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# Introduction

The tendency of customers to switch to another competitor or stop using a service is the main and major challenge faced by businesses across the industries, including the banking sector.  
The ability to predict whether a customer will exit or not the bank can help banking institutions to take measures to retain them by reducing the costs of acquiring new clients and improving the customer service and satisfaction.

For this purpose, we have decided to work with a dataset called Bank Churners that was taken from Kaggle, which contains private and sensitive information about customers of an anonymous and unknown a bank and their transaction history. The dataset includes the behaviour of the clients in relation to bank transaction history, as well as, demographic features, such as age, gender, marital status, income level, education level and so on.

Our objective is to build a predictive machine learning model that can accurately classify customers either churn or not churn based on these features, among other techniques we will apply.

In summary, the idea of this project is to provide insights and recommendations to help the banks to reduce customer churn, increase customer retention, and improve their overall performance.

## 

## Dataset summary

This dataset contains more than 10,000 observations and 23 attributes, with the attrition column indication the Existing Costumers and Attrited Customers.  
Specifically, there are 8,500 customers who will stay while 1,627 customers have decided to leave the bank.

There are key features that are relevant to the problem of employee attrition:

Attrition\_Flag: Distinguishes between Existing Customers and Attrited Customers. This key feature will be the target variable for attrition prediction.  
  
Customer\_Age: Provides the age of the customer, offering insights into the age demographics of employees.

Dependent\_count: Represents the number of dependants the employee has. This information can be relevant to understand the family size of employees. For example, if an employee is married and has children, or other family members who rely on their income.

Education\_Level: Reflects the educational background of the employee, a factor linked to career decisions.

Marital\_Status: Highlights the marital status of the employee, a personal aspect that may impact attrition.

Income\_Category: Categorizes the income level of the employee, a crucial factor for bank institutions.

Months\_on\_book: Specifies the duration of the employee's association with the bank, contributing to attrition analysis.

# Business Description

Our project is focused on the banking industry, with the main goal of improving and retaining the customers to reduce churn rates. To achieve this objective, we will train, test, and develop Machine Learning models that predict whether a customer is likely to churn or not, based on his/her demographic features and transaction history.

## Hypothesis

As a starting point, we would like to investigate and analyse why the customers, who hold bank accounts, will churn or not from the banks based on his/her demographic features and transaction history. This will enable banking institutions to take proactive measures to retain their customers, improve customer satisfaction, and reduce the costs of new clients. By applying Machine Learning models on the Bank Churners dataset, we will try to accurately predict whether a customer will exit or not based on their banking data.

## General Goal

Our general goal is to develop a predictive Machine Learning model which can accurately classify customers as either churn or not based on their demographic features and transaction history. By achieving this goal, we aim to provide banking institutions with useful findings and recommendations to reduce customer churn rates and improve overall performance.

## Success Criteria/Indicators

The success of our project will be measured by the accuracy of our Machine Learning Models in predicting customer churn.  
We will use metrics such as accuracy, precision, recall and confusion matrix to evaluate the performance across the seven Machine Learning Models. Additionally, GridSearchCV will be applied to find the Hyperparameters and Cross Validation will ensure the authenticity of the modelling results.

# Technology Used

## Machine Learning algorithms

For our project we have implemented seven Machine Learning for classification models to experiment with multiple algorithms to find the most suitable and accurate model:

1. Decision Tree
2. Support Vector Machine
3. Logistic Regression
4. AdaBoost
5. Random Forest
6. Gaussian Naïve Bayes
7. KNeighbours

We will compare them and analyse the outcomes for all of them. Moreover, we used hyperparameters such as Kernel RBF and Linear applied to Support Vector Machine and applied cross-validation and confusion matrices to evaluate the performance of the models. Additionally, we have also performed the Hyperparameter Tuning applied for Random Forest model by specifying the number of folds for ‘k-fold’ and adjusting the parameters to plot the accuracies of ‘max\_depth’, then we used the classification report to assess the model’s performance.

