BA 723 – Business Analytics Capstone

Governance

Mitigating Customer Churn: Leveraging Historical Data Analysis and Predictive Modelling to Formulate Effective Customer Retention Strategies

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1. Validation, Monitoring and Governance

With companies largely utilizing predictive models to more accurately forecast their business performance, enhance their performance and eventually accelerate their profitability, governing predictive models becomes extremely vital (Collibra, 2017, para. 1). Model governance refers to the systematic approach of managing a machine learning model throughout its lifecycle and can be considered as the set of guidelines to ensure that machine learning models are developed, deployed and preserved effectively and ethically (MarkovML, 2024, para. 3). Deepchecks (2022) explains that organizations that utilize machine learning to scale the business need to develop a model governance strategy to safeguard against ethical, legal and regulatory risks. If a governance strategy is not incorporated, any company, such as Nova Apex Bank, may experience revenue losses, unfavorable compliance and reputation, and a lack of trust (para. 1).

As part of establishing the model governance structure (Figure 1), it is vital to look after the possession of a predictive model and pertinent regulations, the training data, validation and approval at every phase of development, and monitoring the model both before and after deployment (Deepchecks, 2022, para. 2).

Figure 1: Model Governance Lifespan (Deepchecks, 2022)

1.1. Variable-Level Monitoring

From the viewpoint of this project on using historical data analysis and predictive modeling to comprehend customer churn at Nova Apex Bank in its European operations, variable-level monitoring is the process of closely observing and analyzing independent variables of customer attributes (features) to ensure that they behave as anticipated over time. This process is vital because it maintains the accuracy and reliability of the best predictive model over time, in this case, the random forest model.

Feature	Importance (Gini Impurity)
Age	0.190698
NumOfProducts	0.164777
Balance	0.117053
EstimatedSalary	0.100888
CreditScore	0.094838
CategorizedAge_Late Career Adults	0.060458
IsActiveMember_Yes	0.059714
Tenure	0.054995
Geography_Germany	0.035899
CategorizedAge_Near-Retirement Adults	0.026268
Gender_Male	0.019433
HasCrCard_Yes	0.011651
CategorizedCreditScore_Good	0.010125
Geography_Spain	0.010078
CategorizedCreditScore_Fair	0.009665
CategorizedAge_Mid-Career Adults	0.009597
CategorizedCreditScore_Very Good	0.00806
CategorizedCreditScore_Poor	0.007543
CategorizedAge_Retired Adults	0.006026
CategorizedAge_Young Adults	0.002232

Based on the above table, it is essential to ensure that the importance, i.e., Gini Impurity, of each variable within the random forest model remains stable over time to maintain its predictive effectiveness. Any significant variation in the importance of critical variables, such as the top three features of age, number of products and balance in an account, may stipulate changes in customer behavior or shifts in the data that may necessitate model recalibration through retraining. Moreover, with the original dataset of customer information modified for easier comprehension, a simple way of comprehending change in customer behavior at Nova Apex Bank is to utilize the customer churn analysis dashboard, which provides valuable insights into how the historical data on customer behavior has evolved compared to another period (Figure 2, Figure 3, Figure 4).

