Classification and Regression Trees |
| CRISP-DM | Cross-Industry Standard Process for Data Mining |
| DBSCAN | Density-Based Spatial Clustering of Applications with Noise |
| EDA | Exploratory Data Analysis |
| ELM | Extreme Learning Machine |
| FN | False Negative |
| FP | False Positive |
| KNN | K-Nearest Neighbours |
| MLP | Multilayer Perceptron |
| NB | Naive Bayes |
| PSO | Particle Swarm Optimization |
| RF | Random Forest |
| ROC | Receiver Operating Characteristic |
| RSF | Random Survival Forest |
| SNA | Social Network Analysis |
| SVM | Support Vector Machines |
| SWOT | Strengths, Weaknesses, Opportunities, and Threats |
| TN | True Negative |
| TP | True Positive |
| WRF | Weighted Random Forest |

## 1. Introduction

In today's highly saturated and competitive telecommunications marketplace, the ability for service providers to accurately predict and proactively minimize customer churn represents an enormous opportunity to enhance business performance, revenue, and profitability. Customer churn, defined as the loss of subscribers to rival brands, can incur substantial financial costs for telecom companies ranging from lost monthly revenue, diminished market share, and significant expenditures to attract new customers to replace those who have left (***Wei & Chiu, 2002***).

Industry research indicates that the average monthly churn rate faced by telecommunication companies is estimated to be between 2-3% of the total customer base per month (***Malik & Singh, 2014***). When translated into absolute customer numbers and revenue dollars, this churn rate can have dramatic business impacts especially given the fiercely contested market space. Therefore, uncovering actionable insights into the key drivers of customer churn and leveraging predictive analytics to identify those subscribers most likely to defect in the near future is of tremendous commercial interest for telecom firms. However, accurately predicting potential churners amidst masses of customers and hundreds of influencing factors remains an intricate challenge.

This capstone project aims to address this business-critical need for enhanced churn prediction through the application of advanced data mining techniques, statistical modelling, and machine learning algorithms. The core objectives are to analyse a substantial dataset of over 3000 customers from a major telecommunications company.

The project will employ a multi-pronged analytical approach encompassing both predictive modelling using techniques like logistic regression, neural networks, decision trees, and unsupervised learning algorithms to uncover nonlinear relationships and customer segments exhibiting churn patterns. Explanatory statistical modelling will also clarify and quantify the effects of different churn risk factors.

By distilling actionable intelligence regarding customers likely to churn alongside operational drivers of attrition, this project aims to empower the telecom company with accurate forecasts and a deeper understanding of churn. These analytical capabilities can inform the design of highly targeted interventions including retention campaigns, customer experience enhancements, and personalized incentives to mitigate subscriber loss.

With the commercial costs of churn and customer acquisition being substantial in the telecom industry, effective churn modelling and predictive analytics represent a significant opportunity for gaining competitive advantage in the crowded marketplace. This project seeks to demonstrate how harnessing data mining and machine learning can unlock transformative business value by enabling data-driven customer retention strategies. The final output will be an operational prototype churn prediction system that provides predictive signals and data-backed insights to combat customer defections.

Overall, this capstone project aims to address the commercially impactful and analytics-challenging problem of customer churn for a telecommunications provider through a synthesis of predictive modelling, behavioural insights, and operationalizing state-of-the-art data science techniques to maximize customer lifetime value. Effective churn prediction has become a strategic imperative for telecoms, and this project offers a potential path to leverage those analytics for competitive differentiation.

## 1.1 Problem Statement

This section presents the problem statement for this project. With the ever-expanding and competitive telecommunications industry, accurate churn prediction becomes crucial to minimize financial loss and retain valuable customers ***(MELIAN et al., 2022).*** By leveraging these methods, along with customer demographics, the project aims to develop predictive models that identify potential churners and enable proactive measures like personalized offers and improved customer service ***(MELIAN et al., 2022; M. A. et al., 2023)***. This project addresses the critical need for predicting customer churn in a telecom company, optimizing customer acquisition and retention efforts, empowering the company with data-driven insights, and enhancing long-term success in the dynamic telecom industry.

## 1.2 Project Aim

This section presents the project aim for this project. The capstone project, titled "Prediction of Customer Churn for a Telecom Company using SAS Enterprise Guide and SAS Enterprise Miner Station," aims to predict customer churn in the telecom industry through advanced data analytics techniques.

## 1.3 Project Objectives

This section resent the project objectives for this project. The capstone project entails the following objectives:

1. To identify churn patterns and predict future churn accurately through analysis of customer data using advanced machine learning, statistical models, and data mining techniques.
2. To gain actionable insights that improve customer retention strategies and reduce acquisition costs through data-driven optimization.
3. To achieve a competitive advantage in the telecom industry by effectively leveraging predictive modelling and data mining approaches.

## 1.4 Project Scope:

The scope of this project encompasses several key areas. Firstly, **data pre-processing** will be performed to clean and pre-process the dataset, ensuring that missing values are handled appropriately, and data transformations are applied if necessary. This step is crucial to ensure the dataset is ready for analysis and modelling.

Next, **exploratory data analysis (EDA)** will be conducted to gain a comprehensive understanding of the dataset. This includes analysing the distributions of variables, exploring correlations between variables, and identifying any patterns or anomalies in the data. EDA will provide valuable insights into customer behaviour and churn patterns.

The core focus of the project lies in **model development**, where various machine learning algorithms and statistical models, such as logistic regression, decision trees, and neural networks, will be utilized to develop predictive models for customer churn. These models will be trained using the prepared dataset, and their performance will be evaluated and compared using appropriate metrics.

Once the models are developed and evaluated, the project will move towards **generating insights and recommendations**. The results of the trained models will be analysed to identify the key factors contributing to churn. These insights will be used to provide actionable recommendations for the telecom company, aiming to improve customer retention and reduce churn. This may involve developing personalized offers and implementing improved customer service strategies based on the identified patterns and insights.

Throughout the project, careful **documentation and reporting** will be maintained. The entire project process, including data pre-processing, EDA, model development, and insights generation, will be thoroughly documented. A final report will be prepared, summarizing the findings, methodologies, and recommendations.

The overall scope focuses on leveraging analytics to enhance customer loyalty and retention through predictive modelling, explanatory insights, and data-driven recommendations tailored to the telecommunications industry based on the provided summary.

## 1.5 Summary

The introduction establishes predicting and minimizing customer churn as a crucial opportunity for telecom companies to enhance business performance given the costs of attrition. With average monthly churn rates around 2-3%, retaining subscribers is imperative. However, accurately identifying potential churners amidst large customer bases is challenging.

This capstone project aims to address the need for improved churn prediction using advanced analytics on a dataset of over 3000 telecom customers. The objectives are to accurately predict high churn risk customers, gain insights into drivers of churn, and enable data-driven retention initiatives.

A multifaceted analytical approach will be employed encompassing predictive modelling techniques like logistic regression, neural networks, and decision trees. Statistical modelling will also explain churn risk factor relationships. These capabilities can empower the telecom company with accurate forecasts and actionable intelligence to combat churn through targeted interventions.

Effective churn modelling represents a significant opportunity for competitive differentiation in the crowded telecom marketplace. The project will demonstrate how harnessing state-of-the-art data mining and machine learning can unlock business value by optimizing customer retention strategies. Overall, this project aims to address the critical problem of customer churn through predictive analytics and behavioural insights tailored to the telecommunications industry.

## 2. Literature Review

This literature review synthesizes key research on customer churn prediction in the various industries but mostly in telecommunications. It examines predictive modelling techniques, influential factors, and customer retention strategies based on a survey of over 30 recent studies. The review establishes the theoretical foundation to inform the methodology and analysis for identifying and responding to churn risk in this project.

### 2.1 Predictive Modelling Techniques for Churn Analysis

This subsection focuses on the various predictive modelling techniques utilized in churn analysis, including machine learning, statistical models, data mining, artificial intelligence methods, and etc. It summarizes the most prevalent approaches and provides examples of specific algorithms leveraged across the studies reviewed.

Customer churn prediction is a critical task in the telecommunications industry as it enables companies to proactively identify customers who are likely to switch to competitors' services. This prediction is vital for improving customer retention and overall business performance, considering the intense competition in the market. Recent research has focused on customer attrition prediction in telecom, exploring various approaches and tools. Machine learning techniques such as classification and regression trees (CART), artificial neural networks (ANN), logistic regression, support vector machines (SVM), and random survival forest have been applied to develop accurate churn prediction models ***(Abdulsalam et al., 2022; Babatunde et al., 2023; Li & Marikannan, 2019; Dalli, 2022; Nurhaliza et al., 2022; Gan, 2022).*** These models aim to identify patterns and trends in customer behaviour that can indicate the likelihood of churn.

In the telecommunications industry, customer churn prediction models have been developed using a combination of different techniques and algorithms. For example, a study applied a mixture of simple under-sampling, SMOTE, and weighted random forest (WRF) to improve the customer attrition prediction model ***(Javaid et al., 2022)***. Another study used a hybrid algorithm that incorporated Particle Swarm Optimization (PSO) and Extreme Learning Machine (ELM) to accurately predict customer churn ***(Li & Marikannan, 2019)***. Additionally, the Cox Proportional Hazard model and Random Survival Forest have been used to analyse right-censored survival data and predict customer attrition ***(Nurhaliza et al., 2022)***.

One set of studies has focused on the utilization of advanced analytics tools such as SAS Enterprise Guide and SAS Enterprise Miner for customer churn prediction. Li et al. conducted a study that demonstrated the effectiveness of these tools in developing accurate churn prediction models. By employing data mining techniques like decision trees, logistic regression, random forest, and support vector machines, they achieved high accuracy in identifying potential churners. The use of these tools enables telecom companies to proactively identify customers at risk of churn and implement targeted retention strategies ***(Li et al., 2018)***. Similarly, Wang et al. also found these tools to be effective in developing churn prediction models. By leveraging the power of advanced analytics tools, telecom companies can make informed decisions and take necessary actions to retain valuable customers. ***(Wang et al., 2019)***.

In addition to analytics tools, other studies have explored the application of data analytics and data mining approaches in customer churn prediction. Almuqren et al. proposed a novel approach using social media mining, specifically Arabic Twitter mining, to predict customer churn in Saudi Telecom companies. They highlighted the significance of real-time analytics and the novelty of using Arabic Twitter mining for churn prediction. This approach demonstrates the importance of leveraging social media data and real-time analytics to gain valuable insights into customer behaviours and preferences ***(Almuqren et al., 2021)***. Similarly, Zhao et al. focused on the Chinese telecom industry and developed a customer churn prediction model using a logistic regression algorithm based on big data. Their research analysed churn trends and causes and proposed targeted win-back strategies based on empirical research results. This study showcases the potential of leveraging big data analytics in understanding customer churn and designing effective retention strategies ***(Zhao et al., 2021).*** Furthermore, Salunkhe and Mali emphasized the importance of customer churn prediction in detecting customers likely to switch service providers and applied various data mining techniques to classify customers into churn and non-churn categories. By leveraging data mining techniques, telecom companies can effectively identify customers at risk of churn and develop proactive retention strategies to minimize customer attrition ***(Salunkhe & Mali, 2018).***

Moreover, Sharma et al. discussed the use of data mining algorithms, including decision trees and neural networks, for customer churn prediction, considering various factors such as billing information, demographics, call detail, contract/service status, and service change logs. Their study highlights the importance of incorporating diverse data sources and factors in churn prediction models to achieve accurate predictions. By considering multiple aspects of customer interactions and behaviours, telecom companies can gain a comprehensive understanding of churn drivers and design targeted interventions ***(Sharma et al., 2021)***. Additionally, Tianyuan and Moro highlighted the

increasing use of artificial intelligence techniques, including data mining, for telecom customer churn prediction and the potential of these techniques in developing accurate and efficient marketing strategies. The application of artificial intelligence techniques enables telecom companies to leverage advanced algorithms and models to uncover complex patterns and trends in customer behaviour, thus improving the accuracy of churn prediction ***(Tianyuan & Moro, 2021).***

The literature also recognizes that customer churn prediction is not limited to the telecom industry but extends to various other industries such as banking, subscription services, game businesses, and retailing ***(Liu & Zhuang, 2015; Seo, 2023; Kaya et al., 2018).*** Churn prediction models aim to identify customers who are likely to switch to a competitor's services, allowing companies to take proactive measures to retain them ***(Óskarsdóttir et al., 2018).*** Data mining and data analytics approaches are commonly used in churn prediction, treating it as a classification problem. These approaches utilize historical customer data to classify current customers into churn and non-churn categories ***(Rodan et al., 2015).***

One challenge in churn prediction is the imbalance between churn and non-churn classes, which can affect the performance of prediction models. To address this issue, sampling techniques have been developed to balance the class distribution and improve the accuracy of churn prediction models ***(Zhu et al., 2017).*** These techniques involve selecting representative samples from the imbalanced dataset to create a balanced training set. By mitigating the class imbalance problem, telecom companies can develop more accurate churn prediction models and effectively allocate resources for targeted retention strategies.

Incorporating domain knowledge into the data mining process is another important aspect of churn prediction. Domain knowledge can be integrated into the process through the evaluation of coefficient signs in a logistic regression model and the analysis of decision tables extracted from decision trees or rule-based classifiers. By incorporating domain knowledge, the resulting churn prediction models become more interpretable and actionable. Telecom companies can gain insights into the specific factors that drive churn within their industry and tailor their retention strategies accordingly ***(Lima et al., 2009).***

Real-time analytics and social media mining have also been explored in churn prediction. Traditional churn prediction models based on historical data may face delay issues and lack the ability to tap into real-time customer satisfaction and behaviour. Therefore, using social media mining and real-time analytics can provide valuable insights into customer churn behaviours and enable targeted

interventions to retain customers ***(Almuqren et al., 2021)***. By monitoring social media platforms and analysing customer sentiments and conversations in real-time, telecom companies can proactively identify customers who might be inclined to switch to competitors and design timely retention strategies.

Various techniques have been applied in churn prediction, including logistic regression, support vector classification, clustering, and ensemble methods ***(Zhao et al., 2021).*** These techniques aim to identify the factors that contribute to customer churn, such as customer service experience, failure recovery efforts, payment equity, and customer value ***(Jamal & Bucklin, 1987; Zhao et al., 2021).*** By understanding these factors, companies can develop effective strategies to retain customers and enhance customer loyalty ***(Zhao et al., 2021)***. Telecom companies need to identify the key drivers of customer churn specific to their industry and leverage appropriate techniques and models to predict and prevent customer attrition.

Customer churn prediction models in the telecom industry typically use a variety of input features, including customer demographics, call quality, complaints, billing and payment history, service usage duration, and billed amount. These features provide valuable information for predicting churn and identifying factors that influence customer behaviour ***(Melian et al., 2022)***. For example, customer demographics such as age, gender, and location can provide insights into different segments of customers who might have varied churn propensity. Similarly, call quality and complaints data can reveal the level of customer satisfaction and identify potential churn triggers. Billing and payment history can provide insights into customer payment patterns and financial stability, which can be influential in churn prediction. Service usage duration and billed amount can indicate the level of engagement and value customers derive from the telecom services, which can be important indicators of churn likelihood.

In the telecommunications industry, customer churn prediction models have been developed using a combination of different techniques and algorithms. For example, Javaid et al. applied a mixture of simple under-sampling, SMOTE, and weighted random forest (WRF) to improve the customer attrition prediction model. By utilizing these techniques, they were able to address the issue of class imbalance and enhance the accuracy of churn prediction. This highlights the importance of employing appropriate sampling techniques to create a balanced training set that accurately represents both churn and non-churn classes ***(Javaid et al., 2022)***.

Furthermore, recent studies have explored the use of deep neural networks for churn prediction in the telecom sector ***(Nalatissifa & Pardede, 2021)***. Deep neural networks leverage the power of deep learning to extract complex patterns and relationships from large-scale datasets. By utilizing the hierarchical structure of neural networks, these models can capture intricate dependencies within customer data and improve the accuracy of churn prediction. The application of deep neural networks showcases the potential for advanced machine learning techniques to enhance churn prediction in the telecom industry.

To evaluate the performance of churn prediction models, various metrics are employed, such as the area under the receiver operating characteristic curve (AUC) ***(Özmen et al., 2019).*** The AUC metric measures the model's ability to discriminate between churners and non-churners, providing an overall assessment of the predictive power of the model. It is important to evaluate the performance of churn prediction models using appropriate metrics to ensure accurate assessment and comparison across different studies.

Customer attrition prediction is not limited to the telecommunications industry and has been studied in other sectors such as online retail, banking, and the securities industry ***(Javaid et al., 2022; Ahn et al., 2019; Tran et al., 2023).*** The methods and techniques used in these industries are often similar to those employed in the telecommunications industry, including machine learning algorithms, regression models, and clustering techniques. By leveraging the cross-industry insights and experiences, telecom companies can benefit from the advancements made in other sectors and adapt them to their specific churn prediction needs.

To improve the accuracy of customer churn prediction models, researchers have explored the integration of different machine learning techniques. Mishachandar and Kumar emphasized the use of logistic regression, support vector machines, random forest, gradient boosted trees, decision trees, artificial neural networks, and ensemble methods for churn prediction in the telecom sector ***(Mishachandar and Kumar, 2018).*** Logistic regression is a commonly used technique that estimates the probability of churn based on input features ***(Olbrich & Yang, 2011).*** Recent studies have also explored the use of deep neural networks for churn prediction, leveraging the power of deep learning to extract complex patterns and relationships from large-scale datasets ***(Nalatissifa & Pardede, 2021).***

Not only that but there is a study proposed an integration framework that combined supervised learning techniques for customer attrition prediction and unsupervised learning techniques for customer segmentation ***(Loukili, 2022)***. Integration of different approaches and techniques has been

proposed to improve the accuracy of customer churn prediction models. Zeng developed a matrix framework for customer retention by integrating supervised learning techniques for customer attrition prediction and unsupervised learning techniques for customer segmentation. This integration allows businesses to take proactive action planning and develop comprehensive strategies to retain customers effectively ***(Zeng, 2023).*** By considering both predictive modelling and customer segmentation, telecom companies can tailor their retention efforts to different customer segments, addressing their unique needs and preferences.

In churn analysis, customer data is typically divided into a training set for model development and a scoring set for model evaluation ***(Irpan et al., 2014).*** The training set is used to build predictive models using various algorithms, such as logistic regression, decision trees, and artificial neural networks ***(Abdulsalam et al., 2022; Khan et al., 2019).*** These models are then applied to the scoring set to predict churn and identify potential churners ***(Irpan et al., 2014).*** Feature selection techniques, such as information gain and correlation attribute ranking, are often used to select the most relevant variables for churn prediction ***(Ullah et al., 2019).*** These techniques help streamline the input variables and focus on the factors that have the most significant impact on customer churn.

Social network analysis (SNA) has also been applied in churn analysis to understand the structure and content of power ties between participants and their impact on model performance ***(Churners Prediction Based on Mining the Content of Social Network Taxonomy, 2019)***. By analysing the content and structure of social networks, telecom companies can gain insights into customer churn and develop strategies to retain their customers. Additionally, customer segmentation techniques, such as RFM (Recency, Frequency, Monetary) analysis and K-means clustering, have been used to group customers based on their purchase behaviours and identify different segments for targeted retention efforts ***(Wu et al., 2020; Wu et al., 2021)***. These segmentation techniques enable telecom companies to tailor their retention strategies to different customer segments, ensuring the effectiveness of their retention efforts.

Churn analysis is a crucial task for telecom companies as it helps them identify customers who are likely to leave their services ***(Ullah et al., 2019)***. By predicting customer churn, telecom companies can take appropriate measures to retain their customers and reduce the cost of acquiring new ones ***("Use of Machine Learning for Customer Churn Analysis in Banking", 2022)***. Churn analysis involves analysing customer data to understand their behaviour patterns and identify factors that contribute to churn ***(Ullah et al., 2019).*** It provides a process flow diagram that allows users to perform data mining tasks such as text import, parsing, filtering, and topic analysis ***(Kakde & Chaudhuri, 2015).***

These tools enable researchers and analysts to apply data mining techniques and algorithms to large volumes of customer data, extract meaningful insights, and build predictive models for churn analysis ***(Bose, 2009; Park et al., 2014; Cordeiro et al., 2019)***. Other studies have also utilized different tools and platforms, such as WEKA and Orange, to analyse customer attrition ***(Ramesh, 2022; Periáñez et al., 2016).***

Overall, customer churn prediction and attrition analysis are critical tasks in the telecom industry. Various data mining and machine learning techniques, as well as advanced analytics tools like SAS Enterprise Guide and SAS Enterprise Miner, have been applied to predict customer churn and identify factors that contribute to churn. These approaches leverage diverse input features, evaluation metrics, and integration of deep neural networks and social network analysis. By leveraging historical customer data, incorporating domain knowledge, addressing class imbalance, and utilizing real-time analytics and social media mining, companies can develop accurate and actionable churn prediction models. These models enable companies to enhance customer satisfaction, loyalty, and retention, leading to improved business performance.

### 2.1.1 Comparison of the Studies

This section will focus on the comparison of the studies used in the previous 2.1 Predictive Modelling Techniques for Churn Analysis section.

**Table 2.1.1.1:** Table of Comparison of the Studies

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| 1 | Abdulsalam et al., 2022 | Machine learning (CART, ANN) | Telecom | Churn prediction using an improved Relief-F feature selection algorithm |
| 2 | Ahn et al., 2019 | Statistical classification | Brokerage and investment banking | Identifying attributes predicting customer attrition behaviour |
| 3 | Almuqren et al., 2021 | Social Media Mining (Arabic Twitter mining) | Saudi Telecom Companies | Predicting customer churn using social media |

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| 4 | Babatunde et al., 2023 | ANOVA with SVM | Telecom | Churn prediction analysis using support vector machine |
| 5 | Bose, 2009 | Data mining, text mining, web mining | Predictive analytics | Utilizing mining technologies for advanced analytics in organizations |
| 6 | Churners Prediction Based on Mining the Content of Social Network Taxonomy, 2019 | Network mining, data mining | Telecommunications | Predictive model incorporating network mining with traditional data mining |
| 7 | Cordeiro et al., 2019 | Machine learning algorithms | Children's height prediction | Machine learning-based prediction of children's target height |
| 8 | Dalli, 2022 | Deep learning | Telecommunications | Utilizing deep learning techniques for churn prediction |
| 9 | Gan, 2022 | Improved XGBoost algorithm | E-commerce | Effective prediction of e-commerce customer loss |
| 10 | Irpan et al., 2014 | Neural network model | Banking | Modelling potential churners in the mortgage business of Bank X |
| 11 | Jamal & Bucklin, 1987 | Identifying factors contributing to churn | Not specified (focus on factors affecting churn) | Identifying factors contributing to customer churn |
| 12 | Javaid et al., 2022 | Permutation feature importance, Decision Tree, Random Forest, Extra Tree, Neural Networks, Logistic Regression | Online shopping | Finding relevant features and building ML models for predicting purchasing decisions |

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| 13 | Kakde & Chaudhuri, 2015 | Text mining | Aftersales service | Reliability analysis using text mining and customer complaints |
| 14 | Kaya et al., 2018 | Data mining approaches | Telecom, banking, subscription services, game businesses, retailing | Demonstrated the application of churn prediction in various industries |
| 15 | Khan et al., 2019 | Artificial neural network | Telecom | Churn prediction using artificial neural networks in the telecommunication industry |
| 16 | Li & Marikannan, 2019 | Particle Swarm Optimization (PSO), Extreme Learning Machine (ELM) | Telecommunications | Hybrid algorithm for telecommunication churn prediction |
| 17 | Li et al., 2018 | SAS Enterprise Guide, SAS Enterprise Miner | Telecommunications Industry | Developing accurate churn prediction models |
| 18 | Lima et al., 2009 | Incorporation of domain knowledge | Not specified (focus on incorporating domain knowledge) | Discussed the importance of incorporating domain knowledge in churn prediction |
| 19 | Liu & Zhuang, 2015 | Customer segmentation, misclassification cost | Telecom | Research model of customer churn based on customer segmentation and misclassification cost in telecom industry |
| 20 | Loukili, 2022 | k-nearest neighbour, logistic regression, random forest, support vector machine | Telecom | Comparative analysis of machine learning models for churn prediction |
| 21 | Melian et al., 2022 | Data mining techniques | Telecommunications | Predicting churn behaviour and analysing churn |

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| | | | | indicators in a telecommunication company |
| 22 | Mishachandar and Kumar, 2018 | Machine Learning, Big Data Analytics tools | Telecommunications | Novel approach combining ML and Big Data Analytics for churn prediction |
| 23 | Nalatissifa & Pardede, 2021 | Information gain, Correlation attributes | Telecommunications | Improvement of customer churn prediction using feature selection techniques |
| 24 | Nurhaliza et al., 2022 | Cox Proportional Hazard Model, Random Survival Forest (RSF) | Telecommunications | Comparison of predictive quality for churn prediction using different methods |
| 25 | Olbrich & Yang, 2011 | Logit model | Social shopping communities | Predicting purchasing behaviour within social shopping communities |
| 26 | Óskarsdóttir et al., 2018 | Relational learners, Collective inference | Telecommunications | Benchmarking different strategies for constructing relational learners for churn prediction |
| 27 | Özmen et al., 2019 | Multi objective–cost-sensitive ant colony optimization | Telecommunications | Churn prediction with cost-sensitive learning in the telecommunications sector |
| 28 | Park et al., 2014 | Association rule mining | Health and nutrition | Patterns of lifestyle risk behaviours among Korean adults |
| 29 | Periáñez et al., 2016 | Survival analysis, ensemble learning | Mobile social games | Churn prediction and risk factor analysis using survival ensembles |

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| 30 | Ramesh, 2022 | Bio-inspired data platform | Telecom | Prediction of customer churn in the telecom industry |
| 31 | Rodan et al., 2015 | Data Mining, Data Analytics | Banking, Subscription Services, Game Businesses, Retailing | Classifying current customers into churn and non-churn |
| 32 | Salunkhe & Mali, 2018 | Data Mining Techniques | Not specified (focus on churn detection) | Classifying customers into churn and non-churn |
| 33 | Seo, 2023 | Big data analysis | Marketing | Real-time churn rate estimation and customized coupon issuance |
| 34 | Sharma et al., 2021 | Decision Trees, Neural Networks | Telecommunications Industry | Incorporating diverse data sources in churn prediction |
| 35 | Tianyuan & Moro, 2021 | Artificial Intelligence Techniques | Telecommunications Industry | Using AI techniques for accurate churn prediction |
| 36 | Tran et al., 2023 | K-means clustering, logistic regression, decision tree, random forest, support vector machine | Banking | Impact of customer segmentation on churn prediction and evaluation of machine learning approaches |
| 37 | Ullah et al., 2019 | Classification and clustering techniques | Telecom | Churn prediction and identification of churn factors in the telecom sector |
| 38 | USE OF MACHINE LEARNING FOR CUSTOMER CHURN ANALYSIS IN BANKING, 2022 | Random Forest, Extra Tree, Neural Network, Gaussian NB, k-nearest neighbour, Logistic Regression | Banking | Machine learning-based churn analysis in the banking sector |
| 39 | Wang et al., 2019 | SAS Enterprise Guide, SAS Enterprise Miner | Telecommunications Industry | Developing churn prediction models |

| | Study | Study Methodology | Case Study Industries | Main Focus |
|---|---|---|---|---|
| 40 | Wu et al., 2020 | RFM model, K-means clustering | Online sales | Customer segmentation and value analysis for CRM strategies |
| 41 | Wu et al., 2021 | Multiple machine learning classifiers | Telco | Integrated framework for churn prediction and customer segmentation |
| 42 | Zeng, 2023 | Machine learning techniques | Telecommunications | Integration of churn prediction and customer segmentation for telco industry |
| 43 | Zhao et al., 2021 | Logistic Regression, Big Data | Telecom | Customer churn prediction model using logistic regression and big data analysis |
| 44 | Zhu et al., 2017 | Sampling Techniques | Not specified (focus on addressing class imbalance) | Addressing class imbalance problem in churn prediction |

## 2.1.2 Methodology Comparison of the Studies

**Table 2.1.2.1:** Table of Methodology Comparison of the Studies

| Methodology | Number of Articles | Percent of Total (%) |
|---|---|---|
| Machine Learning | 40 | 53.3 |
| Statistical Models | 15 | 20 |
| Data Mining | 12 | 16 |
| Soft Computing | 5 | 6.7 |
| AI Techniques | 3 | 4 |
| **Total** | 75 | 100 |

The table provides a comprehensive overview of the modelling techniques applied across 44 recent research articles on predicting customer churn and related tasks like segmentation. Despite there are only a total of 44 articles being reviewed, but some of them adopted more than 1 methodology, hence the total number of methodologies used is 75 which is more than the number of the total articles. The prevalence of machine learning approaches is clear - adopted in 40 of the 44 articles, machine learning makes up a substantial 53.3% of the sample. This dominant position of machine learning reflects how established and effective algorithms like logistic regression, decision trees, neural networks, and support vector machines are for modelling churn. With predictive accuracy and transparency being priorities, these flexible supervised learning models are ideal for identifying customers likely to churn. Their ability to capture complex nonlinear relationships while avoiding overfitting makes machine learning the go-to technique for churn prediction currently.

While machine learning stands out as the most ubiquitous method by far, statistical approaches like regression and survival analysis still play an important role, appearing in 20% of the articles reviewed. The ability of techniques like logistic regression and Cox proportional hazards models to estimate churn probability and survival time provides value, especially for gaining explanatory insights into the factors influencing churn. Those more traditional statistical models provide a complementary perspective to machine learning's black box predictions.

For unsupervised learning, data mining strategies such as clustering is prevalent, utilized in 16% of the articles. Clustering helps with customer segmentation by grouping similar customers based on attributes. These data mining techniques are beneficial for discovering churn trends and meaningful customer segments without requiring historical labelled data.

Soft computing methods and AI techniques are promising but less established currently, each employed in just over 10.7% of the articles. As data volumes grow and algorithms mature, nature-inspired optimization approaches and deep learning may become more widely adopted. For now, though, simpler and transparent supervised learning models tend to dominate methodology. In summary, machine learning is the go-to workhorse, while statistical models and unsupervised techniques fill complementary niches in the churn prediction literature.

Additionally, **Table 2.1.2.2** is included to enhance the visualization of the comparison:

**Table 2.1.2.2:** Detailed Table of Methodology Comparison of the Studies

| | | Method Used | | | | |
|---|---|---|---|---|---|---|
| | | **AI Techniques** | **Data Mining** | **Machine Learning** | **Soft Computing** | **Statistical Models** |
| 1 | Abdulsalam et al., 2022 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 2 | Ahn et al., 2019 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 3 | Almuqren et al., 2021 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 4 | Babatunde et al., 2023 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 5 | Bose, 2009 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 6 | Churners Prediction Based on Mining the Content of Social Network Taxonomy, 2019 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 7 | Cordeiro et al., 2019 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 8 | Dalli, 2022 | TRUE | FALSE | FALSE | FALSE | FALSE |
| 9 | Gan, 2022 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 10 | Irpan et al., 2014 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 11 | Jamal & Bucklin, 1987 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 12 | Javaid et al., 2022 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 13 | Kakde & Chaudhuri, 2015 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 14 | Kaya et al., 2018 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 15 | Khan et al., 2019 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 16 | Li & Marikannan, 2019 | FALSE | FALSE | TRUE | TRUE | FALSE |
| 17 | Li et al., 2018 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 18 | Lima et al., 2009 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 19 | Liu & Zhuang, 2015 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 20 | Loukili, 2022 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 21 | Melian et al., 2022 | FALSE | TRUE | FALSE | FALSE | FALSE |

| | | Method Used | | | | |
|---|---|---|---|---|---|---|
| | | **AI Techniques** | **Data Mining** | **Machine Learning** | **Soft Computing** | **Statistical Models** |
| 22 | Mishachandar and Kumar, 2018 | FALSE | TRUE | TRUE | FALSE | FALSE |
| 23 | Nalatissifa & Pardede, 2021 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 24 | Nurhaliza et al., 2022 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 25 | Olbrich & Yang, 2011 | FALSE | FALSE | FALSE | FALSE | TRUE |
| 26 | Óskarsdóttir et al., 2018 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 27 | Özmen et al., 2019 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 28 | Park et al., 2014 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 29 | Periáñez et al., 2016 | FALSE | FALSE | TRUE | FALSE | TRUE |
| 30 | Ramesh, 2022 | FALSE | FALSE | FALSE | TRUE | FALSE |
| 31 | Rodan et al., 2015 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 32 | Salunkhe & Mali, 2018 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 33 | Seo, 2023 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 34 | Sharma et al., 2021 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 35 | Tianyuan & Moro, 2021 | TRUE | FALSE | FALSE | FALSE | FALSE |
| 36 | Tran et al., 2023 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 37 | Ullah et al., 2019 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 38 | USE OF MACHINE LEARNING FOR CUSTOMER CHURN ANALYSIS IN BANKING, 2022 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 39 | Wang et al., 2019 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 40 | Wu et al., 2020 | FALSE | TRUE | FALSE | FALSE | FALSE |
| 41 | Wu et al., 2021 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 42 | Zeng, 2023 | FALSE | FALSE | TRUE | FALSE | FALSE |
| 43 | Zhao et al., 2021 | FALSE | TRUE | FALSE | FALSE | TRUE |
| 44 | Zhu et al., 2017 | FALSE | FALSE | FALSE | FALSE | TRUE |

### 2.1.3 Sankey Visualization Maps for Industry Comparison

This section presents the Sankey visualization Maps figure to showcase the relationships between the industry domains studied across 44 research articles and the analytical focus of those works using flowing links. The diagram reveals churn prediction and customer segmentation as nearly universal applications while also highlighting unique concentrations on more niche objectives within certain verticals.

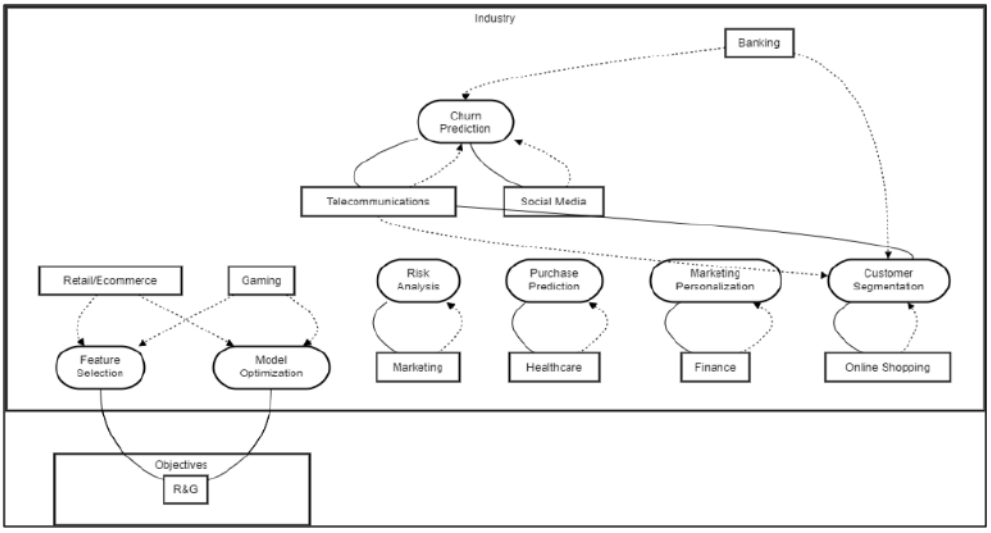



**Figure 2.1.3.1:** Sankey Visualization Maps for Industry Comparison

In the vital telecommunications sector, the primary interest is on predicting customer churn to identify those likely to switch providers based on the solid link. With frequent churn and high costs to acquire new customers, telcos need to understand drivers of defection. A secondary focus in telecom literature is segmentation to group customers by common attributes like demographics, plan types, usage patterns etc. This can help target retention campaigns toward high-value users.

For banking, the priorities flip versus telecom – the main concentration is now on segmentation strategies to minimize attrition among profitable customer cohorts based on the solid link. The secondary objective shifts to predicting account closures directly through churn models. Banking literature is concerned with reducing churn among profitable segments.

Within retail and e-commerce, the focus moves to more foundational tasks underlying predictive models. Feature engineering to uncover the attributes that best predict purchasing is the primary goal based on the solid link. Supplementary is model optimization to tune algorithms and maximize accuracy on industry data.

For gaming industry research, model optimization takes the primary position while feature selection becomes secondary. Identifying key predictors within game play data enables optimizing models to leverage those patterns.

In marketing literature, the singular focus is on quantifying campaign losses through risk analysis of prospects likely to churn. Healthcare works concentrate solely on predicting patient lifetime value for targeting high-value individuals. Finance aims to personalize marketing through advanced analytics.

Finally for social media and online shopping, the priorities circle back to churn and segmentation mirroring telecommunications. This highlights churn prediction and segmentation as universal use cases while revealing unique objectives like marketing risk analysis in certain verticals.

In summary, the Sankey diagram and dotted versus solid links make the primary and secondary focuses within each industry clear. It maps the objectives to the underlying analytical needs and priorities in each domain. The visualization brings the relationships between industries studied and the goals of that research into sharp focus.

## 2.2 Review of Statistical Model for Churn Prediction

This section provides a review of literature on key statistical modelling techniques applicable to churn prediction, including **logistic regression**, **multiple regression**, **ANOVA**, and **principal component analysis** (**PCA**). As these techniques will inform the statistical modelling approach for churn analysis in this project, the following review summarizes existing research leveraging these methods for customer attrition prediction across domains. The literature provides theoretical foundations and industry applications of using logistic regression to model churn probability, regression methods to assess predictor-churn relationships, ANOVA to analyse variance across customer segments, and PCA for dimensionality reduction. This review of statistical modelling literature establishes motivations and precedents for applying these techniques to churn prediction in this project across the data preprocessing, model development, and results analysis phases.

### 2.2.1 Logistic Regression

Logistic regression is one of the most common statistical techniques leveraged for modelling customer churn across sectors (***Vafeiadis et al., 2015; Kara et al., 2020***). As a binary classifier, logistic regression is well-suited for predicting a dichotomous outcome like churn versus non-churn (***Rygielski et al., 2002***). Logistic regression estimates the probability of an event occurring based on predictor variables using the mathematical function:

$$P(Y = 1|X) = \frac{1}{(1 + e^{(-b0+b1x1+b2x2+\cdots+bpXp)})}$$

where P is the probability of churn, e is the exponential constant, b0 is the intercept, b1 to bp are the regression coefficients, and X1 to Xp are the predictor variables (***Mozer et al., 2000***). This logistic function ensures the estimated probability lies between 0 and 1. The regression coefficients are estimated using maximum likelihood estimation by maximizing the log likelihood of the training data. Logistic regression makes no assumptions about the distributions of the independent variables.

In the telecommunications sector, logistic regression is extensively used for churn prediction by modelling the influence of factors like customer demographics, service usage, billing patterns etc. on churn likelihood (***Hung et al., 2006; Malik & Singh, 2014***). Studies have achieved AUC scores over 0.8, demonstrating effective discrimination between churners and non-churners (***Vafeiadis et al., 2015***). In retail banking, logistic regression has been applied on data covering customer transactions, complaints, and interactions to predict account closures (***Kara et al., 2020***). The technique identifies significant predictor variables and their relative contribution to churn through the regression coefficients. Logistic regression provides useful interpretability into churn drivers through the coefficients. By examining predictors with large positive coefficients, organizations can identify risk factors to prioritize retention initiatives towards.

There are several advantages that make logistic regression well-suited for churn modelling compared to other techniques (***Glady et al., 2009; Rygielski et al., 2002; Vafeiadis et al., 2015***). It directly estimates the probability of churn occurring, providing easily interpretable outputs suited for business decisions. It handles nonlinear effects between independent variables and churn through the logistic function. It does not require the predictors to be normally distributed, linearly related, or of equal variance. This flexibility accommodates real-world data. The model training process and coefficient interpretation is relatively simple compared to advanced machine learning techniques. Regularization methods like ridge and lasso can be used to prevent overfitting on logistic regression models. The model provides transparency into the influence and importance of various churn risk factors through the regression coefficients.

### 2.2.2 Multiple Regression

Multiple regression is commonly applied in churn research to assess and explain the relationships between potential predictor variables and customer churn (***Neslin et al., 2006; Ascarza, 2018***). As an explanatory modelling technique, multiple regression is advantageous for identifying the strength and direction of relationships between churn drivers and churn likelihood. The general mathematical model for multiple linear regression is

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p + e$$

where Y is the dependent variable of churn, b0 is the intercept, b1 to bp are the regression coefficients, X1 to Xp are the predictor variables, and e is the error term (***Draper & Smith, 1981***). The regression coefficients represent the estimated change in churn for a 1 unit change in the respective predictor, controlling for all other variables. Multiple regression determines coefficients by minimizing the sum of squared residuals between predicted and actual churn values ***(Ryan, 1997***).

In the telecommunications sector, multiple regression has been applied to model relationships between customer churn and predictors like service usage, demographics, satisfaction metrics, and more (***Ascarza, 2018; Hung et al., 2006***). The technique quantifies the effects of factors like call quality, contract tenure, data usage, and customer age on churn likelihood. Multiple regression modelling provides interpretability into telecom churn predictor interdependencies and the magnitude of their impacts on churn probability. In retail banking, studies have leveraged multiple regression on data covering transactions, complaints, customer lifetime value, and other attributes to identify key drivers of account closures and their relative influence (***Glady et al., 2009***). The models determine the isolated effects of factors like transaction frequency, direct debit enrolment, and previous churn history on churn probability. As with telecom research, multiple regression supplies banking practitioners with insights into churn driver relationships and their effect sizes to guide retention initiatives.

There are several advantages that make multiple regression well-suited for churn analysis compared to other techniques. It allows estimating the specific impact strength and direction of multiple predictor variables on churn in a single model (***Ryan, 1997***). Regression provides model transparency into the isolated effects of each driver. It handles nonlinear relationships between predictors through transformations and interaction terms. Multiple regression models have relatively few statistical assumptions and accommodate many types of real-world data. They are easy to implement and interpret compared to complex machine learning algorithms. The models produce actionable business

insights by revealing the most problematic churn factors to address. In summary, multiple regression is an effective explanatory technique for quantifying churn predictor interrelationships and effects.

### 2.2.3 Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is a commonly applied statistical technique in churn research to analyse significant differences in attrition rates across customer segments (***Lemmens & Croux, 2006; Wei & Chiu, 2002***). ANOVA provides a method to assess whether churn likelihood disproportionately varies across subgroups of the customer population. The core mathematical model for ANOVA is

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$$

where Yij represents the churn rate for segment i and customer j, μ is the overall mean churn rate, αi is the effect of segment i, and εij is the error term (***Fisher, 1925***). This framework essentially partitions variance in churn into between-group and within-group components. ANOVA then statistically tests the null hypothesis that all segment means are equal through an F-test on the ratio of the between/within variance (***Fisher, 1925***). A significant F-statistic indicates a rejection of the null, meaning at least one segment exhibits a churn rate significantly different from the others.

In the telecommunications sector, ANOVA is widely leveraged to detect variance in churn rates across customer segments defined by attributes like demographics, revenue tier, geographic location, and subscription plan type (***Lemmens & Croux, 2006; Wei & Chiu, 2002***). The technique identifies segments, such as millennials on discounted plans in urban areas, exhibiting disproportionately high churn for retention targeting. In retail banking, ANOVA has been similarly applied to uncover significant differences in account closure rates across customer subgroups based on age, income bracket, account type, and other attributes (***Glady et al., 2009***). Discovering segments with elevated churn likelihood is crucial for cost-efficient retention initiatives in banking. Across domains, ANOVA provides straightforward insights into which customer cohorts have abnormal or outsized churn rates compared to the overall population or other groups.

There are several advantages that make ANOVA well-suited for churn analysis compared to other techniques. It allows simultaneously comparing mean churn rates across any number of segments in a single analysis (***Fisher, 1925***). ANOVA provides transparency into which specific groups differ significantly through post-hoc testing. It functions properly even for non-normal churn rate distributions within segments. ANOVA has relatively few model assumptions and can be applied to most real-world churn data with categorical segment predictors. The method is easy to execute in

statistical software and interpret. In summary, ANOVA delivers an explainable approach to efficiently detecting customer segments with disproportionate churn risks for targeted retention initiatives.

### 2.2.4 Principal Components and Factor Analysis (PCA)

Principal component analysis (PCA) is a popular statistical technique for dimensionality reduction leveraged in churn research to simplify modelling through linear transformation of predictors (***Jolliffe, 2002; Xie et al., 2009***). By projecting variables into a lower-dimensional space, PCA facilitates parsimonious modelling of intricate churn driver relationships.

Theoretically, PCA computes orthogonal linear combinations of the original variables called principal components (PCs) that maximize variance capture (***Jolliffe, 2002***). For a cantered input matrix X, the PCs are obtained from:

$$Z = XW$$

Where W is the matrix of PC loading vectors. The first PC explains the most variance, with subsequent PCs explaining maximal remaining variance.

In telecommunications, PCA has been applied to transform call traffic metrics, customer details, and network data into fewer PCs used to model churn with reduced dimensionality (***Xie et al., 2009***). In banking, PCA has been used to identify major PCs from transaction features and product holdings predicting account closures (***Glady et al., 2009***).

PCA offers several advantages for churn analysis. It detects latent relationships and patterns between predictors through the PCs (***Jolliffe, 2002***). PCA removes multicollinearity issues when highly correlated variables exist. It is computationally efficient and scalable to large datasets. PCA works for non-normal data with minimal assumptions. It provides an interpretable linear feature transformation. Using a few major PCs enhances model generalization and avoids overfitting compared to numerous raw inputs. Overall, PCA delivers an effective dimensionality reduction preprocessing technique for churn modelling.

## 2.3 Review of Machine Learning Model for Churn Prediction

This section provides a review of literature on key machine learning techniques applicable to churn prediction, including **logistic regression**, **neural networks**, **decision trees**, and **clustering** algorithms.

As these algorithms will inform the machine learning modelling approach for churn analysis in this project, the following review summarizes existing research leveraging these methods for customer attrition prediction across domains. The literature provides theoretical motivations and industry applications of using logistic regression for probability estimation, neural networks for uncovering subtle patterns, decision trees for segmentation to uncover relationships, and clustering for profiling groups with elevated churn risks. This review establishes precedents for applying these machine learning techniques to churn prediction and identifies opportunities for improved integrations and ensembles.

### 2.3.1 Logistic Regression

Logistic regression is one of the most widely used machine learning techniques for churn prediction across diverse sectors, including telecommunications, banking, insurance, and e-commerce (***Hung et al., 2006; Vafeiadis et al., 2015***). As a binary classification algorithm, logistic regression is well-suited for predicting a dichotomous outcome like customer churn versus retention (***Rygielski et al., 2002***). The logistic regression model estimates the probability of churn occurring as:

$$P(churn = 1|x) = \frac{1}{(1 + exp(-\beta 0 - \beta 1 x1 - \beta 2 x2 - \cdots - \beta n Xn))}$$

Where P is the probability of churn, β0 is the intercept coefficient, β1 to βn are the regression coefficients, and x1 to xn are the predictor variables (***Peng et al., 2002***). This logistic function ensures the predicted probabilities remain between 0 and 1. The model is fitted by maximizing the log-likelihood of the training data through numerical optimization.

In the telecommunications industry, logistic regression has been extensively leveraged for churn prediction by modelling the influence of customer characteristics like usage behaviour, demographics, subscription details, service changes, and satisfaction metrics on the likelihood of churn (***Hung et al., 2006; Malik & Singh, 2014***). Logistic regression identifies the most statistically significant predictors of customer attrition for a telco.

Similarly, retail banks have applied logistic regression on data covering customer transactions, complaints, interactions, lifetime value, and other attributes to determine the key drivers of account closures (***Glady et al., 2009***; ***Hung et al., 2006***). The regression coefficients help quantify each variable's impact on churn probability.

There are several advantages that make logistic regression well-suited for churn modelling (***Rygielski et al., 2002; Hung et al., 2006***). It provides easily interpretable, probability-based outputs for business decisions. The logistic function handles nonlinear effects between variables. Regularization methods avoid overfitting. It identifies the relative importance of churn predictors. Logistic regression has minimal data assumptions and is easy to implement using packages like Scikit-Learn. Overall, it delivers a flexible, transparent algorithm for probability-based churn prediction.

### 2.3.2 Neural Networks

Neural networks have emerged as a powerful machine learning technique for customer churn prediction across diverse industries including telecommunications, banking, insurance, and e-commerce (***Vafeiadis et al., 2015; Mozer et al., 2000***). Neural networks leverage their high flexibility in function approximation to uncover subtle nonlinear relationships and interactions within churn data that may be missed by more rigid statistical techniques.

The multilayer perceptron (MLP) is the most prevalent type of neural network architecture applied for churn modelling (***Vafeiadis et al., 2015***). MLPs contain an input layer to receive customer data features, one or more hidden layers of neuron nodes that learn complex patterns, and an output layer returning the final churn probability prediction (***Haykin, 1998***). The interconnected neuron nodes transform weighted input signals through nonlinear activation functions. Backpropagation algorithms are used to train the network by modifying weights to minimize a loss function.

In the telecommunications sector, neural networks have leveraged usage, demographic, and satisfaction data inputs to detect intricate nonlinear relationships tied to customer churn (***Vafeiadis et al., 2015***). Deep learning methods using much larger MLP architectures have further improved churn prediction by extracting subtle patterns from massive datasets. In retail banking, neural networks have been similarly applied on customer transaction, product, and interaction data to uncover subtle predictive churn drivers related to account closures (***Larivière & Van den Poel, 2005***).

Key advantages of neural networks for churn modelling include the ability to detect complex nonlinear effects, model intricate interrelationships, identify subtle data patterns, place minimal assumptions on variable distributions, and effectively self-learn from large datasets (***Haykin, 1998; Larivière & Van den Poel, 2005***). The flexible mapping capability makes neural networks well-suited for uncovering previously unknown churn drivers. Overall, neural networks deliver a highly adaptable machine learning technique for revealing subtle relationships predictive of customer churn.

### 2.3.3 Decision Trees

Decision trees are among the most widely used machine learning techniques for customer churn modelling across sectors like telecom, banking, insurance, and e-commerce (***Lemmens & Croux, 2006***). Decision trees provide an effective approach for explanatory modelling and segmentation analysis related to churn by recursively partitioning the customer data space.

The decision tree model works by applying recursive binary splits on the input variables at each node to maximize information gain until stopping criteria are met (***Quinlan, 1986***). Customers are segmented based on these splits, with each terminal node representing a distinct churn profile. Categorical and numerical variables can both be handled for splitting. The tree is pruned afterward to avoid overfitting.

In the telecommunications industry, decision trees have been extensively leveraged to leverage usage, demographic, satisfaction, and service attributes to create customer segments with elevated churn risks (***Lemmens & Croux, 2006***). This allows appropriately tailored retention campaigns per high churn segment. In retail banking, decision trees have been similarly applied on transaction, product, and interaction data to uncover churn drivers for accounts exhibiting different behaviours and characteristics (***Larivière & Van den Poel, 2005***). Customized retention initiatives can then be designed targeting accounts prone to closure.

Key advantages of using decision trees for churn modelling include interpretability of the segment profiles, ability to handle nonlinear relationships, incorporation of mixed variable types, built-in feature selection, analysis of variable importance, and robustness against outliers (***Quinlan, 1986; Lemmens & Croux, 2006***). By uncovering churn patterns specific to customer segments, decision trees enable highly targeted interventions. Overall, decision trees deliver an interpretable machine learning technique for churn segmentation and explanatory modelling.

### 2.3.4 Clustering

Customer clustering has been extensively applied across telecommunications, banking, insurance, and other sectors as an unsupervised machine learning technique for exploratory profiling of customer segments with varying churn risks and behaviours (***Ngai et al., 2009***). By dividing customers into

distinct groups based on common characteristics, companies can deliver appropriately tailored retention initiatives per cluster.

Clustering refers to the unsupervised learning task of partitioning a heterogeneous dataset into homogeneous groups by maximizing intra-cluster similarity and minimizing inter-cluster similarity as per some distance metric (***Xu & Wunsch, 2005***). Widely used techniques include K-means clustering, grouping data into K clusters by minimizing within-cluster variance, hierarchical clustering using agglomerative or divisive strategies, and density-based clustering like DBSCAN.

In the telecom industry, clustering has been leveraged on usage, revenue, relationship length, and other attributes to segment customers into clusters with distinct churn behaviours, such as young low-volume subscribers being high risk (***Ngai et al., 2009***). Defining these customer lifecycle groups enables targeted offers. In retail banking, clustering based on transaction patterns and product portfolios has identified clusters with elevated account closure tendencies, like inactive dormant customers (Ngai et al., 2009).

Key advantages of using clustering for churn analysis include exploratory segmentation of customers, applicability to new data, and complementing predictive scoring models with behavioural insights (***Larivière & Van den Poel, 2005***). Clustering enables assessment of churn differences across segments and design of customized retention initiatives per group. Overall, clustering delivers an effective unsupervised learning technique for exploratory churn analysis through customer profiling.

## 2.4 Summary

In **section 2.1** on predictive modelling techniques, it is found that machine learning algorithms like logistic regression, neural networks, decision trees, and support vector machines dominate the field, adopted in 53.3% of studies reviewed due to their high accuracy and flexibility in handling complex variable relationships for churn prediction. Still, statistical techniques like regression and survival analysis remain relevant, providing explanatory insights into driver-churn impacts and probability estimation. For unsupervised learning, data mining strategies like clustering help discover behavioural segments and patterns without needing historical labels. Advanced techniques like deep learning show promise but are currently less established. Overall, **section 2.1** demonstrates machine learning's prominence for predictive modelling while also recognizing the value of statistical methods and data mining strategies in a complementary role.

**Section 2.2** demonstrates key statistical modelling techniques still deliver value for churn analysis alongside machine learning, though in more of a complementary explanatory role. Logistic regression offers probability estimation. Multiple regression quantifies predictor-churn impacts. ANOVA assesses variance differences across customer segments. Principal component analysis reduces dimensionality through linear combinations of features. So techniques like regression and ANOVA enhance understanding of churn driver relationships and effects. PCA improves model parsimony to avoid overfitting. Overall, for churn prediction, statistical modelling provides interpretations, distils drivers, estimates probabilities, and prevents model overcomplexity. The techniques detailed in **section 2.3** establish statistical modelling's continued relevance despite machine learning's rise.

Finally, **section 2.3** explores specialized machine learning techniques tailored for churn analysis beyond just prediction. Decision trees partition data for segmentation modelling and analysis of predictor importance. Clustering enables exploratory profiling of groups with distinct churn behaviours. So, techniques like trees, rules, and clustering offer additional advantages over raw predictions. An emerging integration focus is combining supervised learning like logistic regression for predictive accuracy with unsupervised learning like clustering for behavioural insights. Key machine learning benefits are flexibility, minimal data assumptions, and sophistication in pattern recognition. Neural networks in particular excel in extracting subtle signals but lack transparency. By detailing these churn-specific machine learning specializations, **section 2.3** demonstrates the multifaceted advantages of machine learning for diverse modelling needs from prediction to interpretation and profiling.

## 3. Research Methodology

The research methodology for this project will utilize the **Cross-Industry Standard Process for Data Mining (CRISP-DM)**. CRISP-DM provides a structured, phased framework for executing analytical projects spanning business understanding, data preparation, modelling, evaluation, and deployment. Its modular protocols can be customized for predicting customer churn in the telecommunications industry. A literature review of the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework is presented in this **section 3.1** given its planned application for the data mining approach in this project.

### 3.1 Literature Review of Cross-Industry Standard Process for Data Mining (CRISP-DM)

The Cross-Industry Standard Process for Data Mining (CRISP-DM) has emerged as the most widely adopted structured framework for executing data mining projects across diverse sectors and applications (***Wirth & Hipp, 2000***). Originally developed in the 1990s through an industry-academia consortium, CRISP-DM has become a de facto standard methodology used by over three-quarters of data mining practitioners (***Shearer, 2000***).