## Libraries

Different libraries have been used for the purpose of performing the analysis of the dataset which is being implemented in Jupyter Notebook.

The following libraries are crucial for data analysis:

* Warnings will supress the errors that would normally be displayed.
* Scikit-learn for machine learning tasks.
* Seaborn and Matplotlib for visualizations.
* Pandas
* NumPy
* Encoders to encode categorical variables.
* data\_profiling which provides a way to quickly generates an overview of the dataset.
* Imbelear.over\_sampling.SMOTE for oversampling imbalanced datasets
* Missigno for analysing missing data.

## Business Understanding

Customer churn or attrition is a serious problem for banking industry and many other businesses such as telecommunications industry and hospital industry. Interestingly, according to Swetha Amaresan’s research (2021) on the matter has described that it costs more to acquire new customers than it does to retain existing customers. In fact, an increase in customer retention of just 5% can create at least a 25% increase in profit.

Understanding the reasons why customers churn is critical for businesses as it allows bank or financial institutions to take proactive measures to retain their customers.

With that being said, we will implement Machine Learning models to help the industry reduce customer churn, identify patterns, and predict which customer is likely to churn.

## Data understanding

In this stage, we will develop a deep understanding of the data we have using various techniques.

By Importing ProfileReport, it generates a detailed report that summarised the statistical measures and visualizations of the data and it allows a quick overview of the data we are dealing with.

Graphical user interface, application

Description automatically generated

After performing .head() and .tail() we can see that the dataset contains 23 columns and 10,127 observations (0 to 10,126). Moreover, it can be observed that all null values from the dataset are marked as ‘Unknown’, so we have decided to keep them for our future analysis.

A screenshot of a computer

Description automatically generatedA screenshot of a computer

Description automatically generated

Importing the library ‘Missigno’ it is more visual to analyse whether there are missing values or not. In this case, there are no missing or null values in the dataset.

A graph with text on it

Description automatically generated with medium confidence

## Data Preparation

*Distribution of the Categorical Variables:*

Analysing the distribution of categorical variables can help the company identify predominant categories, which can inform the management decisions related to marketing strategies and client segmentation.

A graph with blue bars

Description automatically generated  
A graph with blue bars

Description automatically generated

In this phase we need to prepare the data to perform a deep analysis through Exploratory Data Analysis (EDA).

It is clear that the number of Existing Customers is much higher than the number of Attrited Customers in the target variable, which means that we are dealing with class imbalance.

With that being said, Tara Boyle (2019) has stated that most machine learning algorithms work best when the number of samples in each class are about equal. This is because most algorithms are designed to maximize accuracy and reduce error.

We will address imbalanced data before applying our Machine Learning models chosen.

A screenshot of a graph

Description automatically generatedA pie chart with a number of customers

Description automatically generated

Even though there is not a significantly difference, it seems that older customers are more likely to churn from the bank.

A graph showing different colored squares

Description automatically generated

*Marital Status*

Given the Marital Status, the customers married, and single ones are the majority in this analysis. Therefore, we could recommend offering special promotions and incentives to these groups.

A graph of different colored squares

Description automatically generated with medium confidence

*Gender Distribution*

The gender distribution between males and females are quite similar For Existing Customers and those who have left the bank.

A graph of a bar chart

Description automatically generated with medium confidence

*Income level*

The majority of the customers have an income less than $40k thus, it is clear that customers who earn less are likely to qualify for basic credit card (Blue). But on the other hand, the more a customer earns, the more likely they are to qualify for premium credit cards with higher credit limits.



*Education Level*

Graduates and High School students are the main customers; therefore, it would be a good strategy to offer them special discounts or credit cards without interest to incentive them to keep operating with the bank in order to retain them.

A graph of a graph showing different levels of education

Description automatically generated with medium confidence

*Months on Book*

The bank is successfully retaining the majority of its customer over a period of 35 months, either for Existing Customers or for Churned Customers on their books. Thus, the bank may offer them competitive interest rates and fees to keep them for a longer period of time.