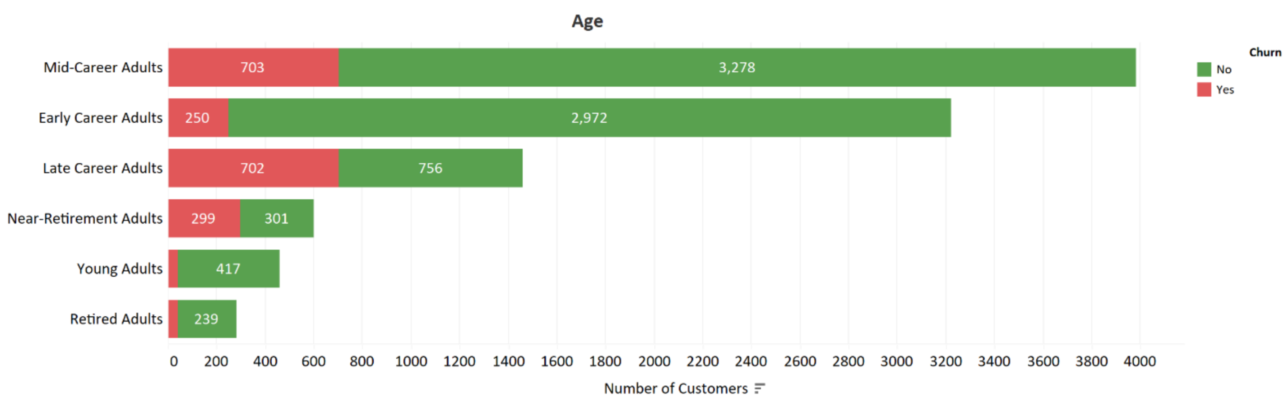

Figure 2: Age of Customers Categorized by Ranges

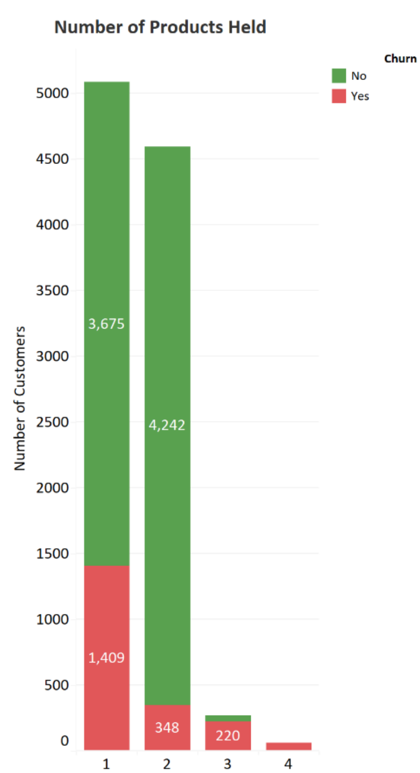

Figure 3: Number of Products Held by Customers

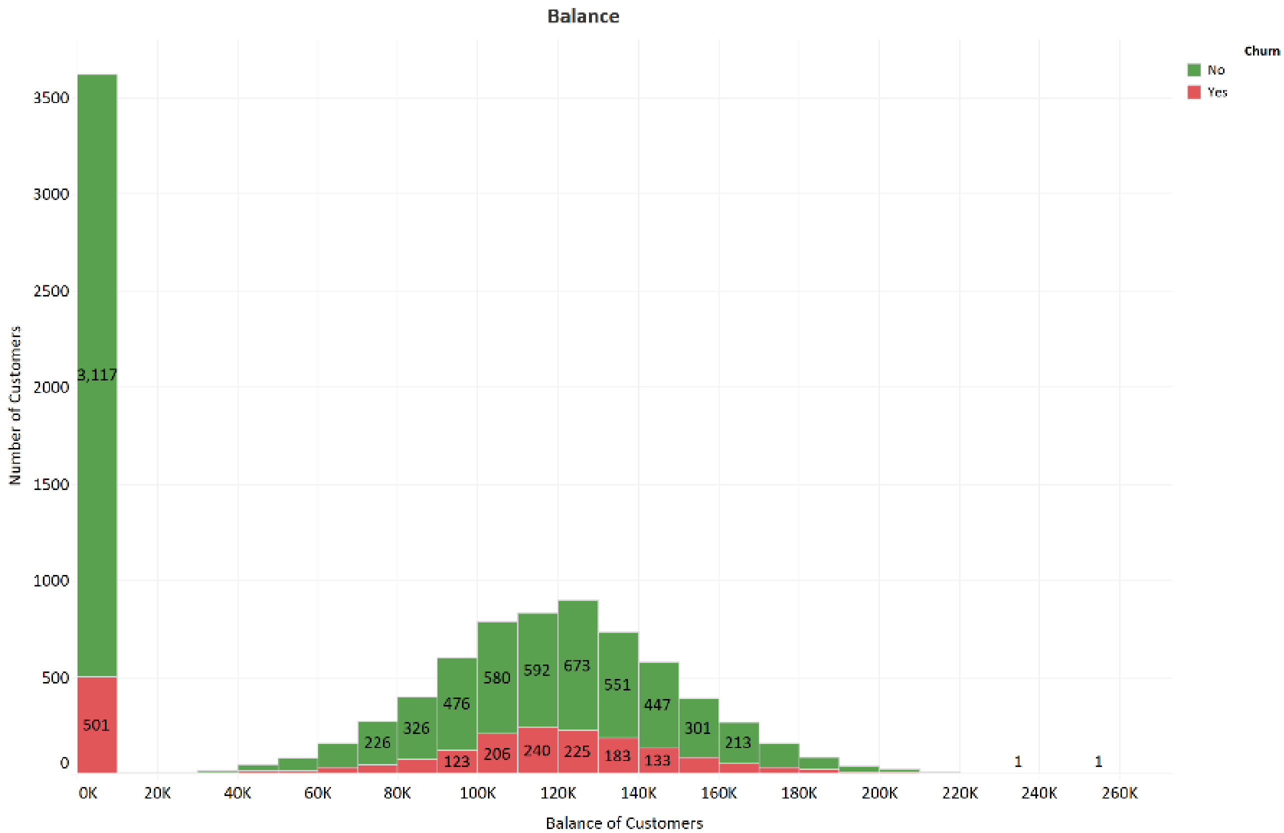

Figure 4: Balance of Customers in their Accounts

By tracking any notable changes in the attributes of customers at Nova Apex Bank (Figure 2, Figure 3, Figure 4) it may be assumed that such changes will also impact the random forest model's performance. In this way, the random forest model may be altered or retrained if the historical data suggests that the data distributions of customer behaviors have shifted.

1.2. Acceptable Ranges

To maintain the data integrity and consistency of predicting customer churn at Nova Apex Bank in its European operations, it is vital to establish acceptable ranges for each customer attribute in the company's historical customer data. By defining these limits, any anomalies that may impact the prediction power of the model can be controlled. Adhering to these ranges ensures a reliable analysis and enables any predictive model, such as the random forest model, to forecast customer churn effectively.