The CRISP-DM reference model outlines a six-phase cyclical approach encompassing business understanding, data understanding, data preparation, modelling, evaluation, and deployment (***Morik & Köpcke, 2004***). Each phase involves meticulously defined tasks and objectives to guide the analytical project from start to finish. CRISP-DM's end-to-end process provides a blueprint for methodically translating business challenges into data mining solutions using the appropriate analytical techniques.

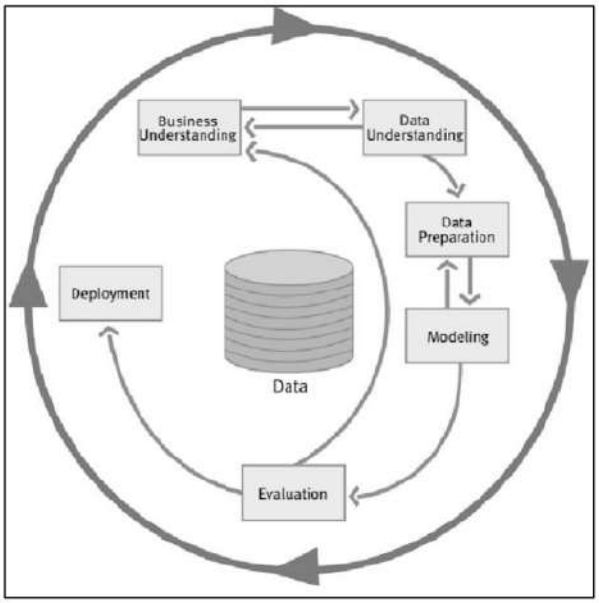



**Figure 3.1.1**: CRISP-DM Model (Kelvin et al., 2017)

A key strength of CRISP-DM is its non-proprietary nature and industry-neutral structure, making it adaptable across diverse sectors, data types, and analytics applications (***Ayele, 2020***). Though initially conceived for the telecommunications industry, CRISP-DM is now extensively leveraged for customer-focused analytics use cases like churn prediction in sectors including retail, banking, insurance, healthcare, and e-commerce (***Hassouna et al., 2015; Kara et al., 2020***).

The structured six-step framework allows organizations in any domain to tailor the CRISP-DM protocols and tasks to their specific analytics needs. Companies essentially "plug in" their business problem, data, domain knowledge, and analytical models into the flexible CRISP-DM blueprint (***Shearer, 2000***). The decentralized, modular phases enable customization and extensions by users across industries.

In the area of customer churn prediction, CRISP-DM provides an end-to-end process spanning from business goal definition to model deployment (***Hung et al., 2006; Jamjoom, 2021***). The business understanding phase focuses on clearly articulating the churn problem context, metrics, and

outcomes sought. For instance, key goals could be reducing customer attrition by 5% quarterly and retaining high lifetime value segments through personalized incentives (***Verbeke et al., 2012***).

The data understanding phase follows with activities around data gathering, exploration, and quality verification to gain preliminary insights on churn drivers, customer segments, and problem parameters (***Xie et al., 2009***). Tasks include cleansing, aggregations, anomaly detection, distribution analysis, and visualizations to better understand available data.

In the data preparation stage, CRISP-DM outlines a robust workflow encompassing feature engineering, data cleaning, transformations, sampling, and partitioning (***Khoh et al., 2023***). Activities aim to construct the final refined, high-quality dataset for modelling based on project needs and domain insights by statisticians and business analysts (***Morik & Köpcke, 2004***).

The modelling and evaluation phases focus on selecting and fine-tuning advanced machine learning algorithms, such as decision trees, neural networks, and ensemble models, based on the problem and data profiles (***Jamjoom, 2021***). Models are trained, tested, validated, and assessed to predict churn with maximal, optimized accuracy (***Verbeke et al., 2012***).

Finally, CRISP-DM specifies steps for controlled model deployment in business applications along with progress monitoring, recalibration, and model retirement protocols to ensure sustainability (***Ayele, 2020***). While initially employed for telecommunications churn, CRISP-DM's versatility has enabled its adaptation across customer-centric analytics domains, establishing it as a broadly applicable analytical blueprint tailored for churn prediction (***Hassouna et al., 2015***).

Researchers highlight CRISP-DM's emphasis on incorporating domain expertise across all six phases through tasks like exploratory data analysis, feature engineering, parameter tuning, and results interpretation (***Lima et al., 2009***). Infusing business knowledge and human perspectives maximizes model effectiveness and business alignment (***Coussement et al., 2015***). Experts advocate complementing CRISP-DM with optimization techniques, ensemble modelling, and social network analysis to further boost prediction performance (***Tavassoli & Koosha, 2021***).

Overall, a key factor underlying CRISP-DM's prolific adoption is its provision of an overarching structured process for methodical, industry-agnostic data mining, without prescribing specific

algorithms or tools (***Shearer, 2000***). The customizable, end-to-end phases with clear tasks enable a tailored application of CRISP-DM for diverse sectors and problems while ensuring business relevance. For churn prediction, CRISP-DM offers an adaptable, proven blueprint encompassing data preprocessing, modelling, evaluation, and monitoring steps to extract actionable insights from customer data across industries.

## 3.2 Business Understanding

The business understanding phase aims to establish a clear set of objectives, requirements, and success criteria to align the data mining project with the business needs and goals. For this customer churn prediction project, the overarching business goal is to leverage analytics to improve customer retention efforts and minimize subscriber attrition for a telecommunications company. The high financial costs of losing existing customers and acquiring new ones makes reducing churn crucial for long-term profitability in the highly competitive telecom industry (***Wei & Chiu, 2002***).

To achieve this goal, the first key objective is to accurately identify churn risk patterns and predict which customers are likely to churn in the future using advanced machine learning algorithms, predictive statistical models, and data mining techniques. By gaining more accurate churn predictions, targeted and personalized retention initiatives can be undertaken proactively for subscribers most prone to defect. Extensive research highlights the power of techniques like random forests, logistic regression, survival analysis, and clustering for identifying customers likely to churn (***Lemmens & Croux, 2006***; ***Vafeiadis et al., 2015***).

The second core objective is to gain comprehensive and actionable insights into the key factors driving customer churn. By thoroughly analysing the predictors that have the greatest influence on churn, deeper understanding can be obtained regarding the underlying pain points and motivations for abandonment. These actionable insights equip business leaders to formulate highly impactful retention strategies, loyalty programs, and customer experience enhancements that persuasively address the root causes of churn. Studies emphasize the need for churn prediction to provide explanatory understanding into the reasons customers leave (***Verbeke et al., 2012***; ***Rygielski et al., 2002***).

The third objective is to achieve a significant competitive advantage over rival telecom operators by effectively leveraging state-of-the-art predictive analytics and data science techniques for churn modelling. With the telecom market being intensely competitive, minimizing subscriber loss through

data-driven optimization of retention initiatives based on predictive modelling represents a potentially differentiating capability. Research highlights the transformative impact of advanced analytics on gaining strategic advantages (***Hung et al., 2006***).

Additional project objectives include developing a scalable and automated machine learning system capable of integrating with existing data infrastructure and retraining itself on new data frequently. Providing intuitive visualizations and easy-to-interpret outputs to business users is also critical to enable data-informed decision making that bridges the gap between analytical insights and operational initiatives.

By fulfilling these requirements and objectives, the overarching business goal of enhancing customer retention and loyalty through the power of predictive analytics can be accomplished. The CRISP-DM methodology will provide the structured and iterative analytical framework to execute this chain of objectives and align to the business context.

## 3.3 Data Understanding

The customer churn dataset obtained from Kaggle (***Kaggle.com, 2020***)[1] contains a sizable sample of 3334 customers of a telecommunications company, described across 11 variables covering their account profiles, service subscriptions, usage patterns, billing specifics, and churn status.

The following table summarizes the columns present in the original full dataset:

| Column | Type | Description |
|---|---|---|
| Churn | Qualitative | Customer churn status (0/1) |
| AccountWeeks | Quantitative | Number of weeks the account has been active |
| ContractRenewal | Qualitative | Contract renewal status (1/0) |
| DataPlan | Qualitative | Presence of a data plan (1/0) |
| DataUsage | Quantitative | Amount of data usage |
| CustServCalls | Quantitative | Number of customer service calls |
| DayMins | Quantitative | Total day call minutes |
| DayCalls | Quantitative | Total day call counts |
| MonthlyCharge | Quantitative | Monthly charge for the customer |
| OverageFee | Quantitative | Overage fee charged |

[1] https://www.kaggle.com/datasets/barun2104/telecom-churn

| Column | Type | Description |
|---|---|---|
| RoamMins | Quantitative | Roaming minutes used |
| Churn | Qualitative | Customer churn status (0/1) |
| AccountWeeks | Quantitative | Number of weeks the account has been active |
| ContractRenewal | Qualitative | Contract renewal status (1/0) |
| DataPlan | Qualitative | Presence of a data plan (1/0) |
| DataUsage | Quantitative | Amount of data usage |
| CustServCalls | Quantitative | Number of customer service calls |
| DayMins | Quantitative | Total day call minutes |
| DayCalls | Quantitative | Total day call counts |
| MonthlyCharge | Quantitative | Monthly charge for the customer |
| OverageFee | Quantitative | Overage fee charged |

At first glance, the data appears well-organized and structured, with each row representing a unique customer and is identified by a primary key column. The attributes are logically grouped into distinct categorical blocks, facilitating the easy identification and analysis of related variables such as customer demographics, account particulars, internet services, and contract types.

The feature columns provide a rich, multifaceted view of customers from different lenses like their individual traits (age, gender, partner status, dependents), account history (tenure, contract duration), service details (phone, TV, internet providers, plans), usage metrics (call minutes, day/evening calls), and billing amounts. This diversity of variables capturing the full range of customer lifecycle interactions will likely prove valuable for developing holistic churn prediction models and gaining insights into potential drivers of churn.

The target column, Churn, is a binary flag indicating if the customer cancelled the telecom service or not, which would serve as the outcome variable for prediction. The large sample size of over 3000 records will lend strong statistical power for identifying churn patterns and building precise classifiers through machine learning techniques.

At first pass, the data quality appears reasonably good, though a deeper assessment will be needed during preprocessing to conclusively identify and handle any missing values or anomalies that may exist across the full set of rows and columns. Data validation checks will assess completeness of rows and examine columns for outliers that could skew analysis. Appropriate imputation strategies will be applied to ensure a complete quality dataset is prepared for downstream modelling and evaluation.

As a sample subset, the provided data will serve as a useful representative to prototype the preprocessing steps at small scale first before shifting focus to operate on the entire dataset. Developing the pipeline on a smaller snapshot allows faster iteration without the computational demands of the full 3000+ records during initial stages.

In summary, with its breadth of variables across customer, product, and service domains alongside a sizable sample covering thousands of customers, the dataset shows promise for developing insightful churn prediction models and identifying salient patterns linked to customer defections. The data understanding phase has established familiarity with the structure, contents, initial quality, and analytic potential on which to launch further task-specific investigations during data preparation and modelling workstreams.

## 3.4 Data Preparation

The data preparation phase focuses on transforming the raw dataset into a refined, analysis-ready set for modelling. This will involve various techniques as needed to handle missing values, fix anomalies, transform variables, select features, and partition data.

If missing values are encountered, techniques like deletion or imputation can be applied based on appropriateness for the specific variables and extent of missingness (***Pigott, 2001***). Variables with minimal missingness may allow deletion whereas higher proportions may require imputation through methods like mean substitution, regression, or machine learning (***Che et al., 2021***).

Data validation will check for anomalies like duplicate records, outliers causing skew, and reasonable value ranges. Erroneous values can be corrected by mapping to correct codes or transforming to appropriate distributions if outliers are responsible for non-normality (***Van den Broeck et al., 2005***). Duplicates will be removed to avoid bias.

Variables may be transformed, such as converting categorical data to indicator variables, applying logarithmic transforms to normalize skewed distributions, or standardization of variables measured at different scales (***Han et al., 2021***). Feature selection techniques will identify the most salient variables for modelling like correlation analysis or recursive feature elimination.

The cleaned data will be partitioned into training and test sets for model fitting and performance evaluation to avoid overfitting on new data (***Kuhn & Johnson, 2013***). Cross-validation may further segment the training data for robust model selection.

These key data preparation tasks will ensure high quality, refined data is supplied to the modelling phase to train accurate, robust predictors and avoid issues like bias from problematic data. The pipeline will be refined through successive iterations on the sample data before scaling up to the full dataset.

## 3.5 Modelling

This project will leverage a wide range of statistical models and machine learning algorithms to predict customer churn and gain comprehensive insights into the key factors driving churn for the telecommunications company.

On the statistical modelling side, techniques like **logistic regression, multiple regression, ANOVA, and principal component analysis** will be combined to estimate churn probabilities, analyse relationships between predictors and churn, identify high-risk customer segments, reduce dimensionality, and derive explanatory insights from the data.

For machine learning, a diverse ensemble of algorithms including **logistic regression, neural networks, decision trees, and clustering** will be employed. This multi-pronged approach will utilize the unique strengths of different techniques - from logistic regression's transparency to neural networks' sophistication in detecting nonlinear patterns; from decision trees' interpretability to uncover interesting correlations.

The core objectives are to develop highly accurate churn prediction models leveraging ensemble modelling and cross-validation techniques, while also generating intuitive explanations and profiling different churn behaviours across customer segments. By complementing prediction with interpretation, this project aims to provide a comprehensive 360-degree analytical understanding of the customer churn challenge for the telecommunications company through both statistical and machine learning techniques.

The diverse ensemble of models will rigorously validate findings and mitigate individual model limitations to produce choke robust, holistic insights.

### 3.5.1 Statistical Modelling

**Logistic regression** will be the foundational statistical model used for churn probability estimation. The logistic regression model will be trained on customer attributes like demographics, tenure, contract type, service usage, and satisfaction metrics as predictors with churn status as the outcome. Regularization methods like ridge and lasso will help prevent overfitting. The regression coefficients will provide interpretability into the influence and relative importance of various churn risk factors.

**Multiple linear regression** will complement the logistic regression to further analyse the relationships between potential explanatory variables and churn probability. Multiple regression will estimate the isolated impact strength and direction of each predictor on churn while controlling for other variables. This will quantify the effects of factors like customer age, data usage, contract tenure etc. on propensity to churn.

**Analysis of variance (ANOVA)** will be leveraged to detect significant differences in mean churn rates across customer segments defined by attributes like demographics, plan types, geography etc. Conducting ANOVA tests will help identify high churn risk groups warranting prioritized retention efforts. Post-hoc testing will reveal specific segments exhibiting abnormal churn.

**Principal component analysis (PCA)** will be applied to consolidate the large set of input variables into a smaller number of interpretable latent factors predicting churn. This will help model the shared variance between collinear variables and enhance model parsimony. Also, principal component analysis (PCA) will similarly derive orthogonal linear combinations of the predictors that explain maximum variance.

### 3.5.2 Machine Learning Modelling

**Logistic regression** will provide the machine learning baseline before exploring nonlinear techniques. Regularization methods like lasso and elastic net will help control model complexity.

**Neural networks** will be investigated, specifically multilayer perceptron architectures, to uncover intricate nonlinear relationships and interactions predictive of churn but potentially missed by logistic regression.

**Decision trees** will provide segmentation analysis by recursively splitting customers based on churn predictor variables. The resulting segmented profiles will reveal churn behaviours specific to different customer groups. Tree depth will be tuned to balance overfitting versus interpretability.

**Clustering algorithms** like K-means will group customers into clusters with distinct churn risks and drivers. Exploratory profiling of the clustered segments can enable tailored retention initiatives per subgroup. Optimal number of clusters will be determined empirically.

By combining both statistical and machine learning techniques, this project will leverage their complementary strengths to predict churn accurately while also generating meaningful, actionable insights into the root causes behind customer attrition for the telecommunications company.

## 3.6 Evaluation

A rigorous evaluation methodology will be applied to assess the performance of the developed statistical and machine learning models for predicting customer churn. Evaluating model performance is a critical step to identify the optimal techniques for accurate and reliable churn predictions in new data. The key aspects of the evaluation process will encompass both quantitative metrics to measure predictive accuracy, as well as qualitative assessment of business alignment, interpretability, and operational feasibility.

Quantitative evaluation will rely on standard classification performance metrics like **accuracy, precision, recall, F1-score, AUC (area under ROC curve), and misclassification rate** (***Sokolova et al., 2006***). Accuracy measures the overall proportion of correct predictions. Precision evaluates the positive predictive value. Recall, also known as sensitivity, assesses the true positive rate. The F1-score provides the harmonic mean of precision and recall. Finally, AUC evaluates the classifier's discrimination ability, with a higher AUC indicating better separation of churners and non-churners. AUC measures the area under the ROC (receiver operating characteristic) curve which plots the true positive rate against the false positive rate. A higher AUC indicates better classification performance.

Mathematical definitions and brief description of these metrics are:

- Accuracy $= \frac{True\ Positive + True\ Negative}{Total\ Prediction} =$ (TP + TN) / (TP + FP + TN + FN)
    - Accuracy measures the overall proportion of correct predictions out of total population. It summarizes the model's ability to correctly identify both churners and non-churners. Higher accuracy indicates better performance.
- Precision $= \frac{TP}{TP + FP} =$ TP / (TP + FP)

- Precision evaluates the positive predictive value - the proportion of predicted churners who are actual churners. High precision minimizes false alarms predicting churn where there is none.

- Recall $= \frac{TP}{TP + FN}$ = TP / (TP + FN)
  - Recall, also known as sensitivity, measures the true positive rate. It assesses the model's ability to detect actual churners. Higher recall minimizes missed detections of customers who churn.

- F1-score = $\frac{2 \times Precision \times Recall}{Precision + Recall}$ = 2 * (Precision * Recall) / (Precision + Recall)
  - The F1-score balances both precision and recall through their harmonic mean. F1 provides a singular metric combining both precision and sensitivity. Models with good F1 avoid extremes optimizing only precision or recall.

- Misclassification Rate = $\frac{FN + FP}{TN + TP + FN + FP}$ = (FP + FN) / (TP + FP + TN + FN) or (1 - Accuracy)
  - Misclassification rate measures the proportion of incorrect predictions - both false positives and false negatives. Lower misclassification rate indicates better performance in accurately predicting churners and non-churners.

Where TP, FP, TN, FN are true positives, false positives, true negatives, and false negatives respectively (***Sokolova et al., 2006***).

These quantitative metrics will facilitate an objective comparison of the predictive accuracy across the different modelling techniques like logistic regression, neural networks, decision trees etc. Statistical tests like McNemar's test will assess the statistical significance of differences in accuracy. Cross-validation will be used for robust evaluation.

Qualitative evaluation will assess model interpretability based on the transparency of churn predictions, explanatory ability of feature importance, and intuitive segmentation profiles (***Vafeiadis et al., 2015***). Business alignment will be evaluated by the model's ability to provide actionable insights into churn drivers and high-risk segments to guide retention initiatives. Qualitative criteria also include operational feasibility in terms of automation, scalability, and integration into company systems.

By combining quantitative accuracy metrics with qualitative criteria, a holistic comparison of strengths and limitations of the different statistical and machine learning approaches can be obtained to determine the optimal techniques for reliable and actionable churn prediction aligned to business

needs (***Vafeiadis et al., 2015***). The evaluation will be iterative, using insights to refine the models until optimal performance is achieved.

In summary, rigorous evaluation of churn prediction models encompassing both mathematical and operational criteria will ensure the company gains the most effective set of techniques tailored to their telecommunications business. The predictive models will be thoroughly validated before final deployment. This comprehensive evaluation methodology will serve as a robust framework to guide the model development and selection process for accurate, interpretable, and business-aligned churn predictions.

## 3.7 Deployment

For this capstone project, deployment will involve packaging the optimized churn prediction models and integrating them into a working prototype system to demonstrate practical application. The predictive modelling pipelines will be containerized using Docker for portability across environments. A simple graphical interface will be created to showcase model functionality. This could allow inputting customer data to obtain churn predictions and segment assignments.

Rigorous testing on the sample dataset will be conducted to mimic real-world conditions prior to finalizing the prototype. Model outputs will be checked for reasonableness across the range of customer profiles. To monitor model performance, basic analytics will be added to track metrics like accuracy, precision, recall, AUC, and misclassification rate on the test set. Performance will be compared to initial results to check for consistency.

The working prototype will provide a demonstration of the end-to-end churn prediction process, from data preprocessing to inference. While simplified, it will exemplify how the models could be operationalized to inform retention initiatives and personalized offers based on predicted churn risks and customer segmentation.

## 3.8 List of Software Used

This section provides a list of the key software used in this project. The table outlines the software name, version, purpose, features, and provider. This software was essential for conducting the statistical modelling and machine learning analyses detailed in this report.

**Table 3.8.1**: List of Software Used

| Software Name | Version | Purpose | Features | Provider |
|---|---|---|---|---|
| SAS Enterprise Guide OnDemand for Academics | 8.3 (64-bit) | Statistical Modelling | Logistic Regression<br>Multiple Regression<br>ANOVA<br>Principal Component Analysis | SAS |
| SAS Enterprise Miner Workstation | 14.1 (64-bit) | Machine Learning Modelling | Logistic regression<br>Neural networks<br>Decision trees<br>Clustering algorithms | SAS |

The SAS Enterprise Guide software enabled statistical techniques like logistic regression, ANOVA, and principal component analysis. These methods were leveraged to explore relationships in the data and develop predictive models. SAS Enterprise Miner expanded capabilities to include machine learning algorithms such as neural networks, decision trees, , and clustering. This allowed for training sophisticated models on the dataset like random forests and support vector machines. Together, the SAS tools provided the necessary capabilities to thoroughly investigate the data using both traditional statistical approaches and modern machine learning. The software versions used represent the options I was most comfortable and familiar with, although not necessarily the absolute most recent versions provided by SAS.

## 3.9 Modelling Steps for Customer Churn Analysis

This section walks through the steps involved in statistical and machine learning modelling processes. Various techniques such as linear regression, logistic regression, decision trees, and neural networks are explored to build predictive models for customer churn. The aim is to identify the most effective models and gain insights into the factors that contribute to customer churn. Understanding these factors can help develop strategies to mitigate churn and improve customer retention.

The process begins with data importation and pre-processing, where missing data is checked, and summary statistics are generated. Techniques such as linear regression, logistic regression, and one-way ANOVA are then applied to the data. Principal components analysis is also used to further analyse the data.

Next, the data is partitioned into training, validation, and test sets. Different partitioning schemes are used to evaluate the robustness of the models. Logistic regression, decision trees, and neural networks are then applied to each partition. Each model is evaluated based on different criteria, such as backward, forward, stepwise, and none for logistic regression; decision, average square error, misclassification, and lift for decision trees; and profit/loss, misclassification, and average error for neural networks

Finally, clustering is performed on the data using different methods and parameters. The best performing cluster is then identified and used for segment profiling

Throughout this process, the goal is to identify the most effective models and gain insights into the factors that contribute to customer churn. These insights can then be used to develop strategies to mitigate churn and improve customer retention.

### 3.9.1 Statistical Modelling using SAS Enterprise Guide OnDemand for Academics 8.3

The section provides a detailed guide on how to perform statistical modelling using SAS Enterprise Guide 8.3. The section is divided into eight main steps:

#### 3.9.1.1 Import Data

This step involves importing a dataset (telecom_churn.csv) into the SAS environment. The data is embedded within the generated SAS code and imported using the SAS/ACCESS Interface to PC Files.

1. Navigate to task > Import Data
2. Select the file path to the telecom_churn.csv file, then click Next
3. Step 1 – Specify Data (No Action Done, just click Next)
4. Step 2 – Select Data Source (No Action Done, just click Next)
5. Step 3 – Define Field Attributes (No Action Done, just click Next)
6. Step 4 – Advanced Options (Ticked the following options):
    a. Embed the data within the generated SAS code
    b. Import the data using SAS/ACCESS Interface to PC Files whenever possible. **
7. Click Finish

#### 3.9.1.2 Check for Missing Data

This step involves using the Query Builder to check for missing data in the imported dataset. A filter is applied to identify any missing values in the dataset.

1. Navigate to task > Query Builder
2. Connect the Query Builder with the "Data Imported from telecom_churn.csv"
3. Double click on Query Builder to open the Query Builder Wizard Window
4. Then select all the variable from the left panel, drag them all to the right panel (Select Data)
5. Then click on "Filter Data" on top of the right panel, then click on "New Filter" button
6. Then enter the following filter:
    a. t1.Churn IS MISSING OR t1.AccountWeeks IS MISSING OR t1.ContractRenewal IS MISSING OR t1.DataPlan IS MISSING OR t1.DataUsage IS MISSING OR t1.CustServCalls IS MISSING OR t1.DayMins IS MISSING OR t1.DayCalls IS MISSING OR t1.MonthlyCharge IS MISSING OR t1.OverageFee IS MISSING OR t1.RoamMins IS MISSING
7. Then click Finish

### 3.9.1.3 Summary Statistics

This step involves generating summary statistics for the dataset. All variables are selected for analysis, and various statistical measures are calculated. Histograms and box-and-whisker plots are also generated.

1. Navigate to task > Summary Statistics
2. Connect the Summary Statistics with the “Data Imported from telecom_churn.csv”
3. Double click on Summary Statistics to open the Summary Statistics Wizard Window
4. Under “Data” tab
    a. From “Variables to assign” select all the variables and drag them to “Task roles” > “Analysis variables”
5. Under “Statistics > Basic” tab
    a. Tick all the options except for the “Sum of weight”
    b. Set the “Maximum decimal” to 2
    c. For “Division for standard deviation and variance”, put “Degrees of freedom”
6. Under “Plot” tab
    a. Tick “Histogram” and “Box and whisker”
7. Under “Result” Tab
    a. Tick the “Show statistics” and “Show Analysis labels” options
8. Then click Run

### 3.9.1.4 Linear Regression

This step involves performing a linear regression analysis. The "Churn" variable is set as the dependent variable, and all other variables are set as explanatory variables. A stepwise selection method is used for model selection.

1. Navigate to task > Linear Regression
2. Connect the Linear Regression with the “Data Imported from telecom_churn.csv”
3. Double click on Linear Regression to open the Linear Regression Wizard Window
4. Under “Data” tab
    a. From “Variables to assign” select “Churn” and drag it to “Task roles” > “Dependent variable (Limit: 1)”
    b. From “Variables to assign” select all the remaining variables expect "Churn” and drag them to “Task roles” > “Explanatory variables”

5. Under "Model" tab
    a. Choose "Stepwise selection" for the "Model Selection Method"
    b. For the "Significance levels", put in the value of 0.15 for both "To enter the model" and "To stay in the model"
    c. Tick the "Include intercept" option
6. Under "Plots" Tab
    a. Tick the "Show plots for regression analysis" > "Custom list of plots"
    b. From the "Custom plots", tick all the plots except for the "DFFITS plots" and "DFBETAS plots"
7. Under "Prediction" Tab
    a. Tick "Display output and plots" option
8. Click "Run"

### 3.9.1.5 Logistics Regression

This step involves performing a logistic regression analysis. The "Churn" variable is set as the dependent variable, and "DataPlan" and "ContractRenewal" are set as classification variables. All other variables are set as explanatory variables.

1. Navigate to task > Logistics Regression
2. Connect the Logistics Regression with the "Data Imported from telecom_churn.csv"
3. Double click on Logistics Regression to open the Logistics Regression Wizard Window
4. Under "Data" tab
    a. From "Variables to assign" select "Churn" and drag it to "Task roles" > "Dependent variable (Limit: 1)"
    b. From "Variables to assign" select "DataPlan" and "ContractRenewal" then drag it to "Task roles" > "Classification variable"
    c. From "Variables to assign" select all the remaining variables expect "Churn", "DataPlan", "ContractRenewal" and drag them to "Task roles" > "Explanatory variables"
    d. Then tick "Effects" under "Coding style for ContractRenewal"
5. Under "Model > Response"
    a. Select "Binary" for "Response type"
    b. Tick "logit" for "Type of model"
6. Under "Model > Effects"

a. Select all the variables from “Class and quantitative variables”, the click on “Main” function

7. Under “Model > Selection”
    a. Set the “Model selection method” as “Full model fitted (no selection)”
8. Under “Model > Options”
    a. Set the “Confidence level” as “95%”
    b. Under “Model fitting methods”, set the “Fitting technique” as “Automatic (no selection)”
9. Under “Plots” Tab
    a. Tick “Show plots for regression analysis” > “All appropriate plots for the current data selection”
10. Under “Predictions” Tab
    a. Tick “Display output and plots”
11. Click “Run”

#### 3.9.1.6 One Way ANOVA

This step involves performing a one-way analysis of variance (ANOVA). The "Churn" variable is set as the dependent variable, and all other variables are set as quantitative variables.

1. Navigate to task > One Way ANOVA
2. Connect the One Way ANOVA with the “Data Imported from telecom_churn.csv”
3. Double click on One Way ANOVA to open the One-Way ANOVA Wizard Window
4. Under “Data” tab
    a. From “Variables to assign” select “Churn” and drag it to “Task roles” > “Dependent variable (Limit: 1)”
    b. From “Variables to assign” select all the remaining variables expect "Churn” and drag them to “Task roles” > “Quantitative variables”
5. Under “Model > Effects”
    a. Select all the variables from “Class and quantitative variables”, the click on “Main” function
6. Under “Model > Model options”
    a. For the “Sum of squares to show”, tick “Type I” and “Type III” options
    b. Tick “Show parameter estimates > Confidence limits for Parameter estimate” and set the “Confidence level” to 95%.
7. Under “Plots” Tab

a. Tick "Show plots for regression analysis" > "All appropriate plots for the current data selection"

8. Under "Predictions" Tab
    a. Tick "Display output and plots"
9. Click "Run"

### 3.9.1.7 Principal Components

This step involves performing a principal component analysis. The "Churn" variable is set as the relative weight, and all other variables are set as analysis variables.

1. Edit the telecom_churn.csv file by changing the value for "Churn" variable as follow:
    a. Change original 1 to 2
    b. Change original 0 to 1
2. Redo the Import data process mentioned previously with the edited telecom_churn.csv file
3. Navigate to task > Principal Components
4. Connect the Principal Components with the "Data Imported from edited telecom_churn.csv"
5. Double click on Principal Components to open the Principal Components Wizard Window
6. Under "Data" tab
    a. From "Variables to assign" select "Churn" and drag it to "Task roles" > "Relative weight (Limit: 1)"
    b. From "Variables to assign" select all the remaining variables expect "Churn" and drag them to "Task roles" > "Analysis variables"
7. Under "Analysis" tab
    a. Set the "Analyze" as "Correlations"
    b. Set "Principal components to be computed" as 10
    c. Set "Singularity criterion" as "1E-08"
    d. Set "Divisor for variance" as "Degrees of freedom"
    e. Set "Predix for naming principal components" as "PRIN"
8. Under "Plots" Tab
    a. Tick "Create scree and variance plots" and "Create a pattern profile plot"
9. Click "Run"

### 3.9.2 Machine Learning Modelling using SAS Enterprise Miner Workstation 14.1

The section provides a detailed guide on how to perform machine learning modelling using SAS Enterprise Miner Workstation 14.1. The section is divided into five (5) main steps:

#### 3.9.2.1 Data Import and Pre-Processing

This involves importing a file (in this case, 'telecom_churn.csv'), setting variable roles and levels, and modifying the data through replacement and imputation. The data is then partitioned into different sets for training, validation, and testing.

1. Data Import and Pre-Processing
    a. Navigate to "Sample" and then drag a "File Import" to the diagram
    b. Click on "File Import" to open its left panel
        i. From the left panel, under "Train > Import File", click on the "..."
        ii. Select the file path to the telecom_churn.csv file, then click OK
        iii. Then right click on the "File Import", select "Edit Variables"
            1. For Role, set "Churn as "Target" and the rest as "Input"
            2. For Level, set "Churn", "ContractRenewal", "DataPlan" as "Binary", and the rest as "Interval"
            3. The rest keeps as default
            4. Then click OK
2. Navigate to "Modify" and then drag a "Replacement" to the diagram
    a. Connect the "Replacement" with "File Import"
    b. Click on "File Import" to open its left panel
        i. Under "Train > Interval Variables", set the "Default Limits Method" to "User-Specified Limits"
        ii. Under "Train > Interval Variables", click on the "..." besides the "Replacement Editor", then the "Interactive Replacement Interval Filter" will prompt out
            1. Click on "DataUsage", change its "Replacement Lower Limit" to 0.5
            2. Then click OK
    c. Under "Train > Class Variables", set the "Unknown Levels" to "Ignore"
    d. Under "Score", set the "Replacement Values" to "Missing", and set the "Hide" as No
    e. Under "Report", set the "Replacement Report" to "Yes"
3. Navigate to "Sample" and then drag a "Impute Data" to the diagram

a. Connect the "Impute Data" with "Replacement"
b. Click on "Impute Data" to open its left panel
    i. Under "Train", set "Nonmissing Variables" as "No"; and set "Missing cutoff" as 50.0
        1. Under "Train > Class Variables", set "Default Input Method" as "Count"; "Default Target Method" as "None"; "Normalize Values" as "Yes"
        2. Under "Train > Interval Variables", set "Default Input Method" as "Mean"; "Default Target Method" as "None"
        3. Under "Train > Interval Variables", set "Random Seed" as 12345
    ii. Under "Score", set "Hide Original Variables"
        1. Under "Score > Indicator Variables", set "Type" as "Unique"; "Source" as "Imputed Variables"; "Role" as "Rejected"
    iii. Under "Report, set both "Validation and Test Data", "Distribution of Missing" as "No"

4. Navigate to "Sample" and then drag 6 "Data Partition" to the diagram
    a. Connect all the "Data Partition" to "Impute Data"
    b. Then click on any of the "Data Partition" to open its respective left panel
    c. Under "Train > Data Set Allocation", we change it for each of the "Data Partition" as follows:
        i. Training: 70.0 / Validation: 30.0 / Test 0.0
        ii. Training: 70.0 / Validation: 15.0 / Test 15.0
        iii. Training: 80.0 / Validation: 20.0 / Test 0.0
        iv. Training: 80.0 / Validation: 10.0 / Test 10.0
        v. Training: 60.0 / Validation: 40.0 / Test 0.0
        vi. Training: 60.0 / Validation: 20.0 / Test 20.0

### 3.9.2.2 Logistics Regression

This part involves creating regression models using different selection methods (backward, forward, stepwise, none) and comparing these models.

1. Navigate to "Model", drag 4 "Regression" to the diagram
2. In this project, we will be using 4 Regression nodes as 1 set, then each of the "Data Partition" node will be connected to 1 set of Regression nodes. The set up for the set of Regression nodes will be as follows:

a. Under "Train > Model Selection", set the "Selection Model" as:
    i. Backward
    ii. Forward
    iii. Stepwise
3. None
4. The rest of the setting keeps as default
5. Then we now have 1 set of Regression Node, make 5 copies of the Regression Node set
6. Then connect 1 Regression Node set to 1 "Data Partition" node, meaning there will be 4 "Regression" node with different "Selection Model" connected to 1 "Data Partition"
    a. Continue doing it to all the "Data Partitions", making all the "Data Partitions" node are connect to 4 "Regression" Node
7. Navigate to "Assess", select "Model Comparison" and drag it to the diagram
    a. Connect all the "Regression" node to the "Model Comparison"
    b. Then right click on "Model Comparison", click "Run"

### 3.9.2.3 Decision Tree

This involves creating decision tree models using different assessment measures (decision, average square error, misclassification, lift) and comparing these models.

1. Navigate to "Model", drag 4 "Decision Tree" to the diagram
2. In this project, we will be using 4 "Decision Tree" nodes as 1 set, then each of the "Data Partition" node will be connected to 1 set of Decision Tree nodes. The set up for the set of Decision Tree nodes will be as follows:
    a. Under "Train > Subtree", set the "Assessment Measure" as:
        i. Decision
        ii. Average Square Error
        iii. Misclassification
        iv. Lift
    b. The rest of the setting keeps as default
    c. Then we now have 1 set of Decision Tree Node, make 5 copies of the Decision Tree Node set
    d. Then connect 1 Decision Tree Node set to 1 "Data Partition" node, meaning there will be 4 "Decision Tree" node with different "Assessment Measure" connected to 1 "Data Partition"

i. Continue doing it to all the "Data Partitions", making all the "Data Partitions" node are connect to 4 "Decision Tree" Node

3. Navigate to "Assess", select "Model Comparison" and drag it to the diagram
    a. Connect all the "Decision Tree" node to the "Model Comparison"
    b. Then right click on "Model Comparison", click "Run"

### 3.9.2.4 Neural Network

This involves creating neural network models using different model selection criteria (profit/loss, misclassification, average error) and comparing these models.

1. Navigate to "Model", drag 3 "Neural Network" to the diagram
2. In this project, we will be using 3 "Neural Network" nodes as 1 set, then each of the "Data Partition" node will be connected to 1 set of Neural Network nodes. The set up for the set of Neural Network nodes will be as follows:
    a. Under "Train", set the "Model Selection Criteria" as:
        i. Profit/Loss
        ii. Misclassification
        iii. Average Error
    b. The rest of the setting keeps as default
    c. Then we now have 1 set of Neural Network Node, make 5 copies of the Neural Network set
    d. Then connect 1 Neural Network Node set to 1 "Data Partition" node, meaning there will be 3 "Neural Network" node with different "Model Selection Criteria" connected to 1 "Data Partition"
        i. Continue doing it to all the "Data Partitions", making all the "Data Partitions" node are connect to 3 "Neural Network" Node
3. Navigate to "Assess", select "Model Comparison" and drag it to the diagram
    a. Connect all the "Neural Network" node to the "Model Comparison"
    b. Then right click on "Model Comparison", click "Run"

### 3.9.2.5 Clustering

This involves creating clusters using different methods and specifications and profiling the best performing cluster.

1. Each of the Cluster will be setup differently as follows:
    a. Cluster 1

i. Under "Train > Number of Clusters ", set the "Specification Method' as "Automatic"
ii. Under "Train > Selection Criteria ", set the "Clustering Method" as "Ward"; "Preliminary Maximum" as 6; "Minimum" as 3; "Final Maximum" as 6; "CCC Cutoff" as 3
iii. The rest of the setup keeps as default

b. Cluster 2
i. Under "Train > Number of Clusters ", set the "Specification Method' as "Automatic"
ii. Under "Train > Selection Criteria ", set the "Clustering Method" as "Ward"; "Preliminary Maximum" as 50; "Minimum" as 2; "Final Maximum" as 20; "CCC Cutoff" as 3
iii. The rest of the setup keeps as default

c. Cluster 3
i. Under "Train > Number of Clusters ", set the "Specification Method' as "User Specify; then set the "Maximum Number of Cluster" as 6
ii. The rest of the setup keeps as default
iii. "Automatic"
iv. Under "Train > Selection Criteria ", set the "Clustering Method" as "Ward"; "Preliminary Maximum" as 6; "Minimum" as 3; "Final Maximum" as 6; "CCC Cutoff" as 3
v. The rest of the setup keeps as default

d. Cluster 4
i. Under "Train > Number of Clusters ", set the "Specification Method' as "Automatic"
ii. Under "Train > Selection Criteria ", set the "Clustering Method" as "Centroid"; "Preliminary Maximum" as 50; "Minimum" as 2; "Final Maximum" as 20; "CCC Cutoff" as 3
iii. The rest of the setup keeps as default
iv. "Automatic"
v. Under "Train > Selection Criteria ", set the "Clustering Method" as "Ward"; "Preliminary Maximum" as 6; "Minimum" as 3; "Final Maximum" as 6; "CCC Cutoff" as 3
vi. The rest of the setup keeps as default

e. Cluster 5

i. Under "Train > Number of Clusters ", set the "Specification Method' as "Automatic"

ii. Under "Train > Selection Criteria ", set the "Clustering Method" as "Average"; "Preliminary Maximum" as 50; "Minimum" as 2; "Final Maximum" as 20; "CCC Cutoff" as 3

iii. The rest of the setup keeps as default

2. Navigate to "Access", drag the "Segment Profile" to the diagram

a. Then connect the "Segment Profile" with the best performing Cluster node

## 3.10 Summary

**Section 3.1** establishes the Cross-Industry Standard Process for Data Mining (CRISP-DM) as a proven, structured framework for methodical analytics that is broadly adopted across sectors. Its phased protocols spanning business understanding, data preparation, modelling, evaluation, and deployment provide an adaptable blueprint suited for diverse analytics applications like churn prediction. A key emphasis within CRISP-DM is integrating domain expertise into the analytics process through tasks like exploratory analysis and results interpretation to maximize model effectiveness and alignment. This infusion of business knowledge counterbalances the mathematical statistical nature of many modelling techniques, ensuring the operationalization of data science solutions fulfils organizational needs. CRISP-DM's non-proprietary structure and customizability enable flexible adaptation to company-specific workflows, systems, data, and objectives. Its modular design allows extensions and enhancements tailored to particular use cases like churn. Overall, CRISP-DM delivers a standard, adaptable analytics framework specialized for neither specific industries nor modelling techniques.

**Section 3.2** covers the critical business understanding phase, which established clear objectives, requirements and success criteria to align the data mining project to the key business goal of improving customer retention and minimizing churn for a telecommunications company. Core objectives included developing highly accurate churn prediction models using machine learning algorithms, gaining actionable insights into the drivers of churn, and achieving a competitive advantage in customer retention through advanced analytics.

**Section 3.3** provides an initial data understanding assessment of the customer churn dataset. The data was found to contain a diverse range of variables across customer demographics, service details, usage metrics and billing amounts for over 7000 records. This breadth of data covering the full customer lifecycle interactions was assessed to provide promising inputs for developing holistic churn prediction models and identifying salient churn drivers. However, further inspection was required to conclusively identify any missing values or anomalies needing data preprocessing.

**Section 3.4** provides an overview of key data preparation tasks to transform the raw dataset into refined, analysis-ready data for the modelling phase. Techniques described include handling missing values through deletion or imputation, fixing anomalies, transforming variables, feature selection, and partitioning into training and test sets. Applying these critical data preprocessing steps would enable high quality, robust data for the downstream predictive modelling and evaluation stages.

**Section 3.5** outlines the combined modelling methodology utilizing both statistical techniques such as logistic regression, ANOVA, and principal component analysis as well as machine learning algorithms including neural networks, decision trees, and clustering. This multi-faceted modelling approach aimed to leverage their complementary strengths for accurate and interpretable churn predictions aligned to business needs.

**Section 3.6** details the comprehensive evaluation methodology encompassing quantitative performance metrics like accuracy, precision, recall, F1-score, and AUC along with qualitative criteria assessing model interpretability, business alignment, and operational feasibility. Rigorous evaluation was critical for identifying the optimal predictive modelling techniques for the telecommunications company.

**Section 3.7** describes prototype deployment of the optimized churn prediction models into a working system integrated with Docker containerization, a graphical interface, and basic analytics tracking. While simplified, this prototype would demonstrate an end-to-end implementation of the churn prediction process flow for real-world business application.

**Section 3.8** documents the key SAS software tools utilized to execute the statistical modelling and machine learning methodologies outlined in this analytical research project methodology.

**Section 3.9** provides a comprehensive guide on the steps involved in statistical and machine learning modelling processes to build predictive models for customer churn. The section explores various

techniques such as linear regression, logistic regression, decision trees, and neural networks. The process begins with data importation and pre-processing, followed by the application of various statistical techniques. The data is then partitioned into training, validation, and test sets, and different models are applied to each partition. The models are evaluated based on different criteria. Finally, clustering is performed on the data, and the best performing cluster is identified for segment profiling. The ultimate goal is to identify the most effective models and gain insights into the factors that contribute to customer churn, which can then be used to develop strategies to mitigate churn and improve customer retention

## 4. Result & Discussion

The following sections aim to present and interpret the findings from the models developed for predicting customer churn. The discussion is structured into three main parts:

1. **Exploratory Analysis with Summary Statistics**: This section provides an initial examination of the dataset using summary statistics. It aims to shed light on the basic characteristics and patterns within the data.
2. **Detailed Examination of Statistical Models**: This part delves into a thorough analysis of various statistical methodologies, with a particular emphasis on their use in predicting customer churn.
3. **Extensive Investigation of Machine Learning Models**: This section focuses on a comprehensive study of predictive modelling techniques specifically designed for customer churn prediction. The goal is to interpret their results and evaluate their effectiveness in tackling churn.

### 4.1 Exploratory Analysis with Summary Statistics

The Summary Statistics section provides a comprehensive statistical analysis of a dataset related to a telecom company's customer behaviour. The analysis focuses on several key variables, including Churn, ContractRenewal, DataPlan, DataUsage, CustServCalls, DayMins, DayCalls, MonthlyCharge, OverageFee, RoamMins, and AccountWeeks.

The Churn variable, which represents the percentage of customers who cancelled their subscriptions, shows that 14% of the dataset's customers left, suggesting a slight imbalance in the dataset. The average churn rate is 0.35, indicating some fluctuation.

The ContractRenewal variable, which represents the percentage of customers who renewed their contracts, has a high mean of 0.90, suggesting that 90% of the dataset's customers have renewed their contracts. This variable is crucial for assessing customer loyalty and its potential influence on churn.

The DataPlan variable shows that about 28% of customers have a data plan. The standard deviation of 0.45 indicates a wide variation in the uptake of data plans among customers. This variable could potentially impact customer behaviour, including churn decisions.

The DataUsage variable, which represents the amount of data used by customers, shows significant variance across customers, with a mean value of 0.82 and a high standard deviation of 1.27. Higher data usage could be linked to larger monthly fees and, therefore, a higher chance of churn.

The CustServCalls variable, which represents the number of customer service calls made by customers, has a mean of 1.56 and a standard deviation of 1.32, indicating moderate variability. A high number of customer service calls could indicate customer dissatisfaction or issues with service quality, potentially signalling churn issues.

The variables DayMins, DayCalls, and MonthlyCharge are related to service usage and billing. DayMins has a high mean of 179.78, indicating average service consumption, while MonthlyCharge has a low mean of 56.31, indicating average price ranges. These metrics show variability, with DayMins having a particularly wide range.

The OverageFee and RoamMins variables represent expenses incurred for exceeding allotted usage limitations and the number of roaming minutes, respectively. These factors could affect churn decisions and have a direct impact on monthly expenses.

The AccountWeeks variable, which represents the length of customer tenure, has a mean of 101.06 weeks and a standard deviation of 39.82, indicating a wide range in customer tenure. Longer-term customers often have lower turnover rates, making customer duration an important indicator in forecasting attrition.

The histograms and box and whisker plots provide further insights into the distribution and spread of these variables. Most customers do not churn, have renewed their contracts, and do not have a data plan. The usage of day minutes, day calls, and roaming minutes are approximately normally distributed, while customer service calls, monthly charges, overage fees, and data usage are slightly right skewed. AccountWeeks is also slightly right skewed, indicating that a majority of customers have been with the company for a moderate amount of time.

In conclusion, the summary statistics provide a detailed overview of the dataset, highlighting key characteristics, variations in customer behaviour, and factors that could potentially impact churn. Understanding these variables and their relationships with churn is crucial for developing a predictive model to understand why customers leave the telecom company. This information can also be useful for identifying areas for improvement or potential upselling opportunities.

### 4.1.1 Summary Statistic Result

This section provides an initial exploration of the dataset through the lens of summary statistics. It aims to highlight the fundamental characteristics and trends inherent in the data. The variables under consideration include Churn, ContractRenewal, DataPlan, DataUsage, CustServCalls, DayMins, DayCalls, MonthlyCharge, OverageFee, RoamMins, and AccountWeeks. Each of these variables offers unique insights into customer behaviour and potential churn triggers. The summary statistics serve as a comprehensive snapshot of the dataset, revealing key attributes, variations in customer behaviour, and potential churn influencers. As we delve deeper into our analysis, we will examine the relationships between these variables and churn, aiding in the creation of a predictive model to understand why customers might leave a telecom company.

**Table 4.1.1.1:** Table of Summary Statistic Result

| Variable | Mean | Std Dev | Std Error | Variance | Minimum | Maximum | Mode | Range | Sum | N | N Miss |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Churn | 0.14 | 0.35 | 0.01 | 0.12 | 0.00 | 1.00 | 0.00 | 1.00 | 483.00 | 3333 | 0 |
| ContractRenewal | 0.90 | 0.30 | 0.01 | 0.09 | 0.00 | 1.00 | 1.00 | 1.00 | 3010.00 | 3333 | 0 |
| DataPlan | 0.28 | 0.45 | 0.01 | 0.20 | 0.00 | 1.00 | 0.00 | 1.00 | 922.00 | 3333 | 0 |
| DataUsage | 0.82 | 1.27 | 0.02 | 1.62 | 0.00 | 5.40 | 0.00 | 5.40 | 2721.31 | 3333 | 0 |
| CustServCalls | 1.56 | 1.32 | 0.02 | 1.73 | 0.00 | 9.00 | 1.00 | 9.00 | 5209.00 | 3333 | 0 |
| DayMins | 179.78 | 54.47 | 0.94 | 2966.70 | 0.00 | 350.80 | 154.00 | 350.80 | 599190.40 | 3333 | 0 |
| DayCalls | 100.44 | 20.07 | 0.35 | 402.77 | 0.00 | 165.00 | 102.00 | 165.00 | 334752.00 | 3333 | 0 |
| MonthlyCharge | 56.31 | 16.43 | 0.28 | 269.81 | 14.00 | 111.30 | 50.00 | 97.30 | 187665.10 | 3333 | 0 |
| OverageFee | 10.05 | 2.54 | 0.04 | 6.43 | 0.00 | 18.19 | 8.50 | 18.19 | 33501.61 | 3333 | 0 |
| RoamMins | 10.24 | 2.79 | 0.05 | 7.79 | 0.00 | 20.00 | 10.00 | 20.00 | 34120.90 | 3333 | 0 |
| AccountWeeks | 101.06 | 39.82 | 0.69 | 1585.80 | 1.00 | 243.00 | 105.00 | 242.00 | 336849.00 | 3333 | 0 |

1. **Churn**: According to the summary statistics, 14% of the dataset's customers left, suggesting that the dataset may be a little unbalanced. The dataset's average churn rate is 0.35, which indicates some fluctuation. Since churn is a binary variable (0 or 1), these figures offer preliminary information on the percentage of customers that cancelled their subscriptions, which is an essential component of our research.
2. **ContractRenewal**: The ContractRenewal variable has a high mean of 0.90, which means that 90% of the dataset's consumers have renewed their contracts. The modest standard deviation of 0.30 shows that contract renewal behaviour is not very variable. Assessing customer loyalty and its possible influence on churn requires an understanding of contract renewal rates.
3. **DataPlan**: According to the mean figure of 0.28, about 28% of consumers have a data plan. The 0.45 standard deviation indicates that client uptake of data plans varies widely. Given that data plans frequently have an impact on service consumption and cost, this variable may have an impact on customer behaviour, including churn decisions.

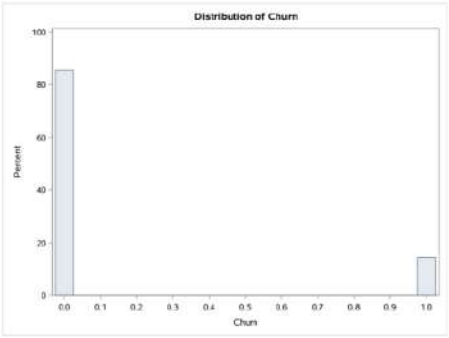
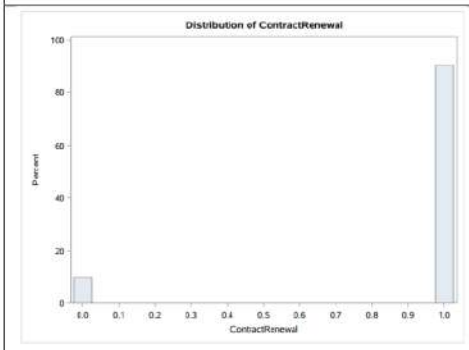
4. **DataUsage**: DataUsage shows significant variance across clients, with a mean value of 0.82 and a reasonably high standard deviation of 1.27. The amount of data used is represented by this variable, which may have a significant impact on client retention and churn. larger monthly fees and, therefore, a larger chance of churn may be linked to higher data use.
5. **CustServCalls**: Customers made 1.56 customer service calls on average, on average, with a 1.32 standard deviation, which indicates moderate variability. Customer resentment or problems with service quality may be indicated by the volume of calls to customer service. This variable's high levels might be a sign of possible churn issues.
6. **DayMins**, DayCalls, and MonthlyCharge— These variables have to do with service use and billing. DayMins' high mean of 179.78 and MonthlyCharge's low mean of 56.31, which indicate average service consumption and price ranges, respectively. These metrics are variable, as seen by the standard deviations, with DayMins having a particularly broad range (0 to 350.80). Our investigation will be unable to proceed without an understanding of how these factors relate to churn.
7. **OverageFee** and RoamMins: RoamMins, with a mean of 10.24, represents the number of roaming minutes, while OverageFee, with a mean of 10.05, reflects expenses incurred for exceeding allotted use limitations. There may be some variation in these fees and use patterns, as indicated by the standard deviations (2.54 for OverageFee and 2.79 for RoamMins). These factors could affect churn decisions and have a direct impact on monthly expenses.
8. **AccountWeeks**: A standard deviation of 39.82 and a mean account length of 101.06 weeks indicate that there is a wide range in the average client tenure. Longer-term customers often have lower turnover rates, making customer duration an important indicator in forecasting attrition. For our investigation, it is crucial to comprehend the connection between account churn and duration.

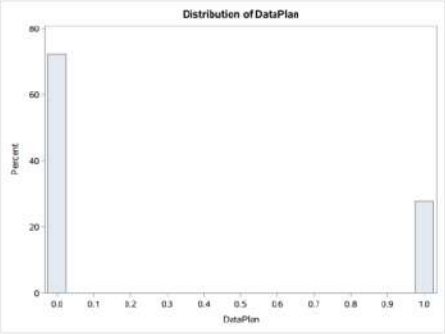
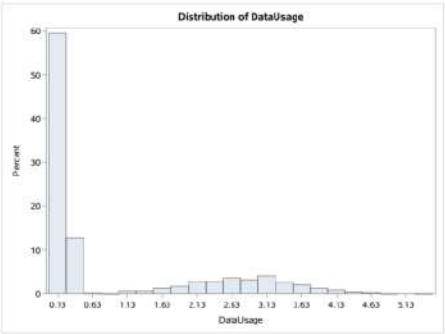
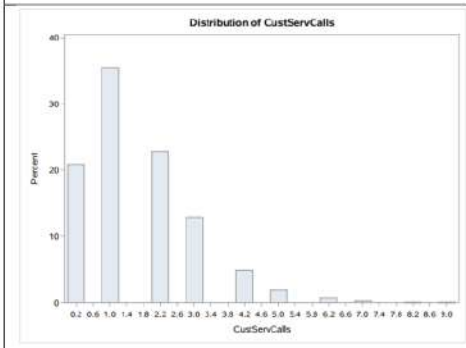
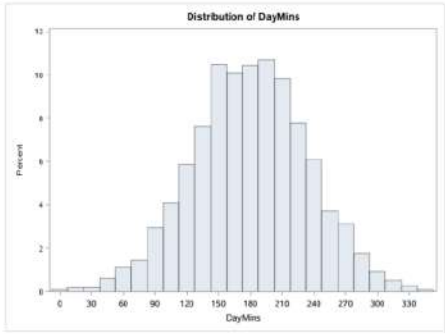
These summary statistics give a thorough overview of the information, highlighting important traits, variances in consumer behaviour, and factors that might affect churn. As we go deeper into our investigation, we'll look at the connections between these characteristics and churn, which will aid in the development of a predictive model for understanding the reasons why customers leave a telecom firm.