The table below highlights each variable of the historical customer data of Nova Apex Bank and their acceptable ranges before carrying out the feature engineering process, such as creating dummy variables and standardizing numerical features. Any value of variables that fall outside the expected ranges need to be addressed by the analytical team of Nova Apex Bank promptly, whether correction, adjustment or exclusion, to maintain the integrity of the analysis.

Variable	Acceptable Ranges	Action
Gender	• 'Female': Female customers • 'Male': Male customers	Customers whose gender is neither male nor female must be verified for accuracy.
Age	Customers aged between 18 and 92 years	Customers below 18 years or above 100 years must be verified for accuracy.
CategorizedAge	• 'Young Adults': Customers aged between 18 years and 24 years • 'Early Career Adults': Customers aged between 25 years and 34 years • 'Mid-Career Adults': Customers aged between 35 years and 44 years • 'Late Career Adults': Customers aged between 45 years and 54 years • 'Near-Retirement Adults': Customers aged between 55 years and 64 years • 'Retired Adults': Customers aged 65 years and above	Customers aged outside the defined range for each age category must be verified for accuracy.
Geography	• 'France': Customers are in France • 'Germany': Customers are in Germany • 'Spain': Customers are in Spain	Customers' geography outside the European countries of France, Germany and Spain must be verified for accuracy.

Variable	Acceptable Ranges	Action
Balance	Customers' bank balance between €0 and €250,898.09	Customers' bank balances of €0 may represent inactive or new accounts, while balances at the upper limit may stipulate high-net-worth customers.
EstimatedSalary	Customers' estimated salary between €11.58 and €199,992.48	Customers' estimated salary below €10.00 or above €250,000.00 should be reviewed for data entry errors or outlier scenarios.
CreditScore	Customers' credit score between 300 to 850 using a FICO score	Customers' FICO credit scores below 300 or above 850 must be verified for accuracy.
CategorizedCreditScore	• 'Poor': Customers' credit score below 580 • 'Fair': Customers' credit score between 580 and 669 • 'Good': Customers' credit score between 670 and 739 • 'Very Good': Customers' credit score between 740 and 799 • 'Exceptional': Customers' credit score above 800	Customers aged outside the defined range for each FICO credit score rating must be verified for accuracy.
NumOfProducts	• 1: Customers hold 1 product • 2: Customers hold 2 products	Customers holding more than 4 products must be verified for accuracy.

Variable	Acceptable Ranges	Action
	• 3: Customers hold 3 products • 4: Customers hold 4 products	
HasCrCard	• ‘No’: Customers do not hold a credit card • ‘Yes’: Customers hold a credit card	Customers should have this binary variable listed as 'No' or 'Yes ' only. Any other values are not valid and should be corrected.
Tenure	Customers’ tenure between 0 and 10 years	Customers’ tenure outside the possible range must be verified for accuracy.
IsActiveMember	• ‘No’: Customers are not an active member of Nova Apex Bank • ‘Yes’: Customers are an active member of Nova Apex Bank	Customers should have this binary variable listed as 'No' or 'Yes ' only. Any other values are not valid and should be corrected.
Exited	• ‘No’: Customers have not churned • ‘Yes’: Customers have churned	Customers should have this binary variable listed as 'No' or 'Yes ' only. Any other values are not valid and should be corrected.

1.3. Variable Drift Monitoring

Based on the numerous predictive models developed for predicting customer churn at Nova Apex Bank, variable drift monitoring is essential for preserving the accuracy and relevance of a predictive model for customer churn over time. Variable drift monitoring is concerned with monitoring any change in the distribution of key predictors; for instance, *Gender*, *CategorizedCreditScore*, *EstimatedSalary* and more variables. When customer behavior at Nova Apex Bank and market conditions evolve, the key predictor variables may shift, possibly decreasing any model’s predictive power if not properly tracked and modified.

Major changes that could affect the performance of a predictive model can be ascertained using the customer churn analysis dashboard to frequently compare new customer data with the previous customer data used for training the model. In this way, any model’s predictions would remain the same as the present business operations at Nova Apex Bank, prolonging its effectiveness in forecasting customer churn at the company.

1.3.1. Tolerance of Drift for Variables

For each predictive model, it is important to determine specific drift thresholds for key variables to maintain the models' accuracy. These thresholds specify how much a variable can be altered before it negatively affects the models’ prediction of customer churn at Nova Apex Bank. By monitoring these thresholds, each predictive model adapts to modifications in customer behavior and market conditions, preserving its predictions over time.

The following points describe the thresholds that have been stipulated for the variables representing key attributes of Nova Apex Bank customers that can be monitored using the customer churn analysis dashboard:

- **Age group of customers:** A change of more than 10% in the distribution of age categories, i.e., *CategorizedAge*, from young adults to retired adults, may represent a significant change in the customer demographics of Nova Apex Bank that must be evaluated.

- **Gender of customers:** A shift exceedingly more than 15% in the ratio of male to female individuals, i.e. *Gender*, could suggest a notable alteration in the customer gender composition, potentially indicating a large change in customer demographics of Nova Apex Bank that requires an investigation.

- **Balance of customers:** A spike of more than 10% in the balance of customers in their Nova Apex Bank account, i.e., *Balance*, could suggest a significant change in how customers are managing their finances, possibly reflecting broader changes in spending or saving habits.

- **Estimated Salary of Customers:** A fluctuation of over 5% in the estimated salary of Nova Apex Bank customers, i.e., *EstimatedSalary*, may hint at a substantial shift in their earning patterns, which could influence their financial decisions and behavior.