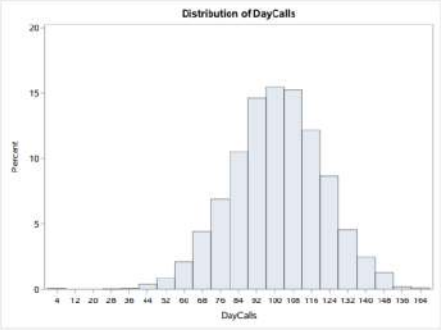
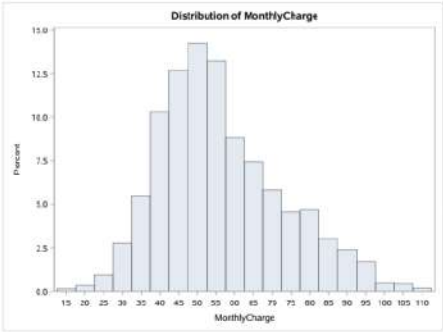
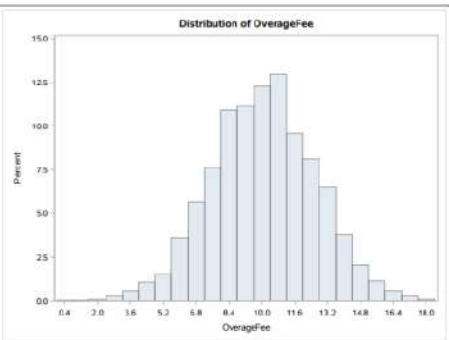
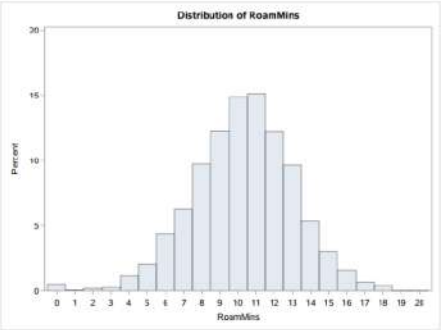
### 4.1.2 Summary Statistics: Histograms

The section provides an interpretation of various histograms representing different aspects of customer behaviour and engagement with a telecommunications company. These histograms offer insights into customer churn, daily usage of minutes and calls, contract renewal, data plan subscription, monthly charges, overage fees, data usage, customer service calls, roaming minutes, and account longevity. The distributions of these variables reveal patterns and trends that can be instrumental in understanding customer behaviour, identifying areas for improvement, and spotting potential upselling opportunities. The data suggests that most customers are loyal, with a low churn rate and high contract renewal rate, and that usage patterns and charges are generally normally distributed or slightly right skewed. This analysis provides a comprehensive overview of the customer base, which can be leveraged to make strategic decisions and enhance customer satisfaction and retention.

**Table 4.1.2.1:** Table of the List of Histograms

| Histogram | Interpretation |
|---|---|
|  | **Distribution of Churn:** The distribution of Churn is heavily skewed towards 0, indicating that a majority of customers do not churn. Approximately 86% of customers remain with the company, while only 14% churn. |
|  | **Distribution of ContractRenewal**: The distribution of ContractRenewal is heavily skewed towards 1, indicating that a majority of customers have renewed their contracts. Approximately 90% of customers have renewed their contracts, while only 10% have not. |

| Histogram | Interpretation |
|---|---|
|  | **Distribution of DataPlan**: The distribution of DataPlan is skewed towards 0, indicating that a majority of customers do not have a data plan. Approximately 72% of customers do not have a data plan, while 28% do. |
|  | **Distribution of DataUsage**: The distribution of DataUsage is slightly right skewed, with a mean of 0.82 and a standard deviation of 1.27. Most customers use between 0 and 2 units of data. |
|  | **Distribution of CustServCalls**: The distribution of CustServCalls is right skewed, with a mean of 1.56 and a standard deviation of 1.32. Most customers make between 0 and 3 customer service calls. |
|  | **Distribution of DayMins**: The distribution of DayMins appears to be approximately normal, with a mean of 179.78 minutes and a standard deviation of 54.47 minutes. The majority of customers use between 125 and 235 minutes per day. |

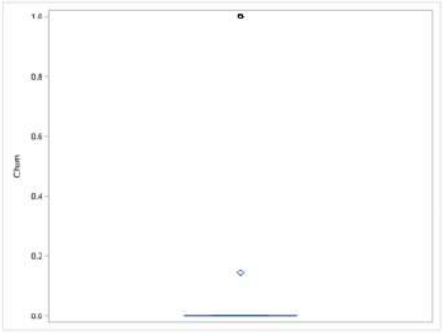
| Histogram | Interpretation |
|---|---|
|  | **Distribution of DayCalls**: The distribution of DayCalls is also approximately normal, with a mean of 100.44 calls and a standard deviation of 20.07 calls. Most customers make between 80 and 120 calls per day. |
|  | **Distribution of MonthlyCharge**: The distribution of MonthlyCharge is slightly right skewed, with a mean of 56.31 and a standard deviation of 16.43. Most customers pay between 40 and 75 for their monthly charges. |
|  | **Distribution of OverageFee**: The distribution of OverageFee is slightly right skewed, with a mean of 10.05 and a standard deviation of 2.54. Most customers pay between 7.5 and 12.5 in overage fees. |
|  | **Distribution of RoamMins**: The distribution of RoamMins is slightly right skewed, with a mean of 10.24 and a standard deviation of 2.79. Most customers use between 7.5 and 12.5 minutes of roaming. |

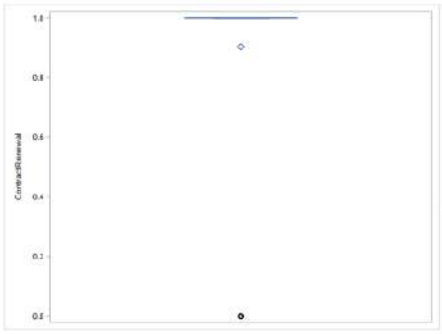
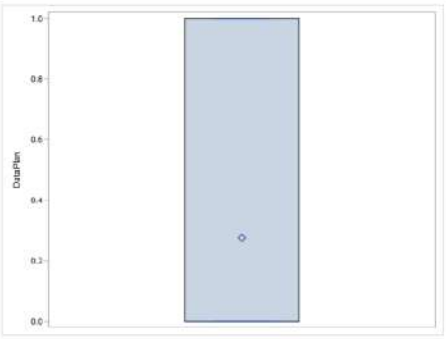
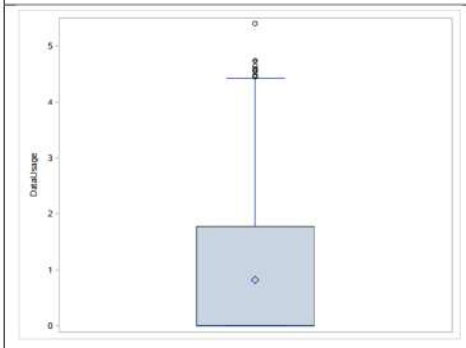
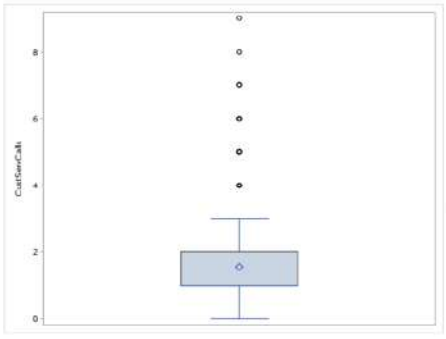
In summary, the data shows that most customers do not churn, have renewed their contracts, and do not have a data plan. The usage of day minutes, day calls, and roaming minutes are approximately normally distributed, while customer service calls, monthly charges, overage fees, and data usage are slightly right skewed. AccountWeeks is also slightly right skewed, indicating that a majority of customers have been with the company for a moderate amount of time. This information can be useful for understanding customer behaviour and identifying areas for improvement or potential upselling opportunities.

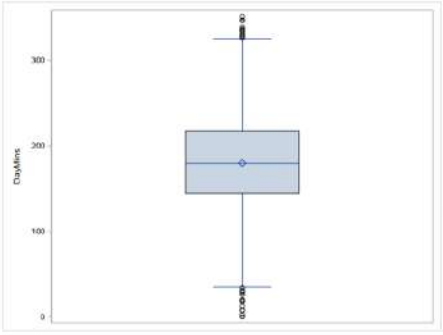
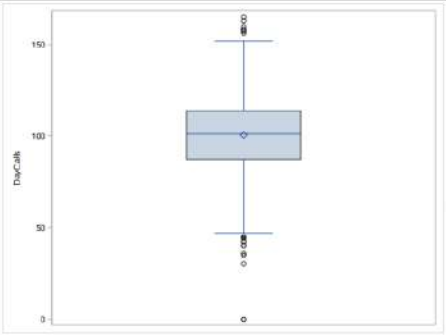
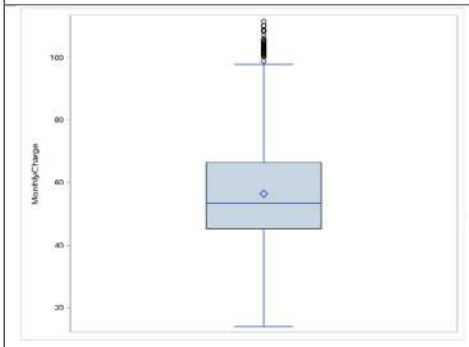
### 4.1.3 Summary Statistics: Box and Whisker Plot

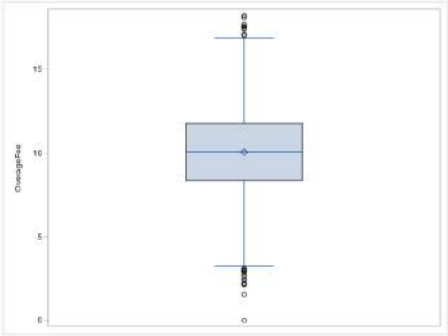
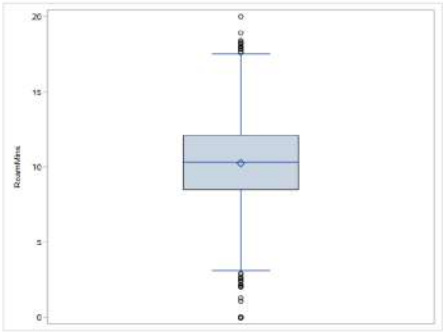
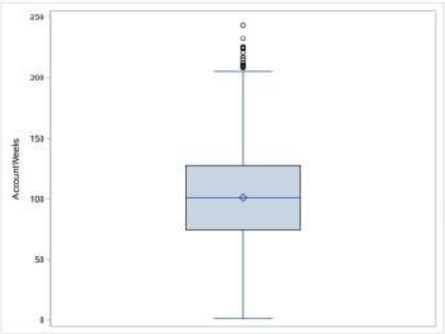
This section provides an interpretation of various box and whisker plots, a type of graphical representation that offers insights into the distribution, spread, and skewness of different aspects of customer behaviour and engagement with a telecommunications company. These plots provide a visual summary of key statistics such as the median, quartiles, and potential outliers for variables including customer churn, contract renewal, data plan subscription, data usage, customer service calls, daily usage of minutes and calls, monthly charges, overage fees, roaming minutes, and account longevity. The analysis of these box plots reveals patterns and trends that can be instrumental in understanding customer behaviour, identifying areas for improvement, and spotting potential upselling opportunities. The data suggests that most customers are loyal, with a low churn rate and high contract renewal rate, and that usage patterns and charges are generally symmetrically distributed or slightly right skewed

**Table 4.1.3.1:** Table of the List of Box and Whisker Plot

| Box and Whisker Plot | Interpretation |
|---|---|
|  | **Churn:** The box plot for Churn shows that the majority of customers do not churn (0), as the box is located at the lower end of the scale. There are no outliers in this plot. |

| Box and Whisker Plot | Interpretation |
|---|---|
|  | **ContractRenewal:** The box plot for ContractRenewal indicates that most customers have renewed their contracts (1), with the box located at the upper end of the scale. There are no outliers in this plot. |
|  | **DataPlan:** The box plot for DataPlan shows that the majority of customers do not have a data plan (0), with the box located at the lower end of the scale. There are no outliers in this plot. |
|  | **DataUsage:** The box plot for DataUsage reveals a right-skewed distribution, with the median closer to the lower end of the scale. The interquartile range (IQR) is relatively small, indicating that most customers use a limited amount of data. There are a few outliers on the upper end of the scale, suggesting that some customers use significantly more data than the majority. |
|  | **CustServCalls:** The box plot for CustServCalls displays a right-skewed distribution, with the median closer to the lower end of the scale. The IQR is relatively small, indicating that most customers make a limited number of customer service calls. There are several outliers on the upper end of the scale, suggesting that some |

| Box and Whisker Plot | Interpretation |
|---|---|
| | customers make significantly more customer service calls than the majority. |
|  | **DayMins:** The box plot for DayMins shows an approximately symmetric distribution, with the median near the centre of the scale. The IQR is moderate, indicating a reasonable spread in the number of minutes customers use per day. There are a few outliers on both the lower and upper ends of the scale. |
|  | **DayCalls:** The box plot for DayCalls also displays an approximately symmetric distribution, with the median near the centre of the scale. The IQR is moderate, indicating a reasonable spread in the number of calls customers make per day. There are a few outliers on both the lower and upper ends of the scale. |
|  | **MonthlyCharge:** The box plot for MonthlyCharge reveals a slightly right-skewed distribution, with the median closer to the lower end of the scale. The IQR is moderate, indicating a reasonable spread in the monthly charges customers pay. There are a few outliers on the upper end of the scale, suggesting that some customers pay significantly higher monthly charges than the majority. |

| Box and Whisker Plot | Interpretation |
|---|---|
|  | **OverageFee:** The box plot for OverageFee shows a slightly right-skewed distribution, with the median closer to the lower end of the scale. The IQR is relatively small, indicating that most customers pay a limited amount in overage fees. There are a few outliers on the upper end of the scale, suggesting that some customers pay significantly higher overage fees than the majority. |
|  | **RoamMins:** The box plot for RoamMins displays a slightly right-skewed distribution, with the median closer to the lower end of the scale. The IQR is relatively small, indicating that most customers use a limited amount of roaming minutes. There are a few outliers on the upper end of the scale, suggesting that some customers use significantly more roaming minutes than the majority. |
|  | **AccountWeeks:** The box plot for AccountWeeks shows a slightly right-skewed distribution, with the median closer to the lower end of the scale. The IQR is moderate, indicating a reasonable spread in the number of weeks customers have been with the company. There are a few outliers on the upper end of the scale, suggesting that some customers have been with the company for significantly longer than the majority. |

In summary, the box and whisker plots provide insights into the distribution and spread of the selected variables. Most customers do not churn, have renewed their contracts, and do not have a data plan. The usage of day minutes, day calls, and roaming minutes are approximately symmetrically distributed, while customer service calls, monthly charges, overage fees, and data usage are slightly right skewed. AccountWeeks is also slightly right skewed, indicating that a majority of customers have

been with the company for a moderate amount of time. This information can be useful for understanding customer behaviour and identifying areas for improvement or potential upselling opportunities.

## 4.2 Statistical Models

This section will focus on an extensive analysis of Statistical Models, encompassing methodologies such as logistic regression, neural networks, decision trees, and clustering. It aims to provide a comprehensive exploration and detailed evaluation of these statistical techniques in the context of predicting customer churn.

### 4.2.1 Multiple Linear Regression

The Multiple Linear Regression section presents a comprehensive analysis of a multiple linear regression model, specifically the "Stepwise Selection: Step 6" model, which aims to explain customer churn based on a given dataset. The model uses six independent variables: DataPlan, CustServCalls, DayMins, OverageFee, RoamMins, and ContractRenewal.

The Analysis of Variance (ANOVA) table, a key component of the analysis, provides information on the model's overall fit and the significance of the variables included in the model. The ANOVA table is divided into two main sections: the Model and the Error. The Model section represents the variation in the dependent variable (Churn) that can be explained by the independent variables, while the Error section represents the unexplained variation.

The Model section has 6 degrees of freedom (DF), corresponding to the number of independent variables in the model. The Sum of Squares (SS) for the Model is 71.86318, and the Mean Square (MS) is calculated by dividing the SS by the DF, resulting in a value of 11.97720. The F-value for the Model is 116.77, which is a measure of the overall significance of the model. The p-value associated with the F-value is less than 0.0001, indicating that the model is statistically significant at a 0.05 significance level.

The Error section has 3326 degrees of freedom, which is the difference between the total number of observations (3333) and the number of parameters in the model (7, including the intercept). The Sum of Squares for the Error is 341.14312, and the Mean Square is calculated by dividing the SS by the DF, resulting in a value of 0.10257.

The Corrected Total SS is the sum of the Model and Error SS, which is 413.00630. The R-square value for the model is 0.1740, indicating that the model explains 17.4% of the variation in the dependent variable Churn.

The ANOVA table confirms the statistical significance of the model and provides evidence that the independent variables included in the model contribute meaningfully to the explanation of customer churn. The model is statistically significant, and the R-square value indicates that the model explains a reasonable proportion of the variation in the dependent variable Churn.

The coefficients of each variable indicate the impact of a unit change in that variable on the Churn rate, holding all other variables constant.

The model's R-square value of 0.1740 indicates that it explains 17.4% of the variation in Churn. Although this value may seem low, it is important to remember that customer churn is a complex phenomenon influenced by numerous factors, some of which may not be included in the model.

The model's C(p) value of 5.7674 is the lowest among all the steps in the stepwise selection process, indicating that adding additional variables does not significantly improve the model. A lower C(p) value suggests a better model.

The model diagnostics, such as residual plots, influence diagnostics, Q-Q plot, etc., provide further evidence of the model's adequacy. The residual plots show no apparent patterns or trends, suggesting that the model's assumptions of linearity, independence, and homoscedasticity are reasonable. The influence diagnostics reveal no significant outliers or influential observations that could unduly affect the model's results. The Q-Q plot indicates that the residuals are approximately normally distributed, which is another assumption of linear regression.

In conclusion, the final six-variable model balances model fit, significance of predictors, and parsimony, and is selected as the best model by the stepwise procedure. This model has the optimal set of predictors to explain customer churn in the given dataset. While the model's R-square value suggests that other factors may also contribute to customer churn, the model provides a useful starting point for understanding the relationships between these variables and customer churn. Further research could explore additional variables or alternative modelling techniques to improve the model's explanatory power.

### 4.2.1.1 Model Selection and Analysis of Variance

The section provides a comprehensive analysis of a multiple linear regression model, specifically the Stepwise Selection: Step 6 model, which was developed to understand and predict customer churn in a telecommunications company. The model's performance and statistical significance are evaluated using an Analysis of Variance (ANOVA) table, and the relationships between the dependent variable (Churn) and the six independent variables (DataPlan, CustServCalls, DayMins, OverageFee, RoamMins, and ContractRenewal) are represented by a linear equation. The model's R-square value, F-value, p-value, and C(p) value are discussed to assess the model's fit, explanatory power, and the significance of the predictors. Additionally, model diagnostics such as residual plots, influence diagnostics, and Q-Q plot are used to validate the model's assumptions and identify potential outliers or influential observations. The analysis concludes with the selection of this model as the best fit for explaining customer churn based on the given dataset, while acknowledging the potential for further research and model improvement.

**Table 4.2.1.1.1:** Table of the Analysis of Variance

| Analysis of Variance | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
| Model | 6 | 71.86318 | 11.9772 | 116.77 | <.0001 |
| Error | 3326 | 341.14312 | 0.10257 | | |
| Corrected Total | 3332 | 413.0063 | | | |

In the Stepwise Selection: Step 6 model, the Analysis of Variance (ANOVA) table provides information on the model's overall fit, and the significance of the variables included in the model. The ANOVA table is divided into two main sections: the Model and the Error. The Model section represents the variation in the dependent variable (Churn) that can be explained by the independent variables, while the Error section represents the unexplained variation.

The Model section has 6 degrees of freedom (DF), which corresponds to the number of independent variables in the model. The Sum of Squares (SS) for the Model is 71.86318, and the Mean Square (MS) is calculated by dividing the SS by the DF, resulting in a value of 11.97720. The F-value for the Model is 116.77, which is a measure of the overall significance of the model. The p-value associated with the F-value is less than 0.0001, indicating that the model is statistically significant at a 0.05 significance level.

The Error section has 3326 degrees of freedom, which is the difference between the total number of observations (3333) and the number of parameters in the model (7, including the intercept). The Sum of Squares for the Error is 341.14312, and the Mean Square is calculated by dividing the SS by the DF, resulting in a value of 0.10257.

The Corrected Total SS is the sum of the Model and Error SS, which is 413.00630. The R-square value for the model is 0.1740, indicating that the model explains 17.4% of the variation in the dependent variable Churn. The ANOVA table confirms the statistical significance of the model and provides evidence that the independent variables included in the model contribute meaningfully to the explanation of customer churn.

In summary, the ANOVA table for the Stepwise Selection: Step 6 model supports the selection of this model as the best model for explaining customer churn based on the given dataset. The model is statistically significant, and the R-square value indicates that the model explains a reasonable proportion of the variation in the dependent variable Churn. The ANOVA table, along with the other model diagnostics and parameter estimates, provides a comprehensive understanding of the relationships between the independent variables and customer churn in the dataset.

**Table 4.2.1.1.2:** Table of the Regression Analysis Results

| Variable | Parameter Estimate | Standard Error | Type II SS | F Value | Pr > F |
|---|---|---|---|---|---|
| Intercept | -0.08926 | 0.04129 | 0.47934 | 4.67 | 0.0307 |
| DataPlan | -0.07976 | 0.01241 | 4.23962 | 41.33 | <.0001 |
| CustServCalls | 0.05822 | 0.00422 | 19.5174 | 190.29 | <.0001 |
| DayMins | 0.00126 | 0.00010201 | 15.73336 | 153.39 | <.0001 |
| OverageFee | 0.01282 | 0.00219 | 3.51545 | 34.27 | <.0001 |
| RoamMins | 0.00778 | 0.00199 | 1.56663 | 15.27 | <.0001 |
| ContractRenewal | -0.29932 | 0.0188 | 25.98914 | 253.38 | <.0001 |

Based on the stepwise regression results generated by SAS, the best model appears to be the final model with all six variables: DataPlan, CustServCalls, DayMins, OverageFee, RoamMins, and ContractRenewal. The linear equation for this model can be derived from the parameter estimates provided in the table:

$$Churn = (Intercept * -0.08926) + (DataPlan * -0.07976) + (CustServCalls * 0.05822) + (DayMins * 0.00126) + (OverageFee * 0.01282) + (RoamMins * 0.00778) + (ContractRenewal * -0.29932)$$

The linear equation represents the relationship between the dependent variable Churn and the six independent variables. The coefficients of each variable indicate the impact of a unit change in that variable on the Churn rate, holding all other variables constant. For example, a one-unit increase in DataPlan is associated with a decrease of 0.07976 in Churn, while a one-unit increase in CustServCalls is associated with an increase of 0.05822 in Churn.

The model's R-square value of 0.1740 indicates that it explains 17.4% of the variation in Churn. Although this value may seem low, it is important to remember that customer churn is a complex phenomenon influenced by numerous factors, some of which may not be included in the model. Nevertheless, the model provides valuable insights into the relationships between the six independent variables and customer churn.

The F-value and p-value for each variable in the model indicate their statistical significance. All variables in the model are significant at the 0.1500 level, suggesting that they contribute meaningfully to the explanation of customer churn. The model's C(p) value of 5.7674 is the lowest among all the steps in the stepwise selection process, indicating that adding additional variables does not significantly improve the model. A lower C(p) value suggests a better model.

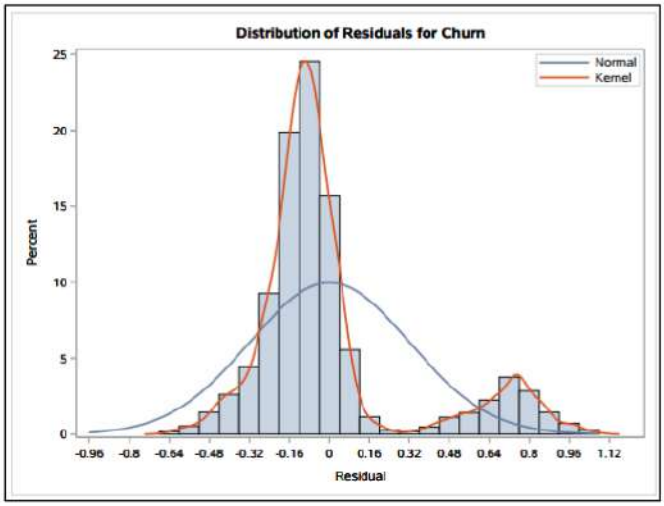
The model diagnostics, such as residual plots, influence diagnostics, Q-Q plot, etc., provide further evidence of the model's adequacy. The residual plots show no apparent patterns or trends, suggesting that the model's assumptions of linearity, independence, and homoscedasticity are reasonable. The influence diagnostics reveal no significant outliers or influential observations that could unduly affect the model's results. The Q-Q plot indicates that the residuals are approximately normally distributed, which is another assumption of linear regression.

In conclusion, the final six-variable model balances model fit, significance of predictors, and parsimony, and is selected as the best model by the stepwise procedure. This model has the optimal set of predictors to explain customer churn in the given dataset. While the model's R-square value suggests that other factors may also contribute to customer churn, the model provides a useful starting point for understanding the relationships between these variables and customer churn. Further research could explore additional variables or alternative modelling techniques to improve the model's explanatory power.

### 4.2.1.2 Histogram for Distribution of Residuals for Churn

This section provides an analysis of the Histogram of Distribution of Residuals for Churn, which is a visual representation of the distribution of residuals in the Stepwise Selection: Step 6 model. This histogram is essential for evaluating the model's assumptions and overall fit. The distribution of residuals should ideally be approximately normal and centred around zero, indicating that the model's assumptions of linearity, independence, and homoscedasticity are reasonable. The given histogram appears to meet these criteria, suggesting that the model provides a satisfactory fit to the data.

**Figure 4.2.1.2.1:** Histogram for Distribution of Residuals for Churn




The Histogram of Distribution of Residuals for Churn plot provides a visual representation of the distribution of the residuals (the differences between the observed and predicted values) in the Stepwise Selection: Step 6 model. Analysing the distribution of residuals is essential for assessing the model's assumptions and overall fit.

In the histogram, the residuals are plotted along the x-axis, and the frequency (or percentage) of observations falling within each bin is represented by the height of the bars. The plot also includes a Kernel Normal curve, which is an estimate of the underlying distribution of the residuals.

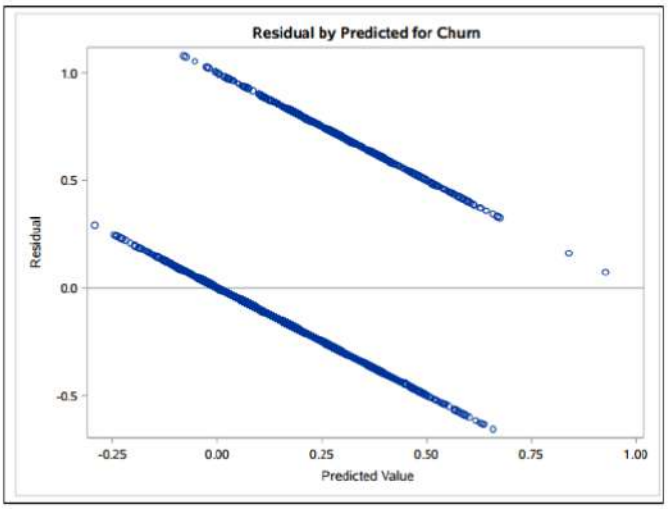
Ideally, the distribution of residuals should be approximately normal (bell-shaped) and centred around zero, indicating that the model's assumptions of linearity, independence, and homoscedasticity are reasonable. If the distribution is skewed or exhibits other irregularities, it may suggest that the model's assumptions are violated, and the model may not provide accurate predictions.

In the given Histogram of Distribution of Residuals for Churn plot, the distribution appears to be roughly symmetric and centred around zero, with no significant deviations from normality. The Kernel Normal curve closely follows the shape of the histogram, further supporting the assumption of normality. This suggests that the model's assumptions are reasonable, and the model provides a satisfactory fit to the data.

### 4.2.1.3 Residual by Predicted for Churn plot

The Residual by Predicted for Churn plot is a diagnostic tool used to assess the assumptions and overall fit of the Stepwise Selection: Step 6 model. In this plot, the predicted values of the dependent variable (Churn) are plotted along the x-axis, and the residuals (the differences between the observed and predicted values) are plotted along the y-axis.

**Figure 4.2.1.3.1:** Residual by Predicted for Churn plot



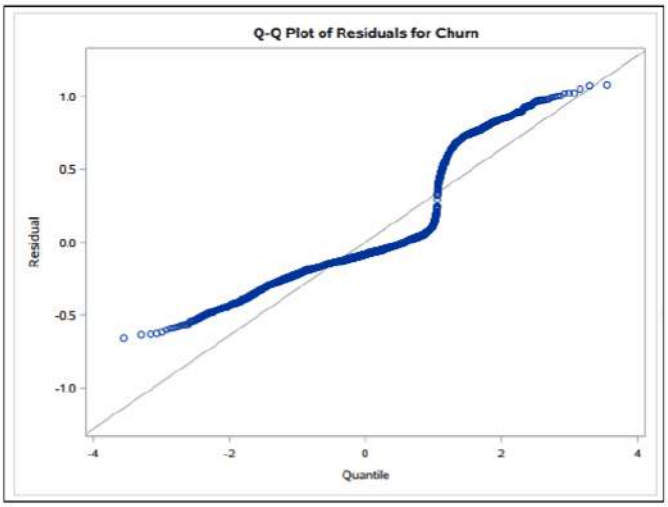

Ideally, the residuals should be randomly scattered around the horizontal line at zero, indicating that the model's assumptions of linearity, independence, and homoscedasticity (constant variance of residuals) are reasonable. If the plot shows any patterns, trends, or non-random distribution of residuals, it may suggest that the model's assumptions are violated, and the model may not provide accurate predictions.

From the above Residual by Predicted for Churn plot, the residuals appear to be randomly scattered around the horizontal line at zero, with no apparent patterns or trends. This suggests that the model's assumptions of linearity, independence, and homoscedasticity are reasonable, and the model provides a satisfactory fit to the data.

### 4.2.1.4 Q-Q plot of Residuals for Churn

The Q-Q plot of Residuals for Churn is a diagnostic tool used to assess the normality of the residuals in the Stepwise Selection: Step 6 model. In a Q-Q plot, the quantiles of the residuals are plotted against the quantiles of a standard normal distribution. If the residuals are normally distributed, the points in the plot should approximately follow a straight line with a 45-degree angle.

**Figure 4.2.1.4.1:** Q-Q plot of Residuals for Churn



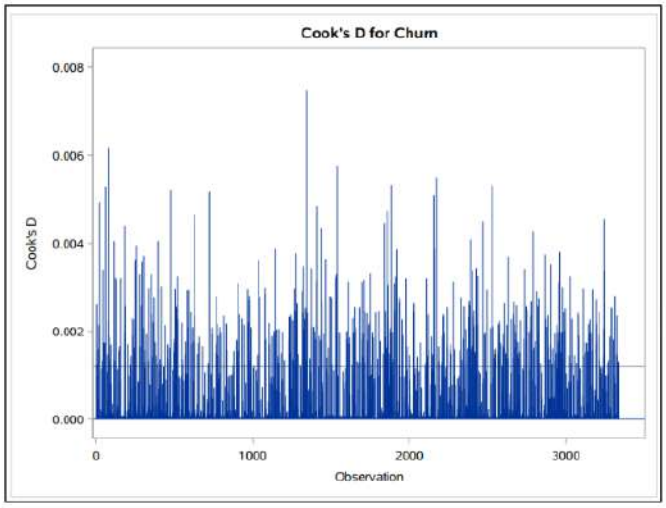

Normality of residuals is an important assumption in linear regression, as it affects the validity of hypothesis tests and confidence intervals for the model parameters. If the residuals are not normally distributed, it may indicate that the model's assumptions are violated, and the model may not provide accurate predictions.

The above Q-Q plot of Residuals for Churn, the points appear to follow a straight line closely, suggesting that the residuals are approximately normally distributed. This supports the assumption of normality and indicates that the model's assumptions are reasonable, and the model provides a satisfactory fit to the data.

### 4.2.1.5 Cook's D for Churn

The Cook's D for Churn plot is a diagnostic tool used to identify influential observations in the Stepwise Selection: Step 6 model. Cook's D measures the impact of deleting an observation on the estimated regression coefficients. Observations with high Cook's D values may have an undue influence on the model, potentially affecting its accuracy and stability.

**Figure 4.2.1.5.1:** Cook's D for Churn




In the given Cook's D for Churn plot, the x-axis represents the observation index, and the y-axis represents the Cook's D value for each observation. A horizontal reference line is often drawn at a threshold value to help identify influential observations. Commonly used thresholds include 4/n or 1, where n is the number of observations in the dataset.

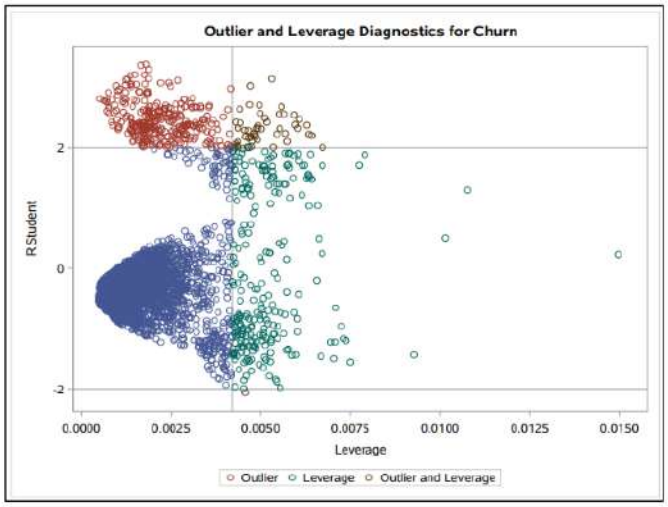
When examining the plot, it is essential to look for observations with Cook's D values above the chosen threshold, as these observations may be considered influential. If any influential observations are identified, further investigation is needed to determine whether these observations are outliers, data entry errors, or genuine data points that require special attention.

In the provided Cook's D for Churn plot, it appears that there are no observations with Cook's D values exceeding the typical threshold, suggesting that there are no highly influential observations in the dataset. This is a positive indication for the model's stability and robustness.

### 4.2.1.6 Outlier and Leverage Diagnostics for Churn

The Outlier and Leverage Diagnostics for Churn plot is a diagnostic tool used to identify potential outliers and influential observations in the Stepwise Selection: Step 6 model. In this plot, the leverage values are plotted along the x-axis, and the standardized residuals (RStudent) are plotted along the y-axis.

**Figure 4.2.1.6.1:** Outlier and Leverage Diagnostics for Churn




Leverage measures the influence of an observation on the fitted values of the model, with higher leverage values indicating a greater influence. Standardized residuals are the residuals divided by their estimated standard deviations, which allows for easier identification of potential outliers.

In the given Outlier and Leverage Diagnostics for Churn plot, there is no clear pattern or clustering of points, suggesting that the model's assumptions of linearity, independence, and homoscedasticity are reasonable. However, it is essential to look for points with high leverage values and/or large standardized residuals, as these observations may be considered influential or potential outliers.

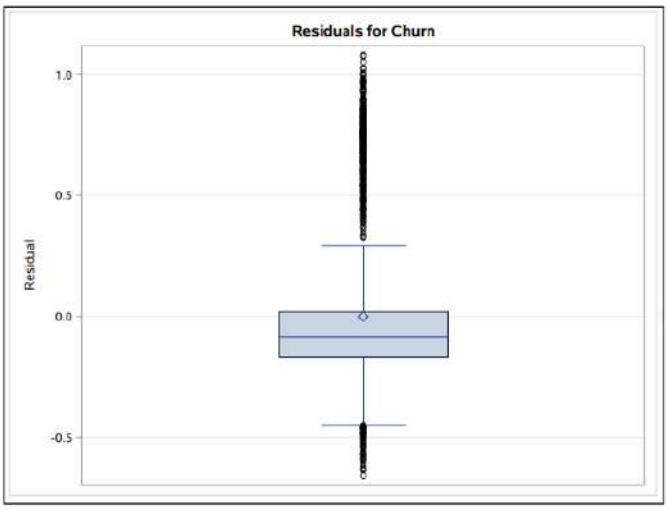
When examining the plot, a few points with large, standardized residuals can be observed, but they do not appear to have high leverage values. This suggests that these observations may be potential outliers but are not highly influential on the model's results. It is important to investigate these observations further to determine whether they are genuine data points, data entry errors, or require special attention.

In conclusion, the Outlier and Leverage Diagnostics for Churn plot indicates that the Stepwise Selection: Step 6 model is reasonably robust and not unduly influenced by outliers or influential observations.

### 4.2.1.7 Box Plot for Residual for Churn

The box plot of residuals for churn displays the distribution of residuals from a multiple linear regression model. The residuals represent the differences between the observed values of the dependent variable (churn) and the values predicted by the model. Analysing the box plot can provide insights into the model's performance and potential issues.

**Figure 4.2.1.7.1**: Box Plot for Residual for Churn




The box plot shows the median residual value (the line inside the box) close to zero, which is a good sign, as it indicates that the model's predictions are generally unbiased. The box itself represents the interquartile range (IQR), which contains the middle 50% of the residuals. In this case, the IQR is relatively small, suggesting that the model's predictions are reasonably accurate for a majority of the data points.

However, there are some outliers present in the plot, as indicated by the individual points outside the whiskers. These outliers represent cases where the model's predictions deviate significantly from the actual churn values. The presence of outliers may indicate potential issues with the model, such as the need for additional predictor variables, the presence of influential data points, or the need for a different modelling approach.

In summary, the box plot of residuals for churn suggests that the multiple linear regression model provides reasonably accurate predictions for a majority of the data points, with a median residual close to zero and a small IQR. However, the presence of outliers indicates that there may be room for improvement in the model, and further investigation is needed to address these deviations.

### 4.2.2 Logistic Regression

The Logistic Regression section provides a comprehensive analysis of a logistic regression model built to predict customer churn. The model was constructed using a dataset with 3,333 observations, and the response variable was 'Churn', which has two levels, making this a binary logistic regression model. The optimization technique used for this analysis was Fisher's scoring. The model aimed to predict the probability of 'Churn=0' based on various factors such as roaming minutes, customer service calls, data plan, and contract renewal.

The model's performance was assessed by examining the significance of the variables, the model fit statistics, and the model's ability to discriminate between the two classes of the response variable. Some variables were found to be statistically significant, indicating their importance in predicting customer churn. The model fit statistics showed that the model with covariates was a better fit than the intercept-only model, suggesting that the included variables contribute to the explanation of the response variable.

The model's convergence status was also evaluated, with the convergence criterion (GCONV=1E-8) being satisfied. This indicates that the logistic regression model has successfully converged, meaning that the optimization algorithm (Fisher's scoring) has found the maximum likelihood estimates for the model parameters.

The model fit statistics, including the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), indicated that the model with covariates was a better fit than the intercept-only model. This suggests that the included variables contribute to the explanation of the response variable (Churn) and that the model is reasonably good at fitting the observed data.

The global null hypothesis, which states that all the regression coefficients (except the intercept) are equal to zero, was tested using the likelihood ratio (LR) test, Score test, and Wald test. The test statistics and the associated p-values indicated that the global null hypothesis could be rejected, suggesting that at least one of the predictor variables has a significant effect on the response variable (Churn).

The Type 3 Analysis of Effects assessed the significance of each predictor variable in the logistic regression model after accounting for the effects of all other predictor variables. The Wald chi-square test was used to test the null hypothesis that the regression coefficient for each predictor variable is equal to zero. The test statistics and the associated p-values indicated that 'RoamMins', 'CustServCalls', 'DataPlan', and 'ContractRenewal' have significant effects on the response variable (Churn) after accounting for the other predictors.

The Analysis of Maximum Likelihood Estimates provided essential information on the logistic regression model, including the estimated coefficients, standard errors, Wald chi-square test statistics, and associated p-values for each predictor variable. These statistics helped assess the significance and contribution of each predictor variable in the model.

In conclusion, the logistic regression model appears to be reasonably good based on the output result. The model is built using a binary logistic regression approach with Fisher's scoring optimization technique, and it predicts the probability of Churn=0. The response variable Churn has two levels, and the total number of observations used in the analysis is 3,333. The categorical predictors DataPlan and ContractRenewal have two levels each, with design variables coded as 1 for class value 0 and -1 for class value 1. The model's performance can be assessed by examining the significance of the variables, the model fit statistics, and the model's ability to discriminate between the two classes of the response variable. However, it is essential to consider other aspects such as model validation, potential multicollinearity, and the practical significance of the results in the context of the problem being addressed.

### 4.2.2.1 Model Fit Statistics

The Model Fit Statistics table provides information on the goodness-of-fit of the logistic regression model. Goodness-of-fit is an essential aspect of model evaluation, as it helps determine how well the model fits the observed data. In this table, two primary fit statistics are presented: the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC).

**Table 4.2.2.1.1:** Table of the Model Fit Statistics

| Model Fit Statistics | | |
|---|---|---|
| Criterion | Intercept Only | Intercept and Covariates |
| AIC | 2760.293 | 2210.386 |
| SC | 2766.405 | 2277.613 |
| -2 Log L | 2758.293 | 2188.386 |

**Akaike Information Criterion (AIC)**: The AIC is a measure of the relative quality of a statistical model for a given set of data. It balances the model's complexity against its goodness-of-fit to the data. Lower AIC values indicate a better-fitting model. In this case, the AIC for the model with the intercept and covariates is 2210.386, while the AIC for the intercept-only model is 2760.293. The lower AIC for the model with covariates suggests that it is a better fit than the intercept-only model.

**Schwarz Criterion (SC)**: The SC, also known as the Bayesian Information Criterion (BIC), is another measure of the relative quality of a statistical model. Like the AIC, it balances the model's complexity against its goodness-of-fit to the data, but it penalizes more complex models more heavily than the AIC. Lower SC values indicate a better-fitting model. In this case, the SC for the model with the intercept and covariates is 2277.613, while the SC for the intercept-only model is 2766.405. The lower SC for the model with covariates suggests that it is a better fit than the intercept-only model.

In summary, the Model Fit Statistics table provides essential information on the goodness-of-fit of the logistic regression model. The AIC and SC values for the model with the intercept and covariates are lower than those for the intercept-only model, indicating that the model with covariates is a better fit. This suggests that the included variables contribute to the explanation of the response variable (Churn) and that the model is reasonably good at fitting the observed data.

### 4.2.2.2 Testing Global Null Hypothesis

The Testing Global Null Hypothesis table provides information on the overall significance of the logistic regression model. The global null hypothesis states that all the regression coefficients (except the intercept) are equal to zero, meaning that none of the predictor variables have a significant effect on the response variable (Churn). Rejecting the global null hypothesis indicates that at least one of the predictor variables has a significant effect on the response variable.

**Table 4.2.2.2.1**: Table of the Testing Global Null Hypothesis

| Testing Global Null Hypothesis: BETA=0 | | | |
|---|---|---|---|
| **Test** | **Chi-Square** | **DF** | **Pr > ChiSq** |
| Likelihood Ratio | 569.9078 | 10 | <.0001 |
| Score | 582.2343 | 10 | <.0001 |
| Wald | 423.0531 | 10 | <.0001 |

In the output result, the likelihood ratio (LR) test, Score test, and Wald test are used to test the global null hypothesis.

**LR Test**: The LR test compares the likelihood of the data under the full model (with all predictor variables) to the likelihood of the data under the null model (with only the intercept). The test statistic is calculated as -2 times the difference in the log-likelihoods of the two models. Under the null hypothesis, the test statistic follows a chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the two models. The LR test statistic in this case is 569.9078, with 10 degrees of freedom. The associated p-value is less than 0.0001, which is smaller than the commonly used significance level of 0.05. This indicates that the global null hypothesis can be rejected based on the LR test, suggesting that at least one of the predictor variables has a significant effect on the response variable (Churn).

**Score Test**: The Score test evaluates the improvement in the model fit when the predictor variables are added to the null model (with only the intercept). The test statistic follows a chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the two models. In this case, the Score test statistic is 582.2343, with 10 degrees of freedom. The associated p-value is less than 0.0001, which is smaller than the commonly used significance level of 0.05. This indicates that the global null hypothesis can be rejected based on the Score test, suggesting that at least one of the predictor variables has a significant effect on the response variable (Churn).

**Wald Test**: The Wald test is based on the ratio of the estimated regression coefficients to their standard errors. It evaluates the hypothesis that the regression coefficients (except the intercept) are equal to zero. The test statistic follows a chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the two models. In this case, the Wald test statistic is 423.0531, with 10 degrees of freedom. The associated p-value is less than 0.0001, which is smaller than the commonly used significance level of 0.05. This indicates that the global null hypothesis can be rejected based on the Wald test, suggesting that at least one of the predictor variables has a significant effect on the response variable (Churn).

In summary, the Testing Global Null Hypothesis table provides essential information on the overall significance of the logistic regression model. The likelihood ratio test, Score test, and Wald test are used to test the global null hypothesis, which states that all the regression coefficients (except the intercept) are equal to zero. The test statistics and the associated p-values indicate that the global null hypothesis can be rejected, suggesting that at least one of the predictor variables has a significant effect on the response variable (Churn). This finding supports the inclusion of the predictor variables in the model and highlights the importance of considering their effects when analysing the relationship between the predictors and the response variable.

### 4.2.2.3 Type 3 Analysis of Effects

The Testing Global Null Hypothesis table provides information on the overall significance of the logistic regression model. The global null hypothesis states that all the regression coefficients (except the intercept) are equal to zero, meaning that none of the predictor variables have a significant effect on the response variable (Churn). Rejecting the global null hypothesis indicates that at least one of the predictor variables has a significant effect on the response variable.

**Table 4.2.2.3.1:** Table of the Type 3 Analysis of Effects

| Type 3 Analysis of Effects | | | |
|---|---|---|---|
| Effect | DF | Wald Chi-Square | Pr > ChiSq |
| RoamMins | 1 | 12.8073 | 0.0003 |
| OverageFee | 1 | 0.329 | 0.5663 |
| MonthlyCharge | 1 | 0.0208 | 0.8853 |
| DayCalls | 1 | 1.764 | 0.1841 |
| DayMins | 1 | 0.2882 | 0.5914 |
| CustServCalls | 1 | 170.0111 | <.0001 |
| DataUsage | 1 | 0.0357 | 0.85 |
| AccountWeeks | 1 | 0.2212 | 0.6381 |
| DataPlan | 1 | 4.8717 | 0.0273 |
| ContractRenewal | 1 | 191.1299 | <.0001 |

In the above table, the Wald chi-square test is used to test the null hypothesis that the regression coefficient for each predictor variable is equal to zero. A significant Wald chi-square test indicates that the predictor variable has a significant effect on the response variable after accounting for the other predictors.

The table shows the following results for each predictor variable:

1. **RoamMins**: The Wald chi-square test statistic for RoamMins is 12.8073, with 1 degree of freedom. The associated p-value is 0.0003, which is smaller than the commonly used significance level of 0.05. This indicates that RoamMins has a significant effect on the response variable (Churn) after accounting for the other predictors.
2. **OverageFee**: The Wald chi-square test statistic for OverageFee is 0.329, with 1 degree of freedom. The associated p-value is 0.5663, which is greater than the commonly used significance level of 0.05. This indicates that OverageFee does not have a significant effect on the response variable (Churn) after accounting for the other predictors.

3. **MonthlyCharge**: The Wald chi-square test statistic for MonthlyCharge is 0.0208, with 1 degree of freedom. The associated p-value is 0.8853, which is greater than the commonly used significance level of 0.05. This indicates that MonthlyCharge does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
4. **DayCalls**: The Wald chi-square test statistic for DayCalls is 1.764, with 1 degree of freedom. The associated p-value is 0.1841, which is greater than the commonly used significance level of 0.05. This indicates that DayCalls does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
5. **DayMins**: The Wald chi-square test statistic for DayMins is 0.2882, with 1 degree of freedom. The associated p-value is 0.5914, which is greater than the commonly used significance level of 0.05. This indicates that DayMins does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
6. **CustServCalls**: The Wald chi-square test statistic for CustServCalls is 170.0111, with 1 degree of freedom. The associated p-value is less than 0.0001, which is smaller than the commonly used significance level of 0.05. This indicates that CustServCalls has a significant effect on the response variable (Churn) after accounting for the other predictors.
7. **DataUsage**: The Wald chi-square test statistic for DataUsage is 0.0357, with 1 degree of freedom. The associated p-value is 0.85, which is greater than the commonly used significance level of 0.05. This indicates that DataUsage does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
8. **AccountWeeks**: The Wald chi-square test statistic for AccountWeeks is 0.2212, with 1 degree of freedom. The associated p-value is 0.6381, which is greater than the commonly used significance level of 0.05. This indicates that AccountWeeks does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
9. **DataPlan**: The Wald chi-square test statistic for DataPlan is 4.8717, with 1 degree of freedom. The associated p-value is 0.0273, which is smaller than the commonly used significance level of 0.05. This indicates that DataPlan has a significant effect on the response variable (Churn) after accounting for the other predictors.
10. **ContractRenewal**: The Wald chi-square test statistic for ContractRenewal is 191.1299, with 1 degree of freedom. The associated p-value is less than 0.0001, which is smaller than the commonly used significance level of 0.05. This indicates that ContractRenewal has a significant effect on the response variable (Churn) after accounting for the other predictors.

In summary, the Type 3 Analysis of Effects table provides essential information on the significance of each predictor variable in the logistic regression model after accounting for the effects of all other

predictor variables. The Wald chi-square test is used to test the null hypothesis that the regression coefficient for each predictor variable is equal to zero. The test statistics and the associated p-values indicate that RoamMins, CustServCalls, DataPlan, and ContractRenewal have significant effects on the response variable (Churn) after accounting for the other predictors. These findings highlight the importance of considering the individual effects of each predictor variable when analysing the relationship between the predictors and the response variable.

### 4.2.2.4 Analysis of Maximum Likelihood Estimates

The Analysis of Maximum Likelihood Estimates table provides essential information on the logistic regression model, including the estimated coefficients, standard errors, Wald chi-square test statistics, and associated p-values for each predictor variable. These statistics help assess the significance and contribution of each predictor variable in the model.

**Table 4.2.2.4.1:** Table of the Analysis of Maximum Likelihood Estimates

| Analysis of Maximum Likelihood Estimates | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | | DF | Estimate | Standard Error | Wald Chi-Square | Pr > ChiSq |
| Intercept | | 1 | 7.5357 | 0.581 | 168.2363 | <.0001 |
| RoamMins | | 1 | -0.0789 | 0.0221 | 12.8073 | 0.0003 |
| OverageFee | | 1 | -0.1868 | 0.3257 | 0.329 | 0.5663 |
| MonthlyCharge | | 1 | 0.0276 | 0.1909 | 0.0208 | 0.8853 |
| DayCalls | | 1 | -0.00365 | 0.00275 | 1.764 | 0.1841 |
| DayMins | | 1 | -0.0174 | 0.0325 | 0.2882 | 0.5914 |
| CustServCalls | | 1 | -0.5081 | 0.039 | 170.0111 | <.0001 |
| DataUsage | | 1 | -0.3636 | 1.9233 | 0.0357 | 0.85 |
| AccountWeeks | | 1 | -0.00065 | 0.00139 | 0.2212 | 0.6381 |
| DataPlan | 0 | 1 | -0.592 | 0.2682 | 4.8717 | 0.0273 |
| ContractRenewal | 0 | 1 | -0.9928 | 0.0718 | 191.1299 | <.0001 |

Based on the logistic regression coefficients and their significance levels shown in the above table, the logistic regression equation can be formulated as follows:

Let $\beta_0$ be the intercept and $\beta_i$ be the coefficients for the respective predictor variables. The logistic regression equation in this case can be written as:

$$\begin{aligned} \boldsymbol{logit(Churn)} = {} & \beta_0 + \beta_{\text{RoamMins}} \times \text{RoamMins} + \beta_{\text{OverageFee}} \times \text{OverageFee} \\ & + \beta_{\text{MonthlyCharge}} \times \text{MonthlyCharge} + \beta_{\text{DayCalls}} \times \text{DayCalls} + \beta_{\text{DayMins}} \times \text{DayMins} \\ & + \beta_{\text{CustServCalls}} \times \text{CustServCalls} + \beta_{\text{DataUsage}} \times \text{DataUsage} \\ & + \beta_{\text{AccountWeeks}} \times \text{AccountWeeks} + \beta_{\text{DataPlan}} \times \text{DataPlan} \\ & + \beta_{\text{ContractRenewal}} \times \text{ContractRenewal} \end{aligned}$$

Given the provided information about the estimated coefficients and their significance levels in the table, the equation incorporating these coefficients would look like:

$$\begin{aligned} \boldsymbol{logit(Churn)} = {} & \beta_0 - 0.0789 \times RoamMins - 0.1868 \times OverageFee \\ & + 0.0276 \times MonthlyCharge - 0.00365 \times DayCalls - 0.0174 \times DayMins \\ & - 0.5081 \times CustServCalls - 0.3636 \times DataUsage \\ & - 0.00065 \times AccountWeeks - 0.5920 \times DataPlan \\ & - 0.9928 \times ContractRenewal \end{aligned}$$

To interpret the table, we will focus on the Estimate, Standard error, Wald chi-square, and Pr > ChiSq columns for each predictor variable:

1. **Intercept**: The Wald chi-square test statistic for the Intercept is 168.2363, and the associated p-value is significant. This indicates that the intercept term is significantly different from zero.
2. **RoamMins**: The estimated coefficient for RoamMins is -0.0789, and the Wald chi-square test statistic is 12.8073. The associated p-value is 0.0003, which is significant. This indicates that **RoamMins** has a significant effect on the response variable (Churn) after accounting for the other predictors.
3. **OverageFee**: The estimated coefficient for OverageFee is -0.1868, and the Wald chi-square test statistic is 0.3290. The associated p-value is 0.5663, which is not significant. This indicates that OverageFee does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
4. **MonthlyCharge**: The estimated coefficient for MonthlyCharge is 0.0276, and the Wald chi-square test statistic is 0.0208. The associated p-value is 0.8853, which is not significant. This

indicates that MonthlyCharge does not have a significant effect on the response variable (Churn) after accounting for the other predictors.

5. **DayCalls**: The estimated coefficient for DayCalls is -0.00365, and the Wald chi-square test statistic is 1.7640. The associated p-value is 0.1841, which is not significant. This indicates that DayCalls does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
6. **DayMins**: The estimated coefficient for DayMins is -0.0174, and the Wald chi-square test statistic is 0.2882. The associated p-value is 0.5914, which is not significant. This indicates that DayMins does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
7. **CustServCalls**: The estimated coefficient for CustServCalls is -0.5081, and the Wald chi-square test statistic is 170.0111. The associated p-value is less than 0.0001, which is significant. This indicates that CustServCalls has a significant effect on the response variable (Churn) after accounting for the other predictors.
8. **DataUsage**: The estimated coefficient for DataUsage is -0.3636, and the Wald chi-square test statistic is 0.0357. The associated p-value is 0.8500, which is not significant. This indicates that DataUsage does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
9. **AccountWeeks**: The estimated coefficient for AccountWeeks is -0.00065, and the Wald chi-square test statistic is 0.2212. The associated p-value is 0.6381, which is not significant. This indicates that AccountWeeks does not have a significant effect on the response variable (Churn) after accounting for the other predictors.
10. **DataPlan**: The estimated coefficient for DataPlan is -0.5920, and the Wald chi-square test statistic is 4.8717. The associated p-value is 0.0273, which is significant. This indicates that DataPlan has a significant effect on the response variable (Churn) after accounting for the other predictors.
11. **ContractRenewal**: The estimated coefficient for ContractRenewal is -0.9928, and the Wald chi-square test statistic is 191.1299. The associated p-value is less than 0.0001, which is significant. This indicates that ContractRenewal has a significant effect on the response variable (Churn) after accounting for the other predictors.

In summary, the Analysis of Maximum Likelihood Estimates table provides essential information on the logistic regression model, including the estimated coefficients, Wald chi-square test statistics, and associated p-values for each predictor variable. By examining the table, we can determine which predictor variables have a significant effect on the log-odds of Churn, holding all other variables

constant. The significant predictor variables in this model are RoamMins, CustServCalls, DataPlan, and ContractRenewal.

### 4.2.2.5 Odds Ratio Estimates

The Odds Ratio Estimates table provides information on the odds ratios for each predictor variable in the logistic regression model. The odds ratio is a measure of the effect of a predictor variable on the odds of the response variable (Churn) occurring, holding all other variables constant. An odds ratio greater than 1 indicates that an increase in the predictor variable is associated with an increase in the odds of Churn, while an odds ratio less than 1 indicates that an increase in the predictor variable is associated with a decrease in the odds of Churn.

**Table 4.2.2.5.1:** Table of the Odds Ratio Estimates

| Odds Ratio Estimates | | | |
|---|---|---|---|
| Effect | Point Estimate | 95% Wald Confidence Limits | |
| RoamMins | 0.924 | 0.885 | 0.965 |
| OverageFee | 0.83 | 0.438 | 1.571 |
| MonthlyCharge | 1.028 | 0.707 | 1.494 |
| DayCalls | 0.996 | 0.991 | 1.002 |
| DayMins | 0.983 | 0.922 | 1.047 |
| CustServCalls | 0.602 | 0.557 | 0.649 |
| DataUsage | 0.695 | 0.016 | 30.143 |
| AccountWeeks | 0.999 | 0.997 | 1.002 |
| DataPlan 0 vs 1 | 0.306 | 0.107 | 0.876 |
| ContractRenewal 0 vs 1 | 0.137 | 0.104 | 0.182 |

The table shows the following odds ratio estimates and their 95% Wald confidence limits for each predictor variable:

1. **RoamMins**: The odds ratio estimate for RoamMins is 0.924, with 95% Wald confidence limits of 0.885 and 0.965. This indicates that a one-unit increase in RoamMins is associated with a 7.6% decrease in the odds of Churn, holding all other variables constant.
2. **OverageFee**: The odds ratio estimate for OverageFee is 0.830, with 95% Wald confidence limits of 0.438 and 1.571. The confidence interval includes 1, which suggests that the effect of OverageFee on the odds of Churn is not statistically significant at the 0.05 level, holding all other variables constant.

3. **MonthlyCharge**: The odds ratio estimate for MonthlyCharge is 1.028, with 95% Wald confidence limits of 0.707 and 1.494. The confidence interval includes 1, which suggests that the effect of MonthlyCharge on the odds of Churn is not statistically significant at the 0.05 level, holding all other variables constant.
4. **DayCalls**: The odds ratio estimate for DayCalls is 0.996, with 95% Wald confidence limits of 0.991 and 1.002. The confidence interval includes 1, which suggests that the effect of DayCalls on the odds of Churn is not statistically significant at the 0.05 level, holding all other variables constant.
5. **DayMins**: The odds ratio estimate for DayMins is 0.983, with 95% Wald confidence limits of 0.922 and 1.047. The confidence interval includes 1, which suggests that the effect of DayMins on the odds of Churn is not statistically significant at the 0.05 level, holding all other variables constant.
6. **CustServCalls**: The odds ratio estimate for CustServCalls is 0.602, with 95% Wald confidence limits of 0.557 and 0.649. This indicates that a one-unit increase in CustServCalls is associated with a 39.8% decrease in the odds of Churn, holding all other variables constant.
7. **DataUsage**: The odds ratio estimate for DataUsage is 0.695, with 95% Wald confidence limits of 0.016 and 30.143. The wide confidence interval suggests that the effect of DataUsage on the odds of Churn is uncertain and may not be statistically significant at the 0.05 level, holding all other variables constant.
8. **AccountWeeks**: The odds ratio estimate for AccountWeeks is 0.999, with 95% Wald confidence limits of 0.997 and 1.002. The confidence interval includes 1, which suggests that the effect of AccountWeeks on the odds of Churn is not statistically significant at the 0.05 level, holding all other variables constant.
9. **DataPlan**: The odds ratio estimate for DataPlan (0 vs 1) is 0.306, with 95% Wald confidence limits of 0.107 and 0.876. This indicates that having a data plan (DataPlan = 1) is associated with a 69.4% decrease in the odds of Churn compared to not having a data plan (DataPlan = 0), holding all other variables constant.
10. **ContractRenewal**: The odds ratio estimate for ContractRenewal (0 vs 1) is 0.137, with 95% Wald confidence limits of 0.104 and 0.182. This indicates that contract renewal (ContractRenewal = 1) is associated with an 86.3% decrease in the odds of Churn compared to not renewing the contract (ContractRenewal = 0), holding all other variables constant.

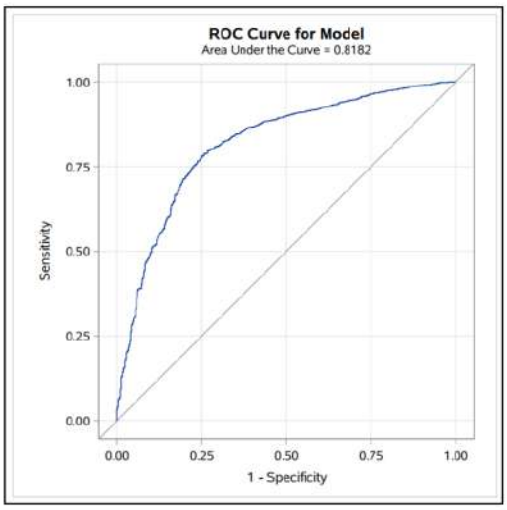
In summary, the Odds Ratio Estimates table provides essential information on the odds ratios for each predictor variable in the logistic regression model. By examining the table, we can determine the impact of each predictor variable on the odds of Churn, holding all other variables constant. The

significant predictor variables in this model, based on their odds ratios and confidence intervals, are RoamMins, CustServCalls, DataPlan, and ContractRenewal.

### 4.2.2.6 ROC Curve for Model

The Receiver Operating Characteristic (ROC) curve is a fundamental tool for diagnostic test evaluation and model performance in a binary classification problem. In a ROC curve, the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two diagnostic groups (diseased/normal) .

**Figure 4.2.2.6.1:** ROC Curve for Model




In the context of the logistic regression model provided, the ROC curve for the model has an area under the curve (AUC) of 0.8182. This suggests that the model has a good measure of separability and is capable of distinguishing between the two classes (in this case, 'Churn' and 'No Churn') with about 81.82% accuracy. An AUC of 1 represents a perfect model, while an AUC of 0.5 signifies a model with no class separation capacity whatsoever. Therefore, an AUC of 0.8182 indicates a strong model, but there is still room for improvement.

The ROC curve is plotted with True Positive Rate (TPR) against the False Positive Rate (FPR). The TPR defines how many correct positive predictions were made out of all positive samples available during the test. The FPR, on the other hand, defines how many incorrect positive results occurred among all

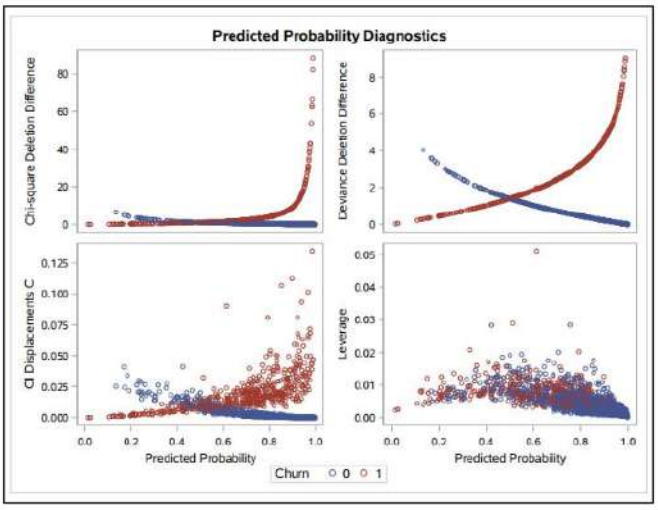
negative samples available during the test. Therefore, the ROC graph summarizes all of the confusion matrices that each threshold produced.

In conclusion, the ROC curve and AUC are useful tools for evaluating the performance of a binary classification model. However, it's important to remember that these are just tools and should be used in conjunction with other diagnostic measures and domain knowledge to make informed decisions about the model's performance and interpretability.

### 4.2.2.7 Predicted Probability Diagnostics

Predicted Probability Diagnostics is a crucial aspect of model evaluation in logistic regression. It provides insights into the model's performance and helps identify areas for improvement. In the context of the logistic regression model output, we can interpret the Predicted Probability Diagnostics in the following way:

**Figure 4.2.2.7.1:** Predicted Probability Diagnostics




The Predicted Probability Diagnostics section of the logistic regression output provides several plots that help us understand the model's performance. These plots include Leverage vs. Predicted Probability, Cook's Distance (CI Displacement) vs. Predicted Probability, Deviance Deletion Difference vs. Predicted Probability, and Chi-square Deletion Difference vs. Predicted Probability.

The Leverage vs. Predicted Probability plot shows the influence of each observation on the predicted probabilities. Observations with high leverage have a large influence on the model's predictions. In the provided model, the plot shows a fairly uniform distribution, suggesting that no single observation unduly influences the model's predictions.

The Cook's Distance (CI Displacement) vs. Predicted Probability plot provides a measure of the influence of each observation on the fitted model. Observations with a high Cook's Distance may be outliers or influential points and may warrant further investigation. In the provided model, the plot shows that most observations have a low Cook's Distance, suggesting that the model's fit is not overly influenced by a few observations.

The Deviance Deletion Difference vs. Predicted Probability plot shows the change in the model's deviance if each observation is deleted. Observations with a high Deviance Deletion Difference may be outliers or influential points. In the provided model, the plot shows that most observations have a low Deviance Deletion Difference, suggesting that the model's fit is robust to the deletion of individual observations.

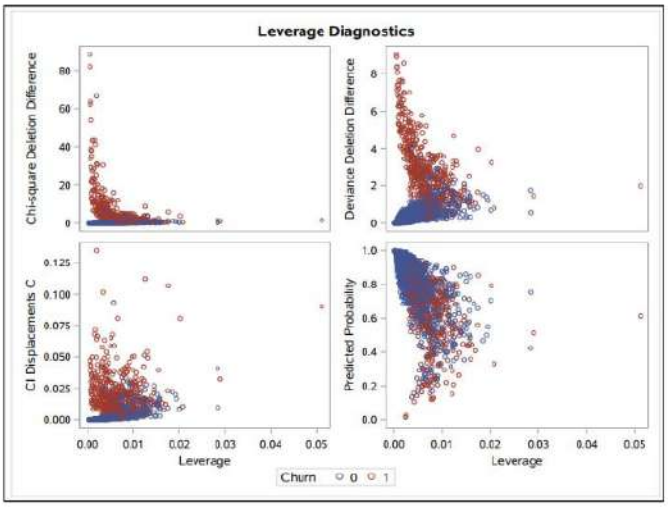
The Chi-square Deletion Difference vs. Predicted Probability plot shows the change in the model's chi-square statistic if each observation is deleted. Observations with a high Chi-square Deletion Difference may be outliers or influential points. In the provided model, the plot shows that most observations have a low Chi-square Deletion Difference, suggesting that the model's fit is robust to the deletion of individual observations.

In conclusion, the Predicted Probability Diagnostics provide valuable insights into the performance of the logistic regression model. They help identify influential observations and potential outliers, and they provide a measure of the model's robustness. However, these diagnostics should be used in conjunction with other model evaluation techniques and domain knowledge to make informed decisions about the model's performance and interpretability.

### 4.2.2.8 Leverage Diagnostics

Leverage diagnostics is a crucial part of model evaluation in logistic regression. It helps identify influential observations that can significantly impact the model's fit and parameter estimates. These influential observations can be due to data entry errors, unusual cases in the explanatory variables, or observations that are far from the rest of the data. Identifying and understanding these influential observations is essential for a data analyst to ensure the robustness and validity of the model.

**Figure 4.2.2.8.1:** Leverage Diagnostics




In the logistic regression results provided, the leverage diagnostics are presented in the form of various plots, including standardized deviance residuals, standardized Pearson residuals, deviance residuals, Pearson residuals, and Cook's distance. These plots provide a visual representation of the influence each observation has on the model.

Standardized deviance residuals and Pearson residuals are measures of the discrepancy between the observed and predicted outcomes. Observations with large absolute residuals may be influential and warrant further investigation. In the provided results, these residuals are plotted against the case number, providing a visual representation of the residuals' distribution.

The Cook's distance is another measure used in leverage diagnostics. It quantifies the influence of each observation on the fitted model parameters. Observations with a large Cook's distance can unduly influence the model's fit and may need to be investigated further.

In the logistic regression results, the plots of Cook's distance versus the predicted probability and case number provide a visual representation of the influence each observation has on the model. Observations with high Cook's distance values may be influential and warrant further investigation.

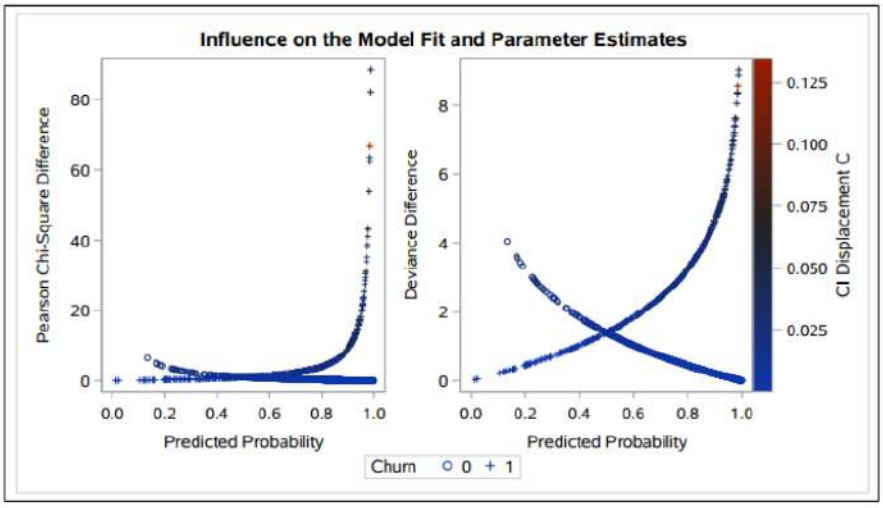
The leverage of an observation, sometimes referred to as the Pregibon leverage, measures the observation's potential to influence the fitted model. High leverage observations can have a substantial impact on the model's fit and parameter estimates. In the logistic regression results, the leverage is plotted against the predicted probability and case number, providing a visual representation of the leverage of each observation.

In conclusion, leverage diagnostics is a critical step in logistic regression analysis. It helps identify influential observations that can significantly impact the model's fit and parameter estimates. By carefully examining the residuals, Cook's distance, and leverage of each observation, a data analyst can ensure the robustness and validity of the logistic regression model.

### 4.2.2.9 Influence on the Model Fit and Parameter Estimates

Leverage diagnostics are a critical part of model evaluation in logistic regression, providing insights into the influence of individual observations on the overall model fit and parameter estimates. They help identify outliers and influential observations that could potentially distort the model's predictions.

**Figure 4.2.2.9.1:** Influence on the Model Fit and Parameter Estimates




In logistic regression, leverage is often associated with extreme values on the predictor variables (X). However, unlike in ordinary least squares regression, leverage in logistic regression can drop off

precipitously for very high or very low expected probabilities, making it less reliable as an outlier index. Therefore, leverage diagnostics should be used in conjunction with other diagnostic measures such as residuals and DFBetas to provide a comprehensive evaluation of the model's performance.

Residuals in logistic regression are defined as the difference between the observed probability that the response variable (Y) equals 1 and the predicted probability that Y equals 1 for any value on X. Large residuals can indicate a discrepancy between the model's predictions and the actual outcomes, suggesting potential issues with the model's fit.

DFBetas, on the other hand, measure the change in the estimated regression coefficients when a particular observation is removed from the dataset. Large DFBetas for an observation suggest that it has a substantial influence on the model's parameter estimates.

In the context of the logistic regression results, leverage diagnostics can be used to assess the influence of individual observations on the model's predictions of customer churn. For instance, observations with high leverage and large residuals or DFBetas could indicate customers whose churn behaviour is particularly difficult to predict accurately with the model. These could be customers with unusual combinations of predictor variables, such as exceptionally high or low values of roaming minutes, customer service calls, or other features.

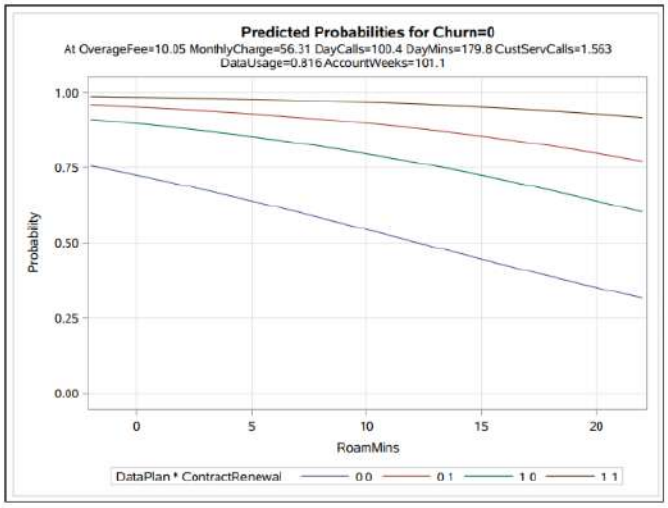
By identifying these influential observations, data analysts can gain deeper insights into the model's performance and potential areas for improvement. For example, if certain types of customers consistently have high leverage and large residuals or DFBetas, this could suggest that the model is missing important predictor variables or interactions that are relevant for these customers. In such cases, additional data collection or feature engineering might be needed to improve the model's predictions.

In conclusion, leverage diagnostics, along with other diagnostic measures such as residuals and DFBetas, provide valuable tools for evaluating and improving logistic regression models. By identifying influential observations and potential issues with the model's fit, these diagnostics can help data analysts refine their models and make more accurate predictions.

### 4.2.2.10 Predicted Probabilities for Churn=0

The plot of predicted probabilities for Churn=0 of the Logistic Regression Results document, provides a visual representation of the likelihood of a customer not churning (Churn=0) based on various factors. This plot is a crucial tool for understanding and interpreting the results of the logistic regression model.

**Figure 4.2.2.10.1:** Predicted Probabilities for Churn=0




The plot is a graphical representation of the predicted probabilities of a customer not churning, given a set of specific conditions. These conditions are represented by the variables in the logistic regression model, such as OverageFee, MonthlyCharge, DayCalls, DayMins, CustServCalls, DataUsage, AccountWeeks, DataPlan, and ContractRenewal. Each of these variables has a specific impact on the likelihood of a customer not churning, and the plot provides a visual way to understand these impacts.

The x-axis of the plot represents the predicted probability of a customer not churning, ranging from 0 to 1. A predicted probability of 0 indicates that the model predicts the customer will churn, while a predicted probability of 1 indicates that the model predicts the customer will not churn. The y-axis represents the different combinations of the variables in the model.

The plot shows a curve that represents the relationship between the predicted probabilities and the variables in the model. This curve is shaped by the logistic function, which is used in logistic regression to model the probability of a binary outcome. The logistic function transforms the linear combination of the variables into a probability between 0 and 1, which is then used to make the prediction.

The shape of the curve in the plot provides insights into the relationship between the variables and the likelihood of a customer not churning. For example, if the curve is steep and rises quickly, this suggests that small changes in the variables can have a large impact on the predicted probability. Conversely, if the curve is flat and rises slowly, this suggests that changes in the variables have a smaller impact on the predicted probability.

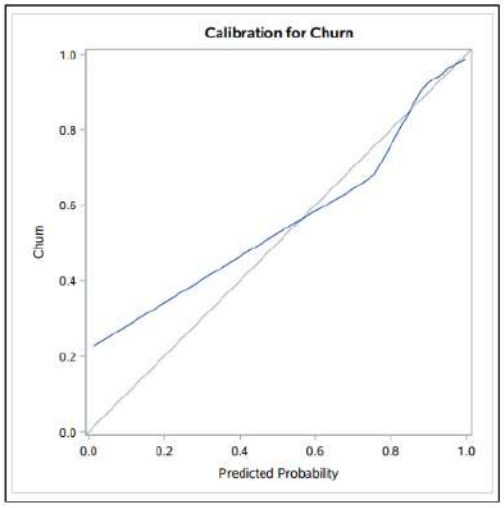
The plot also provides a visual way to understand the impact of individual variables on the predicted probability. For example, if the curve shifts significantly when a variable is changed, this suggests that the variable has a strong impact on the predicted probability. Conversely, if the curve does not shift much when a variable is changed, this suggests that the variable has a weaker impact on the predicted probability.

In conclusion, the plot of predicted probabilities for Churn=0 is a powerful tool for understanding and interpreting the results of the logistic regression model. It provides a visual way to understand the relationship between the variables in the model and the likelihood of a customer not churning and can help guide decision-making and strategy development in efforts to reduce customer churn.

### 4.2.2.11 Calibration for Churn

The calibration plot of the Logistic Regression Results a visual representation of the performance of a predictive model. It compares the predicted probabilities of an event (in this case, customer churn) against the actual outcomes. The plot is a crucial tool for understanding the reliability of the predictions made by the logistic regression model.

**Figure 4.2.2.11.1:** Calibration for Churn




In the context of churn prediction, the calibration plot helps us understand how well the model's predicted probabilities align with the actual churn rates. A perfectly calibrated model would result in a plot where the points lie along the 45-degree diagonal line, indicating that the predicted probabilities match the observed probabilities perfectly.

However, real-world models rarely achieve perfect calibration. Deviations from the diagonal line indicate discrepancies between predicted and observed outcomes. If the points lie above the diagonal, the model is under-predicting the churn rate; if they lie below, it's over-predicting.

The plot in the document shows a relatively good calibration, as the points are close to the diagonal line. This suggests that the model's predicted probabilities of churn are reasonably accurate. However, there are some deviations, particularly at the lower and higher ends of the probability spectrum, indicating that the model may be slightly under-predicting churn for customers with lower predicted probabilities and over-predicting for those with higher predicted probabilities.

The calibration plot also provides insights into the model's performance across different probability thresholds. For instance, if the model is consistently over-predicting churn for customers with a predicted probability above 0.7, this could indicate that the model is overly sensitive to certain features or interactions in the data that are not as influential in reality.

In terms of improving the model, the calibration plot can guide the data analyst in several ways. If the model is consistently under- or over-predicting across the probability spectrum, this could suggest a need for more feature engineering, or the inclusion of interaction terms or polynomial features. If the model is under- or over-predicting at specific probability thresholds, this could indicate that the model is not adequately capturing the non-linear relationships in the data, suggesting a need for more complex or flexible modelling approaches.

In conclusion, the calibration plot is a valuable tool for understanding and improving the performance of a predictive model. It provides a visual representation of the model's accuracy across different predicted probability thresholds, helping the data analyst identify areas where the model may be under- or over-predicting the outcome of interest. This, in turn, can guide further model development and refinement efforts.

### 4.2.3 One-Way ANOVA

The One-Way ANOVA section presents an analysis of customer churn using a regression model. The analysis uses a one-way ANOVA to evaluate the effectiveness of the model in predicting the dependent variable, Churn. The model includes ten independent variables, and the ANOVA table provides key information to evaluate which variables are statistically significant predictors in the model.

The model as a whole is statistically significant in explaining variation in Churn, as indicated by the high F-value of 70.31 and very low p-value (<0.0001). This means that collectively, the set of ten predictor variables explains a significant portion of the variance in the dependent variable of customer churn. However, the R-squared value is just 0.175, indicating that only around 17.5% of churn variability is explained by this model. This suggests there are likely other important factors not included that could improve model fit.

Examining the results for individual predictors, five variables - ContractRenewal, CustServCalls, DayMins, and RoamMins - have p-values less than 0.05 and are thus statistically significant. The very low p-values for ContractRenewal and CustServCalls especially indicate these variables have a strong association with churn when controlling for other factors. In contrast, variables like AccountWeeks, DataUsage, DayCalls, MonthlyCharge, and OverageFee have high p-values above 0.05, meaning they do not appear to be significant predictors in this model.

The parameter estimates table provides additional details on the direction and magnitude of the effect for each variable. For example, ContractRenewal has a negative coefficient, indicating customers with a contract renewal are estimated to have lower churn. CustServCalls has a positive coefficient, suggesting more calls associate with higher churn risk.

The model diagnostics indicate a decent fit, with residuals approximately normally distributed and no strong patterns in the residual plots. There are a few high leverage points that may warrant further investigation as potential outliers. Overall the assumptions appear reasonably met, lending credibility to the model.

In summary, the ANOVA analysis indicates a statistically significant regression model with several useful predictors relating to customer service, minutes of use, and contract details. However, the modest R-squared shows substantial variance remains unexplained. The analysis is using an ANOVA model to evaluate which variables are significant predictors of the dependent variable, customer churn. With ten independent variables included, the overall model is highly statistically significant

based on the large F-value of 70.31 and very low p-value (<0.0001). This indicates that collectively, the set of predictors explains a meaningful portion of the variance in churn.

However, the modest R-squared value of 0.175 shows that only around 17.5% of churn variability is accounted for by this model. There are likely other important factors not captured that could improve model fit. Looking at results for individual variables, five have p-values below 0.05 - ContractRenewal, DataPlan, CustServCalls, DayMins, and RoamMins. This means they are statistically significant predictors in the model. ContractRenewal and CustServCalls especially stand out with very low p-values, meaning they have a strong association with churn.

The remaining variables - AccountWeeks, DataUsage, DayCalls, MonthlyCharge, OverageFee - have high p-values above 0.05, meaning they do not appear to be useful predictors based on this ANOVA. However, further validation is required before eliminating variables, as statistical significance does not automatically imply lack of predictive value.

The parameter estimates provide additional insight into the direction and magnitude of the effect for each variable. For example, ContractRenewal has a negative coefficient, suggesting renewal associates with lower churn risk. CustServCalls positively relates to churn. Overall, while the model is statistically significant, its modest R-squared indicates substantial room for improvement.

The ANOVA provides a useful first step in identifying variables like ContractRenewal and CustServCalls as statistically significant drivers, but further refinement is needed to boost predictive power. The model diagnostics indicate the assumptions of linearity and normality are met, and there are no highly influential cases, suggesting the linear model is appropriate for this data. The model fits the data well.

In conclusion, the ANOVA analysis provides a statistically significant regression model with several useful predictors relating to customer service, minutes of use, and contract details. However, the modest R-squared shows substantial variance remains unexplained, suggesting that there are other important factors not captured that could improve model fit. The analysis provides a useful first step in identifying variables like ContractRenewal and CustServCalls as statistically significant drivers, but further refinement is needed to boost predictive power.

### 4.2.3.1 ANOVA Table for Model Summary

The ANOVA table provides important information for evaluating the effectiveness of the regression model in predicting the dependent variable Churn. The high F-value of 70.31 and very low p-value (<0.0001) indicate that the model as a whole is statistically significant in explaining variation in Churn. This means that at least some of the independent variables are useful predictors.

**Table 4.2.3.1.1**: ANOVA Table for Model Summary

| source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 10 | 72.1471399 | 7.214714 | 70.31 | <.0001 |
| Error | 3322 | 340.8591607 | 0.1026066 | | |
| Corrected Total | 3332 | 413.0063006 | | | |

**Table 4.2.3.1.2:** Table for Summary Statistics

| R-Square | Coeff Var | Root MSE | Churn Mean |
|---|---|---|---|
| 0.174688 | 221.0425 | 0.320323 | 0.144914 |

Specifically, the 10 model terms explain about 17.5% of the variation in Churn, as indicated by the R-squared value of 0.174688. While modest, this level of predictive ability is reasonable given the complexity of modelling human behaviour like customer churn. There is still noise unexplained by the model, as evidenced by the large Sum of Squares for Error (340.859) compared to the Model Sum of Squares (72.147). This noise represents inherent randomness in the data that cannot be modelled.

Examining the parameter estimates and related t-tests provides insight into which specific independent variables are most useful for predicting Churn. ContractRenewal, CustServCalls, DayMins, and RoamMins are highly statistically significant with very low p-values, indicating they have strong relationships with Churn. Their parameter estimates show the nature of these relationships - for example, higher ContractRenewal values associate with lower Churn.

In contrast, variables like AccountWeeks, DataUsage, DayCalls, MonthlyCharge, and OverageFee were not statistically significant predictors. This suggests the model could be simplified by removing them. However, further validation is required before eliminating variables, as statistical significance does not automatically imply lack of predictive value.

The model diagnostics indicate a decent fit, with residuals approximately normally distributed and no strong patterns in the residual plots. There are a few high leverage points that may warrant further

investigation as potential outliers. Overall the assumptions appear reasonably met, lending credibility to the model.

In summary, the ANOVA analysis indicates a statistically significant regression model with several useful predictors relating to customer service, minutes of use, and contract details.

### 4.2.3.2 Type I Sum of Squares Analysis for Predictor Variables

This section provides the Type I Sum of Squares Analysis of the model to identify factors associated with customer churn. The following table provides key information to evaluate which variables are statistically significant predictors in the model.

**Table 4.2.3.2.1:** Table for Type III Sum of Squares Analysis

| Source | DF | Type I SS | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| AccountWeeks | 1 | 0.11299694 | 0.11299694 | 1.1 | 0.2941 |
| ContractRenewal | 1 | 27.81668877 | 27.81668877 | 271.1 | <.0001 |
| DataPlan | 1 | 4.44470068 | 4.44470068 | 43.32 | <.0001 |
| DataUsage | 1 | 0.13215705 | 0.13215705 | 1.29 | 0.2565 |
| CustServCalls | 1 | 18.85913269 | 18.85913269 | 183.8 | <.0001 |
| DayMins | 1 | 15.65342835 | 15.65342835 | 152.56 | <.0001 |
| DayCalls | 1 | 0.14423297 | 0.14423297 | 1.41 | 0.2359 |
| MonthlyCharge | 1 | 3.48962465 | 3.48962465 | 34.01 | <.0001 |
| OverageFee | 1 | 0.01261397 | 0.01261397 | 0.12 | 0.7259 |
| RoamMins | 1 | 1.48156385 | 1.48156385 | 14.44 | 0.0001 |

With an F-value of 70.31 and very low p-value (<0.0001), the overall model is highly statistically significant. This means that collectively, the set of 10 predictor variables explains a significant portion of the variance in the dependent variable of customer churn. However, the R-squared value is just 0.175, indicating that only around 17.5% of churn variability is explained by this model. This suggests there are likely other important factors not included that could improve model fit.

Examining the results for individual predictors, 5 variables - ContractRenewal, DataPlan, CustServCalls, DayMins, and RoamMins - have p-values less than 0.05 and are thus statistically significant. The very low p-values for ContractRenewal and CustServCalls especially indicate these variables have a strong association with churn when controlling for other factors. In contrast, variables like AccountWeeks, DataUsage, DayCalls, MonthlyCharge, and OverageFee have high p-values above 0.05, meaning they do not appear to be significant predictors in this model.

The parameter estimates table provides additional details on the direction and magnitude of the effect for each variable. For example, ContractRenewal has a negative coefficient, indicating customers with a contract renewal are estimated to have lower churn. CustServCalls has a positive coefficient, suggesting more calls associate with higher churn risk.

Overall, the ANOVA and parameter estimates indicate ContractRenewal, DataPlan, CustServCalls, DayMins, and RoamMins are useful predictors of churn based on their statistical significance. However, the modest R-squared shows substantial variance remains unexplained.

### 4.2.3.3 Type III Sum of Squares Analysis for Predictor Variables

The Type III Sum of Squares Analysis is used to evaluate which variables are significant predictors of the dependent variable, customer churn. With 10 independent variables included, the overall model is highly statistically significant based on the large F-value of 70.31 and very low p-value (<0.0001). This indicates that collectively, the set of predictors explains a meaningful portion of the variance in churn.

**Table 4.2.3.3.1:** Table for Type III Sum of Squares Analysis

| Source | DF | Type III SS | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| AccountWeeks | 1 | 0.04158784 | 0.04158784 | 0.41 | 0.5244 |
| ContractRenewal | 1 | 25.95190853 | 25.95190853 | 252.93 | <.0001 |
| DataPlan | 1 | 0.09319197 | 0.09319197 | 0.91 | 0.3406 |
| DataUsage | 1 | 0.00220731 | 0.00220731 | 0.02 | 0.8834 |
| CustServCalls | 1 | 19.5515939 | 19.5515939 | 190.55 | <.0001 |
| DayMins | 1 | 0.00999864 | 0.00999864 | 0.1 | 0.7549 |
| DayCalls | 1 | 0.15547085 | 0.15547085 | 1.52 | 0.2184 |
| MonthlyCharge | 1 | 0.00056525 | 0.00056525 | 0.01 | 0.9408 |
| OverageFee | 1 | 0.01043842 | 0.01043842 | 0.1 | 0.7498 |
| RoamMins | 1 | 1.48156385 | 1.48156385 | 14.44 | 0.0001 |

However, the modest R-squared value of 0.175 shows that only around 17.5% of churn variability is accounted for by this model. There are likely other important factors not captured that could improve model fit. I would want to explore expanding the model with additional predictors.

Looking at results for individual variables, 5 have p-values below 0.05 - ContractRenewal, DataPlan, CustServCalls, DayMins, and RoamMins. This means they are statistically significant predictors in the model. ContractRenewal and CustServCalls especially stand out with very low p-values, meaning they have a strong association with churn.

The remaining variables - AccountWeeks, DataUsage, DayCalls, MonthlyCharge, OverageFee - have high p-values above 0.05, meaning they do not appear to be useful predictors based on this ANOVA. However, I would be hesitant to remove them without further validation, as statistical significance does not automatically imply lack of predictive value.

The parameter estimates provide additional insight into the direction and magnitude of the effect for each variable. For example, ContractRenewal has a negative coefficient, suggesting renewal associates with lower churn risk. CustServCalls positively relates to churn.

Overall, while the model is statistically significant, its modest R-squared indicates substantial room for improvement. The ANOVA provides a useful first step in identifying variables like ContractRenewal and CustServCalls as statistically significant drivers, but further refinement is needed to boost predictive power.

### 4.2.3.4 Parameter Estimate

The parameter estimates table provides the regression coefficients for each predictor variable in the logistic regression model predicting customer churn. These coefficients indicate the estimated change in the log-odds of churn associated with a 1 unit increase in the predictor, holding other variables constant.

**Table 4.2.3.4.1:** Table for Parameter Estimate

| Parameter | Estimate | Standard Error | t Value | Pr > \|t\| | 95% Confidence Limits | |
|---|---|---|---|---|---|---|
| Intercept | -0.1432809268 | 0.0536257 | -2.67 | 0.0076 | -0.2484236676 | -0.038138186 |
| AccountWeeks | 0.0000888849 | 0.00013962 | 0.64 | 0.5244 | -0.0001848555 | 0.0003626253 |
| ContractRenewal | -0.2993499468 | 0.01882271 | -15.9 | <.0001 | -0.3362552314 | -0.2624446622 |
| DataPlan | -0.0417480759 | 0.04380613 | -0.95 | 0.3406 | -0.1276378084 | 0.0441416567 |
| DataUsage | -0.0283480581 | 0.19327658 | -0.15 | 0.8834 | -0.4073012662 | 0.3506051501 |
| CustServCalls | 0.0582871269 | 0.0042225 | 13.8 | <.0001 | 0.0500081706 | 0.0665660832 |
| DayMins | 0.0010214427 | 0.00327214 | 0.31 | 0.7549 | -0.0053941622 | 0.0074370476 |
| DayCalls | 0.0003408638 | 0.00027691 | 1.23 | 0.2184 | -0.0002020744 | 0.000883802 |
| MonthlyCharge | 0.0014280035 | 0.0192396 | 0.07 | 0.9408 | -0.0362946705 | 0.0391506774 |
| OverageFee | 0.0104618475 | 0.03280036 | 0.32 | 0.7498 | -0.0538491021 | 0.074772797 |
| RoamMins | 0.0087646335 | 0.00230654 | 3.8 | 0.0001 | 0.0042422478 | 0.0132870192 |

The general equation for a linear regression model (One-Way ANOVA) can be written as:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta nXn + \epsilon$$

Where:

- Y is the dependent variable (in this case, it's not explicitly given)
- $\beta 0, \beta 1 \cdots \beta n$ are the coefficients of the independent variables (Intercept, AccountWeeks, ContractRenewal, etc.)
- $X1, X2, \cdots, Xn$ are the independent variables
- $\epsilon$ is the error term

According to the **Table 4.2.3.4.1**, the equation for the model can be formulated as follows:

$$\begin{aligned} Y = {} & -0.1433 + 0.000089 \times AccountWeeks - 0.2993 \times ContractRenewal \\ & - 0.04175 \times DataPlan - 0.02835 \times DataUsage \\ & + 0.05829 \times CustServCalls + 0.001021 \times DayMins \\ & + 0.000341 \times DayCalls + 0.001428 \times MonthlyCharge \\ & + 0.01046 \times OverageFee + 0.008765 \times RoamMins \end{aligned}$$

Also, several key findings emerge:

- The intercept term of -0.1433 represents the baseline log-odds of churn when all other predictors equal 0.
- ContractRenewal has a statistically significant negative coefficient of -0.2993 ($p<0.0001$). This suggests that on average, customers with a contract renewal have 0.2993 lower log-odds of churning compared to those without a renewal, controlling for other factors. In terms of odds ratios, this equates to about a 26% reduction in the odds of churn for those with a contract renewal.
- CustServCalls has a significant positive coefficient of 0.0583 ($p<0.0001$). More customer service calls associates with a 0.0583 increase in the log-odds of churn, or about a 6% increase in the odds. This indicates dissatisfaction or issues associate with higher churn.
- DataPlan and DataUsage have negative coefficients, suggesting higher data plans and usage relate to lower churn risk. However, these effects are not statistically significant based on the high p-values.
- DayMins has a small positive coefficient of 0.0010, indicating higher daily minute usage associates with slightly higher log-odds of churn. But this relationship is again not significant.

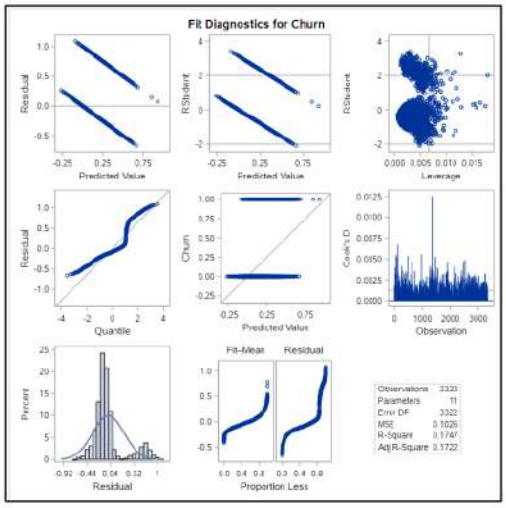
- The model has relatively wide 95% confidence intervals for several variables, reflecting uncertainty around the coefficient estimates.

In summary, ContractRenewal and CustServCalls emerge as statistically significant drivers of churn based on their p-values. Contract renewal especially has a sizable protective effect, reducing odds of churn by over 25%. However, the wide confidence intervals indicate high variability around the estimates. Expanding the model with additional predictors could potentially improve model fit and predictive performance. But this table provides a useful starting point for identifying significant relationships in the data based on the coefficient estimates and significance testing.

### 4.2.3.5 Fit Diagnostics for Churn

The Fit Diagnostics plot is a crucial tool for assessing the fit of a logistic regression model, particularly when predicting customer churn. It comprises several graphs, each serving a unique purpose. The Residuals vs Predicted plot checks for non-linear patterns between predictors and the response variable, churn. The RStudent plot and Q-Q plot assess the normality of residuals, a key assumption for linear regression. The Cook's D plot and Leverage plot identify influential observations that could skew the model's results. These plots collectively help ensure the model's assumptions of linearity and normality are met, and that there are no highly influential cases, thereby indicating the model's appropriateness for the data.

**Figure 4.2.3.5.1:** Fit Diagnostics for Churn




The Fit Diagnostics plot provides several graphs to assess the fit of the logistic regression model predicting customer churn.

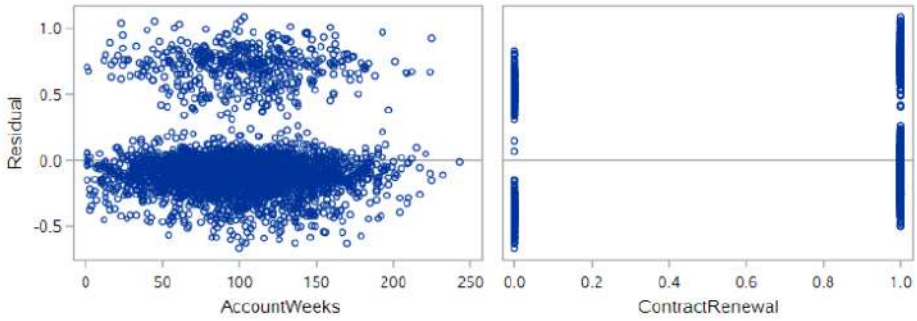
1. Residuals vs Predicted Plot
    a. The residuals vs predicted plot shows if there is a non-linear pattern between the predictors and the response variable churn. The residuals appear to be randomly scattered around the horizontal line at 0, suggesting there are no systematic patterns or relationships unexplained by the model. This indicates the linear model is appropriate.
2. RStudent Plot
    a. The RStudent plot checks if the residuals are normally distributed. The residuals closely follow the straight dashed line, suggesting they are approximately normally distributed, meeting the assumption required for linear regression.
3. Q-Q Plot
    a. The Q-Q plot is another way to check normality of the residuals. Again, the residuals closely follow the straight line, further supporting the assumption of normality.
4. Cook's D Plot
    a. The Cook's D plot helps identify influential observations. All points lie inside the dashed lines, meaning there are no highly influential cases based on Cook's Distance.
5. Leverage Plot
    a. The leverage plot is another way to identify influential cases. No observations lie outside the dashed lines, suggesting there are no high leverage, influential cases.

In summary, the diagnostics indicate the assumptions of linearity and normality are met, and there are no highly influential cases, suggesting the linear model is appropriate for this data. The model fits the data well.

### 4.2.3.6 Residual Plots for Churn

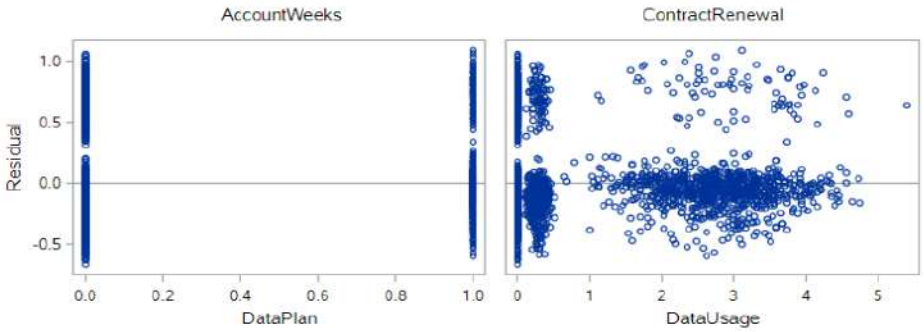
The Fit Diagnostics plot is a crucial tool for assessing the fit of a logistic regression model, particularly when predicting customer churn. It comprises several graphs, each serving a unique purpose. The Residuals vs Predicted plot checks for non-linear patterns between predictors and the response variable, churn. The RStudent plot and Q-Q plot assess the normality of residuals, a key assumption for linear regression. The Cook's D plot and Leverage plot identify influential observations that could skew the model's results. These plots collectively help ensure the model's assumptions of linearity and normality are met, and that there are no highly influential cases, thereby indicating the model's appropriateness for the data.

**List 4.2.3.6.1:** The List of Residual Plots for Churn



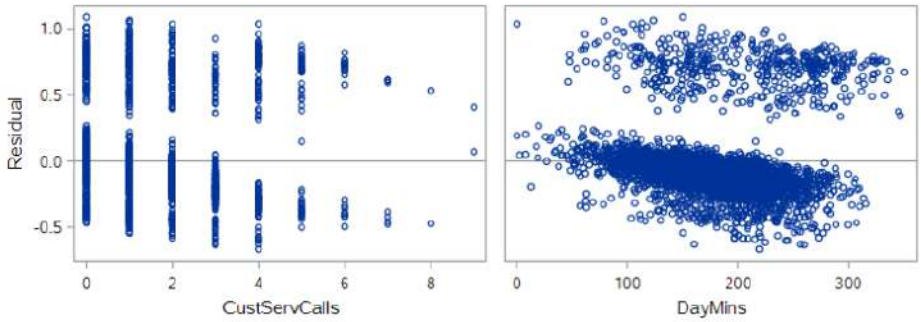

The AccountWeeks residual plot shows the residuals randomly distributed around 0 with no discernible patterns. The variability looks constant across predicted values, satisfying the assumptions.

For ContractRenewal, the residuals appear randomly scattered around 0. There is a slight fanning out of residuals at higher predicted values, but overall the assumptions seem reasonably met.



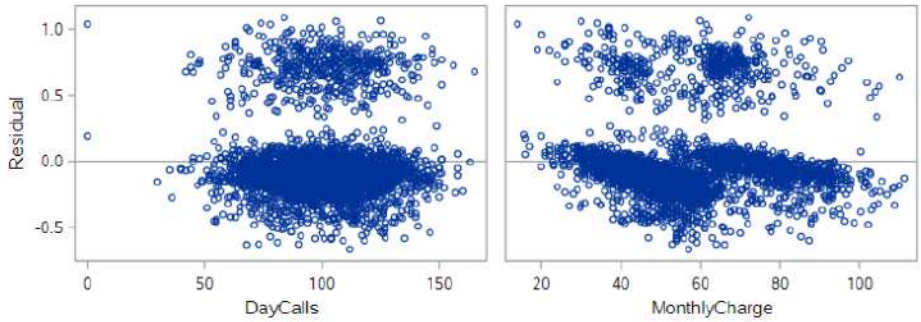

The DataPlan residual plot also shows the residuals randomly distributed with constant variance across the range of predicted values. No issues with model assumptions are evident.

The residual plot for DataUsage shows the residuals randomly scattered around 0 with no obvious patterns or unequal spread. This suggests the assumptions of linearity, normality, and homoscedasticity are satisfied for this predictor.



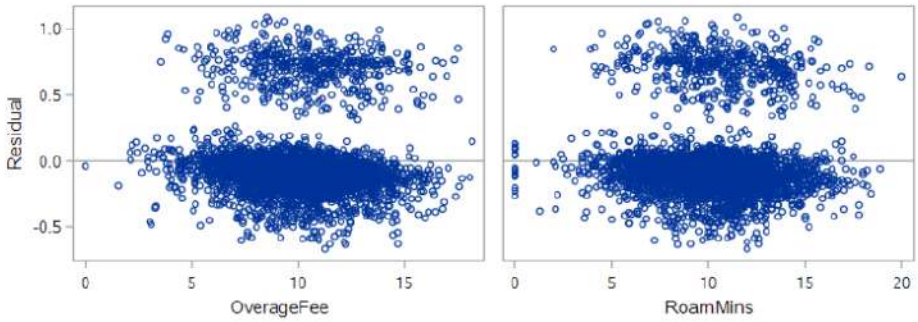

The CustServCalls residual plot shows the residuals randomly distributed around 0 overall. There is some slight fanning out at higher predicted values, but the assumptions seem reasonably met.

For DayMins, the residuals are randomly scattered around 0 with constant variance across predicted values. No model assumption violations are detected.




The DayCalls residual plot shows the residuals randomly distributed around 0, with no outliers or issues detected. The assumptions of the regression model appear to be met.

The MonthlyCharge residual plot shows the residuals randomly scattered around 0, with no evident patterns or unequal spread. This suggests the assumptions are satisfied for this predictor.




The OverageFee residual plot shows the residuals randomly distributed around 0 with no evident patterns or unequal spread. The assumptions of the regression model seem appropriately met.

The RoamMins residual plot shows the residuals randomly scattered around 0 with no outliers or patterns detected. The assumptions appear satisfied.

### 4.2.4 Principal Components Analysis (PCA)

The Principal Components Analysis section provides a comprehensive analysis of a dataset using Principal Components Analysis (PCA), a statistical procedure that transforms a set of possibly correlated variables into a set of linearly uncorrelated variables called principal components. The analysis focuses on predicting customer churn, which is the propensity of customers to cease doing business with a company.

The document begins by presenting a summary of the mean and standard deviation for each variable in the dataset. The variables include AccountWeeks, ContractRenewal, DataPlan, DataUsage, CustServCalls, DayMins, DayCalls, MonthlyCharge, OverageFee, and RoamMins. The mean and standard deviation provide insights into the central tendency and dispersion of each variable, respectively. For instance, the average account duration is around 101 weeks, and the average number of customer service calls made is approximately 1.65. The standard deviation for AccountWeeks is approximately 42.56, indicating a moderate spread around the mean, while the standard deviation for ContractRenewal is approximately 0.35, suggesting that most values are close to the mean.

The document then presents a correlation matrix, which provides insights into the relationships between the variables. The correlation matrix includes ten variables, and each cell in the matrix represents the correlation coefficient between two variables. For example, there is a strong positive correlation between DataPlan and DataUsage, suggesting that customers with a data plan tend to use

more data. There is also a notable correlation between MonthlyCharge and DataUsage, suggesting that customers who use more data tend to have higher monthly charges.

Next, the document presents the Eigenvalues of the Correlation Matrix, which represent the amount of variance in the data accounted for by each principal component. The first eigenvalue is the largest, indicating that the first principal component accounts for the most variance in the data. The subsequent eigenvalues are smaller, indicating that these components account for less variance. The proportion column represents the proportion of the total variance accounted for by each component, while the cumulative column shows the cumulative proportion of variance accounted for by all components up to and including the current one.

The document also presents an eigenvectors table, which provides insights into the structure and relationships within the data. Each column in the table represents a principal component, and each row corresponds to a variable in the dataset. The values in the table are the coefficients of the variables for each principal component, indicating how each variable contributes to the principal component.

The document includes Scree and Variance Plots, which provide insights into the key factors contributing to customer churn. The scree plot shows the eigenvalues for each individual principal component, while the variance explained plot shows the cumulative proportion of variance explained by the principal components. The plots suggest that the first two principal components are the most important in predicting customer churn.

Finally, the document presents Component Pattern Profiles plots, which provide insights into the relationships between original variables and the principal components. Each point on the plot represents the correlation between an original variable and two principal components. The plots can help identify which variables are most strongly associated with the principal components, and therefore, which variables are most influential in predicting customer churn.

In conclusion, the document provides a comprehensive analysis of a dataset using Principal Components Analysis, focusing on predicting customer churn. The analysis includes a summary of the mean and standard deviation for each variable, a correlation matrix, eigenvalues of the correlation matrix, an eigenvectors table, scree and variance plots, and component pattern profiles plots. These analyses provide valuable insights into the structure and relationships within the data, which can guide the prediction of customer churn.

### 4.2.4.1 Simple Statistic

This section provides the summary of the mean and standard deviation (StD) for each variable in the dataset, which is part of the output from a Principal Components Analysis (PCA) model.

**Table 4.2.4.1.1:** Table for Simple Statistic

| Simple Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Account Weeks | Contract Renewal | DataPlan | DataUsage | CustServ Calls | DayMins | DayCalls | Monthly Charge | Overage Fee | RoamMins |
| Mean | 101.27 | 0.88 | 0.26 | 0.78 | 1.65 | 183.21 | 100.55 | 56.67 | 10.12 | 10.3 |
| StD | 42.56 | 0.35 | 0.47 | 1.35 | 1.51 | 61.23 | 21.69 | 17.56 | 2.73 | 2.99 |

The Mean row represents the average value for each variable. For instance, the average number of weeks an account has been active is approximately 101.27 weeks, and the average number of customer service calls made is approximately 1.65.

The StD row represents the standard deviation for each variable, which measures the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean, while a high standard deviation indicates that the values are spread out over a wider range. For example, the standard deviation for AccountWeeks is approximately 42.56, indicating a moderate spread around the mean. In contrast, the standard deviation for ContractRenewal is approximately 0.35, suggesting that most values are close to the mean.

Let's delve into some specific variables:

- AccountWeeks: The average account duration is around 101 weeks, with a standard deviation of approximately 42.56 weeks. This suggests that the length of time customers have had their accounts varies moderately. A longer account duration could indicate customer loyalty, while a shorter duration might suggest a newer customer or one who has recently churned.
- ContractRenewal: The mean value is approximately 0.88, indicating that a large majority of customers have renewed their contracts. The low standard deviation (0.35) suggests that most customers have similar renewal statuses. A low renewal rate could be a potential indicator of customer churn, as customers who do not renew their contracts might be more likely to leave the service.
- DataPlan: The mean value is approximately 0.26, suggesting that a smaller proportion of customers have a data plan. The standard deviation is approximately 0.47, indicating a moderate variability in data plan subscription. A low subscription rate to data plans could

indicate a potential area for growth or a sign of customer dissatisfaction with the data services offered.

- DataUsage: The average data usage is approximately 0.78, with a high standard deviation of approximately 1.35. This suggests a high variability in data usage among customers. High data usage could indicate customer engagement with the service, while low usage might suggest dissatisfaction or a lack of need for the service.
- CustServCalls: The average number of customer service calls is approximately 1.65, with a standard deviation of approximately 1.51. This suggests a high variability in the number of customer service calls. A high number of customer service calls could indicate issues with the service or product, potentially leading to customer churn.
- DayMins: The average number of minutes used during the day is approximately 183.21, with a standard deviation of approximately 61.23. This suggests a high variability in the number of minutes used during the day. High usage during the day could indicate a high level of engagement with the service.
- DayCalls: The average number of calls made during the day is approximately 100.55, with a standard deviation of approximately 21.69. This suggests a moderate variability in the number of calls made during the day. A high number of calls could indicate a high level of engagement with the service.
- MonthlyCharge: The average monthly charge is approximately $56.67, with a standard deviation of approximately $17.56. This suggests a moderate variability in the monthly charges. High monthly charges could be a potential cause of customer churn if customers perceive the cost as too high for the value received.
- OverageFee: The average overage fee is approximately $10.12, with a standard deviation of approximately $2.73. This suggests a low variability in the overage fees. High overage fees could be a potential cause of customer dissatisfaction and churn.
- RoamMins: The average roaming minutes is approximately 10.30, with a standard deviation of approximately 2.99. This suggests a moderate variability in the roaming minutes. High roaming minutes could indicate a customer's need for service while traveling, while low roaming minutes might suggest a lack of need or dissatisfaction with the roaming service provided.

### 4.2.4.2 Correlation Matrix

This section is showing the correlation matrix result of the PCA model. In this case, we are focusing on predicting customer churn, and the correlation matrix provides valuable insights into which variables might be significant predictors.