2. Model Health and Stability

Models represent a vital component of the decision-making process since they are the primary source of quantitative, predictive data and information within financial institutions. To ensure a robust decision-making process, any risks related to models need to be maintained effectively and continuously. When not done, financial institutions, including banking enterprises, may experience a variety of obstacles, both financial and other challenges (Hann & Ferreira, 2024, para. 1).

According to Crespo et al. (2017), many complex models are being developed that utilize advanced analytical techniques, including machine learning to attain higher performance standards. A generally larger banking organization is now expected to incorporate the models within its model risk management (MRM) framework to continue to rise significantly (para. 1).

The following points highlight how each aspect is critical in maintaining the effectiveness of model risk management within this project on understanding customer churn at Nova Apex Bank:

- **Evaluation Metrics:** A proper assessment of each predictive model by using the metrics of ROC-AUC, accuracy and F1-Score. By doing so, the predictive power and reliability of a predictive model are maintained, allowing Nova Apex Bank to make confident decisions concerning customer retention strategies.

- **Continuous Monitoring:** By regularly tracking the performance of a predictive model, any drift or degradation could be identified at the earliest. In this way, a predictive model remains accurate and stable over time, which supports Nova Apex Bank in maintaining customer churn predictions.

- **Feature Importance:** Understanding and regularly reviewing the importance of different features in a predictive model allows detection of key features influencing the likelihood of customer churn at Nova Apex Bank. In this way, the bank can prioritize these critical variables in its retention strategies, thereby mitigating the risk of relying on inaccurate or less relevant data that could lead to flawed predictions and decision-making.

2.1. Initial Fit Model Statistics

When appraising the best predictive model developed in this project out of logistic regression (full, forward, backward, stepwise), decision tree, and random forest, the evaluation metrics of ROC-AUC, accuracy, and F1-Score have been utilized to understand each model's fit and performance. In this regard, the random forest model has been chosen as the optimal predictive model due to its strong performance in each evaluation metric.

From the perspective of the ROC-AUC score, the random forest model has obtained a value of 0.86, implying that the model is 86% effective in distinguishing between customers who are likely to churn and those not likely to churn at Nova Apex Bank. Moreover, the random forest model has attained an accuracy score of 0.86; this means that the proportion of correct predictions (both churned and non-churned customers at Nova Apex Bank) stands at 86%. Lastly, the random forest has generated an F1-Score of 0.57, indicating that at a 57% value, the random forest is moderately effective in correctly detecting customers that are likely to churn at Nova Apex Bank.

2.2. Risk Tiering

Risk tiering is a method utilized by financial institutions like Nova Apex Bank to categorize and manage the risks associated with various predictive models, including those for forecasting customer churn. This process involves assigning a risk level to each model based on its complexity, the impact of its predictions, and the potential consequences of inaccuracies.

As previously described, the ROC-AUC score, accuracy score and F1-Score have been used as evaluation metrics for understanding the performance of each predictive model for predicting customer churn at Nova Apex Bank. If any evaluation metric has a 1% to 10% drift from the existing values, the analytical team of Nova Apex Bank needs to take action according to the risk tiering, enabling a predictive model to still be implemented to forecast customer churn at Nova Apex Bank.

The table below describes how models that forecast customer churn at Nova Apex Bank are categorized into different risk tiers:

Risk Tier	Drift	Action
Low Risk	1% to 3%	Minimal drift that is considered negligible with no significant impact on model performance. Routine monitoring is sufficient and no prompt action is required.
Moderate Risk	3% to 6%	Moderate drift that may start to impact model performance. This requires closer attention and more frequent validation to ensure the model continues to perform well. Adjustments, such as hyperparameter tuning, might be necessary if the drift persists.
High Risk	6% to 10%	Significant drift that likely affects model predictions and key decision-making processes. Immediate review and recalibration, for instance, retraining the updated customer data, are required to maintain accuracy and prevent further performance degradation.
Critical Risk	Above 10%	Severe drift with substantial impact on the model's effectiveness. This poses a critical risk to the Nova Apex Bank, requiring urgent and comprehensive action by potentially completely revamping or replacing the model to restore reliability and accuracy.

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