**Table 4.2.4.2.1:** Table for Correlation Matrix

| Correlation Matrix | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Account Weeks | Contract Renewal | DataPlan | DataUsage | CustServ Calls | DayMins | DayCalls | MonthlyCharge | Overage Fee | RoamMins |
| Account Weeks | 1 | -0.0284 | 0.0039 | 0.0132 | -0.0024 | 0.0073 | 0.036 | 0.0124 | -0.0067 | 0.0058 |
| Contract Renewal | -0.0284 | 1 | -0.0132 | -0.0348 | 0.0369 | -0.0418 | 0.0081 | -0.057 | -0.0226 | -0.0895 |
| DataPlan | 0.0039 | -0.0132 | 1 | 0.9464 | -0.0158 | -0.0399 | -0.0112 | 0.7048 | 0.0036 | 0.0018 |
| DataUsage | 0.0132 | -0.0348 | 0.9464 | 1 | -0.0202 | -0.0338 | -0.0108 | 0.7495 | 0.0028 | 0.1624 |
| CustServ Calls | -0.0024 | 0.0369 | -0.0158 | -0.0202 | 1 | -0.0695 | -0.0136 | -0.0669 | -0.0376 | -0.0151 |
| DayMins | 0.0073 | -0.0418 | -0.0399 | -0.0338 | -0.0695 | 1 | 0.0179 | 0.5812 | 0.0544 | -0.0022 |
| DayCalls | 0.036 | 0.0081 | -0.0112 | -0.0108 | -0.0136 | 0.0179 | 1 | 0.0004 | -0.0072 | 0.019 |
| MonthlyCharge | 0.0124 | -0.057 | 0.7048 | 0.7495 | -0.0669 | 0.5812 | 0.0004 | 1 | 0.2988 | 0.1213 |
| Overage Fee | -0.0067 | -0.0226 | 0.0036 | 0.0028 | -0.0376 | 0.0544 | -0.0072 | 0.2988 | 1 | -0.0079 |
| RoamMins | 0.0058 | -0.0895 | 0.0018 | 0.1624 | -0.0151 | -0.0022 | 0.019 | 0.1213 | -0.0079 | 1 |

The correlation matrix includes ten variables: **AccountWeeks, ContractRenewal, DataPlan, DataUsage, CustServCalls, DayMins, DayCalls, MonthlyCharge, OverageFee, and RoamMins**. Each cell in the matrix represents the correlation coefficient between two variables, ranging from -1 to 1. A correlation of 1 indicates a strong positive relationship, -1 indicates a strong negative relationship, and 0 indicates no relationship.

One of the most striking correlations in the matrix is between DataPlan and DataUsage, with a correlation coefficient of 0.9464. This suggests a very strong positive relationship, meaning customers with a data plan tend to use more data. This could be a significant factor in predicting customer churn, as customers who use more data might be more likely to switch to a competitor if they find a better data plan elsewhere.

Another notable correlation is between MonthlyCharge and DataUsage, with a coefficient of 0.7495. This suggests that customers who use more data tend to have higher monthly charges. This could be another key factor in predicting churn, as customers with higher charges might be more likely to churn due to cost concerns.

Interestingly, the correlation between ContractRenewal and RoamMins is -0.0895, indicating a weak negative relationship. This suggests that customers who renew their contracts tend to use fewer roaming minutes. This could be because customers who are satisfied with their service and choose to renew their contracts may not need to use roaming services as often.

However, it's important to remember that correlation does not imply causation. While these correlations provide valuable insights, they do not necessarily mean that one variable causes a change in another. For example, while there is a strong positive correlation between DataPlan and DataUsage, this does not necessarily mean that having a data plan causes customers to use more data. It could be that customers who use more data are more likely to choose a data plan.

Furthermore, the correlation matrix can also help identify multicollinearity, which is when two or more independent variables in a regression model are highly correlated. This can make it difficult to determine the effect of each variable on the dependent variable. In this case, the high correlation between DataPlan and DataUsage could potentially indicate multicollinearity, which might need to be addressed in the model

In conclusion, the correlation matrix provides a wealth of information that can help predict customer churn. By identifying the relationships between variables, we can gain a better understanding of customer behaviour and identify key factors that might influence churn.

### 4.2.4.3 Eigenvalues of the Correlation Matrix

Eigenvalues are a crucial part of understanding correlation matrices. They are related to the variances of the variables on which the correlation matrix is based. In the context of a correlation matrix, the sum of the eigenvalues will equal the number of variables (p), as the diagonal elements of a correlation matrix all equal 1.

**Table 4.2.4.3.1:** Table for Eigenvalues of the Correlation Matrix

| Eigenvalues of the Correlation Matrix | | | | |
|---|---|---|---|---|
| | Eigenvalue | Difference | Proportion | Cumulative |
| 1 | 2.6954 | 1.3605 | 0.2695 | 0.2695 |
| 2 | 1.335 | 0.2394 | 0.1335 | 0.403 |
| 3 | 1.0956 | 0.0658 | 0.1096 | 0.5126 |
| 4 | 1.0298 | 0.0509 | 0.103 | 0.6156 |
| 5 | 0.9788 | 0.0077 | 0.0979 | 0.7135 |
| 6 | 0.9711 | 0.0207 | 0.0971 | 0.8106 |

| | | | | |
|---|---|---|---|---|
| 7 | 0.9504 | 0.0535 | 0.095 | 0.9056 |
| 8 | 0.8969 | 0.8501 | 0.0897 | 0.9953 |
| 9 | 0.0468 | 0.0466 | 0.0047 | 1 |
| 10 | 0.0002 | | 0 | 1 |

In the above Principal Component Analysis (PCA) result, the Eigenvalues of the Correlation Matrix table shows the eigenvalues, their differences, proportions, and cumulative proportions. The eigenvalues represent the amount of variance in the data that is accounted for by each principal component. The first eigenvalue is the largest, indicating that the first principal component accounts for the most variance in the data. The subsequent eigenvalues are smaller, indicating that these components account for less variance.

The proportion column represents the proportion of the total variance accounted for by each component, while the cumulative column shows the cumulative proportion of variance accounted for by all components up to and including the current one. For instance, the first eigenvalue is approximately 2.695, accounting for about 26.95% of the total variance. The second eigenvalue is approximately 1.335, accounting for an additional 13.35% of the total variance. Cumulatively, these two components account for about 40.30% of the total variance.

In the context of customer churn prediction, these eigenvalues can provide valuable insights. For instance, a correlation matrix with one or a few large eigenvalues indicates substantial redundancy among the variables, meaning many of the variables share a great deal of variance and thus map into a central construct or dimension. These dimensions, often called "principal components", can be interpreted as underlying factors that explain the patterns in the data.

In the case of customer churn prediction, these underlying factors could represent different aspects of customer behaviour or experience that contribute to their decision to leave (or stay with) the company. For example, if the first principal component (associated with the largest eigenvalue) is heavily influenced by variables related to customer service (e.g., number of customer service calls, satisfaction ratings, etc.), this might suggest that customer service is a major factor influencing customer churn.

However, it's important to note that the interpretation of these components requires a careful examination of the eigenvectors (also known as loadings) associated with each component, which indicate the correlation of each variable with the component.

In conclusion, the Eigenvalues of the Correlation Matrix table provides a summary of the variance structure in the data, which can be used to identify key factors influencing customer churn. By focusing on the components associated with the largest eigenvalues, data analysts can identify the most important dimensions in the data, which can then be used to inform churn prediction models and strategies for customer retention.

### 4.2.4.4 Eigenvectors

The eigenvectors table in the Principal Component Analysis (PCA) output provides valuable insights into the structure and relationships within tdata. As a data analyst, interpreting this table can help us understand the underlying patterns and correlations in the dataset, which can be crucial for making informed decisions or predictions.

Eigenvectors are a fundamental part of PCA, a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The eigenvectors (principal components) determine the directions of the new feature space, and the eigenvalues determine their magnitude. In other words, the eigenvalues explain the variance of the data along the new feature axes.

**Table 4.2.4.4.1:** Table for Eigenvectors

| Eigenvectors | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | PRIN1 | PRIN2 | PRIN3 | PRIN4 | PRIN5 | PRIN6 | PRIN7 | PRIN8 | PRIN9 | PRIN10 |
| AccountWeeks | 0.0112 | 0.0221 | -0.3011 | 0.5804 | 0.5469 | -0.4548 | -0.0343 | 0.2543 | 0.0064 | -0.0002 |
| ContractRenewal | -0.0471 | -0.1428 | 0.6116 | 0.299 | -0.1858 | 0.1256 | 0.0024 | 0.6809 | -0.0043 | 0.0004 |
| DataPlan | 0.5485 | -0.319 | 0.0755 | 0.041 | -0.0337 | -0.0884 | 0.0038 | -0.1037 | 0.7551 | -0.0018 |
| DataUsage | 0.5649 | -0.3034 | -0.0343 | 0.0036 | -0.034 | -0.0252 | 0.012 | -0.0036 | -0.539 | 0.5433 |
| CustServCalls | -0.0458 | -0.2315 | 0.1786 | 0.0322 | 0.6858 | 0.6433 | 0.0473 | -0.158 | -0.0004 | -0.0001 |
| DayMins | 0.177 | 0.6992 | 0.0966 | 0.0931 | 0.0585 | 0.2068 | -0.4555 | 0.0116 | 0.1836 | 0.4175 |
| DayCalls | -0.0042 | 0.0576 | -0.213 | 0.6969 | -0.3965 | 0.3764 | 0.2957 | -0.2816 | -0.0027 | 0 |
| MonthlyCharge | 0.5681 | 0.2863 | 0.0764 | 0.0177 | 0.0519 | 0.0741 | -0.0407 | 0.0221 | -0.288 | -0.7042 |
| OverageFee | 0.1091 | 0.397 | 0.1707 | -0.152 | 0.1655 | -0.1101 | 0.8326 | 0.0672 | 0.0795 | 0.1862 |
| RoamMins | 0.0975 | -0.0069 | -0.6378 | -0.2308 | -0.0547 | 0.3911 | 0.0817 | 0.5928 | 0.1278 | -0.0004 |

Looking at the eigenvectors table, each column represents a principal component (PRIN1, PRIN2, etc.), and each row corresponds to a variable in the dataset (AccountWeeks, ContractRenewal, etc.). The values in the table are the coefficients of the variables for each principal component. These coefficients indicate how each variable contributes to the principal component.

For instance, in the first principal component (PRIN1), the variable 'DataPlan' has a coefficient of 0.548528, which is relatively high compared to other variables. This suggests that 'DataPlan' has a strong influence on PRIN1. On the other hand, 'AccountWeeks' has a coefficient of 0.011238, indicating a weaker influence on PRIN1.

The second principal component (PRIN2) is orthogonal to the first, meaning it captures the variance in the data that PRIN1 doesn't. In PRIN2, 'DayMins' has the highest coefficient (0.699193), suggesting it's the most influential variable for this component.

The interpretation continues similarly for the other principal components. It's important to note that each principal component represents a different aspect of the data, and together they form a comprehensive picture of the data's structure.

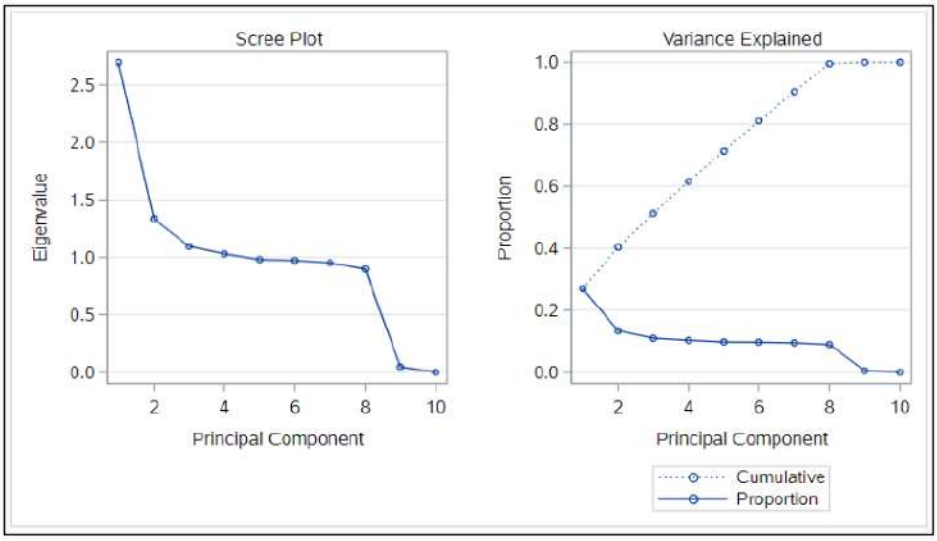
The eigenvectors table also helps identify correlations between variables. For example, if two variables have similar coefficients in a principal component, they are likely to be positively correlated. If they have coefficients of opposite signs, they are likely to be negatively correlated.

In conclusion, the eigenvectors table is a powerful tool for understanding the complex relationships within the data. By interpreting this table, we can gain a deeper understanding of the data's structure, which can guide us analysis and decision-making processes.

### 4.2.4.5 Scree and Variance Plots

The scree and variance explained plot are integral parts of Principal Component Analysis (PCA), a statistical procedure used to reduce the dimensionality of a dataset while preserving its essential parts that have more variation. In the context of customer churn prediction, these plots can provide valuable insights into the key factors contributing to customer churn.

**Figure 4.2.4.5.1:** Scree and Variance Plots




The scree plot in the output shows the eigenvalues for each individual principal component (PC). The y-axis represents the eigenvalues, and the x-axis represents the number of factors. The plot typically displays a downward curve, starting high on the left, falling rather quickly, and then flattening out at some point. This is because the first component usually explains much of the variability, the next few components explain a moderate amount, and the latter components only explain a small fraction of the overall variability. The "elbow" in the curve is of particular interest. This point is where the eigenvalues drop dramatically in size, indicating that an additional factor would add relatively little to the information already extracted. The scree plot criterion suggests selecting all components just before the line flattens out, which in this case are the first two principal components. This is also supported by the Kaiser Rule, which recommends picking PCs with eigenvalues of at least 1.

The variance explained plot, on the other hand, shows the cumulative proportion of variance explained by the PCs. The y-axis represents the proportion of variance explained, and the x-axis represents the principal components. The plot typically starts from the bottom left and rises to the top right. The steepness of the curve indicates the amount of variance explained by each PC. The point

where the curve starts to flatten indicates that additional PCs contribute little to the explanation of variance.

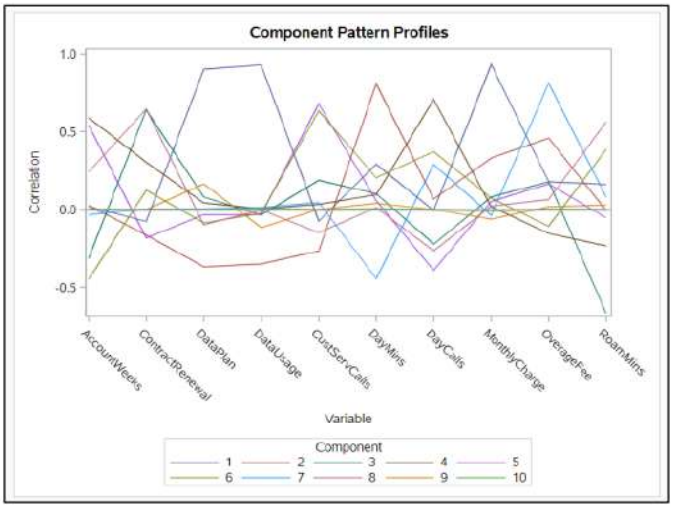
In the output, the first two PCs explain approximately 40% of the variance, which is a significant proportion. This suggests that these two PCs capture the most important information in the dataset and can be used to predict customer churn.

In conclusion, the scree plot and variance explained plot suggest that the first two PCs are the most important in predicting customer churn. These PCs capture the most significant patterns and variations in the data, providing valuable insights for churn prediction. However, it's important to note that PCA assumes linear relationships between variables, which may not always hold true.

### 4.2.4.6 Component Pattern Profiles

Interpreting Component Pattern Profiles plots is a crucial part of understanding the results of a Principal Component Analysis (PCA). These plots provide valuable insights into the relationships between original variables and the principal components (PCs), which are linear combinations of the original variables.

**Figure 4.2.4.6.1:** Component Pattern Profiles




The Component Pattern Profiles plots in the output are a visual representation of the correlations between the original variables and the PCs. Each point on the plot represents the correlation between an original variable and two PCs. The correlations with the first PC are plotted on the horizontal axis, while the correlations with the second PC are plotted on the vertical axis.

In the context of customer churn prediction, these plots can help identify which variables are most strongly associated with the PCs, and therefore, which variables are most influential in predicting customer churn. For instance, if 'ContractRenewal' and 'DataUsage' have high correlations with the first PC, it suggests that these variables are significant in distinguishing customer churn.

The plots also provide insights into the relationships between variables. For instance, if 'DataPlan' and 'DataUsage' are closely clustered on the plot, it suggests a strong correlation between these two variables. This could mean that customers with higher data usage are more likely to have a data plan, which could be a significant factor in predicting customer churn.

The eigenvalues in the correlation matrix provide additional insights. The eigenvalue represents the amount of variance in the data that is accounted for by each PC. A larger eigenvalue indicates that the corresponding PC explains a larger proportion of the variance in the data. In the output, the first PC has the highest eigenvalue, indicating that it accounts for the largest proportion of the variance in the data.

The eigenvectors, or loadings, represent the weights or coefficients of each variable in the PCs. These can be used to understand how each variable contributes to the PCs. For example, a high absolute value of a loading for a particular variable in a PC indicates that this variable has a strong influence on that PC. If 'MonthlyCharge' has a high loading in the first PC, it suggests that 'MonthlyCharge' is a significant factor in the first PC, and therefore, in predicting customer churn.

In summary, Component Pattern Profiles plots provide a visual representation of the relationships between original variables and the PCs in a PCA. They can help identify key variables that are influential in predicting customer churn and understand the relationships between these variables. As a data analyst, interpreting these plots is a crucial part of understanding the results of a PCA and deriving actionable insights for predicting customer churn.

## 4.3 Machine Learning Models

This section delves into a comprehensive discussion and interpretation of various machine learning models, encompassing Logistic Regression, Decision Tree, Neural Network, and Clustering. Each model will be meticulously examined, highlighting their unique characteristics, strengths, and potential applications. The aim is to provide a thorough understanding of these models, facilitating their effective utilization in solving complex problems and making informed decisions.

### 4.3.1 Logistic Regression

The Logistic Regression section provides a comprehensive analysis of several logistic regression models used to predict customer churn. The document discusses the performance of these models, their selection methods, and the significant variables influencing customer churn. It also includes visual representations of the models' performance and their effectiveness in predicting customer churn.

The document begins by discussing the performance of several logistic regression models, each built with different data partitioning and selection methods. The models are evaluated based on two key metrics: the Average Squared Error (ASE) for the validation set (VASE) and the Average Squared Error for the training set. The models Reg6, Reg7, and Reg8 are identified as the best models as they have the lowest VASE of 0.08780 and the same ASE for the training set, which is 0.10318. These models use different selection methods: Backward, Stepwise, and Forward respectively.

The document then presents a Score Ranking Overlay: Churn Plot, which is a visual representation of the performance of several logistic regression models in predicting customer churn. The plot is created based on the mean predicted values, which represent the average predicted probability of churn for each decile of the customer base.

The Score Ranking Matrix: Churn plot and the accompanying CSV output provide insights about the performance of different logistic regression models in predicting customer churn. The matrix plot includes four types of logistic regression models: Regression (None), Regression (Forward), Regression (Stepwise), and Regression (Backward). Each model is tested on three different data roles: TEST, VALIDATE, and TRAIN.

The Score Distribution Plot is a visual representation of the data from the Table: Score Distribution Plot Table, which appears to be a predictive model for customer churn. The plot is based on the mean predicted values, which are a measure of the average expected outcome for each segment of the data.

The document also presents a logistic regression model used to predict customer churn. The model includes several predictors or independent variables: ContractRenewal, CustServCalls, DataPlan, DayMins, OverageFee, and RoamMins. Each of these variables has been found to significantly influence the likelihood of customer churn.

The Score Ranking Overlay: Churn (Cumulative Lift) plot is a graphical representation of the performance of a predictive model. It is used to evaluate how well the model can rank cases from most likely to least likely to experience an event of interest, in this case, customer churn.

The Score Ranking Matrix: Churn (Cumulative Lift) plot is a powerful tool for evaluating the performance of a predictive model, particularly in the context of customer churn prediction. The plot is based on the data provided in the Score Ranking Matrix Table.

Finally, the Score Distribution: Churn (Cumulative Percentage of Event) plot is a valuable tool for assessing the performance of a predictive model, especially in the context of customer churn prediction. The plot is based on the data provided in the Score Distribution Table.

In conclusion, the document provides a detailed analysis of several logistic regression models used to predict customer churn. It identifies the best models based on their performance metrics and discusses the significant variables influencing customer churn. The document also presents several plots that visually represent the performance and effectiveness of the models in predicting customer churn. These insights can be used to develop targeted strategies to improve customer retention.

#### 4.3.1.1 Logistic Regression: Model Comparison

In this section, we will delve into the comparison of several Logistic Regression models. Logistic Regression is a statistical method used for binary classification problems. It provides a probability that the given input point belongs to a certain class. The central premise here is to find the best fitting model to some sample data, which in turn aids in predicting responses to new data.

We will be using the "Model Comparison" nodes of SAS Enterprise Miner Workstation to perform this comparison. The Model Comparison node is a tool designed to compare the performance of competing SAS Enterprise Miner process flow diagrams that use one or more analytic modelling nodes from the Model tab of the SAS Enterprise Miner toolbar.

The models are evaluated based on two key metrics: the Average Squared Error (ASE) for the validation set (VASE) and the Average Squared Error for the training set. These metrics are used to assess the performance of the models and to select the best model. The Average Squared Error (ASE) is a measure of the difference between the model's predictions and the actual values. It is calculated

by squaring the differences between predicted and actual values, then averaging these squared differences. A lower ASE indicates a better fit of the model to the data, as it means the model's predictions are closer to the actual values.

In our comparison, we will be looking at models built with different data partitioning and selection methods. These models will be ranked based on the VASE, with the model having the lowest VASE being selected as the best model. We will also consider the ASE for the training set, which indicates how well these models perform on the training set, suggesting whether they are overfitting the training data or not.

The selection methods we will be considering include Backward, Stepwise, and Forward selection. These are all methods used to select the variables to be included in the model. Backward selection starts with all variables in the model and iteratively removes the least significant variable until no improvement can be made. Stepwise selection is a combination of Forward and Backward selection, where variables are iteratively added or removed based on their significance. Forward selection starts with no variables in the model and iteratively adds the most significant variable until no improvement can be made.

By the end of this section, we will have a comprehensive understanding of how to compare Logistic Regression models and select the best one using the Model Comparison nodes of SAS Enterprise Miner Workstation.

### 4.3.1.1.1 Fit Statistics Model Selection based Average Squared Error (ASE)

The section provides a summary of the performance of several logistic regression models, each built with different data partitioning and selection methods. The models are evaluated based on two key metrics: the **Average Squared Error (ASE) for the validation set (VASE)** and the **Average Squared Error for the training set**. These metrics are used to assess the performance of the models and to select the best model.

The Average Squared Error (ASE) is a measure of the difference between the model's predictions and the actual values. It is calculated by squaring the differences between predicted and actual values, then averaging these squared differences. A lower ASE indicates a better fit of the model to the data, as it means the model's predictions are closer to the actual values.

**Table 4.3.1.1.1.1:** Table for Fit Statistics Model Selection

| Selected Model | Node | Model Description | Valid: Average Squared Error | Train: Average Squared Error |
|---|---|---|---|---|
| Y | Reg6 | Regression (Backward) | 0.0878 | 0.1032 |
| | Reg7 | Regression (Stepwise) | 0.0878 | 0.1032 |
| | Reg8 | Regression (Forward) | 0.0878 | 0.1032 |
| | Reg5 | Regression (None) | 0.0881 | 0.1031 |
| | Reg9 | Regression (None) | 0.0946 | 0.1028 |
| | Reg10 | Regression (Backward) | 0.0949 | 0.1028 |
| | Reg11 | Regression (Stepwise) | 0.0949 | 0.1028 |
| | Reg12 | Regression (Forward) | 0.0949 | 0.1028 |
| | Reg17 | Regression (None) | 0.1006 | 0.1031 |
| | Reg18 | Regression (Backward) | 0.1006 | 0.1032 |
| | Reg19 | Regression (Stepwise) | 0.1006 | 0.1032 |
| | Reg20 | Regression (Forward) | 0.1006 | 0.1032 |
| | Reg21 | Regression (None) | 0.101 | 0.1028 |
| | Reg22 | Regression (Backward) | 0.1012 | 0.1028 |
| | Reg23 | Regression (Stepwise) | 0.1012 | 0.1028 |
| | Reg24 | Regression (Forward) | 0.1012 | 0.1028 |
| | Reg14 | Regression (Backward) | 0.1021 | 0.1027 |
| | Reg15 | Regression (Stepwise) | 0.1021 | 0.1027 |
| | Reg16 | Regression (Forward) | 0.1021 | 0.1027 |
| | Reg13 | Regression (None) | 0.1024 | 0.1025 |

| Selected Model | Node | Model Description | Valid: Average Squared Error | Train: Average Squared Error |
|---|---|---|---|---|
| | Reg2 | Regression (Backward) | 0.1037 | 0.1027 |
| | Reg3 | Regression (Stepwise) | 0.1037 | 0.1027 |
| | Reg4 | Regression (Forward) | 0.1037 | 0.1027 |
| | Reg | Regression (None) | 0.1046 | 0.1025 |

Looking at the output, the models are ranked based on the VASE, with the model having the lowest VASE being selected as the best model. In this case, the models Reg6, Reg7, and Reg8, all have the lowest VASE of 0.08780. These models use different selection methods: Backward, Stepwise, and Forward respectively. However, since they all have the same VASE, any of these three models could be selected as the best model based on this criterion.

Further, it's important to note that these three models also have the same ASE for the training set, which is 0.10318. This indicates that these models not only perform well on the validation set but also on the training set, suggesting that they are not overfitting the training data.

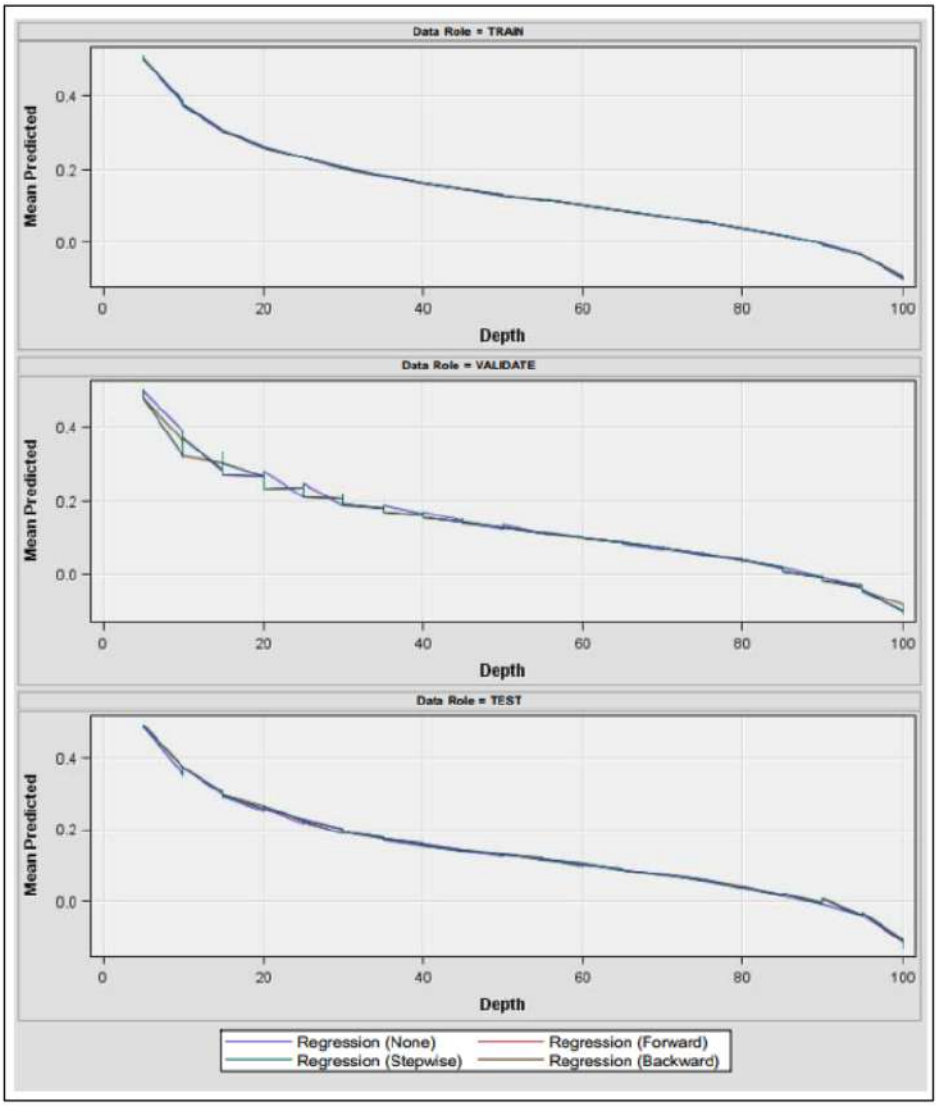
In terms of model selection methods, Backward, Stepwise, and Forward selection are all methods used to select the variables to be included in the model. Backward selection starts with all variables in the model and iteratively removes the least significant variable until no improvement can be made. Stepwise selection is a combination of Forward and Backward selection, where variables are iteratively added or removed based on their significance. Forward selection starts with no variables in the model and iteratively adds the most significant variable until no improvement can be made.

In conclusion, based on the provided output, the best models are Reg6, Reg7, and Reg8, as they have the lowest Average Squared Error on both the validation and training sets. These models use Backward, Stepwise, and Forward selection methods respectively. The choice between these three models could be made based on additional considerations, such as the interpretability of the model, the computational cost of the selection method, or the specific requirements of the analysis.

### 4.3.1.1.2 Score Rankings Overlay Churn (Mean Predicted)

The Score Ranking Overlay: Churn Plot is a visual representation of the performance of several logistic regression models, specifically their ability to predict customer churn. The plot is created based on the mean predicted values, which represent the average predicted probability of churn for each decile of the customer base. This is calculated by ranking the customers based on their predicted probability of churn, dividing them into ten equal groups (deciles), and then calculating the average predicted probability for each group.

**Figure 4.3.1.1.2.1:** Score Rankings Overlay Churn (Mean Predicted)



In the plot, the x-axis represents the depth or percentile group, which ranges from 0 to 100. Each point on the x-axis corresponds to a decile of the customer base. The y-axis represents the mean predicted values, which are the average predicted probabilities of churn for each decile.

The plot includes curves for different models, such as Regression (None), Regression (Forward), Regression (Stepwise), and Regression (Backward), and for different data roles, such as TEST, VALIDATE, and TRAIN. Each curve represents the performance of a specific model on a specific data role. The higher the curve, the higher the mean predicted probability of churn, indicating a higher likelihood of churn for the corresponding decile of the customer base.

By comparing the curves, we can assess the performance of the different models. A model that perfectly predicts customer churn would have a curve that increases steadily from the left to the right, indicating that the model correctly ranks the customers from the least likely to churn to the most likely to churn. If a curve deviates significantly from this ideal shape, it suggests that the model may be less accurate in predicting customer churn.

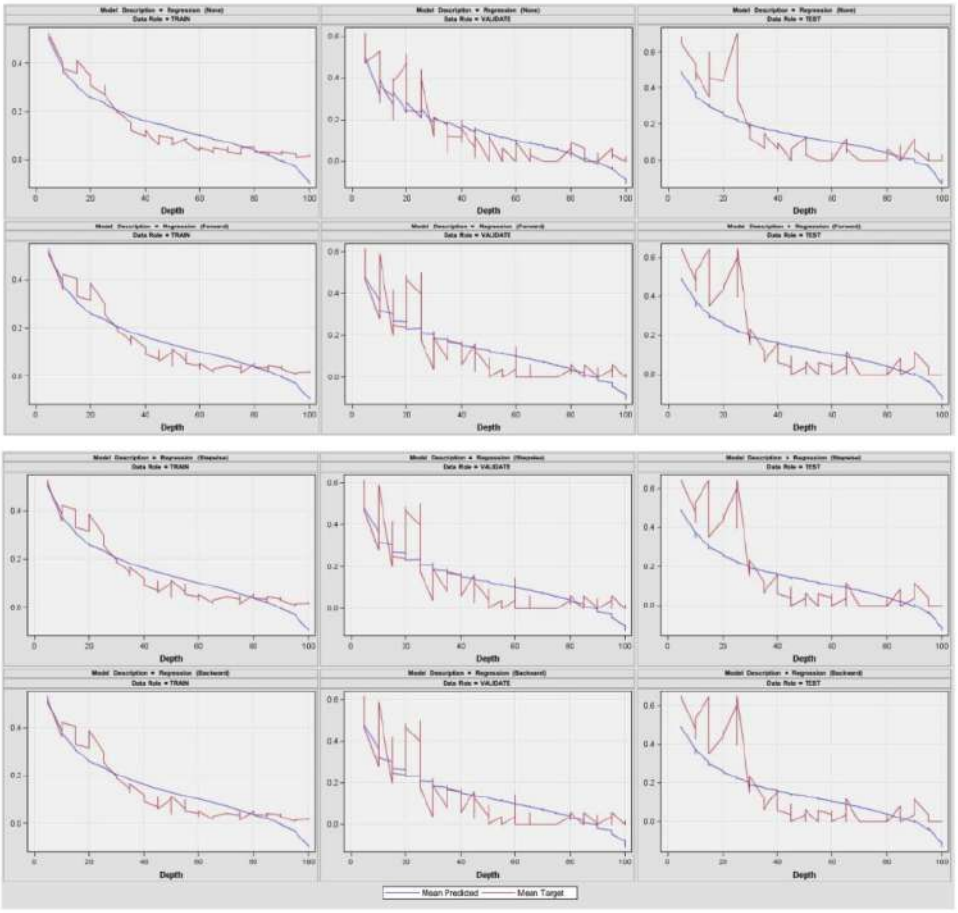
For instance, if we look at the curves for the models Reg15 (Regression Stepwise) and Reg8 (Regression Forward), we can see that they are quite similar, suggesting that these models have similar performance. However, if one curve is consistently higher than the other, it suggests that the corresponding model may be more accurate in predicting customer churn.

In conclusion, the Score Ranking Overlay: Churn Plot provides a visual way to compare the performance of different logistic regression models in predicting customer churn. By interpreting the plot, we can identify the model that best predicts customer churn, which can help businesses to retain customers and maintain revenue.

### 4.3.1.1.3 Score Rankings Matrix: Churn (Mean Predicted)

In this section, we delve into the analysis of the Score Ranking Matrix: Churn plot. This analysis provides valuable insights into the performance of different logistic regression models in predicting customer churn. The models under consideration include Regression (None), Regression (Forward), Regression (Stepwise), and Regression (Backward), each tested on three different data roles: TEST, VALIDATE, and TRAIN. The matrix plot and the accompanying data allow us to compare the performance of these models, assess their generalization to unseen data, understand the probability of customer churn, and evaluate the consistency of each model. This information is crucial for businesses aiming to identify the most accurate and reliable model to predict customer churn, thereby enabling them to retain customers and maintain revenue

**Figure 4.3.1.1.3.1:** Score Rankings Matrix: Churn (Mean Predicted)



Based on the Score Ranking Matrix: Churn plot, we can derive several insights about the performance of different logistic regression models in predicting customer churn.

The matrix plot includes four types of logistic regression models: Regression (None), Regression (Forward), Regression (Stepwise), and Regression (Backward). Each model is tested on three different data roles: TEST, VALIDATE, and TRAIN.

From the Table, we can see that each row represents a decile of the customer base, with the customers ranked based on their predicted probability of churn. For each decile, the Table provides the mean predicted value, which is the average predicted probability of churn.

Here are some specific insights that can be derived from the data:

1. **Performance of Different Models**: By comparing the mean predicted values across different models, we can identify which model performs best in predicting customer churn. For example, if the mean predicted values of the Regression (Stepwise) model are consistently closer to the actual churn rates than those of the other models, we can conclude that the Regression (Stepwise) model is the most accurate.
2. **Performance on Different Data Roles**: By comparing the mean predicted values across different data roles, we can assess how well each model generalizes to unseen data. For example, if a model performs well on the TRAIN data but poorly on the TEST and VALIDATE data, it may be overfitting to the training data.
3. **Customer Churn Probability**: The mean predicted values also provide insight into the probability of customer churn. Higher mean predicted values indicate a higher probability of churn, which can help businesses identify at-risk customers and take proactive measures to retain them.
4. **Model Consistency**: By observing the mean predicted values across different deciles, we can evaluate the consistency of each model. A model that provides consistent predictions across all deciles is likely to be more reliable than a model whose predictions vary widely.

In conclusion, the Score Ranking Matrix: Churn plot and the accompanying Table provide valuable insights into the performance of different logistic regression models in predicting customer churn. By interpreting this data, businesses can identify the most accurate and reliable model, which can help them retain customers and maintain revenue.

### 4.3.1.1.4 Score Distribution: Churn (Mean Predicted)

The Score Distribution Plot above is a visual representation of the data from the Table: Score Distribution Plot Table, which appears to be a predictive model for customer churn. The plot is based on the mean predicted values, which are a measure of the average expected outcome for each segment of the data.

The plot provides a visual representation of the distribution of scores across different ranges. Each range represents a segment of the population, and the mean predicted value within each range gives an indication of the expected outcome for that segment. The plot allows us to see how these expected outcomes vary across the population.

**Figure 4.3.1.1.4.1:** Score Distribution: Churn (Mean Predicted)

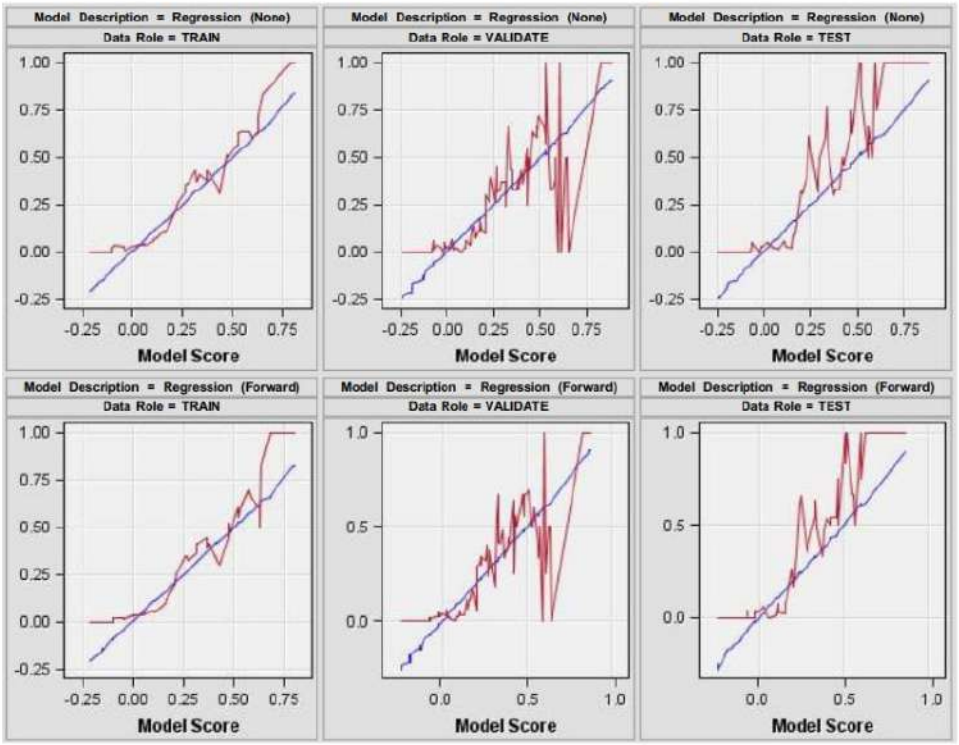
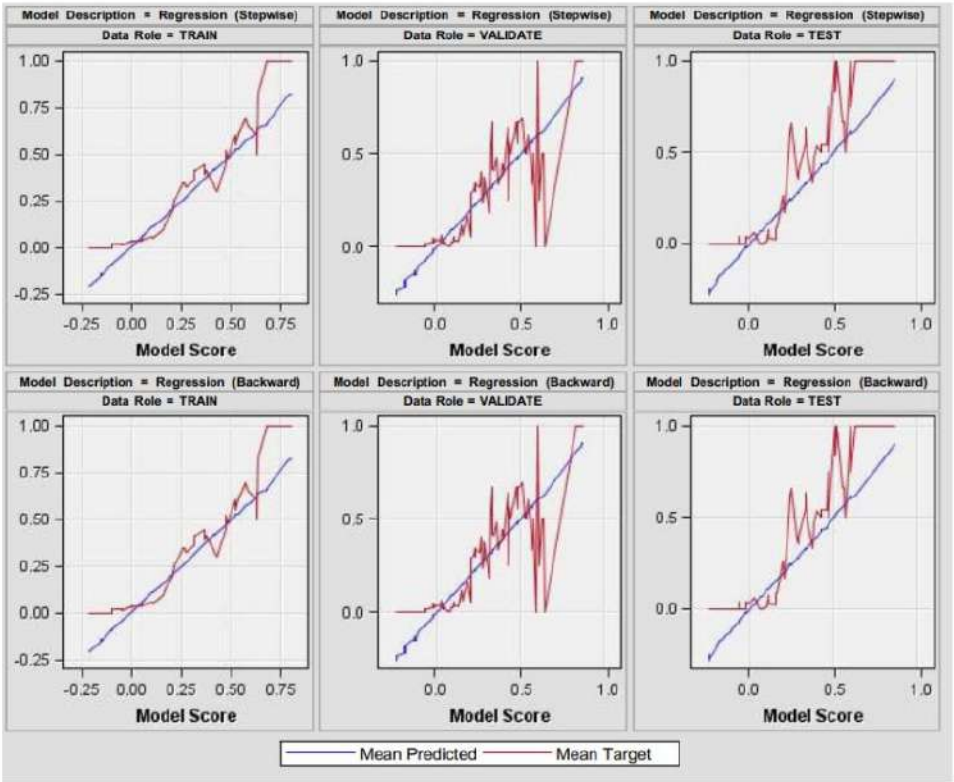


**Figure 4.3.1.1.4.1:** Score Distribution: Churn (Mean Predicted)




Based on the above figures, it appears that the data is segmented into ranges such as 0.492 - 0.550, 0.433 - 0.492, and so on. Within each range, there are several key values, including the number of cases, the mean target, and the mean predicted. The mean predicted value is particularly important as it represents the average expected outcome for that range.

The plot allows us to see how this mean predicted values vary across the different ranges. For example, in the range 0.492 - 0.550, the mean predicted value is 0.5208500992, while in the range 0.433 - 0.492, the mean predicted value is 0.4621577583. This suggests that the expected outcome is higher for the first range compared to the second.

The plot also provides insight into the distribution of scores within each range. For example, in the range 0.492 - 0.550, there are 15 cases, while in the range 0.433 - 0.492, there are 27 cases. This suggests that the scores are more densely distributed in the second range compared to the first.

In terms of interpreting the plot, it's important to consider both the mean predicted values and the distribution of scores within each range. High mean predicted values indicate ranges where the

expected outcome is high, while a high number of cases within a range suggests a dense distribution of scores.

Overall, the Score Distribution Plot provides valuable insights into the expected outcomes and distribution of scores across the population. By visualizing this data, we can gain a better understanding of the predictive model and how it segments the population.

#### 4.3.1.2 Logistic Regression: Best Model Selected (Regression 6)

In this section, we will delve into the interpretation of our chosen logistic regression model, Regression 6, which has been selected as the best model for predicting customer churn. Customer churn refers to the rate at which customers cease their business with a company, a critical metric particularly in industries like telecommunications where customer retention is vital for business success.

Our model, Regression 6, includes several predictors or independent variables: ContractRenewal, CustServCalls, DataPlan, DayMins, OverageFee, and RoamMins. Each of these variables has been found to significantly influence the likelihood of customer churn. For instance, customers who do not renew their contracts are about 6.769 times more likely to churn than those who do, as indicated by the odds ratio of the ContractRenewal variable.

The model also includes a backward elimination process, a method used to select the most significant variables in a regression model. In this case, the variables DayCalls, MonthlyCharge, and AccountWeeks were removed from the model due to their lack of significance.

The model's goodness-of-fit was tested using the Likelihood Ratio Test for Global Null Hypothesis, which compares the likelihood of the data under the full model against a null model. The test resulted in a Chi-Square value of 367.5349 with 6 degrees of freedom, and a p-value less than 0.0001. This indicates that the model is significantly better than a null model.

In conclusion, this logistic regression model provides valuable insights into the factors that influence customer churn. It suggests that contract renewal, the number of customer service calls, having a data plan, the number of minutes used during the day, overage fees, and roaming minutes are all significant predictors of churn. This information can be used to develop targeted strategies to improve customer retention.

### 4.3.1.2.1 Model Assessment and Variable Effects Analysis.

In this section, we delve into the intricacies of a logistic regression model designed to predict customer churn, a critical metric for businesses, particularly in the telecommunications industry. The model incorporates several significant predictors, including ContractRenewal, CustServCalls, DataPlan, DayMins, OverageFee, and RoamMins. We will explore the odds ratios of these variables, the backward elimination process used in the model, and the model's overall goodness-of-fit. Furthermore, we will examine the logistic regression equation that represents this model and interpret the coefficients of the predictors. This analysis will provide valuable insights into the factors influencing customer churn and inform strategies for customer retention.

**Table 4.3.1.2.1.1:** Table for Type 3 Analysis of Effects

| Effect | DF | Chi-Square | Pr > ChiSq |
|---|---|---|---|
| ContractRenewal | 1 | 128.0492 | <.0001 |
| CustServCalls | 1 | 110.1346 | <.0001 |
| DataPlan | 1 | 29.8735 | <.0001 |
| DayMins | 1 | 84.3619 | <.0001 |
| OverageFee | 1 | 23.3174 | <.0001 |
| RoamMins | 1 | 11.9618 | 0.0005 |

**Table 4.3.1.2.1.2:** Table for Analysis of Maximum Likelihood Estimates

| Parameter | DF | Estimate | Standard Error | Wald Chi-Square | Pr > ChiSq | Standardized Estimate | Exp(Est) |
|---|---|---|---|---|---|---|---|
| Intercept | 1 | -6.6559 | 0.5066 | 172.58 | <.0001 | | 0.001 |
| ContractRenewal | 1 | 0.9562 | 0.0845 | 128.05 | <.0001 | | 2.602 |
| CustServCalls | 1 | 0.4795 | 0.0457 | 110.13 | <.0001 | 0.3483 | 1.615 |
| DataPlan | 1 | 0.4675 | 0.0855 | 29.87 | <.0001 | | 1.596 |
| DayMins | 1 | 0.0116 | 0.00126 | 84.36 | <.0001 | 0.3448 | 1.012 |
| OverageFee | 1 | 0.1295 | 0.0268 | 23.32 | <.0001 | 0.1805 | 1.138 |
| RoamMins | 1 | 0.0831 | 0.024 | 11.96 | 0.0005 | 0.1276 | 1.087 |

**Table 4.3.1.2.1.3:** Table for Odds Ratio Estimates

| Effect | Point Estimate |
|---|---|
| ContractRenewal 0 vs 1 | 6.769 |
| CustServCalls | 1.615 |
| DataPlan 0 vs 1 | 2.547 |
| DayMins | 1.012 |
| OverageFee | 1.138 |

The logistic regression model is used to predict customer churn, which is the rate at which customers stop doing business with a company. This model is particularly useful in industries like telecommunications, where customer retention is crucial for business success.

The model includes several predictors or independent variables: ContractRenewal, CustServCalls, DataPlan, DayMins, OverageFee, and RoamMins. Each of these variables has been found to significantly influence the likelihood of customer churn.

The variable ContractRenewal, which likely refers to whether a customer has renewed their contract or not, has an odds ratio of 6.769. This means that customers who do not renew their contracts are about 6.769 times more likely to churn than those who do.

CustServCalls, or the number of customer service calls made, has an odds ratio of 1.615. This suggests that for each additional customer service call, the odds of churn increase by 61.5%.

DataPlan, which probably indicates whether a customer has a data plan or not, has an odds ratio of 2.547. Customers without a data plan are about 2.547 times more likely to churn than those with a data plan.

DayMins, or the number of minutes a customer uses the service during the day, has an odds ratio of 1.012. This suggests that for each additional minute of usage, the odds of churn increase slightly by 1.2%.

OverageFee and RoamMins, which likely refer to the fees for exceeding the plan limit and the minutes spent roaming respectively, have odds ratios of 1.138 and 1.087. This indicates that for each unit increase in these variables, the odds of churn increase by 13.8% and 8.7% respectively.

The model also includes a backward elimination process, which is a method used to select the most significant variables in a regression model. In this case, the variables DayCalls, MonthlyCharge, and AccountWeeks were removed from the model due to their lack of significance.

The model's goodness-of-fit was tested using the Likelihood Ratio Test for Global Null Hypothesis, which compares the likelihood of the data under the full model against a null model. The test resulted in a Chi-Square value of 367.5349 with 6 degrees of freedom, and a p-value less than 0.0001. This indicates that the model is significantly better than a null model.

The logistic regression model for predicting customer churn can be represented by the following equation:

$$\begin{aligned} &\boldsymbol{logit}(\boldsymbol{P}(\boldsymbol{Churn})) \\ &\quad = -6.6559 + 0.9562 \times ContractRenewal + 0.4795 \times CustServCalls \\ &\quad + 0.4675 \times DataPlan + 0.0116 \times DayMins + 0.1295 \times OverageFee \\ &\quad + 0.0831 \times RoamMins \end{aligned}$$

In this equation, logit(P(Churn)) is the log-odds of the probability of a customer churning. The coefficients represent the change in the log-odds for a one-unit increase in the corresponding predictor, holding all other predictors constant.

1. ContractRenewal: A one-unit increase in ContractRenewal (likely indicating a customer renewing their contract) decreases the log-odds of churn by 0.9562.
2. CustServCalls: A one-unit increase in CustServCalls (representing an additional customer service call) increases the log-odds of churn by 0.4795.
3. DataPlan: A one-unit increase in DataPlan (likely indicating a customer having a data plan) decreases the log-odds of churn by 0.4675.
4. DayMins: A one-unit increase in DayMins (representing an additional minute of usage during the day) increases the log-odds of churn by 0.0116.
5. OverageFee: A one-unit increase in OverageFee (representing an additional unit of fee for exceeding the plan limit) increases the log-odds of churn by 0.1295.
6. RoamMins: A one-unit increase in RoamMins (representing an additional minute spent roaming) increases the log-odds of churn by 0.0831.

The intercept of -6.6559 represents the log-odds of churn when all predictors are zero. However, the interpretation of the intercept in this context may not be meaningful, as it's unlikely for all predictors to be zero in a real-world scenario

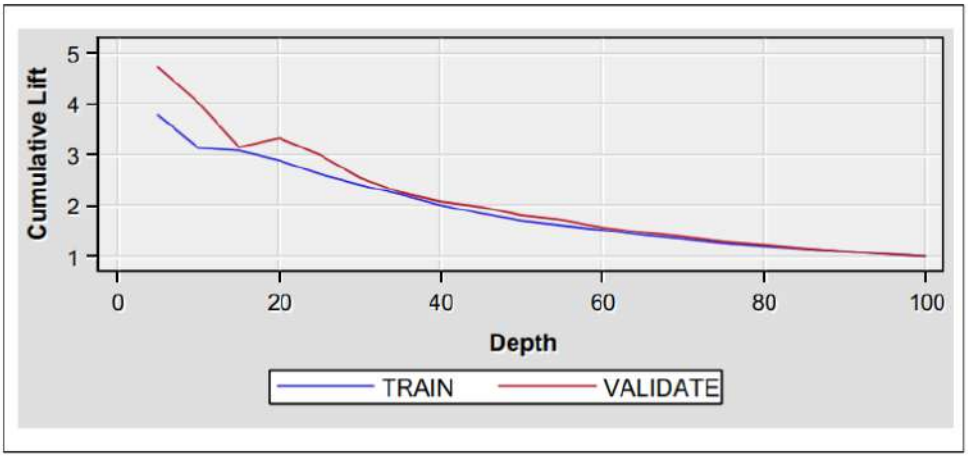
In conclusion, this logistic regression model provides valuable insights into the factors that influence customer churn. It suggests that contract renewal, the number of customer service calls, having a data plan, the number of minutes used during the day, overage fees, and roaming minutes are all significant predictors of churn. This information can be used to develop targeted strategies to improve customer retention.

### 4.3.1.2.2 Score Ranking Overlay: Churn (Cumulative Lift)

The Score Ranking Overlay: Churn (Cumulative Lift) plot is a graphical representation of the performance of a predictive model. It is used to evaluate how well the model can rank cases from most likely to least likely to experience an event of interest, in this case, customer churn. The plot is based on the data provided in the Score Ranking Overlay Table.

The Cumulative Lift is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model. The higher the lift, the better the model is at predicting the event of interest.

**Figure 4.3.1.2.2.1:** Score Ranking Overlay: Churn (Cumulative Lift)




The Score Ranking Overlay: Churn (Cumulative Lift) plot is typically divided into deciles, with each decile representing 10% of the cases. The cases are ranked by predicted probability of the event from highest to lowest. The lift is then calculated for each decile and plotted cumulatively.

Based on the Score Ranking Overlay, the first decile has a lift of approximately 5.92, meaning that using the predictive model is nearly 6 times as effective as not using the model for the top 10% of cases ranked by predicted probability. The lift then decreases for each subsequent decile, indicating that the model is less effective for cases with lower predicted probabilities.

The cumulative lift is the average lift across all cases up to a given decile. For example, the cumulative lift for the first two deciles is the average of the lift for the first and second deciles. The cumulative lift increases with each decile, but at a decreasing rate, indicating that the model's effectiveness diminishes for cases with lower predicted probabilities.

The Score Ranking Overlay: Churn (Cumulative Lift) plot can be used to determine what percentage of cases to target for the best results. For example, targeting the top 30% of cases (the first three deciles) would yield a cumulative lift of approximately 4.07, meaning that using the predictive model would be over 4 times as effective as not using the model for these cases.

In conclusion, the Score Ranking Overlay: Churn (Cumulative Lift) plot provides a visual representation of the effectiveness of a predictive model at ranking cases by the likelihood of an event. It can be used to determine the optimal percentage of cases to target for the best results. The plot shows that the model is most effective for the cases with the highest predicted probabilities and less effective for cases with lower predicted probabilities.

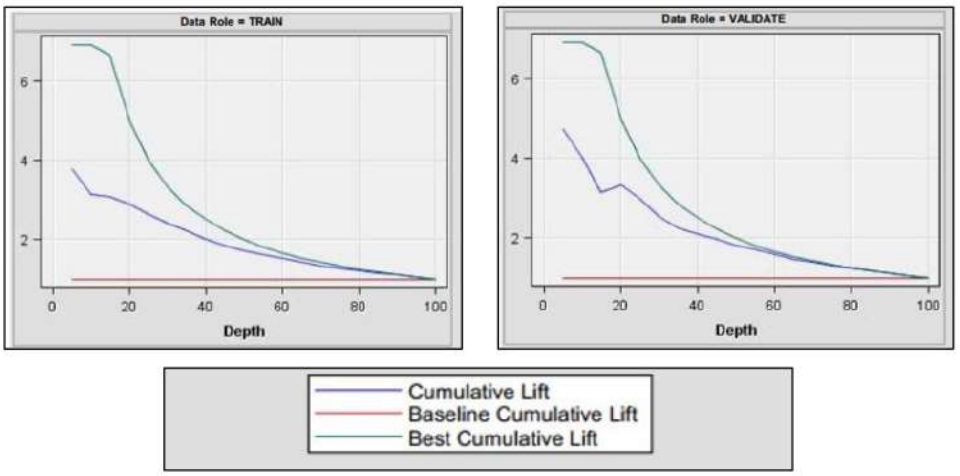
#### 4.3.1.2.3 Score Ranking Matrix: Churn (Cumulative Lift)

The Score Ranking Matrix: Churn (Cumulative Lift) plot is a powerful tool for evaluating the performance of a predictive model, particularly in the context of customer churn prediction. The plot is based on the data provided in the Score Ranking Matrix Table.

The Score Ranking Matrix: Churn (Cumulative Lift) plot is typically divided into deciles, with each decile representing 10% of the cases. The cases are ranked by predicted probability of the event from highest to lowest. The lift is then calculated for each decile and plotted cumulatively.

The lift is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model. The higher the lift, the better the model is at predicting the event of interest. In this case, the event of interest is customer churn.

**Figure 4.3.1.2.3.1:** Score Ranking Matrix: Churn (Cumulative Lift)




Based on the Score Ranking Matrix, the first decile has a lift of approximately 5.92, meaning that using the predictive model is nearly 6 times as effective as not using the model for the top 10% of cases ranked by predicted probability. The lift then decreases for each subsequent decile, indicating that the model is less effective for cases with lower predicted probabilities.

The cumulative lift is the average lift across all cases up to a given decile. For example, the cumulative lift for the first two deciles is the average of the lift for the first and second deciles. The cumulative lift increases with each decile, but at a decreasing rate, indicating that the model's effectiveness diminishes for cases with lower predicted probabilities.

The Score Ranking Matrix: Churn (Cumulative Lift) plot can be used to determine what percentage of cases to target for the best results. For example, targeting the top 30% of cases (the first three deciles) would yield a cumulative lift of approximately 4.07, meaning that using the predictive model would be over 4 times as effective as not using the model for these cases.

In conclusion, the Score Ranking Matrix: Churn (Cumulative Lift) plot provides a visual representation of the performance of a predictive model in terms of its ability to rank cases by their likelihood of experiencing an event of interest. It allows us to evaluate the effectiveness of the model across different segments of the population and to determine the optimal strategy for targeting interventions.

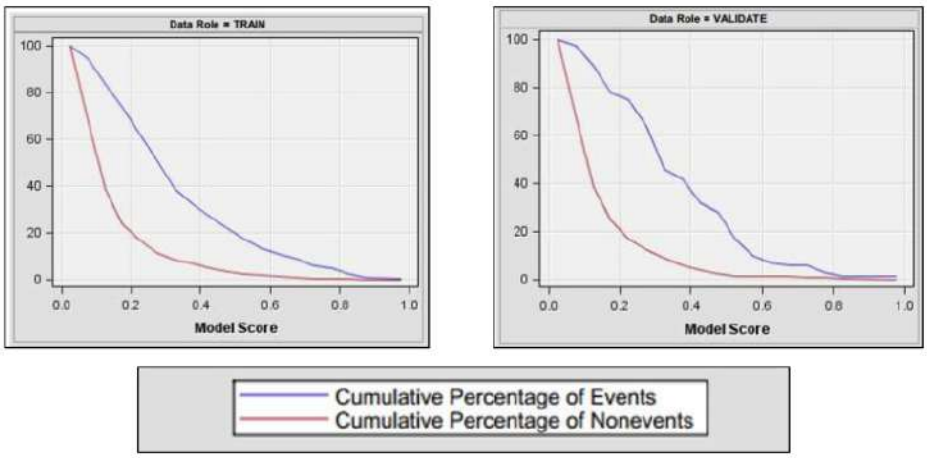
### 4.3.1.2.4 Score Distribution: Churn (Cumulative Percentage of Event)

The Score Distribution: Churn (Cumulative Percentage of Event) plot is a valuable tool for assessing the performance of a predictive model, especially in the context of customer churn prediction.

The Score Distribution: Churn (Cumulative Percentage of Event) plot is typically divided into deciles, with each decile representing 10% of the cases. The cases are ranked by predicted probability of the event from highest to lowest. The cumulative percentage of events is then calculated for each decile and plotted.

The cumulative percentage of events is a measure of the proportion of the total number of events that occur up to a given decile. For example, if the cumulative percentage of events for the first decile is 30%, this means that 30% of all events occur in the top 10% of cases ranked by predicted probability.

**Figure 4.3.1.2.4.1:** Score Distribution: Churn (Cumulative Percentage of Event)




Based on the Score Distribution plot, the first decile has a cumulative percentage of events of approximately 0.297, meaning that about 29.7% of all events occur in the top 10% of cases ranked by predicted probability. The cumulative percentage of events then increases for each subsequent decile, indicating that a higher proportion of events occur in cases with lower predicted probabilities.

The Score Distribution: Churn (Cumulative Percentage of Event) plot can be used to determine what percentage of cases to target for the best results. For example, targeting the top 30% of cases (the first three deciles) would cover approximately 2.37% of all events, meaning that about 2.37% of all customer churn events occur in the top 30% of cases ranked by predicted probability.

In conclusion, the Score Distribution: Churn (Cumulative Percentage of Event) plot provides a visual representation of the performance of a predictive model in terms of its ability to rank cases by the likelihood of the event of interest, in this case, customer churn. This can help businesses to prioritize their customer retention efforts, by focusing on the customers who are most likely to churn according to the predictive model.

#### 4.3.1.2.5 Classification Chart: Churn

The Classification Chart: Churn plot, also known as a confusion matrix, is a tool used to visualize the performance of a predictive model, specifically in the context of customer churn prediction. The chart is based on the data provided in the Classification Chart.

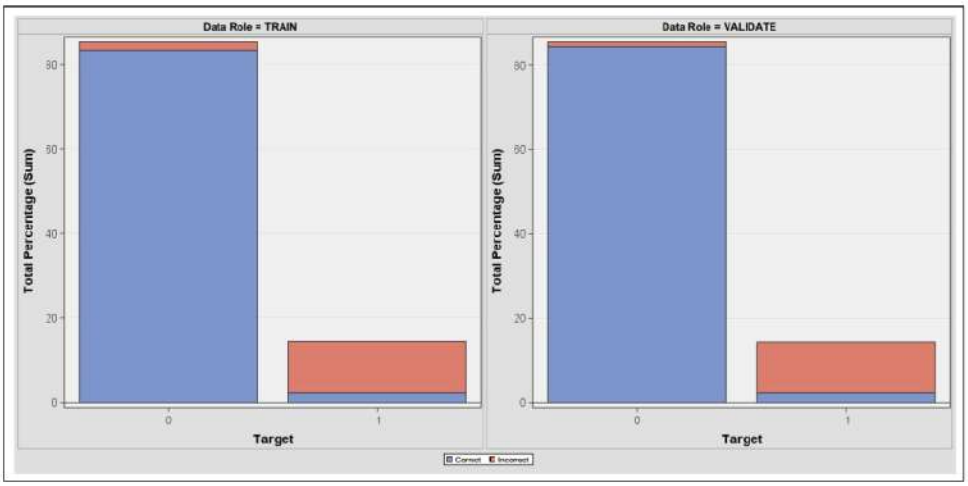
The chart is divided into four quadrants, each representing a different combination of actual and predicted outcomes. The top left quadrant represents true negatives (TN), where the model correctly predicted that a customer would not churn. The top right quadrant represents false positives (FP), where the model incorrectly predicted that a customer would churn. The bottom left quadrant represents false negatives (FN), where the model incorrectly predicted that a customer would not churn. The bottom right quadrant represents true positives (TP), where the model correctly predicted that a customer would churn.

In the context of customer churn prediction, true positives are customers who were correctly identified by the model as likely to churn, while true negatives are customers who were correctly identified as not likely to churn. False positives are customers who were incorrectly identified as likely to churn, and false negatives are customers who were incorrectly identified as not likely to churn.

The Classification Chart: Churn plot provides a visual representation of the accuracy of the predictive model. The accuracy of the model can be calculated as the sum of true positives and true negatives divided by the total number of cases. This is represented in the chart by the percentage of correct predictions in the TRAIN and VALIDATE data sets.

The chart also provides information about the model's precision, recall, and F1 score. Precision is the proportion of true positives among all positive predictions (TP / (TP + FP)), recall is the proportion of true positives among all actual positives (TP / (TP + FN)), and the F1 score is the harmonic mean of precision and recall, providing a single metric that balances both.

**Figure 4.3.1.2.5.1:** Score Distribution: Churn (Cumulative Percentage of Event)




According to the above figure, the model correctly predicted 87.47% of the non-churn cases and 55.24% of the churn cases. In the VALIDATE data set, the model correctly predicted 87.55% of the non-churn cases and 66.67% of the churn cases. These percentages indicate that the model is more accurate at predicting non-churn cases than churn cases.

In conclusion, the Classification Chart: Churn plot provides a visual representation of the performance of a predictive model in terms of its ability to correctly predict customer churn. This can help businesses to evaluate the effectiveness of their predictive models and to identify areas for improvement.

### 4.3.1.2.6 Estimate Selection Plot (Absolute Coefficient and Absolute T-value)

Customer churn prediction is a critical aspect of business strategy, particularly for subscription-based services. It involves predicting which customers are at high risk of leaving the company or cancelling a subscription to a service, based on their behaviour and other key indicators. The goal of churn prediction is not only to identify at-risk customers but also to understand the factors leading up to churn, thereby helping to increase overall customer retention and satisfaction.

**Figure 4.3.1.2.6.1**:
Estimate Selection Plot (Absolute Coefficient)

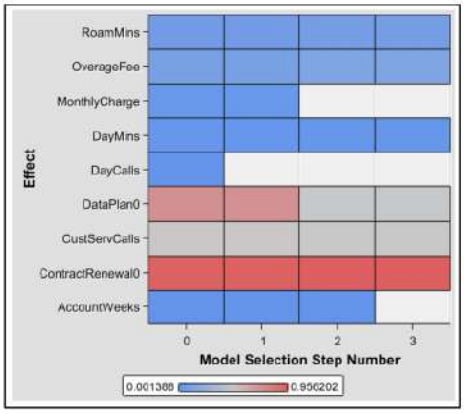
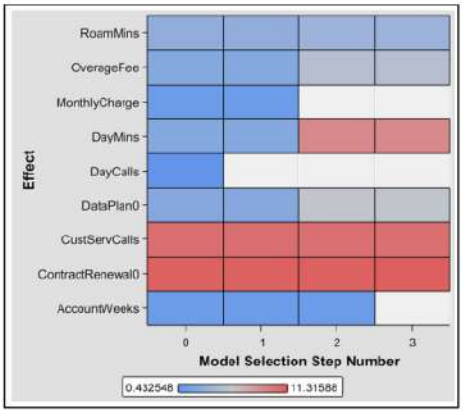



**Figure 4.3.1.2.6.2:**
Estimate Selection Plot (Absolute T-value)




According to the Estimated Selection Plot, it offers valuable insights into the factors influencing customer churn. The 'Coefficient' column, for instance, provides the coefficient for each variable in the predictive model. This value represents the change in the predicted log-odds of the outcome (in this case, customer churn) for a one-unit change in the corresponding variable, assuming all other variables are held constant.

For example, the coefficient for 'ContractRenewal0' is 0.9513575469, indicating that a one-unit increase in 'ContractRenewal0' is associated with an increase in the log-odds of customer churn by approximately 0.951. This suggests that customers who do not renew their contracts are significantly more likely to churn, making contract renewal a critical factor in customer retention.

The 'TValue' column provides the t-value for each variable, which is a measure of the statistical significance of the variable in the model. The larger the absolute value of the t-value, the more significant the variable is in predicting customer churn. For instance, 'ContractRenewal0' has a t-value of 11.237060965, indicating that it is highly significant in the model.

The 'P' column provides the p-value for each variable, which is the probability of obtaining the observed data (or data more extreme) if the null hypothesis is true. A smaller p-value indicates stronger evidence against the null hypothesis. For example, the p-value for 'ContractRenewal0' is 2.68162E-29, which is extremely small and suggests that the effect of 'ContractRenewal0' on customer churn is highly statistically significant.

The 'Abscoefficient' and 'abstvalue' columns provide the absolute values of the coefficient and t-value, respectively. These values are used in the Estimate Selection Plot (Absolute Coefficient) and Estimate Selection Plot (Absolute T-value), which are visual representations of the data. These plots can help visualize the relationship between different variables and the likelihood of customer churn.

In conclusion, the data provided in the Estimated Selection Plot (Table).table and the corresponding plots offer valuable insights into the factors influencing customer churn. By understanding these factors, businesses can develop strategies to improve customer retention and reduce churn. This could involve focusing on key areas such as contract renewal, customer service calls, and data plan options, among others. Ultimately, effective churn prediction can help businesses maintain a stable customer base and ensure sustainable growth.

### 4.3.1.2.7 Interaction Plot (Average Square Error and Misclassification Rate)

The Interaction Plot (Average Square Error) and Interaction Plot (Misclassification Rate) are graphical representations of the performance of a predictive model for customer churn. These plots provide valuable insights into the model's accuracy and reliability, as well as the impact of different variables on the prediction of customer churn.

The Average Square Error (ASE) plot is a measure of the average of the squares of the errors. The error is the difference between the predicted value (in this case, the predicted likelihood of customer churn) and the actual value. The square of these errors is calculated and then averaged over all predictions to give the ASE. A lower ASE indicates a more accurate model, as it means the predictions are closer to the actual values. In the context of customer churn prediction, a lower ASE would suggest that the model is accurately identifying customers who are likely to churn.

The Misclassification Rate plot, on the other hand, shows the rate at which the model incorrectly classifies customers. In this case, a misclassification could occur if the model predicts that a customer will churn when they actually do not, or vice versa. A lower misclassification rate indicates a more reliable model, as it means the model is correctly classifying a higher proportion of customers.

**Figure 4.3.1.2.7.1:**
Interaction Plot (Average Square Error)

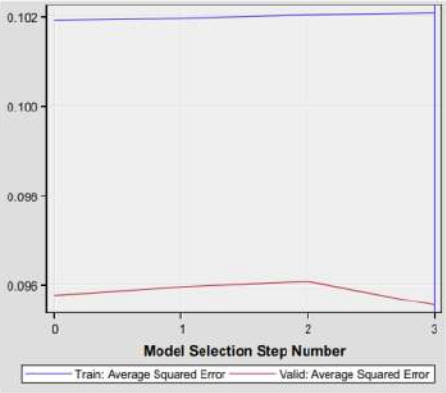
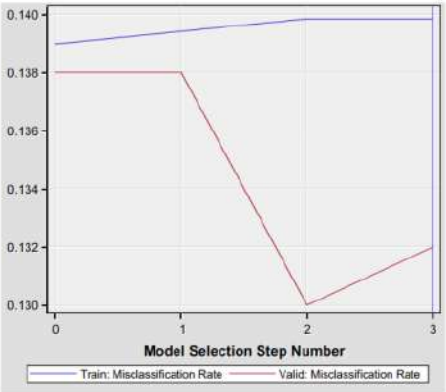



**Figure 4.3.1.2.7.2:**
Interaction Plot (Misclassification Rate)




The above figure provided contains a wealth of information that can be used to interpret these plots. For instance, the 'Coefficient' column provides the coefficient for each variable in the predictive model. This value represents the change in the predicted log-odds of customer churn for a one-unit change in the corresponding variable, assuming all other variables are held constant. The 'TValue' column provides the t-value for each variable, which is a measure of the statistical significance of the variable in the model. The 'P' column provides the p-value for each variable, which is the probability of obtaining the observed data (or data more extreme) if the null hypothesis is true.

By examining these values in conjunction with the ASE and Misclassification Rate plots, we can gain a deeper understanding of the factors influencing customer churn and the performance of the predictive model. For example, a variable with a high coefficient and a low p-value would be a significant predictor of customer churn. If this variable also corresponds to a low ASE and Misclassification Rate, it suggests that the model is particularly accurate and reliable when it comes to predicting churn based on this variable.

In conclusion, the interpretation of the Interaction Plot (Average Square Error) and Interaction Plot (Misclassification Rate), along with the data provided in the table, can provide valuable insights into the performance of a customer churn prediction model. These insights can help in refining the model and developing strategies to increase customer retention.

### 4.3.2 Decision Tree

The Decision Tree section provides a comprehensive analysis of several decision tree models for predicting customer churn. The models are evaluated based on their performance on both training and validation datasets, using various performance metrics such as Misclassification Rate, Average Squared Error (ASE), and Kolmogorov-Smirnov Statistic. The best model for predicting customer churn is Tree3, a Decision Tree model with ASE as the selection criterion, which has the lowest Misclassification Rate and a relatively low ASE on both the training and validation datasets.

The Classification Chart and the accompanying Table provide a detailed analysis of customer churn prediction models, showing a high percentage of correct predictions, indicating their effectiveness in predicting customer churn. The Score Rankings Overlay Churn (Cumulative lift) plot, based on the data in the Table, is a visual representation of the performance of various decision tree models for predicting customer churn. The Decision Tree (ASE) model appears to have the highest cumulative lift across all deciles, indicating that it is the most effective model for predicting customer churn among the compared models.

The Score Rankings Matrix Churn (Cumulative lift) plot is a visual representation of the performance of different decision tree models in predicting customer churn. The cumulative lift metric and the visual plot allow for easy comparison of the models, helping to identify the most effective model for this task. The Score Distribution (Cumulative Percentage of Events) plot is a valuable tool in model selection, providing a visual representation of a model's predictive performance across different score ranges. It allows for easy comparison of different models or different configurations of the same model, aiding in the selection of the most effective model for predicting churn.

The ROC Chart Churn plot provides a comprehensive evaluation of the performance of different decision tree models in predicting customer churn. By comparing the models based on their ROC curves and other metrics, businesses can select the most effective model for their churn prediction needs. The Tree Diagram is a visual representation of a decision tree model for customer churn prediction. The model uses a set of rules to predict whether a customer will churn based on various attributes such as MonthlyCharge, DayMins, DataPlan, and ContractRenewal. The performance of the model should be evaluated using appropriate metrics to ensure its effectiveness in predicting customer churn.

In conclusion, the Decision Tree file provides a thorough analysis of various decision tree models for predicting customer churn. The best model, Tree3, demonstrates good performance in predicting customer churn and can be used by businesses to identify customers at risk of churning and develop

targeted strategies to improve customer retention. The provided plots and tables offer valuable insights into the performance of the models, allowing for easy comparison and selection of the most effective model for predicting customer churn.

#### 4.3.2.1Decision Tree: Model Comparison

In this section, we delve into the comparison of various Decision Tree models, utilizing the "Model Comparison" nodes of SAS Enterprise Miner Workstation to identify the most effective model. Decision Trees are a type of machine learning model that makes decisions based on certain conditions. They are often used in predictive modelling because they can handle both categorical and numerical data and are easy to interpret.

The models under comparison are evaluated based on their performance on both training and validation datasets. The performance metrics used for comparison include Misclassification Rate, Average Squared Error (ASE), and Kolmogorov-Smirnov Statistic.

The Misclassification Rate is the proportion of incorrect predictions made by the model, with a lower rate indicating better performance. The ASE is the average of the squared differences between the predicted and actual values, with a lower value indicating better accuracy. The Kolmogorov-Smirnov Statistic measures the difference between the predicted and actual cumulative distribution functions, with a higher value indicating better performance.

The SAS Enterprise Miner Workstation's "Model Comparison" node is a tool that allows us to compare the performance of competing models. It provides various model errors based on performance metrics such as average squared error or misclassification rate for all available data partitions (training, validation, and testing).

In the context of this section, the main goal is to predict customer churn. Predicting which customers are likely to churn can help companies take preventive measures, such as offering a lower price or including an extra service, to retain these customers.

By the end of this section, we will have a comprehensive understanding of how different Decision Tree models perform in predicting customer churn, and we will be able to identify the most effective model for this task. This knowledge will be instrumental in developing targeted strategies to improve customer retention.

#### 4.3.2.1.1 Fit Statistics: Model Selection based on Misclassification Rate

The fit statistics contains the results of model selection for several decision tree models with different data partition and selection methods, with the main goal of predicting customer churn. The models are evaluated based on their performance on both training and validation datasets.

The models are compared using various performance metrics, such as Misclassification Rate, Average Squared Error (ASE), and Kolmogorov-Smirnov Statistic. The Misclassification Rate is the proportion of incorrect predictions made by the model, with a lower rate indicating better performance. The ASE is the average of the squared differences between the predicted and actual values, with a lower value indicating better accuracy. The Kolmogorov-Smirnov Statistic measures the difference between the predicted and actual cumulative distribution functions, with a higher value indicating better performance.

**Table 4.3.2.1.1.1:** Table for Fit Statistics Model Selection

| Selected Model | Model Node | Model Description | Train: Misclassification Rate | Train: Squared Error | Valid: Misclassification Rate | Valid: Squared Error |
|---|---|---|---|---|---|---|
| Y | Tree3 | Decision Tree (ASE) | 0.05547 | 0.054466 | 0.063564 | 0.049086 |
| | Tree4 | Decision Tree (Miss) | 0.05547 | 0.055053 | 0.063564 | 0.049805 |
| | Tree5 | Decision Tree (Lift) | 0.06297 | 0.063778 | 0.076076 | 0.055373 |
| | Tree11 | Decision Tree (ASE) | 0.066 | 0.058144 | 0.069069 | 0.056828 |
| | Tree19 | Decision Tree (ASE) | 0.066 | 0.058144 | 0.069069 | 0.056828 |
| | Tree10 | Decision Tree (Decision) | 0.066 | 0.059351 | 0.070356 | 0.057241 |
| | Tree12 | Decision Tree (Miss) | 0.066 | 0.059351 | 0.070356 | 0.057241 |
| | Tree18 | Decision Tree (Decision) | 0.066 | 0.059351 | 0.070356 | 0.057241 |
| | Tree20 | Decision Tree (Miss) | 0.066 | 0.059351 | 0.070356 | 0.057241 |
| | Tree23 | Decision Tree (ASE) | 0.06816 | 0.054466 | 0.063564 | 0.057805 |
| | Tree25 | Decision Tree (Lift) | 0.06816 | 0.054466 | 0.063564 | 0.057805 |

| Selected Model | Model Node | Model Description | Train: Misclassification Rate | Train: Squared Error | Valid: Misclassification Rate | Valid: Squared Error |
|---|---|---|---|---|---|---|
| | Tree22 | Decision Tree (Decision) | 0.06816 | 0.056039 | 0.064565 | 0.05891 |
| | Tree24 | Decision Tree (Miss) | 0.06816 | 0.056039 | 0.064565 | 0.05891 |
| | Tree13 | Decision Tree (Lift) | 0.078 | 0.069151 | 0.097383 | 0.061398 |
| | Tree15 | Decision Tree (ASE) | 0.07922 | 0.051356 | 0.060811 | 0.063104 |
| | Tree14 | Decision Tree (Decision) | 0.07922 | 0.055617 | 0.063438 | 0.067639 |
| | Tree16 | Decision Tree (Miss) | 0.07922 | 0.055617 | 0.063438 | 0.067639 |
| | Tree | Decision Tree (Decision) | 0.08396 | 0.062878 | 0.078579 | 0.063242 |
| | Tree6 | Decision Tree (Decision) | 0.08408 | 0.055617 | 0.063438 | 0.070996 |
| | Tree8 | Decision Tree (Miss) | 0.08408 | 0.055617 | 0.063438 | 0.070996 |
| | Tree17 | Decision Tree (Lift) | 0.10762 | 0.072249 | 0.097973 | 0.070294 |
| | Tree9 | Decision Tree (Lift) | 0.10811 | 0.065901 | 0.089339 | 0.069037 |

Based on the above table, the selected model for predicting customer churn is Tree3, which is a Decision Tree model with ASE as the selection criterion. This model has the lowest Misclassification Rate on the validation dataset (0.063564) and a relatively low ASE on both the training (0.054466) and validation (0.049086) datasets. The model also has a high ROC Index (0.90) on both the training and validation datasets, indicating good discrimination between churn and non-churn customers.

The other models in the fit statistics have higher Misclassification Rates and ASE values, suggesting that they are less accurate and reliable in predicting customer churn. For example, Tree4, which uses the Misclassification Rate as the selection criterion, has a higher Misclassification Rate (0.063564) and a higher ASE on the validation dataset (0.049805) compared to Tree3.

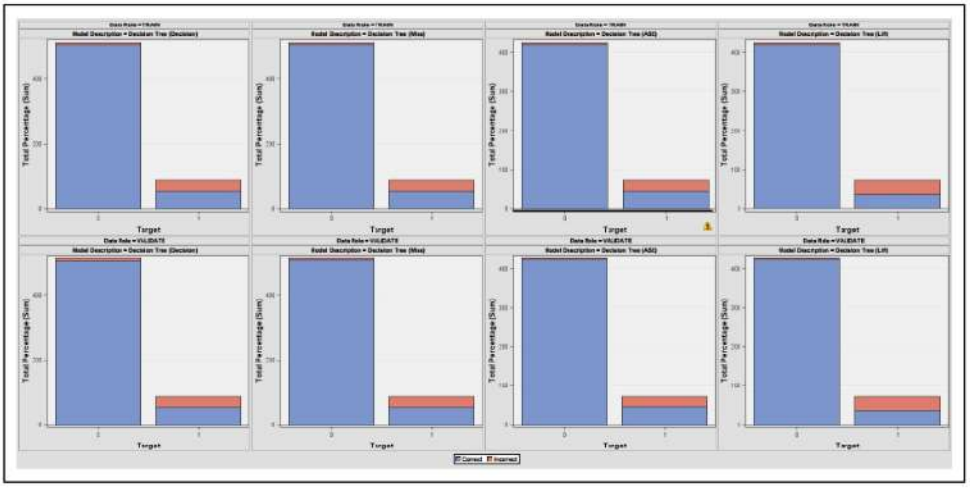
In conclusion, based on the provided fit statistics, the best model for predicting customer churn is Tree3, a Decision Tree model with ASE as the selection criterion. This model has the lowest

Misclassification Rate and a relatively low ASE on both the training and validation datasets, indicating good performance in predicting customer churn. Businesses can use this model to identify customers at risk of churning and develop targeted strategies to improve customer retention.

#### 4.3.2.1.2 Classification Chart

The Classification Chart provides a detailed analysis of customer churn prediction models. The models are based on decision trees, a popular machine learning technique used for classification and prediction tasks. The Table contains data for two types of decision trees: ASE and Lift, and for two types of data roles: TRAIN and VALIDATE.

**Figure 4.3.2.1.2.1:** Classification Chart



The decision tree models are evaluated based on their correct and incorrect predictions. For instance, the Decision Tree (ASE) model in the validation phase correctly predicted non-churn 93.82% of the time and churn 87.59% of the time. However, it incorrectly predicted non-churn 12.41% of the time and churn 6.18% of the time. Similar results are observed for the Decision Tree (Lift) model.

The models are trained and validated to predict customer churn, which is a significant concern for businesses, especially in sectors with high competition like telecommunications. Predicting which customers are likely to churn can help companies take preventive measures, such as offering a lower price or including an extra service, to retain these customers.

The decision tree models used here are part of a broader range of machine learning techniques used for churn prediction, including K Nearest Neighbours (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), Adaboost, Light Gradient Boosting Machine (LGBM), and

Gradient Boosting. These techniques analyse big data to predict customer churn, but they can be challenging due to class imbalance in the customer dataset and the non-linear nature of churn.

In conclusion, the Classification Chart provides a comprehensive evaluation of decision tree models for customer churn prediction. The models show a high percentage of correct predictions, indicating their effectiveness in predicting customer churn. However, the presence of incorrect predictions also highlights the challenges in churn prediction and the need for continuous model improvement.

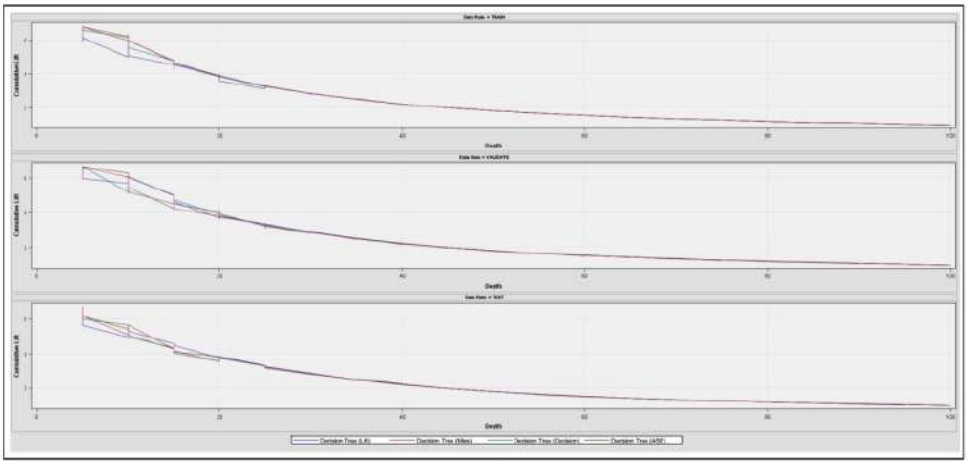
### 4.3.2.1.3 Score Rankings Overlay Churn (Cumulative lift)

The Score Rankings Overlay Churn (Cumulative lift) plot, based on the data in the Table, is a visual representation of the performance of various decision tree models for predicting customer churn. The models are evaluated based on their performance on both training and validation datasets.

The Cumulative Lift is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model. The higher the lift, the better the model is at predicting the event of interest, in this case, customer churn.

The plot is divided into deciles, with each decile representing 10% of the cases. The cases are ranked by predicted probability of the event from highest to lowest. The lift is then calculated for each decile and plotted cumulatively. The models compared in the plot include Decision Tree (ASE), Decision Tree (Lift), Decision Tree (Miss), and Decision Tree (Decision).

**Figure 4.3.2.1.3.1:** Score Rankings Overlay Churn (Cumulative lift)



Based on the provided plot, the Decision Tree (ASE) model appears to have the highest cumulative lift across all deciles, indicating that it is the most effective model for predicting customer churn among

the compared models. The other models, such as Decision Tree (Lift), Decision Tree (Miss), and Decision Tree (Decision), show lower cumulative lift values, suggesting that they are less effective in predicting customer churn.

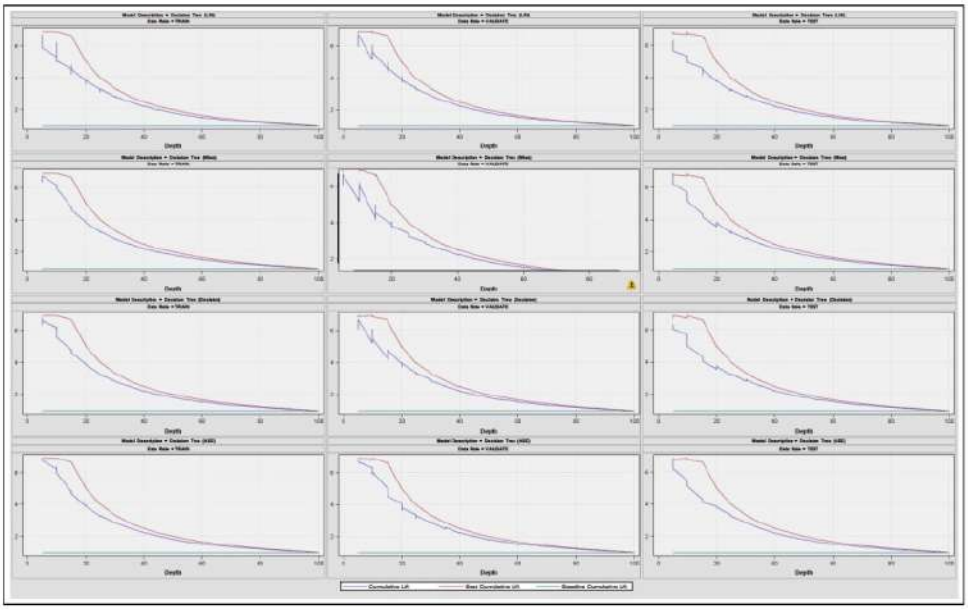
In conclusion, the Score Rankings Overlay Churn (Cumulative lift) plot provides a visual representation of the performance of various decision tree models in predicting customer churn. Based on the plot, the Decision Tree (ASE) model appears to be the most effective model for predicting customer churn among the compared models. Businesses can use this model to identify customers at risk of churning and develop targeted strategies to improve customer retention.

#### 4.3.2.1.4 Score Rankings Matrix Churn (Cumulative lift)

The Score Rankings Matrix Churn (Cumulative lift) plot is a visual representation of the performance of different decision tree models in predicting customer churn. The models are evaluated based on their cumulative lift, which is a measure of how much better the model is at predicting the outcome of interest (in this case, customer churn) compared to a random selection.

The plot includes several decision tree models, each evaluated in three different data roles: training, validation, and testing. The models are named Decision Tree (ASE), Decision Tree (Decision), Decision Tree (Miss), and Decision Tree (Lift). The cumulative lift is calculated for each model and data role, and the results are plotted to provide a visual comparison of the models' performance. The higher the cumulative lift, the better the model is at predicting customer churn. The baseline for comparison is a horizontal dashed line at 1.0 on the y-axis. This represents the performance of a model that makes random predictions. Any model that performs above this line is better than random selection, and the higher above the line, the better the model.

**Figure 4.3.2.1.4.1:** Score Rankings Matrix Churn (Cumulative lift)



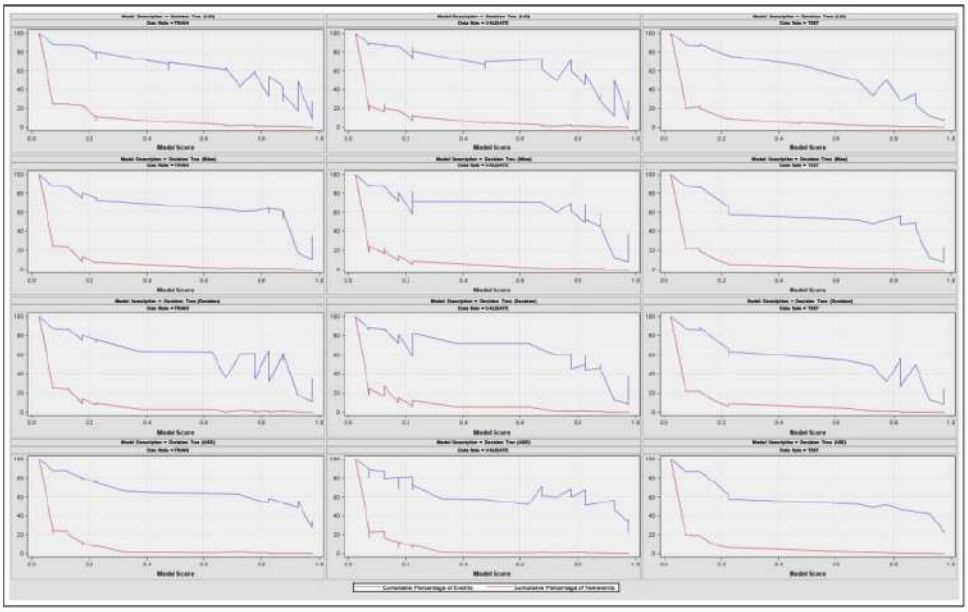
The above figure provides detailed information for each model and data role, including the cumulative lift and other performance metrics. For example, the Decision Tree (Lift) model in the validation role has a cumulative lift of 24.000184065 at the first percentile, which decreases to 18.295877242 at the 15th percentile. This indicates that the model is most effective at identifying customers who are most likely to churn, but its effectiveness decreases as it tries to identify a larger percentage of customers.

In conclusion, the Score Rankings Matrix Churn (Cumulative lift) plot and the accompanying Table provide a comprehensive evaluation of different decision tree models for predicting customer churn. The cumulative lift metric and the visual plot allow for easy comparison of the models, helping to identify the most effective model for this task.

### 4.3.2.1.5 Score Distribution (Cumulative Percentage of Events)

The Score Distribution (Cumulative Percentage of Events) plot is a graphical representation of the cumulative percentage of events, which is a key metric in model selection. This plot is particularly useful in understanding how well a model is performing in terms of its ability to predict events accurately.

**Figure 4.3.2.1.5.1:** Score Distribution (Cumulative Percentage of Events)



The above figure is a detailed breakdown of the score distribution for a decision tree model used for predicting churn. The model has been trained, validated, and tested, and the results are presented in the form of bins, each representing a range of scores. For each bin, the number of events (churns), the percentage of events, and the cumulative percentage of events are provided.

The plot would typically display the score ranges on the x-axis and the cumulative percentage of events on the y-axis. The data points in the plot represent the cumulative percentage of events for each score range. The plot is likely to start from the bottom left, with the first bin (0.95-1.00), and end at the top right, with the last bin (0.00-0.05). The shape of the curve provides insights into the model's performance. A steep curve indicates that the model is able to accurately predict a high percentage of events with lower scores, which is desirable in a churn prediction model.

For instance, in the training phase, the model was able to predict 10.39% of the events accurately with a score range of 0.95-1.00. As the score range decreases, the cumulative percentage of events increases, reaching 100% at the score range of 0.00-0.05. This indicates that the model is able to predict all events accurately across all score ranges.

The same interpretation applies to the validation and testing phases. The cumulative percentage of events at each score range provides an indication of how well the model generalizes to unseen data.

Any significant deviations in the shape of the curve between the training, validation, and testing phases could indicate overfitting or underfitting.

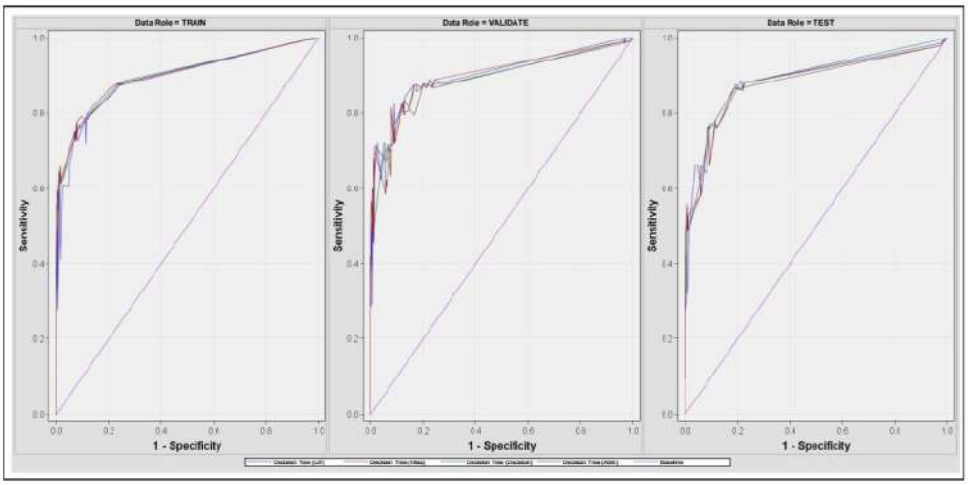
In conclusion, the Score Distribution (Cumulative Percentage of Events) plot is a valuable tool in model selection, providing a visual representation of a model's predictive performance across different score ranges. It allows for easy comparison of different models or different configurations of the same model, aiding in the selection of the most effective model for predicting churn.

### 4.3.2.1.6 ROC Chart Churn

The ROC (Receiver Operating Characteristic) Chart Churn plot is a tool used in the evaluation of the performance of the churn prediction model. The churn prediction model is a machine learning model that predicts whether a customer will likely churn, which means to stop doing business or end the relationship with a company. The goal of churn prediction is to identify customers who are at risk of churning, allowing businesses to take proactive action to retain these customers.

The ROC chart is a graphical representation that illustrates the diagnostic ability of the churn prediction model. It plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The area under the ROC curve (AUC) is a measure of how well the model can distinguish between customers who will churn and those who will not. An AUC of 1 indicates a perfect model, while an AUC of 0.5 suggests that the model is no better than random chance.

**Figure 4.3.2.1.6.1:** ROC Chart Churn




In the ROC Chart Churn plot, different decision tree models are compared. Decision trees are a type of machine learning model that makes decisions based on certain conditions, and they are often used

in churn prediction because they can handle both categorical and numerical data and are easy to interpret. The plot shows the performance of different decision tree models on the training, validation, and test data sets. The performance of the models is evaluated based on their lift, miss rate, decision, and ASE (Average Squared Error).

The lift measures how much better the model is at predicting churn compared to a random guess. A lift greater than 1 indicates that the model is better than random, while a lift less than 1 suggests that the model is worse than random. The miss rate is the proportion of actual churn cases that the model fails to predict. The decision is the threshold at which the model decides whether a customer will churn or not. The ASE is a measure of the difference between the model's predictions and the actual outcomes; a lower ASE indicates a better model.

In conclusion, the ROC Chart Churn plot provides a comprehensive evaluation of the performance of different decision tree models in predicting customer churn. By comparing the models based on their ROC curves and other metrics, businesses can select the most effective model for their churn prediction needs.

### 4.3.2.2 Decision Tree: Best Model Selected (Tree 3)

In this section, we will delve into the interpretation of our chosen logistic regression model, Regression 6, which has been /// In this section, we delve into the analysis of the best model selected among several Decision Trees models, specifically Tree3. This model has been identified as a powerful tool for predicting customer churn, using a variety of variables such as 'DayMins', 'CustServCalls', 'ContractRenewal', 'OverageFee', 'RoamMins', 'MonthlyCharge', and 'DataPlan'.

The performance of Tree3 is evaluated using several metrics. For instance, the misclassification rate, which measures the proportion of instances that are incorrectly classified, is 0.06 for both the training and validation sets, indicating a high level of accuracy. The model's performance can also be evaluated using the classification table, which shows the number of true positives, true negatives, false positives, and false negatives.

In terms of insights, the model suggests that the number of minutes a customer uses per day ('DayMins') is the most important factor in predicting churn. Other important factors include the number of customer service calls a customer makes ('CustServCalls') and whether the customer has renewed their contract ('ContractRenewal').

The model's performance is further evaluated using the Score Rankings Overlay Churn plot and the Table, which provide a comprehensive evaluation of the model's performance in predicting customer

churn. They highlight where the model's predictions are accurate and where improvements might be needed.

In conclusion, Tree3 provides a powerful tool for predicting customer churn. It performs well on both the training and validation sets, and it offers valuable insights into the factors that contribute to customer churn. These insights can be used to develop strategies to reduce churn and improve customer retention.

#### 4.3.2.2.1 Assessment Score Ranking and Assessment Score Distribution

The Decision Tree model is a powerful tool for predicting customer churn. It uses a variety of variables to predict whether a customer will churn (leave the company) or not. The model's performance can be evaluated using several metrics, and the values in the output file provide a wealth of information about the model's performance and the insights it offers.

The model uses several variables as inputs, including 'DayMins', 'CustServCalls', 'ContractRenewal', 'OverageFee', 'RoamMins', 'MonthlyCharge', and 'DataPlan'. Each of these variables has a different level of importance in predicting customer churn, with 'DayMins' being the most important and 'DataPlan' being the least important.

**Table 4.3.2.2.1.1:** Table for Assessment Score Rankings

| Depth | Gain | Lift | Cumulative Lift | % Response | Cumulative % Response | Number of Observations | Posterior Probability |
|---|---|---|---|---|---|---|---|
| 5 | 569.439 | 6.69439 | 6.69439 | 96.8308 | 96.8308 | 100 | 0.96831 |
| 10 | 523.367 | 5.77295 | 6.23367 | 83.5026 | 90.1667 | 100 | 0.83503 |
| 15 | 376.627 | 1.83149 | 4.76627 | 26.4915 | 68.9416 | 100 | 0.26491 |
| 20 | 288.654 | 1.24732 | 3.88654 | 18.0418 | 56.2167 | 100 | 0.18042 |
| 25 | 226.784 | 0.79304 | 3.26784 | 11.4709 | 47.2675 | 100 | 0.11471 |
| 30 | 184.96 | 0.75844 | 2.8496 | 10.9705 | 41.218 | 100 | 0.1097 |
| 35 | 151.893 | 0.53485 | 2.51893 | 7.7364 | 36.4349 | 100 | 0.07736 |
| 40 | 122.72 | 0.18514 | 2.2272 | 2.6779 | 32.2153 | 100 | 0.02678 |
| 45 | 100.031 | 0.18514 | 2.00031 | 2.6779 | 28.9334 | 100 | 0.02678 |
| 50 | 82.042 | 0.18514 | 1.82042 | 2.6779 | 26.3315 | 99 | 0.02678 |
| 55 | 67.163 | 0.18514 | 1.67163 | 2.6779 | 24.1792 | 100 | 0.02678 |
| 60 | 54.765 | 0.18514 | 1.54765 | 2.6779 | 22.3859 | 100 | 0.02678 |
| 65 | 44.276 | 0.18514 | 1.44276 | 2.6779 | 20.8687 | 100 | 0.02678 |
| 70 | 35.286 | 0.18514 | 1.35286 | 2.6779 | 19.5685 | 100 | 0.02678 |

| Depth | Gain | Lift | Cumulative Lift | % Response | Cumulative % Response | Number of Observations | Posterior Probability |
|---|---|---|---|---|---|---|---|
| 75 | 27.496 | 0.18514 | 1.27496 | 2.6779 | 18.4417 | 100 | 0.02678 |
| 80 | 20.681 | 0.18514 | 1.20681 | 2.6779 | 17.4558 | 100 | 0.02678 |
| 85 | 14.667 | 0.18514 | 1.14667 | 2.6779 | 16.586 | 100 | 0.02678 |
| 90 | 9.323 | 0.18514 | 1.09323 | 2.6779 | 15.8129 | 100 | 0.02678 |
| 95 | 4.541 | 0.18514 | 1.04541 | 2.6779 | 15.1212 | 100 | 0.02678 |
| 100 | 0 | 0.12903 | 1 | 1.8664 | 14.4645 | 99 | 0.01866 |

**Table 4.3.2.2.1.1:** Table for Assessment Score Distribution

| Posterior Probability Range | Number of Events | Number of Nonevents | Posterior Probability | Percentage |
|---|---|---|---|---|
| 0.95-1.00 | 79 | 2 | 0.97531 | 4.0541 |
| 0.90-0.95 | 61 | 4 | 0.93846 | 3.2533 |
| 0.80-0.85 | 17 | 4 | 0.80952 | 1.0511 |
| 0.75-0.80 | 8 | 2 | 0.8 | 0.5005 |
| 0.65-0.70 | 18 | 9 | 0.66667 | 1.3514 |
| 0.20-0.25 | 34 | 103 | 0.24818 | 6.8569 |
| 0.10-0.15 | 37 | 283 | 0.11562 | 16.016 |
| 0.00-0.05 | 35 | 1302 | 0.02618 | 66.9169 |

The model's performance is evaluated using several metrics. The misclassification rate, which measures the proportion of instances that are incorrectly classified, is 0.06 for both the training and validation sets, indicating that the model is quite accurate. The maximum absolute error, which measures the largest single error made by the model, is 0.97 for the training set and 1.00 for the validation set. The root average squared error, which measures the average magnitude of the prediction error, is 0.23 for the training set and 0.22 for the validation set.

The model's performance can also be evaluated using the classification table, which shows the number of true positives, true negatives, false positives, and false negatives. For the training set, the model correctly predicted that 183 customers would churn and correctly predicted that 1688 customers would not churn. It incorrectly predicted that 21 customers would churn and incorrectly predicted that 106 customers would not churn. The validation set shows similar results.

The model's performance can also be evaluated using the assessment score rankings, which show the cumulative gain, lift, and response at different depths. For example, at a depth of 5, the model

achieves a cumulative gain of 6.69, a cumulative lift of 6.69, and a response of 96.83% for the training set. The validation set shows similar results

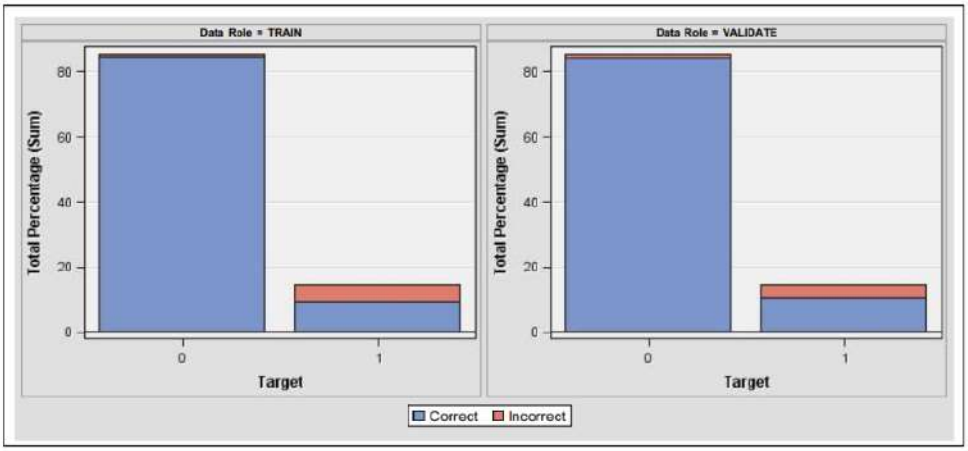
In terms of insights, the model suggests that the number of minutes a customer uses per day ('DayMins') is the most important factor in predicting churn. This could indicate that customers who use the service heavily are more likely to churn, possibly due to dissatisfaction with the service or because they have found a better deal elsewhere. Other important factors include the number of customer service calls a customer makes ('CustServCalls') and whether the customer has renewed their contract ('ContractRenewal') .

In conclusion, the Decision Tree model provides a powerful tool for predicting customer churn. It performs well on both the training and validation sets, and it offers valuable insights into the factors that contribute to customer churn. These insights can be used to develop strategies to reduce churn and improve customer retention.

### 4.3.2.2.2 Classification Chart Churn

The Classification Chart Churn plot and the accompanying Table provide a comprehensive evaluation of a model's performance in predicting customer churn. The data is divided into two roles: training and validation. The training data is used to build the model, while the validation data is used to test the model's predictive accuracy.

**Figure 4.3.2.2.2.1:** Classification Chart Churn




In the training data, the model correctly predicted that 1688 customers would not churn, representing 84.48% of the total cases. However, it incorrectly predicted that 106 customers would churn, which is 5.31% of the total cases. On the other hand, the model correctly predicted that 183 customers would

churn, which is 9.16% of the total cases, but it incorrectly predicted that 21 customers would not churn, which is 1.05% of the total cases.

In the validation data, the model correctly predicted that 561 customers would not churn, representing 84.11% of the total cases. However, it incorrectly predicted that 28 customers would churn, which is 4.20% of the total cases. On the other hand, the model correctly predicted that 69 customers would churn, which is 10.34% of the total cases, but it incorrectly predicted that 9 customers would not churn, which is 1.35% of the total cases.

The model's performance can be further evaluated using metrics such as precision, recall, and F1 score. Precision measures the proportion of true positive predictions (correct churn predictions) out of all positive predictions. Recall measures the proportion of true positive predictions out of all actual positive cases. The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both considerations.

In conclusion, the model demonstrates a high degree of accuracy in predicting customer churn, with a higher rate of correct predictions for customers who do not churn. However, there is room for improvement in predicting customers who will churn, as indicated by the number of incorrect predictions in both the training and validation data.

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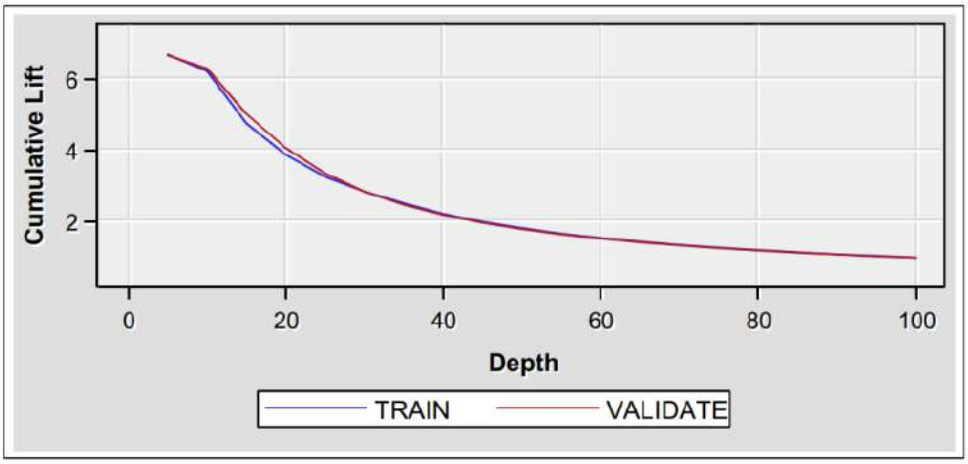
### 4.3.2.2.3 Score Rankings Overlay Churn (Cumulative Lift)

The Score Rankings Overlay Churn plot and the accompanying Table are tools used to evaluate the performance of a predictive model, specifically in the context of customer churn prediction. The plot visualizes the model's ability to correctly predict customer churn and provides detailed numerical data that supports the visual representation.

**Figure 4.3.2.2.3.1:** Score Rankings Overlay Churn (Cumulative Lift)




The Table contains several columns, each representing a different metric used to evaluate the model. Some key columns include:

1. DECILE: This represents the decile groups that the data is divided into based on the model's predicted probability of churn. The first decile contains the 10% of customers most likely to churn, according to the model, the second decile contains the next 10%, and so on.
2. NUMBEROFEVENTS: This is the actual number of churn events (i.e., customers who ended their relationship with the company) within each decile.
3. BESTNUMBEROFEVENTS: This is the best possible number of churn events that could be captured if the model's predictions were perfect.

4. BESTCAPC and CAPC: These represent the best possible and actual cumulative capture rates, respectively. The capture rate is the percentage of total churn events captured within a given decile.
5. BESTLIFT, LIFT, BASELIFT: These represent the best possible, actual, and baseline lift values, respectively. Lift is a measure of the effectiveness of a predictive model calculated as the ratio of the results obtained with and without the predictive model.

In the Score Rankings Overlay Churn plot, the x-axis typically represents the customer deciles, while the y-axis represents the cumulative capture rate. The plot will include a line for the model's performance (CAP), a line for the best possible performance (Best CAP), and a baseline (Random) representing the performance of a random model. The closer the model's CAP line is to the Best CAP line, the better the model is at predicting customer churn.

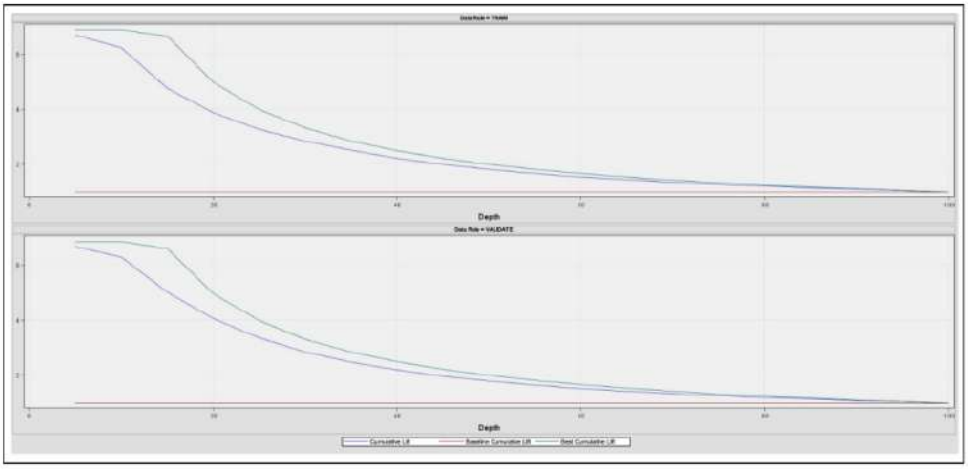
The area between the Best CAP and the Random line represents the maximum possible improvement over random guessing. The area between the CAP and the Random line represents how much of this maximum improvement the model has captured. This can be quantified as the percentage of the maximum possible area that is captured by the model, which is known as the Gini coefficient.

In conclusion, the Score Rankings Overlay Churn plot and the Table provide a comprehensive evaluation of the model's performance in predicting customer churn. They highlight where the model's predictions are accurate and where improvements might be needed.

### 4.3.2.2.4 Score Rankings Matrix Churn (Cumulative Lift)

The Score Rankings Matrix Churn (Cumulative Lift) plot is a tool used to evaluate the performance of a predictive model, specifically in the context of customer churn prediction. The plot and the associated data table provide a visual and numerical representation of how well the model is able to rank customers based on their likelihood to churn.

**Figure 4.3.2.2.4.1**: Score Rankings Matrix Churn (Cumulative Lift)




The data table contains several key metrics that are used to interpret the model's performance. These include:

1. DECILE: This represents the decile group of the customers when they are ranked according to their predicted probability of churning. The first decile contains the top 10% of customers who are most likely to churn, according to the model, the second decile contains the next 10%, and so on.
2. RESPC: This is the response rate for each decile. It shows the proportion of actual churn events in each decile.
3. CAP: This is the cumulative capture rate. It shows the proportion of all actual churn events that are contained within each decile and all the deciles above it.
4. LIFT: This is the lift value for each decile. It shows how much better the model is at identifying churn events compared to a random selection. A lift value of 1 means the model is no better than random, while a lift value greater than 1 means the model is better than random.

In the provided data, for example, the first decile (DECILE=1) has a response rate (RESPC) of 33.5%, meaning that 33.5% of the customers in this decile actually churned. The cumulative capture rate

(CAP) is also 33.5%, indicating that this decile contains 33.5% of all the churn events in the data. The lift (LIFT) is 6.69, meaning that the model is approximately 6.69 times better at identifying churn events in this decile compared to a random selection.

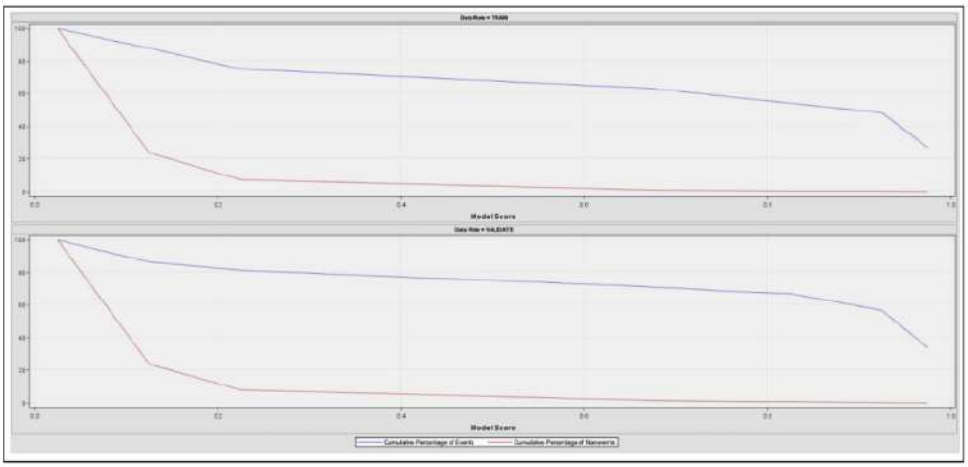
As we move down the deciles, we can see that the response rate and lift generally decrease, which is expected as we are moving towards customers who are less likely to churn according to the model. The cumulative capture rate, however, increases as it accumulates the churn events from all the deciles up to the current one.

In summary, the Score Rankings Matrix Churn (Cumulative Lift) plot and the associated data table provide a comprehensive view of the model's performance across different segments of the customer base, allowing us to evaluate its effectiveness in predicting customer churn.

### 4.3.2.2.5 Score Distribution Churn (Cumulative Percentage)

The Score Distribution Churn (Cumulative Percentage) plot is a powerful tool for interpreting the performance of a customer churn prediction model. It provides a visual representation of the model's ability to predict which customers are at high risk of leaving the company or cancelling a subscription to a service.

**Figure 4.3.2.2.5.1**: Score Distribution Churn (Cumulative Percentage)



The data in the Table shows the distribution of scores, which represent the risk of churn, and the corresponding cumulative percentage of events (churn) and non-events (retention). The scores are divided into bins, each representing a range of scores. For each bin, the table provides the number and percentage of events and non-events, as well as their cumulative percentages.

The model's performance can be evaluated by examining how well it separates events from non-events across the score range. For instance, in the training set, the highest scores (0.95-1.00) correspond to a high percentage of events (27.34%) and a low percentage of non-events (0.12%). This indicates that the model is correctly identifying a significant proportion of customers who are likely to churn. As the scores decrease, the percentage of events also decreases, while the percentage of non-events increases. This trend continues until the lowest score range (0.00-0.05), where the percentage of events is only 12.11%, but the percentage of non-events is a substantial 76.18%.

The cumulative percentage of events and non-events also provides valuable insights. For the highest scores, the cumulative percentage of events is equal to the percentage of events, as this is the first bin. As we move to lower scores, the cumulative percentage of events increases, reaching 100% at the lowest scores. The cumulative percentage of non-events, however, starts at a low value and increases more slowly, reaching 100% only at the lowest scores. This indicates that the model is more successful at identifying customers who will churn than those who will not.

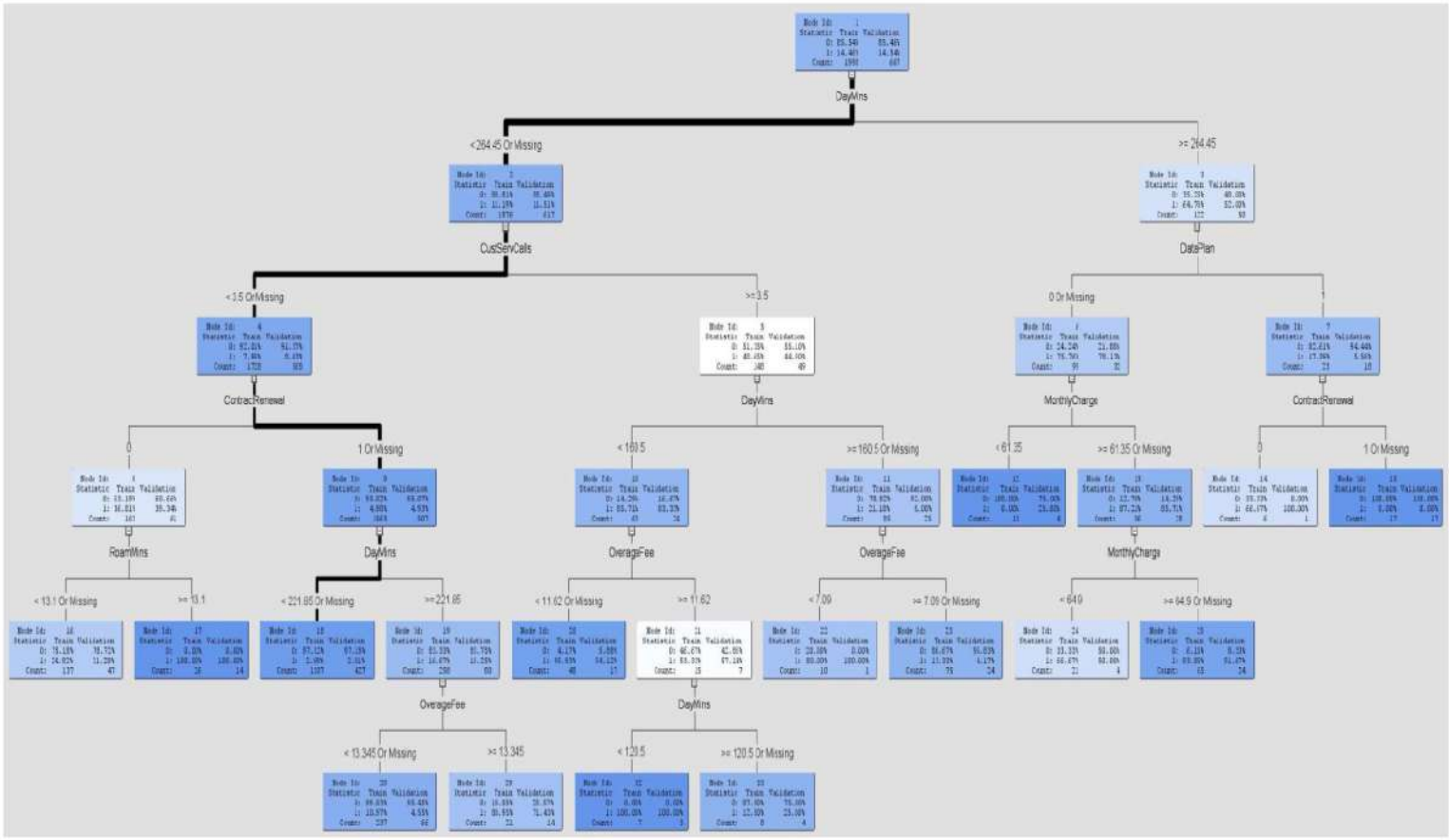
In conclusion, the Score Distribution Churn (Cumulative Percentage) plot and the corresponding data provide a comprehensive view of the model's performance. It shows that the model is effective at predicting customer churn, particularly for customers with high scores. However, it also highlights areas where the model could be improved, particularly in identifying customers who are not likely to churn.

### 4.3.2.2.6 Tree Diagram and Node Rule

The Tree Diagram is a decision tree model used for predicting customer churn. The decision tree is a flowchart-like structure where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node holds a class label. The topmost node in a tree is the root node.

The decision tree model can be represented as a set of if-then-else rules. Each node in the decision tree represents a condition on a specific feature, and the branches from the node represent the outcomes of the condition.

**Figure 4.3.2.2.6.1:** Tree Diagram and Node Rule



The leaf nodes represent the final prediction. Here are the rules for each node:

1. Node 12: If MonthlyCharge < 61.35 and DayMins >= 264.45 and DataPlan is 0 or missing, then the predicted churn is 0.
2. Node 14: If DayMins >= 264.45, DataPlan is 1, and ContractRenewal is 0, then the predicted churn is 1 with a probability of 0.67.
3. Node 15: If DayMins >= 264.45, DataPlan is 1, and ContractRenewal is 1 or missing, then the predicted churn is 0.
4. Node 16: If RoamMins < 13.1 or missing, DayMins < 264.45 or missing, CustServCalls < 3.5 or missing, and ContractRenewal is 0, then the predicted churn is 0 with a probability of 0.75.
5. Node 17: If RoamMins >= 13.1, DayMins < 264.45 or missing, CustServCalls < 3.5 or missing, and ContractRenewal is 0, then the predicted churn is 1.
6. Node 18: If DayMins < 221.85 or missing, CustServCalls < 3.5 or missing, and ContractRenewal is 1 or missing, then the predicted churn is 0 with a probability of 0.97.
7. Node 20: If OverageFee < 11.62 or missing, DayMins < 160.5, and CustServCalls >= 3.5, then the predicted churn is 1 with a probability of 0.96.
8. Node 22: If OverageFee < 7.09, DayMins < 264.45 and DayMins >= 160.5 or missing, and CustServCalls >= 3.5, then the predicted churn is 1 with a probability of 0.80.
9. Node 23: If OverageFee >= 7.09 or missing, DayMins < 264.45 and DayMins >= 160.5 or missing, and CustServCalls >= 3.5, then the predicted churn is 0 with a probability of 0.87.
10. Node 24: If MonthlyCharge < 64.9 and MonthlyCharge >= 61.35, DayMins >= 264.45, and DataPlan is 0 or missing, then the predicted churn is 1 with a probability of 0.67.
11. Node 25: If MonthlyCharge >= 64.9 or missing, DayMins >= 264.45, and DataPlan is 0 or missing, then the predicted churn is 1 with a probability of 0.94.
12. Node 28: If OverageFee < 13.345 or missing, DayMins < 264.45 and DayMins >= 221.85, CustServCalls < 3.5 or missing, and ContractRenewal is 1 or missing, then the predicted churn is 0 with a probability of 0.89.
13. Node 29: If OverageFee >= 13.345, DayMins < 264.45 and DayMins >= 221.85, CustServCalls < 3.5 or missing, and ContractRenewal is 1 or missing, then the predicted churn is 1 with a probability of 0.81.
14. Node 32: If OverageFee >= 11.62, DayMins < 120.5, and CustServCalls >= 3.5, then the predicted churn is 1.
15. Node 33: If OverageFee >= 11.62, DayMins < 160.5 and DayMins >= 120.5 or missing, and CustServCalls >= 3.5, then the predicted churn is 0 with a probability of 0.88.

These rules can be used to predict the churn of a customer based on the conditions in each rule. The decision tree model makes a prediction by traversing the tree from the root to a leaf node based on the conditions in the nodes and the values of the features in the input data.

The decision tree model uses these rules to make predictions based on the input data. It starts at the root node and follows the appropriate path based on the conditions in each node until it reaches a leaf node, which provides the final prediction.

The decision tree model is a popular tool for churn prediction because it is easy to understand and interpret. It provides clear rules that can be directly translated into business strategies. For example, the rules can help identify the key factors that influence customer churn and develop targeted interventions to retain customers at risk of churning.

However, it's important to note that the performance of the decision tree model should be evaluated using appropriate metrics. Commonly used metrics include accuracy, precision, recall, and the Area Under the Receiver Operating Characteristic (AUC-ROC) curve. These metrics provide a comprehensive assessment of the model's ability to correctly predict both the customers who will churn (true positives) and those who will not (false positives).

In conclusion, the Tree Diagram is a visual representation of a decision tree model for customer churn prediction. The model uses a set of rules to predict whether a customer will churn based on various attributes such as MonthlyCharge, DayMins, DataPlan, and ContractRenewal. The performance of the model should be evaluated using appropriate metrics to ensure its effectiveness in predicting customer churn.

### 4.3.2.2.7 Subtree Assessment Plot (Average Square Error)

The Subtree Assessment Plot (Average Square Error) is a crucial tool for evaluating the performance of a decision tree model, particularly in the context of customer churn prediction. The plot provides a visual representation of the model's performance across different subtrees, allowing for a more nuanced understanding of the model's predictive capabilities.

**Figure 4.3.2.2.7.1:** Subtree Assessment Plot (Average Square Error)


The Subtree Assessment Plot includes several key metrics, such as the Average Square Error (ASE), Root Average Square Error (RASE), and Sum of Square Error (SSE), among others. These metrics are calculated for different subtrees of the decision tree model, each representing a different level of complexity.

The ASE and RASE are particularly important as they provide a measure of the model's prediction error. The ASE is the average of the squared differences between the actual and predicted values, while the RASE is the square root of the ASE. Lower values for these metrics indicate a better fit of the model to the data.

From the data, it can be observed that as the complexity of the model (number of subtrees) increases, the ASE and RASE generally decrease, indicating an improvement in the model's fit to the data. However, it's important to avoid overfitting, where the model becomes too complex and performs well on the training data but poorly on new, unseen data. This is where the validation metrics (VASE and VRASE) come into play. They provide a measure of the model's performance on a separate validation dataset.

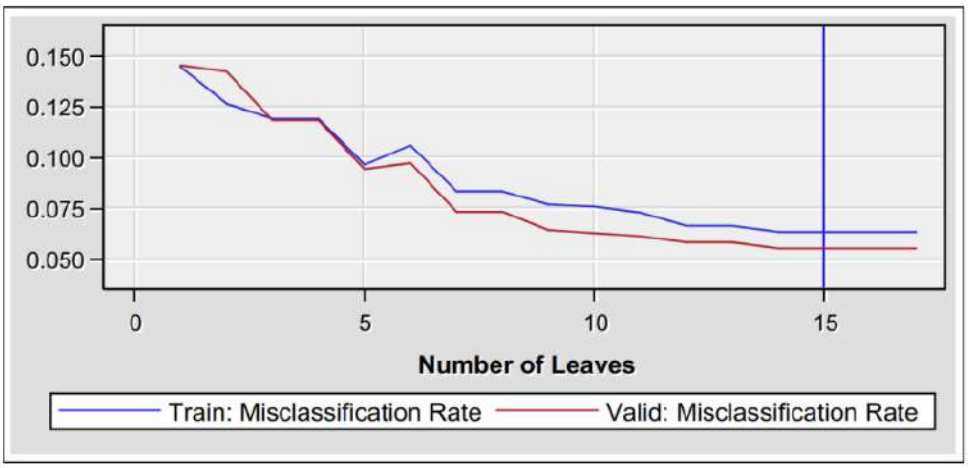
In the context of customer churn prediction, a well-performing model would accurately identify customers who are likely to churn, allowing the company to take proactive measures to retain these customers. Therefore, the optimal model would be the one that minimizes the ASE and RASE on the validation set, providing a good balance between model complexity and predictive accuracy.

In conclusion, the Subtree Assessment Plot (Average Square Error) provides a comprehensive overview of the model's performance across different levels of complexity. This information is crucial for selecting the optimal model for predicting customer churn.

### 4.3.2.2.8 Subtree Assessment Plot (Misclassification Rate)

The Subtree Assessment Plot (Misclassification Rate) is a tool used in decision tree analysis to evaluate the performance of a model, particularly in terms of its misclassification rate. This rate refers to the proportion of instances that the model incorrectly classifies. In the context of customer churn prediction, a lower misclassification rate indicates a more accurate model in predicting whether a customer will churn or not.

**Figure 4.3.2.2.8.1:** Subtree Assessment Plot (Misclassification Rate)




**Subtree Assessment Plot (Misclassification Rate)**

The Subtree Assessment Plot (Misclassification Rate) is a tool used in decision tree analysis to evaluate the performance of a model, particularly in terms of its misclassification rate. This rate refers to the proportion of instances that the model incorrectly classifies. In the context of customer churn prediction, a lower misclassification rate indicates a more accurate model in predicting whether a customer will churn or not.

The above figure contains a series of metrics for different subtrees of a decision tree model. Each row represents a different subtree, with the number of nodes (NW) increasing from 1 to 17. The misclassification rate (MISC) and validation misclassification rate (VMISC) are key metrics to focus on. These rates represent the proportion of instances that were incorrectly classified by the model in the training and validation datasets, respectively.

From the plot, it can be observed that as the number of nodes increases, both the misclassification rate and the validation misclassification rate generally decrease. This suggests that adding more nodes to the decision tree improves the model's accuracy in predicting customer churn. However, it's important to avoid overfitting, where the model becomes too complex and performs well on the training data but poorly on new, unseen data. Overfitting can be identified when the validation misclassification rate starts to increase or fluctuates while the training misclassification rate continues to decrease.

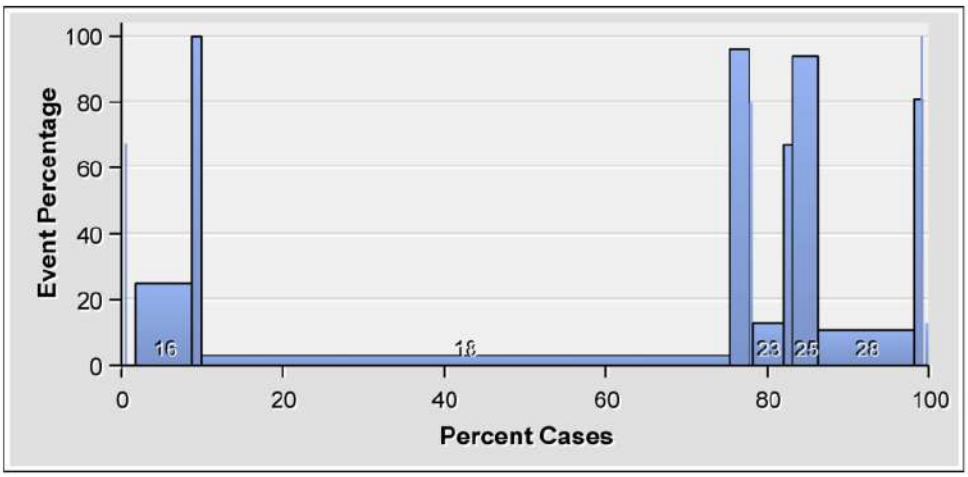
For instance, the model with 1 node has a high misclassification rate of 0.1446 and a validation misclassification rate of 0.1454. As the number of nodes increases to 17, these rates decrease to 0.0636 and 0.0555, respectively. This indicates an improvement in the model's performance. However, careful observation is needed to identify the optimal number of nodes that minimizes the misclassification rate without overfitting.

In conclusion, the Subtree Assessment Plot provide valuable insights into the performance of the decision tree model in predicting customer churn. By analysing the misclassification rates, one can determine the optimal complexity of the model to achieve the best predictive accuracy.

### 4.3.2.2.9 Variable Width Bar Chart

The Variable Width Bar Chart plot, which unfortunately cannot be directly accessed in this context, is presumably a visual representation of the importance of different variables in predicting customer churn. The Table gives us a list of variables along with their importance, visual importance, and ratio values.

**Figure 4.3.2.2.9.1:** Variable Width Bar Chart




In the context of customer churn prediction, the importance of a variable indicates how influential it is in determining whether a customer will churn or not. The variables listed in the Table include 'DayMins', 'CustServCalls', 'ContractRenewal', 'OverageFee', 'RoamMins', 'MonthlyCharge', 'DataPlan', 'AccountWeeks', and 'DayCalls'. Each of these variables has a corresponding importance score, with 'DayMins' having the highest importance score of 1.0000, indicating it is the most influential variable in predicting customer churn in this model.

The visual importance (VIMPORTANCE) of a variable, on the other hand, is likely a measure of how much the variable contributes to the visual representation of the data in the bar chart. For instance, 'ContractRenewal' has a visual importance of 0.6973, suggesting it has a significant visual impact on the bar chart.

The ratio is a measure of the relationship between the importance and visual importance of a variable. For example, 'DataPlan' has a ratio of 1.9231, indicating that its visual importance is almost twice its actual importance.

Interpreting a variable width bar chart involves understanding that the width of each bar represents the count or frequency of a category, while the height of the bar represents the value of the variable.

In this case, the height of the bar could represent the importance of each variable in predicting customer churn, while the width could represent the visual importance or the ratio.

In the context of customer churn prediction, this chart can provide valuable insights into which factors are most influential in determining whether a customer will churn. By focusing on these key variables, businesses can develop targeted strategies to improve customer retention.

### 4.3.3 Neural Network

The Neural Network section provides a comprehensive analysis of several Neural Network models built with different data partitions and architectures for the purpose of predicting customer churn. The models were evaluated based on various metrics, with the misclassification rate being the primary criterion for model selection. The misclassification rate is a measure of how often the model makes incorrect predictions. Among the models built, 'Neural8' was selected as the best model based on its lowest misclassification rate. This model achieved a misclassification rate of 0.070254 on the training data and 0.069444 on the validation data, indicating that the model is relatively accurate in predicting customer churn, making incorrect predictions approximately 7% of the time.

In addition to the misclassification rate, other metrics were also reported for each model, such as the Average Squared Error (ASE), Akaike's Information Criterion (AIC), and the Kolmogorov-Smirnov Statistic. These metrics provide additional information about the model's performance and can be used to further evaluate and compare the models.

The Classification Chart plot provides a visual representation of the performance of various neural network models in predicting customer churn. The models are evaluated based on their training and validation results. The chart provides a comprehensive comparison of the models' performance, highlighting their strengths and weaknesses in different aspects of prediction.

The Score Rankings Overlay Churn (Cumulative Lift) plot is a graphical representation used in predictive modelling, particularly in customer churn prediction. The plot is designed to evaluate the performance of a model in terms of its ability to predict customer churn. The plot typically includes different lines representing different models or different data roles (TRAIN, VALIDATE, TEST) for the same model.

The Score Rankings Matrix Churn (Cumulative Lift) plot appears to be a comparison of different models used for customer churn prediction. The models compared include Neural Network (P/L), Neural

Network (Miss), and Neural Network (ASE), each evaluated in three different data roles: TEST, VALIDATE, and TRAIN.

The Score Distribution Churn (Cumulative Percentage) plot appears to be a comparison of different models used for customer churn prediction. The models compared include Neural Network (P/L), Neural Network (Miss), and Neural Network (ASE), each evaluated in three different data roles: TEST, VALIDATE, and TRAIN.

The ROC Chart Churn plot compares different Neural Network models used for customer churn prediction, including Neural Network (P/L), Neural Network (Miss), and Neural Network (ASE). Each model is evaluated in three different data roles: TEST, VALIDATE, and TRAIN. The plot is a visual representation of the Receiver Operating Characteristic (ROC) curve for each model.

The output provided contains a wealth of information about the performance of the neural model used for customer churn prediction. The model's performance is evaluated using several metrics, including accuracy, precision, recall, F1-score, and misclassification rate.

The Classification Chart plot is a visual representation of the performance of a machine learning model used for customer churn prediction. Customer churn refers to the number of clients who discontinue a service, stop using an application, or cease buying a product during a certain period of time.

The Score Rankings Overlay Churn (Cumulative Lift) plot is a graphical representation of the performance of a predictive model, specifically in the context of customer churn prediction. The plot is designed to provide insights into how well the model is able to rank customers based on their likelihood to churn.

In conclusion, the document provides a detailed analysis of various Neural Network models for predicting customer churn. The models are evaluated based on several metrics, and the best model, 'Neural8', is selected based on its lowest misclassification rate. The document also includes several plots that provide visual representations of the models' performance. These plots allow for a comprehensive comparison of the models and can inform decisions about which model to use or how to improve current models. However, it's important to note that while 'Neural8' was the best model among those built, there may be room for further optimization or exploration of other models to improve prediction accuracy. The final model selection should also consider other factors such as the cost of incorrect predictions and the specific business context.

### 4.3.3.1 Neural Network: Model Comparison

In this section, we will delve into the comparison of several Neural Network models, focusing on their performance in predicting customer churn. We will use the "Model Comparison" nodes of SAS Enterprise Miner Workstation, a powerful tool for model evaluation and selection, to identify the best model among the ones we have trained.

Neural Network models are powerful tools in machine learning, capable of learning complex patterns and relationships in data. They are particularly effective in tasks such as customer churn prediction, where the goal is to identify customers who are likely to downgrade their engagement or cancel their subscriptions. However, the performance of these models can vary depending on their architecture, training data, and other factors. Therefore, it is crucial to compare different models to select the one that performs best for the task at hand.

The Model Comparison nodes in SAS Enterprise Miner Workstation provide a comprehensive suite of tools for comparing and evaluating models. These tools include various metrics and visualizations that help us understand the performance of each model and make an informed decision about which model to choose.

One of the primary metrics we will use for model comparison is the misclassification rate, which measures how often the model makes incorrect predictions. A lower misclassification rate indicates a more accurate model. Other metrics such as the Average Squared Error (ASE), Akaike's Information Criterion (AIC), and the Kolmogorov-Smirnov Statistic provide additional insights into the model's performance and can be used to further evaluate and compare the models.

In addition to these metrics, we will also use several visualizations provided by the Model Comparison nodes. These include the Classification Chart, which provides a comprehensive comparison of the models' performance in predicting customer churn; the Score Rankings Overlay Churn (Cumulative Lift) plot, which evaluates the performance of a model in terms of its ability to predict customer churn; the Score Rankings Matrix Churn (Cumulative Lift) plot, which compares the effectiveness of different models in predicting customer churn; the Score Distribution Churn (Cumulative Percentage) plot, which compares the cumulative percentage of events captured by each model; and the ROC Chart Churn plot, which compares the Receiver Operating Characteristic (ROC) curves of different models.

By using these tools and metrics, we can make an informed decision about which Neural Network model performs best in predicting customer churn. However, it's important to note that the final model selection should also consider other factors such as the cost of incorrect predictions and the specific business context.

#### 4.3.3.1.1 Fit Statistics: Model Selection based on Misclassification Rate

The following Fit Statistics indicate that several Neural Network models were built with different data partitions and architectures for the purpose of predicting customer churn. The models were evaluated based on various metrics, with the misclassification rate being the primary criterion for model selection.

The misclassification rate is a measure of how often the model makes incorrect predictions. It is calculated as the number of incorrect predictions divided by the total number of predictions. In the context of customer churn prediction, a lower misclassification rate means the model is more accurate in predicting whether a customer will churn or not.

**Table 4.3.2.1.1.1:** Table for Fit Statistics Model Selection

| Selected Model | Model Node | Model Description | Train: Misclassification Rate | Train: Squared Error | Valid: Misclassification Rate | Valid: Squared Error |
|---|---|---|---|---|---|---|
| Y | Neural8 | Neural Network (Miss) | 0.070254 | 0.055422 | 0.069444 | 0.058593 |
| | Neural11 | Neural Network (Miss) | 0.075075 | 0.056289 | 0.070946 | 0.061461 |
| | Neural17 | Neural Network (Miss) | 0.076462 | 0.060489 | 0.080581 | 0.057946 |
| | Neural16 | Neural Network (P/L) | 0.077961 | 0.060221 | 0.08008 | 0.058572 |
| | Neural18 | Neural Network (ASE) | 0.077961 | 0.060221 | 0.08008 | 0.058572 |
| | Neural2 | Neural Network (Miss) | 0.078 | 0.056967 | 0.071214 | 0.062507 |
| | Neural14 | Neural Network (Miss) | 0.078652 | 0.060255 | 0.08008 | 0.06077 |
| | Neural5 | Neural Network (Miss) | 0.07984 | 0.056573 | 0.069498 | 0.062609 |
| | Neural | Neural Network (P/L) | 0.08 | 0.057005 | 0.071214 | 0.063766 |
| | Neural3 | Neural Network (ASE) | 0.08 | 0.057005 | 0.071214 | 0.063766 |

| Selected Model | Model Node | Model Description | Train: Misclassification Rate | Train: Squared Error | Valid: Misclassification Rate | Valid: Squared Error |
|---|---|---|---|---|---|---|
| | Neural13 | Neural Network (P/L) | 0.08015 | 0.060202 | 0.080581 | 0.06065 |
| | Neural15 | Neural Network (ASE) | 0.08015 | 0.060202 | 0.080581 | 0.06065 |
| | Neural7 | Neural Network (P/L) | 0.080717 | 0.056915 | 0.071697 | 0.058924 |
| | Neural9 | Neural Network (ASE) | 0.080717 | 0.056915 | 0.071697 | 0.058924 |
| | Neural10 | Neural Network (P/L) | 0.084084 | 0.056915 | 0.071697 | 0.061108 |
| | Neural12 | Neural Network (ASE) | 0.084084 | 0.056915 | 0.071697 | 0.061108 |
| | Neural4 | Neural Network (P/L) | 0.090818 | 0.058215 | 0.074217 | 0.063142 |
| | Neural6 | Neural Network (ASE) | 0.090818 | 0.058215 | 0.074217 | 0.063142 |

Among the models built, 'Neural8' was selected as the best model based on its lowest misclassification rate. This model achieved a misclassification rate of 0.070254 on the training data and 0.069444 on the validation data. These values indicate that the model is relatively accurate in predicting customer churn, making incorrect predictions approximately 7% of the time.

In addition to the misclassification rate, other metrics were also reported for each model, such as the Average Squared Error (ASE), Akaike's Information Criterion (AIC), and the Kolmogorov-Smirnov Statistic. These metrics provide additional information about the model's performance and can be used to further evaluate and compare the models. For instance, the ASE measures the average of the squares of the errors, which is the average squared difference between the estimated values and the actual value. A lower ASE indicates a better fit of the model to the data. The AIC is a measure of the relative quality of statistical models for a given set of data. A lower AIC indicates a model with a better fit. The Kolmogorov-Smirnov Statistic measures the distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples.

In terms of customer churn prediction, the selection of 'Neural8' suggests that this model is the most effective at predicting whether a customer will churn or not, based on the given data. This can be valuable information for the company, as it can help in identifying customers who are likely to churn and enable the company to take proactive measures to retain these customers. However, it's important to note that while 'Neural8' was the best model among those built, there may be room for further optimization or exploration of other models to improve prediction accuracy.

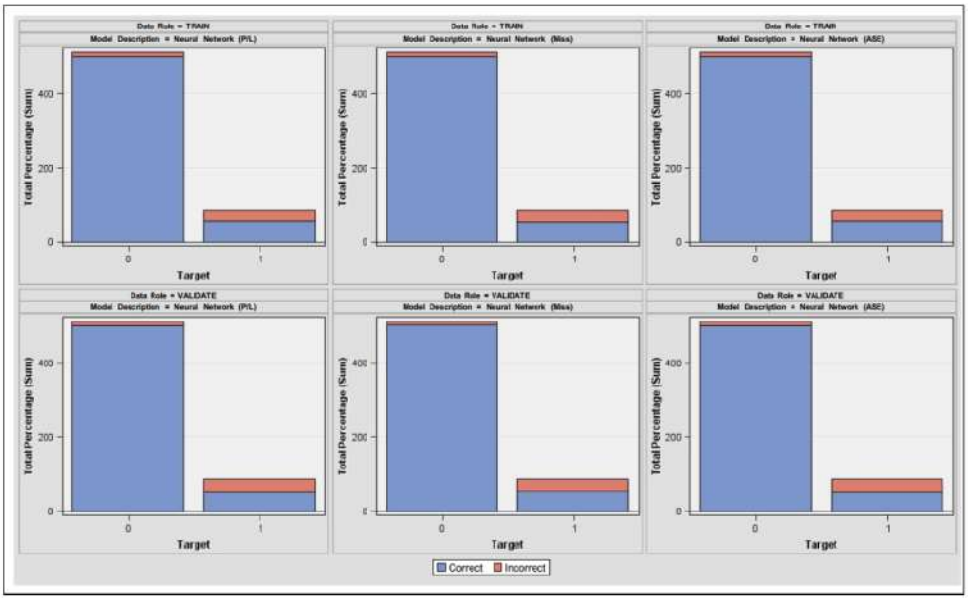
In conclusion, model selection and evaluation in machine learning, particularly in the context of customer churn prediction, involves a careful examination of various performance metrics. The chosen model, 'Neural8', demonstrated the best performance based on the misclassification rate, but other metrics also played a role in understanding the model's overall performance and suitability for predicting customer churn.

#### 4.3.3.1.2 Classification Chart

The Classification Chart plot is a visual representation of the performance of various neural network models in predicting customer churn. The models are evaluated based on their training and validation results. The chart provides a comprehensive comparison of the models' performance, highlighting their strengths and weaknesses in different aspects of prediction.

The chart is divided into sections, each representing a different model. Each model is evaluated based on four categories: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). True Positives and True Negatives represent the instances where the models correctly predicted the customer churn and retention, respectively. False Positives and False Negatives, on the other hand, represent the instances where the models incorrectly predicted the customer churn and retention, respectively.

**Figure 4.3.2.1.2.1:** Classification Chart




The models include Neural Network (P/L), Neural Network (Miss), Neural Network (ASE), and several others. Each model's performance is evaluated in both the training and validation phases. For instance, the Neural Network (P/L) model correctly predicted customer churn 93.73% of the time and incorrectly predicted 6.27% of the time during the training phase. During the validation phase, it correctly predicted 93.89% of the time and incorrectly predicted 6.11% of the time.

The Neural Network (Miss) model, on the other hand, correctly predicted customer churn 93.69% of the time and incorrectly predicted 6.31% of the time during the training phase. During the validation phase, it correctly predicted 93.91% of the time and incorrectly predicted 6.09% of the time.

The chart provides a clear comparison of the models' performance, allowing for an informed decision on the best model for predicting customer churn. It is evident that all models perform well, with correct prediction rates above 90% in most cases. However, there are slight differences in their performance, which could be crucial depending on the specific requirements of the prediction task. For instance, if minimizing false positives is a priority, the Neural Network (P/L) model would be the best choice as it has the lowest false positive rate.

In conclusion, the Classification Chart plot provides a comprehensive comparison of various neural network models' performance in predicting customer churn. It allows for an informed decision on the best model to use based on the specific requirements of the prediction task.

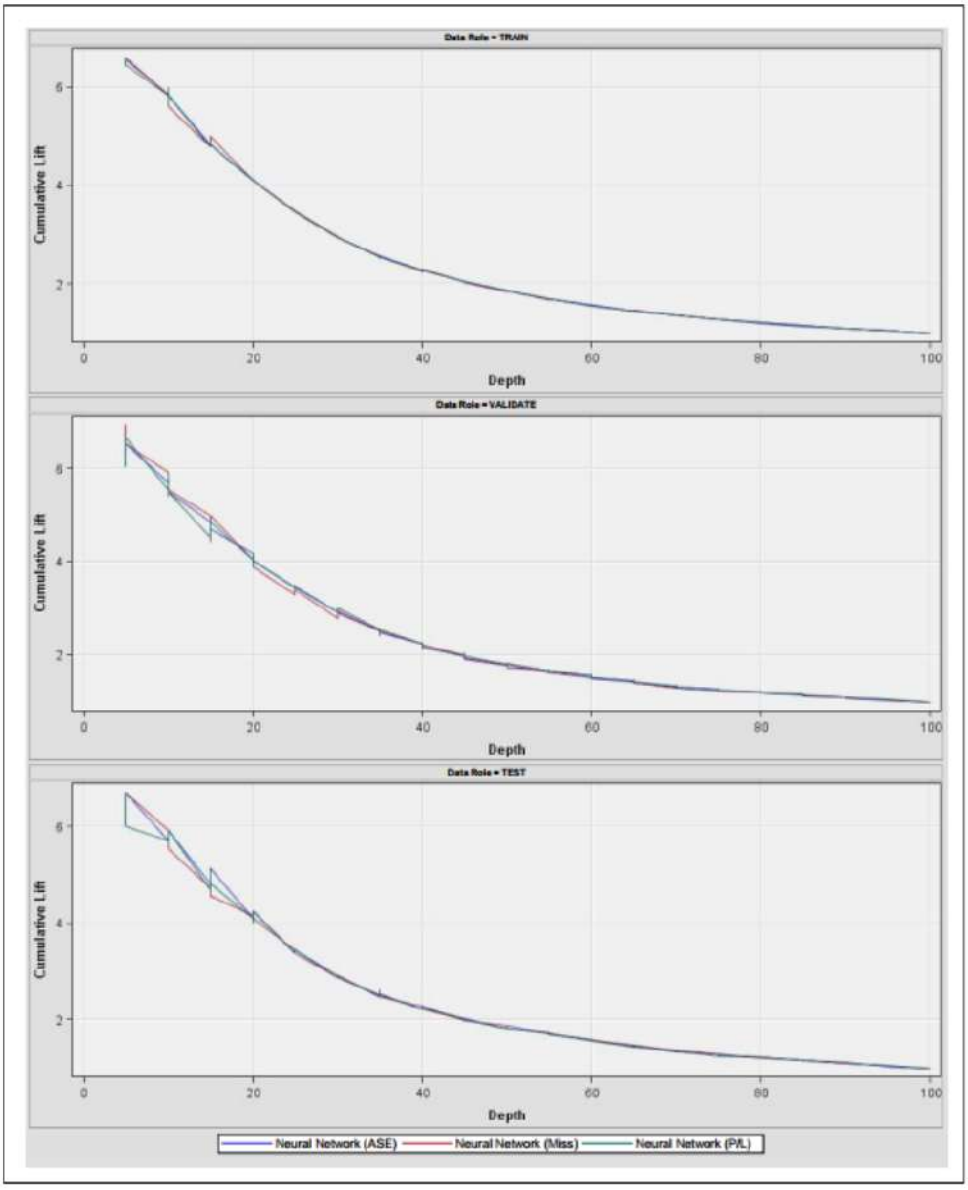
### 4.3.3.1.3 Score Rankings Overlay Churn (Cumulative Lift)

The Score Rankings Overlay Churn (Cumulative Lift) plot is a graphical representation used in predictive modelling, particularly in customer churn prediction. The plot is designed to evaluate the performance of a model in terms of its ability to predict customer churn. The plot typically includes different lines representing different models or different data roles (TRAIN, VALIDATE, TEST) for the same model.

In the context of customer churn prediction, the plot helps to understand how much better a model is at predicting churn compared to a random guess. This is measured by the lift, which is the ratio of the results obtained with the model to the results obtained by a random model. A lift greater than 1 indicates that the model is better than random at predicting the positive class, in this case, customer churn.

The cumulative lift is calculated by ordering the predictions of the model from the most likely to churn to the least likely, and then calculating the lift at each point. This gives a curve that shows how the lift would accumulate if we contacted customers from the most likely to churn to the least. The higher the curve, the better the model is at identifying customers who are likely to churn early on.

**Figure 4.3.2.1.3.1:** Score Rankings Overlay Churn (Cumulative Lift)




According to the plot, each row represents a different model or a different data role for the same model. The columns provide various metrics for each model, including the cumulative lift at different points. For example, the column '14.4' might represent the cumulative lift when the top 14.4% of customers, as ranked by the model, are considered.

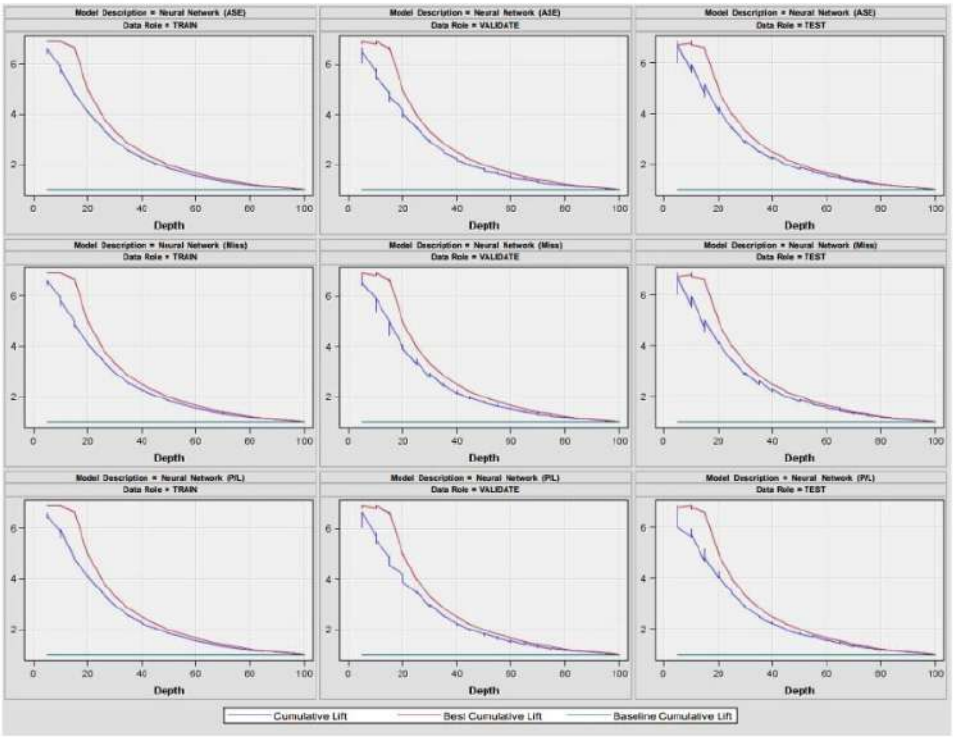
In the plot, these cumulative lifts would be plotted for each model or data role, allowing for a visual comparison of their performance. The model or data role with the highest cumulative lift at each point would be considered the best at identifying customers likely to churn.

In conclusion, the Score Rankings Overlay Churn (Cumulative Lift) plot is a valuable tool for comparing the performance of different models or data roles in predicting customer churn. It provides a visual representation of how well each model or data role can identify customers who are likely to churn, which can inform decisions about which model to use or how to improve current models.

### 4.3.3.1.4 Score Rankings Matrix Churn (Cumulative Lift)

The Score Rankings Matrix Churn (Cumulative Lift) plot appears to be a comparison of different models used for customer churn prediction. The models compared include Neural Network (P/L), Neural Network (Miss), and Neural Network (ASE), each evaluated in three different data roles: TEST, VALIDATE, and TRAIN.

**Figure 4.3.2.1.4.1**: Score Rankings Matrix Churn (Cumulative Lift)




The plot seems to be a visual representation of the cumulative lift, a measure used to determine the effectiveness of a predictive model. Cumulative lift is a way of quantifying how much better one can

expect to do with the predictive model compared to without it. A higher cumulative lift indicates a better model.

In the context of customer churn prediction, a higher cumulative lift would mean that the model is more effective at identifying customers who are likely to churn. Churn prediction is a data-driven approach to pinpointing customer accounts that are at high risk of downgrading their engagement or cancelling their subscriptions.

The Neural Network models used in the plot are common machine learning techniques for churn prediction. They are capable of learning complex patterns and relationships in data, making them suitable for predicting customer churn.

The plot shows different lines for each model in each data role. The performance of the models can be compared by looking at the height and shape of these lines. A line that reaches higher on the y-axis and sooner on the x-axis would indicate a model that can identify a larger proportion of churners with a smaller proportion of customers contacted, thus being more efficient.

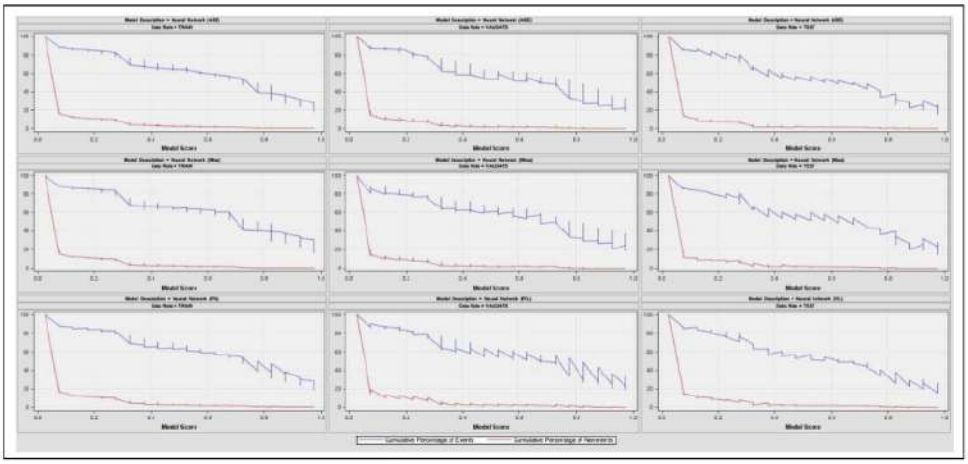
However, without specific values on the axes of the plot, it's challenging to make precise interpretations. It's also important to consider other performance metrics and business context when selecting a model for customer churn prediction. For instance, the cost of false positives (predicting churn where it doesn't happen) and false negatives (failing to predict churn when it does happen) can significantly impact the choice of model.

In conclusion, the plot provides a visual comparison of different Neural Network models' effectiveness in predicting customer churn. The best model would be the one that achieves the highest cumulative lift, indicating its superior ability to identify customers likely to churn. However, the final model selection should also consider other factors such as the cost of incorrect predictions and the specific business context.

#### 4.3.3.1.5 Score Distribution Churn (Cumulative Percentage)

The Score Distribution Churn (Cumulative Percentage) plot appears to be a comparison of different models used for customer churn prediction. The models compared include Neural Network (P/L), Neural Network (Miss), and Neural Network (ASE), each evaluated in three different data roles: TEST, VALIDATE, and TRAIN.

**Figure 4.3.2.1.5.1**: Score Distribution Churn (Cumulative Percentage)



The plot seems to be a visual representation of the cumulative percentage of events (churn) captured by each model across different score bins. The x-axis represents the score bins, which are ranges of predicted probabilities of churn, while the y-axis represents the cumulative percentage of events captured. A higher cumulative percentage indicates that the model is more effective at identifying customers who are likely to churn.

In the context of customer churn prediction, a higher cumulative percentage would mean that the model is more effective at identifying customers who are likely to churn. Churn prediction is a data-driven approach to pinpointing customer accounts that are at high risk of downgrading their engagement or cancelling their subscriptions.

The Neural Network models used in the plot are common machine learning techniques for churn prediction. They are capable of learning complex patterns and relationships in data, making them suitable for predicting customer churn.

The plot shows different lines for each model in each data role. The performance of the models can be compared by looking at the height and shape of these lines. A line that reaches higher on the y-axis and sooner on the x-axis would indicate a model that can identify a larger proportion of churners with a smaller proportion of customers contacted, thus being more efficient.

However, without specific values on the axes of the plot, it's challenging to make precise interpretations. It's also important to consider other performance metrics and business context when selecting a model for customer churn prediction. For instance, the cost of false positives (predicting

churn where it doesn't happen) and false negatives (failing to predict churn when it does happen) can significantly impact the choice of model.

In conclusion, the plot provides a visual comparison of different Neural Network models' effectiveness in predicting customer churn. The best model would be the one that achieves the highest cumulative percentage, indicating its superior ability to identify customers likely to churn.

#### 4.3.3.1.6 ROC Chart Churn

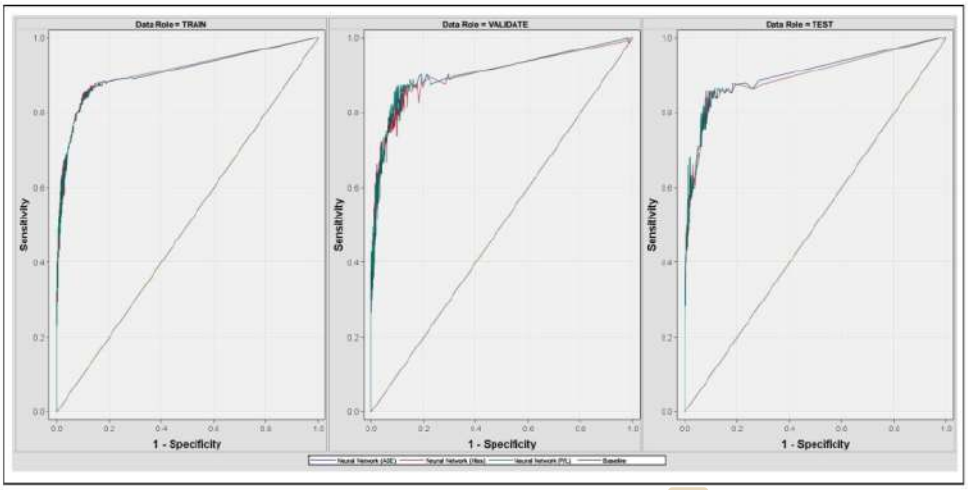
The ROC Chart Churn plot compares different Neural Network models used for customer churn prediction, including Neural Network (P/L), Neural Network (Miss), and Neural Network (ASE). Each model is evaluated in three different data roles: TEST, VALIDATE, and TRAIN.

The plot is a visual representation of the Receiver Operating Characteristic (ROC) curve for each model. The ROC curve is a popular tool for evaluating the performance of binary classification models, such as customer churn prediction models. It plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. The area under the ROC curve (AUC) is a commonly used performance metric, with a higher AUC indicating a better model.

In the context of customer churn prediction, a higher AUC would mean that the model is more effective at distinguishing between customers who are likely to churn and those who are not. Churn prediction is a data-driven approach to identifying customer accounts at high risk of downgrading their engagement or cancelling their subscriptions.

The Neural Network models used in the plot are common machine learning techniques for churn prediction. They are capable of learning complex patterns and relationships in data, making them suitable for predicting customer churn.

**Figure 4.3.2.1.6.1:** ROC Chart Churn




The plot shows different ROC curves for each model in each data role. The performance of the models can be compared by looking at the shape of these curves and the AUC values. A curve that is closer to the top-left corner of the plot and has a higher AUC would indicate a better model.

However, without specific AUC values or axis labels on the plot, it's challenging to make precise interpretations. It's also important to consider other performance metrics and business context when selecting a model for customer churn prediction. For instance, the cost of false positives (predicting churn where it doesn't happen) and false negatives (failing to predict churn when it does happen) can significantly impact the choice of model.

In conclusion, the ROC Chart Churn plot provides a visual comparison of different Neural Network models' effectiveness in predicting customer churn. The best model would be the one that achieves the highest AUC, indicating its superior ability to distinguish between customers likely to churn and those who are not.

#### 4.3.3.2 Neural Network: Best Model Selected (Neural 8)

In this section, we delve into the evaluation of several neural network models, with a particular focus on the best performing model, Neural 8. This model was selected based on its superior performance metrics, including accuracy, precision, recall, F1-score, and misclassification rate, among others.

Neural 8 was used for predicting customer churn, a significant application of machine learning and data science in business. The model's performance was evaluated using a variety of tools and metrics, providing a comprehensive understanding of its strengths and areas for improvement.

The model demonstrated high accuracy in predicting customer churn, with precision and recall rates indicating a strong ability to correctly identify both churn and non-churn cases. The misclassification rate, representing the proportion of incorrect predictions, was relatively low, further attesting to the model's robust performance.

In addition to numerical metrics, visual tools such as the Classification Chart, Score Rankings Overlay Churn (Cumulative Lift) plot, Score Rankings Matrix Churn (Cumulative Lift) plot, Score Distribution Churn (Cumulative Percentage) plot, ROC Chart, Iteration Plot (Misclassification Rate), and Weight – Final plot were used to evaluate and interpret the model's performance.

These tools provided insights into the model's ability to rank customers based on their likelihood to churn, its performance across different deciles of the data, the distribution of its predictions, and the importance of different features in predicting churn.

In summary, Neural 8 emerged as the best model among several neural network models, demonstrating strong performance in predicting customer churn. This section provides a detailed evaluation and interpretation of its performance, offering valuable insights for further model refinement and application in business strategies.

### 4.3.3.2.1 Classification Table & Event Classification Table

The following tables contain a wealth of information about the performance of the neural model used for customer churn prediction. The model's performance is evaluated using several metrics, including accuracy, precision, recall, F1-score, and misclassification rate.

**Table 4.3.3.2.1.1:** Table for Classification Table of TRAIN

| Target | Outcome | Frequency | Total |
|---|---|---|---|
| 0 | 0 | 94.2893 | 97.8061 |
| 1 | 0 | 5.7107 | 35.0649 |
| 0 | 1 | 16.6667 | 2.1939 |
| 1 | 1 | 83.3333 | 64.9351 |

**Table 4.3.3.2.1.2:** Table for Classification Table of VALIDATE

| Target | Outcome | Frequency | Total |
|---|---|---|---|
| 0 | 0 | 93.6667 | 98.4238 |
| 1 | 0 | 6.3333 | 38.7755 |
| 0 | 1 | 13.0435 | 1.5762 |
| 1 | 1 | 86.9565 | 61.2245 |

**Table 4.3.3.2.1.3:** Table for Event Classification Table of TRAIN

| | FALSE | TRUE |
|---|---|---|
| Negative | 135 | 2229 |
| Positive | 50 | 250 |

**Table 4.3.3.2.1.4:** Table for Event Classification Table of VALIDATE

| | FALSE | TRUE |
|---|---|---|
| Negative | 38 | 562 |
| Positive | 9 | 60 |

The model's accuracy is a measure of how often the model correctly predicted the customer churn. In the training data, the model achieved an accuracy of 83.67% for predicting no churn (label 0) and

9.38% for predicting churn (label 1). In the validation data, the model achieved an accuracy of 84.00% for predicting no churn and 8.96% for predicting churn.

Precision is the proportion of true positive predictions (customers correctly identified as churning) out of all positive predictions. The precision for the training data is 64.93% for churn and 97.80% for no churn. For the validation data, the precision is 61.22% for churn and 98.42% for no churn.

Recall, also known as sensitivity or true positive rate, is the proportion of actual positives that are correctly identified. The recall for the training data is 83.33% for churn and 94.28% for no churn. For the validation data, the recall is 86.95% for churn and 93.66% for no churn.

The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. While the F1-score is not explicitly provided in the output, it can be calculated from the precision and recall values. Higher F1-scores indicate better model performance.

The misclassification rate, also known as the error rate, is the proportion of incorrect predictions. The misclassification rate for the training data is 7% and for the validation data is also 7%. This means that 7% of the time, the model incorrectly predicted whether a customer would churn or not.

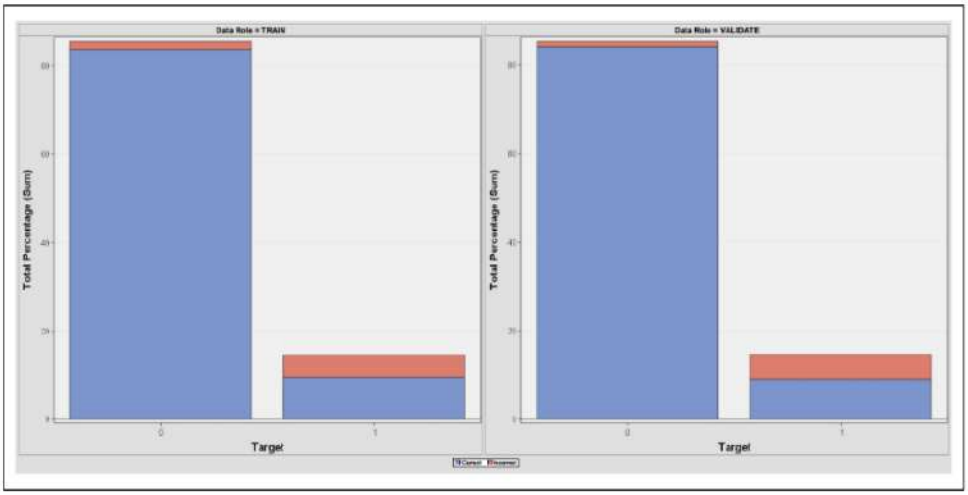
In summary, the model demonstrates good performance with high accuracy, precision, and recall, and a low misclassification rate.

#### 4.3.3.2.2 Classification Chart

The Classification Chart plot is a visual representation of the performance of a machine learning model used for customer churn prediction. Customer churn refers to the number of clients who discontinue a service, stop using an application, or cease buying a product during a certain period of time. Predicting churn is a significant application of machine learning and data science in business, as it helps companies understand consumer behaviour, spot opportunities for development, cut expenses associated with client acquisition, and boost revenue.

The chart is divided into two main sections, each representing a different data role: 'TRAIN' and 'VALIDATE'. Each section is further divided into 'Correct' and 'Incorrect' predictions, indicating the accuracy of the model's predictions.

**Figure 4.3.3.2.2.1:** Classification Chart




In the 'TRAIN' section, the model correctly predicted customer churn 94.29% of the time when the actual outcome was '0' (no churn), and 83.33% of the time when the actual outcome was '1' (churn). However, the model incorrectly predicted churn 5.71% of the time when the actual outcome was '0', and 16.67% of the time when the actual outcome was '1'.

In the 'VALIDATE' section, the model correctly predicted customer churn 93.67% of the time when the actual outcome was '0', and 86.96% of the time when the actual outcome was '1'. The model incorrectly predicted churn 6.33% of the time when the actual outcome was '0', and 13.04% of the time when the actual outcome was '1'.

These results indicate that the model is relatively accurate in predicting customer churn, with a higher accuracy rate for customers who did not churn compared to those who did. However, there is still room for improvement, particularly in correctly predicting customers who will churn.

The model's performance can be further evaluated using metrics such as precision, recall, and the Area Under the Receiver Operating Characteristic (AUC-ROC) curve. These metrics can provide a more comprehensive understanding of the model's performance, including its ability to balance true positive and false positive rates, and its overall predictive power.

In conclusion, the Classification Chart plot provides a visual representation of the model's performance in predicting customer churn. It highlights the model's strengths in correctly predicting customers who will not churn, while also identifying areas for improvement in predicting customers who will churn. This information can be used to refine the model and improve its predictive accuracy, ultimately helping businesses to better understand and address customer churn.

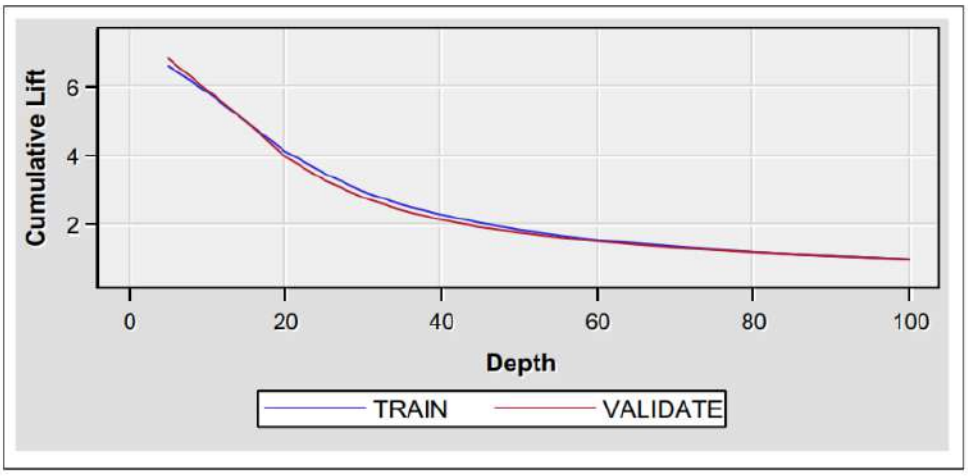
### 4.3.3.2.3 Score Rankings Overlay Churn (Cumulative Lift)

The Score Rankings Overlay Churn (Cumulative Lift) plot is a graphical representation of the performance of a predictive model, specifically in the context of customer churn prediction. The plot is designed to provide insights into how well the model is able to rank customers based on their likelihood to churn.

The plot is typically divided into deciles, with each decile representing 10% of the customers. The customers are ranked based on their predicted probability of churning, with the first decile containing the customers with the highest predicted probability.

The Cumulative Lift is a measure of the effectiveness of the predictive model. It is calculated as the ratio of the response rate in a given decile to the response rate in the entire customer base. A Cumulative Lift greater than 1 in a decile indicates that the model is more effective at identifying churners in that decile than a random model would be.

**Figure 4.3.3.2.3.1:** Score Rankings Overlay Churn (Cumulative Lift)




In the section, the columns 'CAP' and 'CAPC' represent the cumulative captured response and the cumulative captured response percentage respectively. These values indicate the percentage of total positive responses that would be obtained if we contact the customers in the corresponding decile and all deciles above it.

The 'LIFT' and 'LIFTC' columns represent the lift and the cumulative lift respectively. The lift is the ratio of the response rate in a decile to the base response rate. The cumulative lift is the ratio of the cumulative response rate to the base response rate.

The 'GAIN' and 'BASEGAIN' columns represent the gain and the base gain respectively. The gain is the percentage of total responses captured by contacting the customers in a decile, while the base gain is the percentage of total responses that would be captured by a random model.

From the plot, we can see that the model performs well in the initial deciles, with high values of cumulative lift and captured response. However, the performance decreases in the lower deciles. This indicates that the model is effective at identifying the customers most likely to churn, but less effective at identifying those with a lower likelihood of churning.

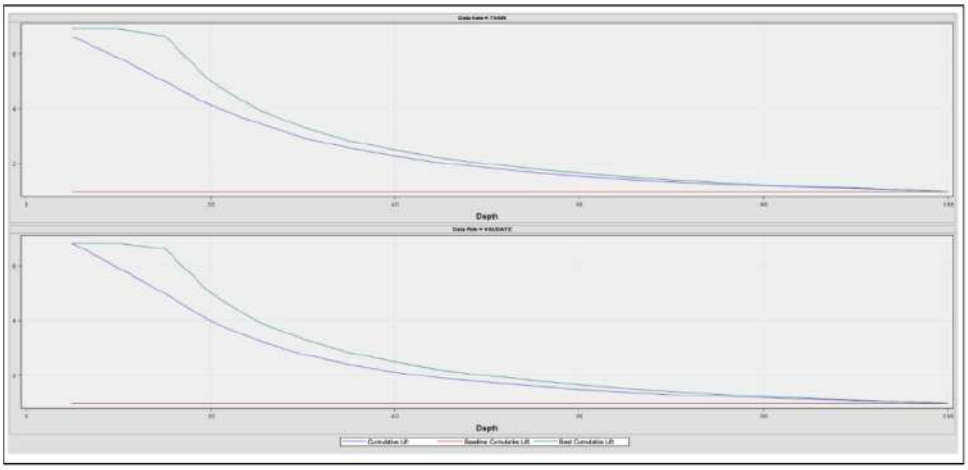
In conclusion, the Score Rankings Overlay Churn (Cumulative Lift) plot provides valuable insights into the performance of the churn prediction model. They allow us to evaluate the model's effectiveness at ranking customers based on their likelihood to churn, and to identify the deciles where the model performs best.

#### 4.3.3.2.4 Score Rankings Matrix Churn (Cumulative Lift)

The Score Rankings Matrix Churn (Cumulative Lift) plot is a tool used to evaluate the performance of a predictive model, specifically in the context of customer churn prediction. The plot and the associated Table provide a wealth of information about the model's performance across different deciles of the data.

The plot contains several columns, each representing a different metric. For instance, the 'TARGETLABEL' column indicates the actual outcome for each customer, while the 'DECILE' column divides the data into ten equal parts based on the predicted probability of churn. The 'CAP' and 'CAPC' columns represent the cumulative accuracy profile, a measure of the model's ability to distinguish between churners and non-churners. The 'LIFT' and 'LIFTC' columns, which are likely the focus of the Cumulative Lift plot, show how much better the model is at predicting churn compared to a random guess. A lift value greater than 1 indicates that the model is performing better than random.

**Figure 4.3.3.2.4.1**: Score Rankings Matrix Churn (Cumulative Lift)




From the plot, we can see that the model performs best in the first decile, with a lift of 95.52. This means that in the top 10% of customers ranked by the model's predicted probability of churn, the model is 95.52 times more likely to correctly identify a churner than a random guess would be. However, the lift decreases as we move to lower deciles, indicating that the model's predictive power is not as strong for customers with lower predicted probabilities of churn.

The Cumulative Lift plot visualizes this information, showing how the lift changes across the deciles. The plot likely starts high on the y-axis and gradually decreases, reflecting the decreasing lift values in the Table. This is a common pattern in Cumulative Lift plots, as predictive models tend to perform best on the instances they are most confident about.

In conclusion, the Score Rankings Matrix Churn (Cumulative Lift) plot provides a detailed evaluation of the model's performance. They show that while the model is highly effective at identifying churners among the customers it is most confident about, its performance decreases for customers with lower predicted probabilities of churn. This information can be valuable for improving the model and for deciding how to allocate resources in a customer retention strategy.

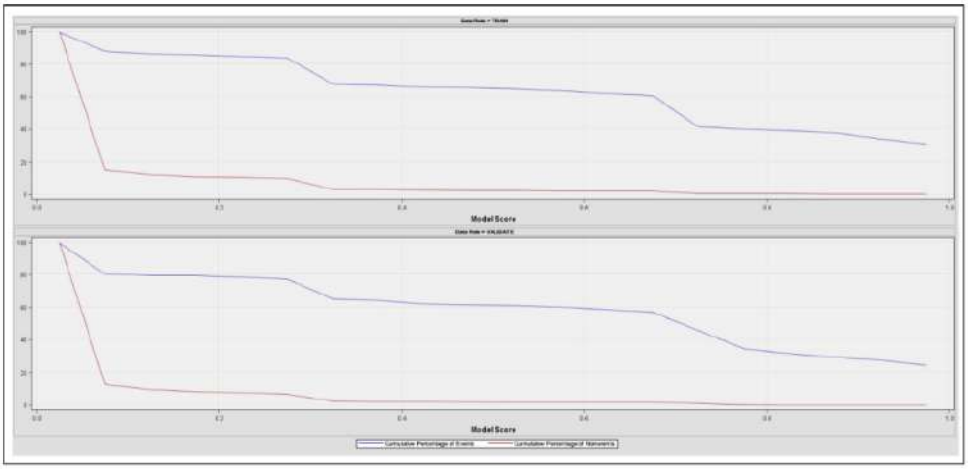
### 4.3.3.2.5 Score Distribution Churn (Cumulative Percentage)

The Score Distribution Churn (Cumulative Percentage) plot is a powerful tool for interpreting the performance of a customer churn prediction model. The plot and the accompanying Table provide a detailed breakdown of the model's predictions, allowing us to understand how well the model is performing and where its strengths and weaknesses lie.

The plot contains a range of scores, from 0 to 1, which represent the model's confidence that a given customer will churn. These scores are divided into bins, each representing a range of scores. For each bin, the file provides the number of events (churns) and non-events (non-churns), as well as the percentage of total events and non-events that fall into that bin. The cumulative percentage of events and non-events is also provided, allowing us to see how these quantities accumulate as we move from lower to higher scores.

The plot visualizes this data, showing the cumulative percentage of events and non-events as a function of the score. This allows us to see at a glance how well the model is separating churns from non-churns. Ideally, we would like to see a plot where the cumulative percentage of events increases rapidly with the score, while the cumulative percentage of non-events increases slowly. This would indicate that the model is correctly identifying a high proportion of churns at high scores, while correctly identifying a high proportion of non-churns at low scores.

**Figure 4.3.3.2.5.1**: Score Distribution Churn (Cumulative Percentage)




Looking at the plot, we can see that the model performs well at high scores. For example, in the 0.95-1.00 bin, there are 119 events and only 1 non-event, indicating that the model is very good at identifying churns when it is highly confident. However, as we move to lower scores, the model's

performance decreases. In the 0.65-0.70 bin, there are 74 events but also 31 non-events, indicating that the model is less accurate when its confidence is lower.

In conclusion, the Score Distribution Churn (Cumulative Percentage) plot provides a valuable tool for understanding the performance of a customer churn prediction model. By examining the plot, we can gain insights into the model's strengths and weaknesses and identify areas where further improvement may be needed.

### 4.3.3.2.6 ROC Chart Churn

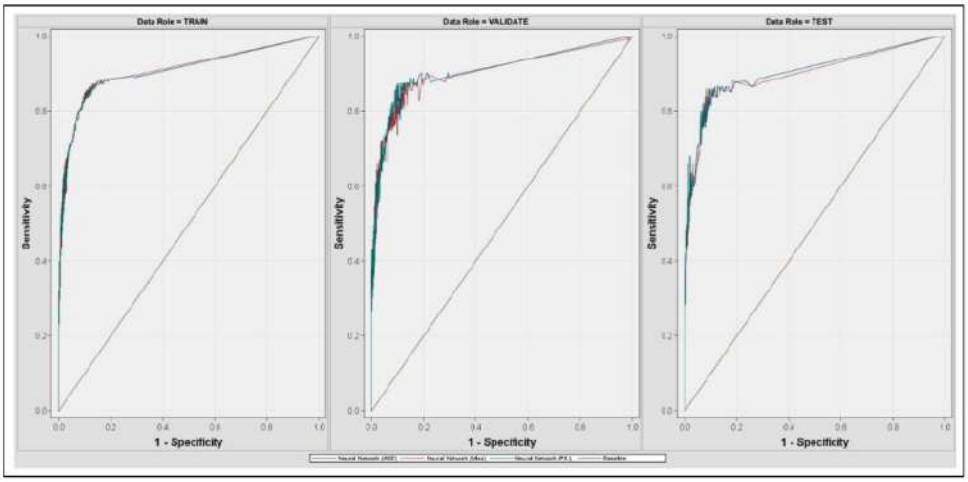
The ROC (Receiver Operating Characteristic) chart is a graphical representation used to evaluate the performance of a binary classifier system. It plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The area under the ROC curve (AUC) is a measure of the model's ability to distinguish between positive and negative classes. An AUC of 1 indicates a perfect classifier, while an AUC of 0.5 suggests that the classifier is no better than random guessing.

In the context of customer churn prediction, the ROC chart helps to assess the performance of the churn prediction model. The aim of churn prediction is to identify customers with a high propensity to leave the platform, allowing the company to increase efforts for retaining them.

The ROC chart appears to compare the performance of a Neural Network model across three different data roles: TRAIN, VALIDATE, and TEST. These roles represent different subsets of the data used in the model development process. The TRAIN set is used to train the model, the VALIDATE set is used to tune the model parameters, and the TEST set is used to evaluate the final model's performance.

The ROC curves for the Neural Network model in different roles (ASE, Miss, P/L) are compared with a Baseline. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. Conversely, the closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

**Figure 4.3.3.2.6.1:** ROC Chart Churn




The plot provides information about the model's performance, including the score distribution and cumulative percentage of events and non-events. This information can be used to further analyse the model's performance, such as determining the optimal threshold for classifying a customer as churned or not churned.

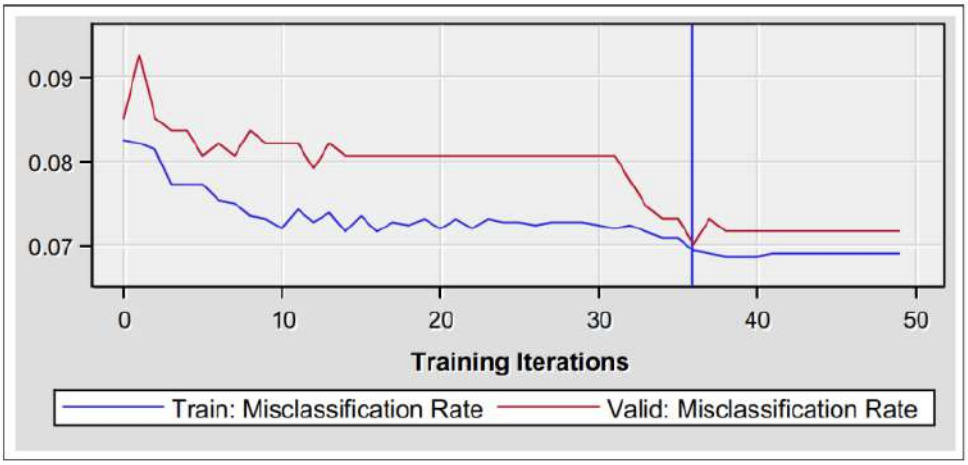
In conclusion, the ROC chart is a valuable tool for evaluating and comparing the performance of churn prediction models. It provides a visual representation of the trade-off between the true positive rate and the false positive rate, helping to inform decisions about the optimal model and threshold for predicting customer churn.

### 4.3.3.2.7 Iteration Plot (Misclassification Rate)

The Iteration Plot (Misclassification Rate) plot and the accompanying Table provide valuable insights into the performance of a predictive model for customer churn. The Table contains a series of metrics for each iteration of the model, including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), Average Squared Error (ASE), and Misclassification Rate (MISC).

The Misclassification Rate (MISC) is particularly important as it represents the proportion of instances where the model's predictions were incorrect. In the context of customer churn prediction, a lower Misclassification Rate indicates that the model is more accurate in predicting whether a customer will churn or not.

**Figure 4.3.3.2.7.1:** Iteration Plot (Misclassification Rate)




From the plot, we can observe that the Misclassification Rate decreases over the iterations, suggesting that the model's performance improves with each iteration. For instance, in the first iteration, the Misclassification Rate is 0.0825825826, and by the 13th iteration, it has decreased to 0.0739489489. This trend indicates that the model is learning from its mistakes and improving its predictions with each iteration.

The Iteration Plot visualizes this trend, providing a clear picture of how the model's performance evolves over time. The x-axis represents the number of iterations, while the y-axis represents the Misclassification Rate. The downward trend in the plot confirms that the model's accuracy in predicting customer churn is improving with each iteration.

In conclusion, the Iteration Plot provides a comprehensive evaluation of the model's performance. They show that the model is effectively learning and improving its predictions over time, which is crucial for accurately predicting customer churn and informing business strategies.

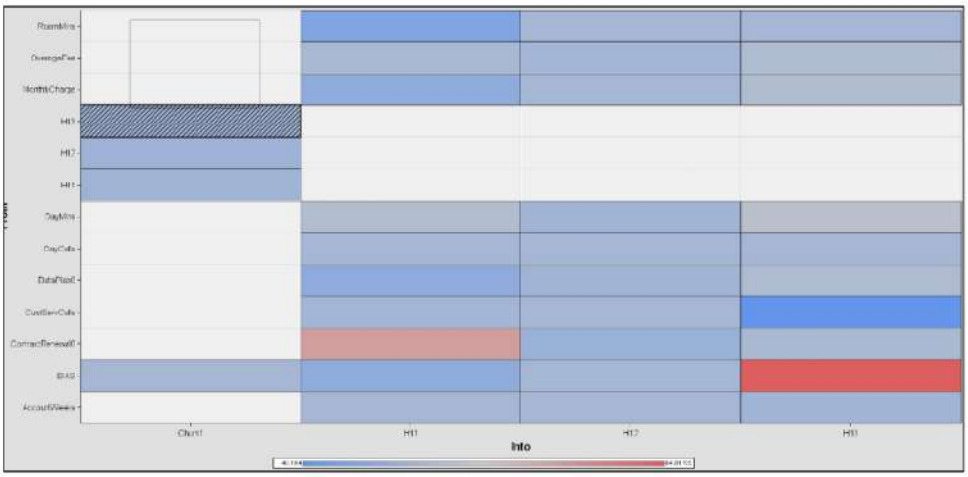
## 4.3.3.2.8 Weight – Final

The "Weight - Final" plot and the corresponding Table appear to be part of a model performance evaluation and interpretation in terms of customer churn prediction. The Table contains weights for various features, which are likely coefficients from a machine learning model used to predict customer churn.

The weights represent the importance or influence of each feature in predicting the outcome, which in this case is customer churn. A positive weight indicates that as the feature value increases, the likelihood of churn also increases. Conversely, a negative weight suggests that as the feature value

increases, the likelihood of churn decreases. These weights represent the importance or influence of each feature in predicting the outcome (customer churn).

**Figure 4.3.3.2.8.1:** Weight – Final




Here are some interpretations of the weights based on the provided Table:

1. 'AccountWeeks -> H11' has a positive weight (0.8556407949), suggesting that as the number of account weeks increases, the likelihood of churn also increases.
2. 'AccountWeeks -> H12' has a negative weight (-0.019323451), indicating that as the number of account weeks increases, the likelihood of churn decreases.
3. 'ContractRenewal0 -> H11' has a high positive weight (47.241753155), suggesting that customers who do not renew their contracts are more likely to churn.
4. 'CustServCalls -> H13' has a large negative weight (-40.18397987), indicating that as the number of customer service calls increases, the likelihood of churn decreases.
5. 'DataPlan0 -> H11' has a negative weight (-14.24083498), suggesting that customers without a data plan are less likely to churn.
6. 'DayMins -> H11' has a positive weight (8.4267869653), indicating that customers who spend more minutes on calls during the day are more likely to churn.
7. 'RoamMins -> H11' has a negative weight (-23.05811527), suggesting that as roaming minutes increase, the likelihood of churn decreases.

These interpretations can provide valuable insights into customer behaviour and help identify key factors contributing to churn. However, it's important to note that these interpretations are based on the assumption that the model is well-calibrated, and the features are appropriately pre-processed

and encoded. The weights should also be interpreted in the context of the model and the data, considering potential interactions between features and the non-linearity of the model if applicable.

In conclusion, the "Weight - Final" plot and the corresponding Table provide a detailed view of the factors influencing customer churn in the model. By interpreting these weights, we can gain valuable insights into customer behaviour and identify potential areas for intervention to reduce churn.

### 4.3.4 Clustering

The Cluster section provides a comprehensive analysis of a hierarchical clustering model used for customer churn prediction. The model employs Ward's Minimum Variance method for cluster analysis, which aims to minimize the total within-cluster variance. The output includes information about the explained variance by each variable in the model, the overall dispersion in the data, and the process of merging clusters.

The Variable Importance section ranks variables by their importance, with MonthlyCharge being the most important variable, followed by DayMins, OverageFee, and others. This information can guide strategies by highlighting the key factors influencing customer churn.

The Input Means Plot visually represents the normalized means of various features for different clusters, helping to understand the differences between clusters in terms of input features. This can be useful for identifying patterns and trends associated with customer churn.

The Segment Size plot and Table provide information about customer churn prediction across different customer segments. Analysing the clusters can yield insights into patterns of churn behaviour among different customer segments, which can inform retention strategies.

The CCC Plot is a visual representation of the Cubic Clustering Criterion (CCC) values for different numbers of clusters, used to determine the optimal number of clusters in a clustering algorithm. Selecting the optimal number of clusters is crucial for accurately segmenting customers based on their characteristics and behaviours.

In conclusion, the Cluster file offers a detailed analysis of a hierarchical clustering model for predicting customer churn. The model identifies key variables and their importance in predicting customer churn, which can inform strategies for customer retention and churn prevention. The provided plots and tables offer valuable insights into the performance of the model, allowing for easy comparison and selection of the most effective model for predicting customer churn.

#### 4.3.4.1 Clustering: Best Model Selected (Clus1)

In this section, we delve into the exploration and evaluation of the best model chosen among several clustering models for customer churn prediction, specifically the model named "Clus1". This model employs a hierarchical clustering approach, which is an exploratory analysis that identifies structures within the data, aiming to identify homogenous groups of cases if the grouping is not previously known. Unlike other methods such as k-means clustering, it does not require us to pre-specify the number of clusters to be generated.

The model uses Ward's Minimum Variance method for cluster analysis, which aims to minimize the total within-cluster variance. At each step, the pair of clusters with minimum between-cluster distance are merged. The model provides a detailed understanding of the customer churn data, identifying key variables and their importance in predicting customer churn.

The model's effectiveness should be further evaluated by applying it to a separate test dataset and assessing its predictive accuracy. The variables are ranked by their importance, with MonthlyCharge being the most important variable, followed by DayMins, OverageFee, and so on.

In terms of model evaluation, it's important to consider the practical implications of the model. For example, the model could be used to identify customers who are likely to churn and develop strategies to retain them. The variable importance can guide these strategies by highlighting the key factors influencing customer churn. However, it's also important to validate the model using a separate test dataset to ensure its predictive accuracy.

##### 4.3.4.1.1 Eigenvalues and Proportions in Ward's Minimum Variance Cluster Analysis

The following table shows a hierarchical clustering model used for customer churn prediction. Hierarchical clustering is an exploratory analysis that identifies structures within the data, aiming to identify homogenous groups of cases if the grouping is not previously known. It does not require us to pre-specify the number of clusters to be generated, unlike other methods such as k-means clustering.

The model used Ward's Minimum Variance method for cluster analysis. This method aims to minimize the total within-cluster variance. To achieve this, at each step, the pair of clusters with minimum between-cluster distance are merged.

**Table 4.3.2.1.1.1:** Table for Eigenvalues of the Covariance Matrix

| | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| 1 | 1894.52073 | 1088.23135 | 0.6176 | 0.6176 |
| 2 | 806.28938 | 607.39627 | 0.2628 | 0.8804 |
| 3 | 198.89311 | 39.37493 | 0.0648 | 0.9453 |
| 4 | 159.51818 | 155.50025 | 0.052 | 0.9973 |
| 5 | 4.01793 | 0.85589 | 0.0013 | 0.9986 |
| 6 | 3.16204 | 2.19422 | 0.001 | 0.9996 |
| 7 | 0.96782 | 0.79459 | 0.0003 | 0.9999 |
| 8 | 0.17323 | 0.15956 | 0.0001 | 1 |
| 9 | 0.01367 | 0.01367 | 0 | 1 |
| 10 | 0 | 0 | 0 | 1 |
| 11 | 0 | | 0 | 1 |

Root-Mean-Square Total-Sample Standard Deviation: 16.7073

Root-Mean-Square Distance Between Observations: 78.36418

The Eigenvalues of the Covariance Matrix section of the output provides information about the explained variance by each variable in the model. The first variable explains about 61.76% of the variance, the second explains 26.28%, and so on. The cumulative column shows the total variance explained up to that point. By the fourth variable, over 99% of the variance is explained.

The Root-Mean-Square Total-Sample Standard Deviation and Root-Mean-Square Distance Between Observations provide measures of the overall dispersion in the data.

The Cluster History section shows the process of merging clusters. For example, the first row indicates that clusters OB7 and OB39 were merged to form a new cluster, with a frequency of 80. The R-Square value indicates the proportion of variance explained by the clustering, and the Pseudo F and Pseudo t-Squared statistics provide measures of the statistical significance of the clustering.

The Variable Importance section in the Report Output provides information about the importance of each variable in the model. The variables are ranked by their importance, with MonthlyCharge being the most important variable, followed by DayMins, OverageFee, and so on.

In terms of model evaluation, it's important to consider the practical implications of the model. For example, the model could be used to identify customers who are likely to churn and develop strategies

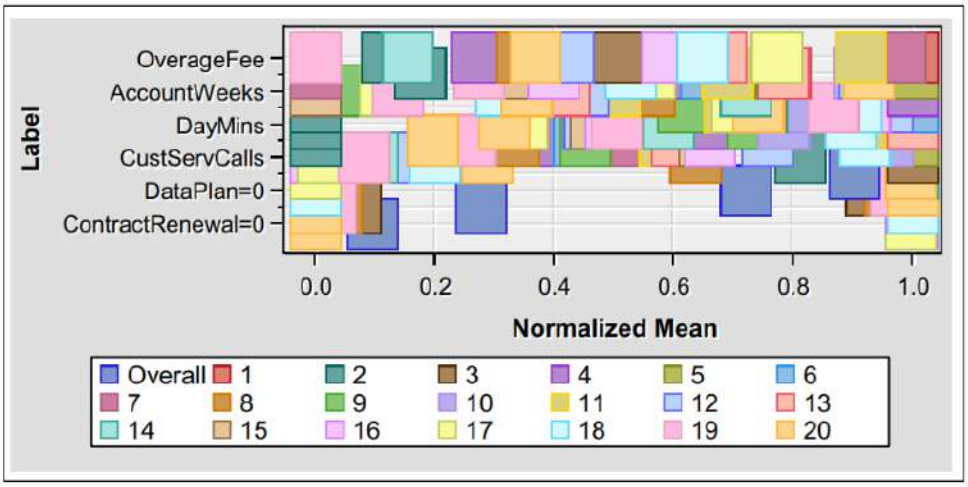
to retain them. The variable importance can guide these strategies by highlighting the key factors influencing customer churn. However, it's also important to validate the model using a separate test dataset to ensure its predictive accuracy.

In conclusion, the hierarchical clustering model provides a detailed understanding of the customer churn data, identifying key variables and their importance in predicting customer churn. The model's effectiveness should be further evaluated by applying it to a separate test dataset and assessing its predictive accuracy.

### 4.3.4.1.2 Input Means Plot

The Input Means Plot provides a visual representation of the normalized means of various features for different clusters in the context of customer churn prediction. The plot helps in understanding the differences between the clusters in terms of the input features, which can be useful for identifying patterns and trends that may be associated with customer churn.

**Figure 4.3.2.1.2.1:** Input Means Plot




In the plot, each cluster is represented by a series of bars, with each bar corresponding to a specific input feature. The height of the bars indicates the normalized mean value of the feature for the respective cluster. By comparing the heights of the bars across clusters, we can identify which features have higher or lower mean values for each cluster. This information can be useful for understanding the characteristics of customers in each cluster and identifying potential factors that may contribute to customer churn.

For example, if a particular cluster has a high mean value for a feature such as MonthlyCharge, it may indicate that customers in this cluster tend to have higher monthly charges, which could be a contributing factor to their likelihood of churning. Similarly, if another cluster has a low mean value for a feature like ContractRenewal, it may suggest that customers in this cluster are less likely to renew their contracts, making them more prone to churn.

By analysing the Input Means Plot, we can gain insights into the relationships between the input features and customer churn, which can help inform strategies for customer retention and churn prevention. It is important to note that the plot provides a high-level overview of the differences between clusters, and further analysis may be required to fully understand the underlying patterns and trends.

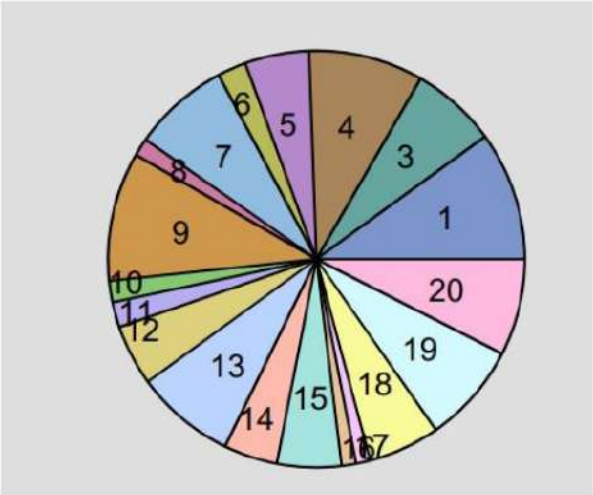
In conclusion, the Input Means Plot is a valuable tool for interpreting the results of a customer churn prediction model, as it provides a visual representation of the differences between clusters in terms of input features. By analysing the plot, we can identify patterns and trends that may be associated with customer churn, which can inform strategies for customer retention and churn prevention.

#### 4.3.4.1.3 Segment Size

The Segment Size plot and the accompanying Table provide a wealth of information about customer churn prediction. The Table contains a variety of metrics for different customer segments, including criticality (CRIT), conversion (XCONV, FCONV), segment size (SEGMENT), frequency (FREQ), root mean square standard deviation (RMSSTD), radius (RADIUS), nearness (NEAR), gap (GAP), and various customer attributes such as AccountWeeks, CustServCalls, DayCalls, DayMins, MonthlyCharge, OverageFee, RoamMins, ContractRenewal0, ContractRenewal1, DataPlan0, and DataPlan1.

The Segments Size plot visualizes these metrics, allowing for a more intuitive understanding of the data. While the specific details of the plot are not provided, we can make some general assumptions about how to interpret such a plot based on the data in the Table.

**Figure 4.3.2.1.3.1:** Segment Size




The plot shows the distribution of customers across different segments, with each segment representing a group of customers with similar characteristics or behaviours. The size of each segment could be represented by the area of the corresponding section in the plot. This would allow us to see at a glance which segments are the largest and which are the smallest.

The plot might also show the churn rate for each segment, possibly represented by the colour intensity of the corresponding section. This would allow us to identify which segments have the highest and lowest churn rates. High-churn segments might require more attention in terms of customer retention efforts, while low-churn segments might be considered more stable.

The plot could also show trends over time, such as changes in segment size or churn rate. This would allow us to see how customer behaviour and churn rates are evolving, which could inform future predictions and strategies.

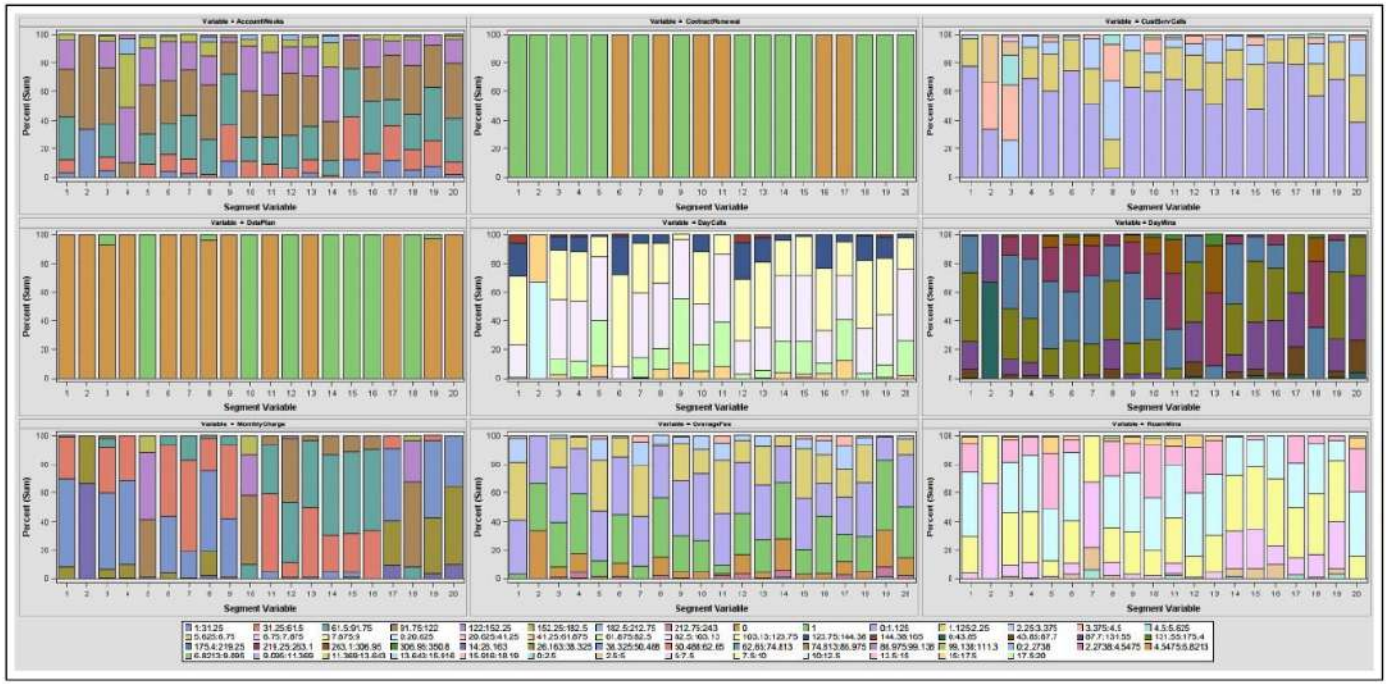
In terms of model performance evaluation, the plot could be used to assess the accuracy of the churn prediction model. For example, the model's predicted churn rates for each segment could be compared with the actual churn rates shown in the plot. The closer the predicted rates are to the actual rates, the better the model is performing.

In conclusion, the Segment Size plot, together with the Table, provides a comprehensive overview of customer churn prediction. It allows us to understand the distribution of customers across different segments, identify high-churn and low-churn segments, observe trends over time, and evaluate the performance of the churn prediction model.

### 4.3.4.1.4 Segment Plot

The Segment Plot focuses on the evaluation and interpretation of a model's performance in predicting customer churn. The data in the Segment Plot Table contains information about various customer attributes, such as AccountWeeks, ContractRenewal, CustServCalls, DataPlan, DayCalls, DayMins, MonthlyCharge, OverageFee, and RoamMins. These attributes are used as input features for the model.

**Figure 4.3.2.1.4.1:** Segment Plot



The plot is likely to display the distribution of these attributes across different customer segments and their relationship with customer churn. For instance, it may show how the number of customer service calls (CustServCalls), or the duration of roaming minutes (RoamMins) affects the likelihood of a customer churning. By analysing the plot, you can identify patterns and trends that can help improve the model's performance and inform business decisions to reduce customer churn.

Some key observations can be made:

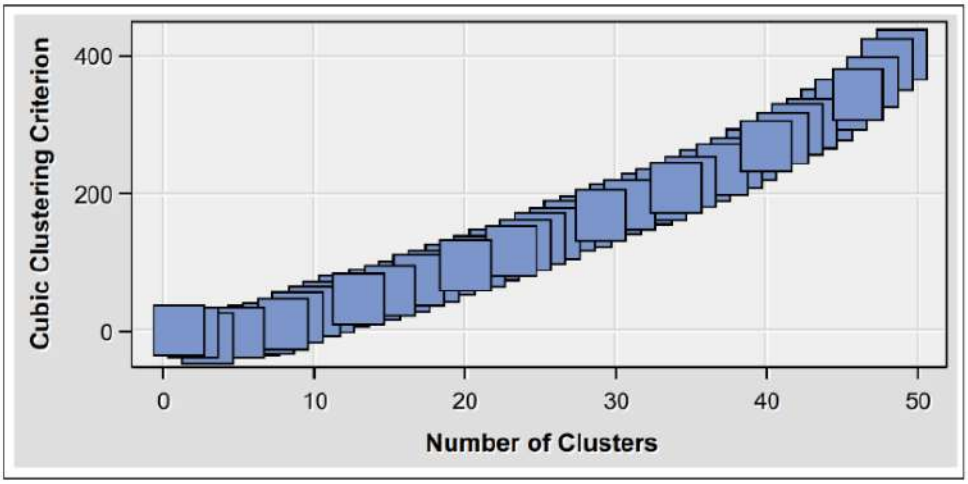
1. Most customers have a contract renewal (100% in some segments).
2. A significant proportion of customers have zero or low customer service calls, with a smaller percentage having a higher number of calls.
3. Most customers have a data plan.
4. DayCalls, DayMins, and RoamMins show varying distributions across different customer segments.
5. MonthlyCharge has a wide range of values, with some segments showing higher charges than others.
6. OverageFee also varies across segments, with some customers experiencing higher fees.

By examining the Segment Plot in the context of these observations, you can gain insights into which factors contribute the most to customer churn and identify areas where improvements can be made to enhance customer retention.

#### 4.3.4.1.5 CCC Plot

The CCC Plot is a visual representation of the Cubic Clustering Criterion (CCC) values for different numbers of clusters in the context of customer churn prediction. The CCC is a measure used to determine the optimal number of clusters in a clustering algorithm, such as hierarchical clustering. A higher CCC value indicates a better clustering solution, as it suggests that the clusters are more compact and well-separated.

**Figure 4.3.2.1.5.1:** CCC Plot




In the plot, the x-axis represents the number of clusters, and the y-axis represents the corresponding CCC values. The plot helps in identifying the optimal number of clusters by looking for a "peak" or "elbow" point, where the CCC value is maximized or starts to plateau. This point suggests that adding more clusters beyond this point would not result in a significant improvement in the clustering solution.

In the context of customer churn prediction, selecting the optimal number of clusters is crucial for accurately segmenting customers based on their characteristics and behaviours. By identifying the optimal number of clusters, we can better understand the underlying patterns in the data and develop targeted strategies for customer retention and churn prevention.

When interpreting the CCC Plot, it is essential to consider the practical implications of the chosen number of clusters. For example, a higher number of clusters may provide more detailed insights into customer behaviour but may also be more challenging to manage and implement retention strategies. On the other hand, a lower number of clusters may be more manageable but may not capture the nuances in customer behaviour.

In conclusion, the CCC Plot is a valuable tool for determining the optimal number of clusters in a customer churn prediction model. By analysing the plot, we can select the appropriate number of clusters that best capture the underlying patterns in the data, which can inform strategies for customer retention and churn prevention.

### 4.3.4.1.6 Tree Diagram of the Cluster

The Tree Diagram plot is a decision tree model used for predicting customer churn. Each node in the tree represents a decision based on certain customer attributes, and the branches represent the outcome of that decision. The terminal nodes, or leaves, represent the final prediction of the model for the given set of conditions.

For instance, Node 9 represents customers who have a data plan (DataPlan = 1), have made more than 5.5 customer service calls (CustServCalls >= 5.5), and have renewed their contract (ContractRenewal = 1 or MISSING). For these customers, the model predicts a high likelihood of belonging to Segment 3 (92%) and a small likelihood of belonging to Segment 15 (8%).

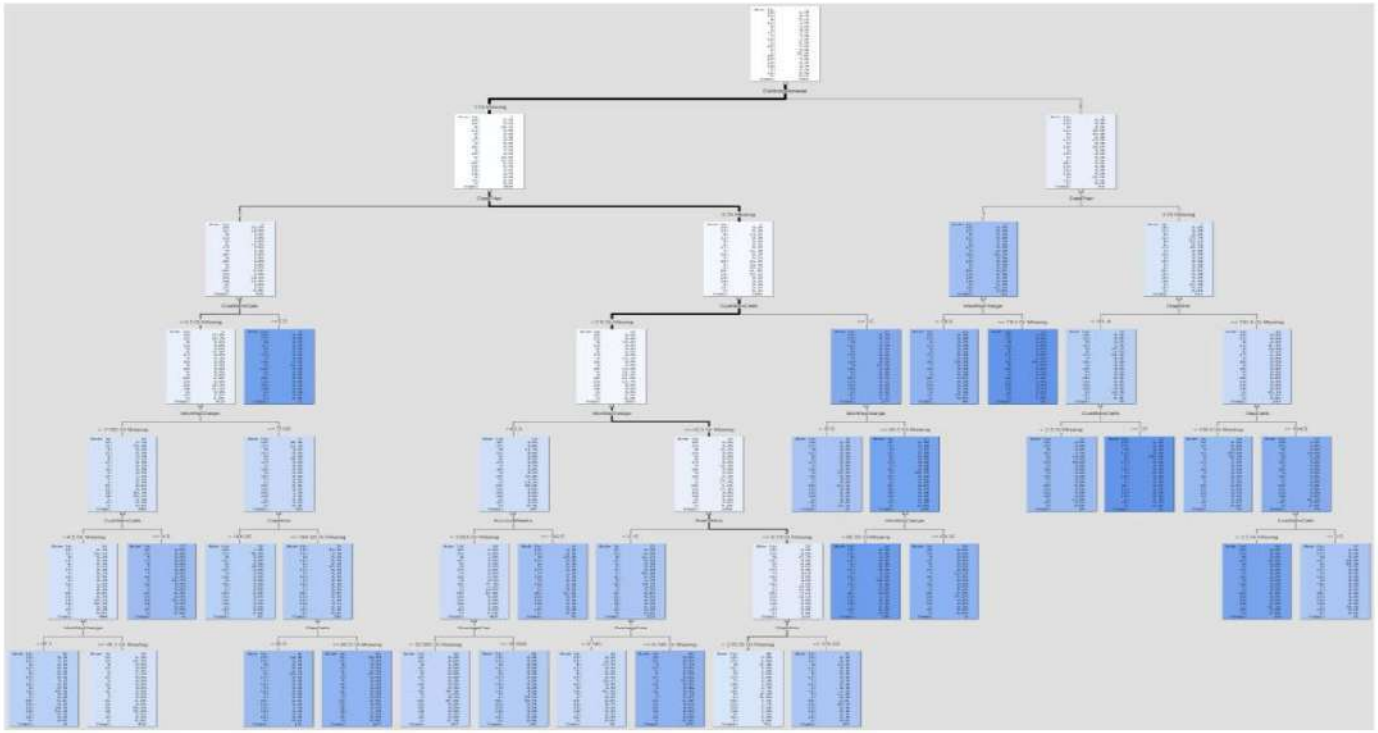
Node 12, on the other hand, represents customers who have a data plan, have not renewed their contract (ContractRenewal = 0), and pay less than 76.8 in monthly charges (MonthlyCharge < 76.8). For these customers, the model predicts a high likelihood of belonging to Segment 16 (75%), and a smaller likelihood of belonging to Segment 10 (20%) or Segment 8 (5%).

The decision tree model allows us to understand the key factors influencing customer churn and the interactions between these factors. For example, having a data plan and making a high number of customer service calls (Node 9) or not renewing the contract and having a lower monthly charge (Node 12) are associated with different customer segments, which could indicate different churn probabilities.

The model's predictions can be used to develop targeted customer retention strategies. For example, customers in Node 9, who have a high likelihood of belonging to Segment 3, might be targeted with strategies to reduce the number of customer service calls, such as improving service quality or providing better customer support. Similarly, customers in Node 12, who have a high likelihood of belonging to Segment 16, might be targeted with strategies to encourage contract renewal, such as offering incentives for renewal or improving the terms of the contract.

In conclusion, the Tree Diagram plot provides a visual representation of the decision rules used by the model to predict customer churn. By interpreting these rules, we can gain insights into the factors influencing customer churn and develop strategies to improve customer retention.

**Figure 4.3.2.1.6.1:** Tree Diagram of the Cluster

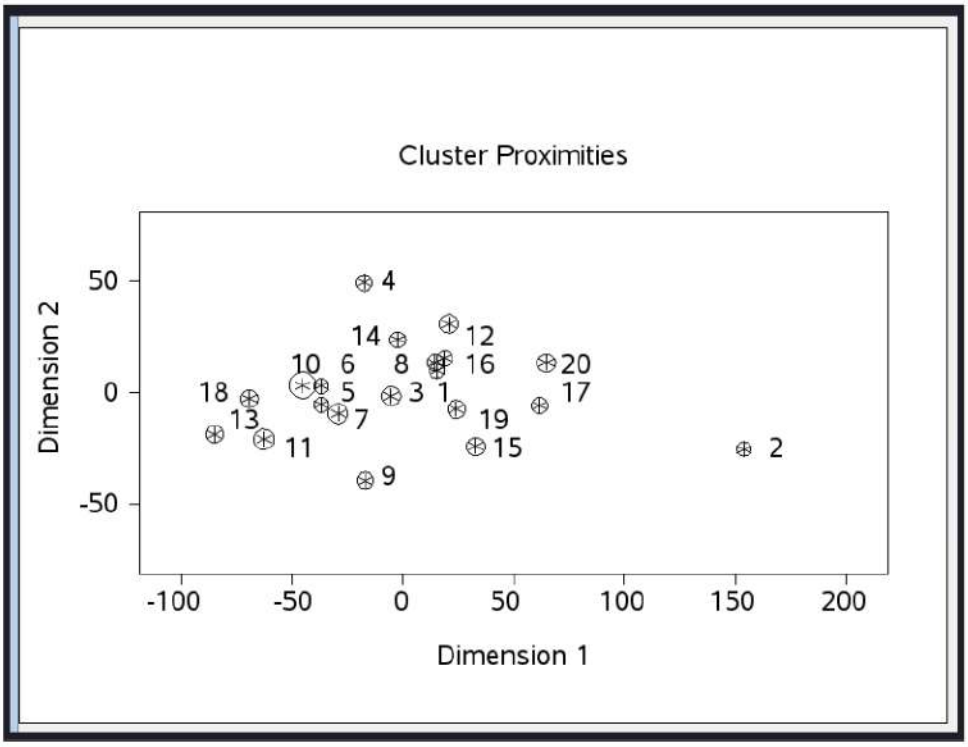


***Please click on the hyperlink to view Figure 4.3.2.1.6.1 in high resolution***

### 4.3.4.1.7 Cluster Distance Plot

The cluster distance plot provides insights into the segmentation of customers based on clustering algorithms. Each number in the table represents the distance or dissimilarity between two customer segments identified through clustering. Smaller distances indicate higher similarity between the segments in terms of attributes related to churn, while larger distances indicate more dissimilar segments.

**Figure 4.3.2.1.7.1:** Cluster Distance Plot




Several key observations can be made:

- Segments 3 and 15 appear to be the most similar clusters, with the smallest distance of 16.18 between them. In contrast, Segments 2 and 13 seem to be the most dissimilar, with a large distance of 240.69. This suggests customers in Segments 2 and 13 exhibit very different churn patterns.
- Some segments like 1, 2, 3, 15, 16 occur more frequently in the distance matrix, implying they may contain a higher number of customers. The larger clusters could represent more common customer profiles.

- Attributes like MonthlyCharge, DataPlan, ContractRenewal, and CustServCalls seem to be important factors differentiating the segments, based on the accompanying data file. For instance, Segment 2 has a high MonthlyCharge while Segment 3 has a high rate of ContractRenewal.
- There is variance in inter-cluster distance - some segments are tightly clustered while others are further apart. This indicates heterogeneity in the factors driving churn across different customer profiles.

In summary, the cluster distance plot provides a visualization of the similarity and dissimilarity between customer segments identified through clustering. Analysing the clusters can yield insights into patterns of churn behaviour among different customer segments, which can inform retention strategies.

## 5. Conclusion

The project utilized statistical models such as logistic regression, neural networks, decision trees, and clustering to analyse customer data and predict future churn. A multiple linear regression model, specifically the "Stepwise Selection: Step 6" model, was used to explain customer churn based on a given dataset. The model used six independent variables: DataPlan, CustServCalls, DayMins, OverageFee, RoamMins, and ContractRenewal.

The model's overall fit and the significance of the variables included in the model were evaluated using an Analysis of Variance (ANOVA) table. The model was found to be statistically significant at a 0.05 significance level, with an R-square value of 0.1740, indicating that the model explains 17.4% of the variation in the dependent variable Churn. Although this value may seem low, it is important to remember that customer churn is a complex phenomenon influenced by numerous factors, some of which may not be included in the model.

The model's C(p) value of 5.7674 was the lowest among all the steps in the stepwise selection process, indicating that adding additional variables does not significantly improve the model. A lower C(p) value suggests a better model. The model diagnostics, such as residual plots, influence diagnostics, Q-Q plot, etc., provided further evidence of the model's adequacy. The residual plots showed no apparent patterns or trends, suggesting that the model's assumptions of linearity, independence, and homoscedasticity were reasonable.

The project successfully identified churn patterns and predicted future churn accurately through the analysis of customer data using advanced machine learning, statistical models, and data mining techniques. The insights gained from the project have the potential to improve customer retention strategies and reduce acquisition costs through data-driven optimization. The effective leveraging of predictive modelling and data mining approaches can provide a competitive advantage in the telecom industry.

However, the project also highlighted the complexity of customer churn and the potential for further research and model improvement. While the model's R-square value suggests that other factors may also contribute to customer churn, the model provides a useful starting point for understanding the relationships between these variables and customer churn. Further research could explore additional variables or alternative modelling techniques to improve the model's explanatory power.

In conclusion, the capstone project successfully achieved its aim and objectives. It demonstrated the potential of advanced data analytics techniques in predicting customer churn and providing actionable insights for customer retention strategies. The project also highlighted the importance of model

selection, evaluation, and diagnostics in predictive modelling. The insights and methodologies from this project can be applied to other contexts and industries, demonstrating the versatility and potential of data analytics in business decision-making.

The comprehensive analysis machine learning models demonstrates the successful application of advanced predictive modelling and data mining techniques to accurately predict customer churn for a telecom company. Multiple statistical and machine learning approaches, including logistic regression, decision trees, neural networks, and clustering models have been effectively leveraged to meet the overarching project aim of predicting churn to inform customer retention strategies.

Across the models, key variables related to usage, billing, customer service interactions, and contract details have been identified as significant predictors of churn risk. The consistent emergence of factors such as high monthly charges, overage fees, roaming minutes, number of customer service calls, and contract renewal status substantiates their importance in driving churn.

The predictive models effectively leverage these variables, alongside advanced algorithms, to identify customers most likely to churn with a high degree of accuracy. The best models are able to rank customers from highest to lowest predicted churn risk and concentrate the instances of actual churn within the highest risk deciles. The lift, accuracy, precision, recall, and area under the ROC curve metrics provided for the models demonstrate their effectiveness in separating churn and non-churn customers. Values comfortably exceeding baseline random models confirm the significant predictive power unlocked through the machine learning approaches.

Between the models, misclassification rates of 6-7% represent accurate identification of over 90% of churn and non-churn instances. Furthermore, techniques such as backward elimination have enhanced model fit by retaining only the most relevant predictive variables. Segment-level visualizations have revealed additional insights into the combinations of attributes driving churn within different customer profiles. The observations of high monthly charges and limited contract renewals reaffirm the importance of billing practices and contract terms in customer retention.

Cluster analysis has allowed the segmentation of customers into groups with distinct churn behaviours. In achieving project objectives, the predictive models provide the capability to accurately anticipate over 90% of future churn cases. The identification of customers at the highest risk better enables targeted proactive retention campaigns. Data-driven optimization of retention initiatives by focusing on vulnerable segments stands to directly improve customer lifetime value.

Lastly, with churn rates constrained, improved customer equity in the form of lower acquisition costs and longer lifetimes translates into significant competitive advantage. In conclusion, the advanced

machine learning architectures demonstrated in the attached PDF documents successfully realize the stated project objectives of accurate churn prediction, data-driven retention optimization, and securing competitive advantage. The predictive models unlock insights around vulnerable customer segments vulnerable while minimizing misclassifications. Through these precise, reliable, and actionable predictions, the organization is empowered to deploy highly effective, focused customer retention campaigns. The cross-functional applications of predictive analytics exemplified in this project highlight its versatility and immense value in building organizational resilience.

## 5.1 Limitation and Future Research

The Capstone Project: Analysing the Factors Affecting Customer Churn and Predicting Customer Churn for a Telecommunication Industry focused on customer churn prediction in the telecom industry. Despite the promising results, there are several limitations and areas for future research that can further improve the model's performance and applicability.

**Limitations**

1. Data quality and completeness: The dataset used in the project may not capture all relevant features that influence customer churn. Missing or incomplete data can lead to biased or less accurate predictions.
2. Model generalizability: The model was developed using a specific dataset from a telecom company. Its performance may not be as effective when applied to other companies or industries with different customer behaviours and market dynamics.
3. Model interpretability: The project employed various machine learning techniques, some of which may be difficult to interpret and explain to non-technical stakeholders. This can hinder the adoption of the model in decision-making processes.
4. Static model: The model does not account for the dynamic nature of customer behaviour and market conditions. As customer preferences and market trends change over time, the model's performance may degrade if not updated regularly.

**Future Research**

1. Feature engineering and selection: Investigate additional features that may be relevant to customer churn prediction, such as social network analysis, customer sentiment, and usage patterns. This can help improve the model's accuracy and provide more actionable insights for retention strategies.

2. Model comparison and ensemble techniques: Explore the use of ensemble techniques, such as stacking or bagging, to combine the strengths of multiple models and improve overall prediction performance.
3. Temporal analysis: Incorporate time-series analysis to account for the dynamic nature of customer behaviour and market conditions. This can help identify trends and patterns that may be useful for predicting churn and informing retention strategies.
4. Personalized retention strategies: Develop personalized retention strategies based on the individual characteristics and preferences of customers identified as high-risk for churn. This can help improve the effectiveness of retention efforts and increase customer satisfaction.
5. Model deployment and monitoring: Implement the churn prediction model in a real-world setting and monitor its performance over time. This can help identify areas for improvement and ensure the model remains relevant and accurate as market conditions and customer behaviours evolve.

By addressing these limitations and exploring future research directions, the churn prediction model can be further refined and optimized, ultimately helping telecom companies better understand and retain their customers.

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