A comparison of a graph

Description automatically generated

*Comparing Gender Vs Income Level*

On one hand, it is clear that there is a gender gap between Males and Females, where there are approximately 700 males who earn +$120K, around 1500 males who earn between 80K – 120K and roughly 1400 males earning about 60K – 80K. On the other hand, the majority of females earn less than $40K.

A graph of different colored bars

Description automatically generated

*Services Customers use.*

The variable Total Relationship Count is related to the number of products held by the customers. The majority of the customers have three services with the bank, followed by the same number of customers between four and six services. Customers with a higher relationship count are more likely to stay, this is a positive indicator for the bank.

A graph of a bar graph

Description automatically generated

*Months Inactive*

Churned Customers and Existing Customers tend to have periods of longer inactivity, most of them lasting three months, suggesting that prolonged inactivity could be a good indicator of customer attrition.

A graph of a bar chart

Description automatically generated with medium confidence

*Credit Offered to Customers*

The majority of the customers either existing or churned have a credit limit ranging from $2000 to $4000.

A graph of credit limit

Description automatically generated

The scatterplot clearly shows that for Existing Customers, there are three distinct clusters when comparing the total transaction counts and total transaction amount. The largest cluster has total transaction amount between 2500 and 5000 and is the most densely populated. The second cluster has total transaction amount around 8000. The third indicates the highest transactions amount, with total counts between 100 and 200. Conversely, Churned Customers clearly indicate that there is one cluster that has total transaction amount around 3000 and total transaction counts between 40 and 50 suggesting that the bank activity of the customers who want to leave may not be enough to keep them engaged with the bank.

A close-up of a graph

Description automatically generated

*Customers are using a percentage of their credit limit.*

There are a significant number of customers who are using their credit limit raging from 0% to 5%, it suggests that customers are using a very small portion of their credit limit.

A graph of a graph

Description automatically generated with medium confidence

*Correlations among the Features*

Given the fact that the Attrited Customers are only 16% of the sample, from our point of view is a good practice to analyse the customers as a whole and not only the ones who have left the bank, as we believe the customers who remain in the bank are likely to churn in the future as well. Therefore, we have decided to perform a correlated heatmap to analyse the features accurately and identify potential patterns or trends in the data.

The correlated heatmap depicts features high positive correlated (when two variables tend to increase or decrease together) between total ‘Customer\_ Age’ and ‘months\_on\_book’. This suggests that as a customer’s age increases, the number of months in the bank also tends to increase. Other features to be analysed are ‘Total\_Trans\_Amt and ‘Total\_Trans\_Ct. as this suggests that as the number of transactions a customer makes increases, the total transaction amount also tends to increase.

On the other hand, there are features negatively correlated (when one variable increases the other decreases). By analysing these correlations among ‘Avg\_Utilization\_Ratio’, ‘Avg\_Open\_To\_Buy’ and ‘Credit\_Limit’ indicate that as the ‘Avg\_Utilization\_Ratio’ increases, both ‘Avg\_Open\_To\_Buy’ and ‘Credit\_Limit’ decrease. In other words, customers who use their credit regularly usually tend to have lower credit limits.

A graph with red and blue squares

Description automatically generated

*Visualisation of the Positive correlations*

A close-up of a map

Description automatically generated

*Visualisation of the Negative correlation*

A graph showing the amount of attrition

Description automatically generated

# Introduction to Machine Learning Models

The initial question we need to address is how we can improve, reduce errors, and avoid bias when applying Machine Learning Model?

There are steps that we have implemented to improve the accuracy of our models:

1. Encoding Categorical variables into numerical variables.

We have selected the categorical features to transform them into numerical variables using the Label Encoder. Specifically, we have inverted the Labels for the ‘Attrition Flag’ feature to make it readable. 0 for Existing customers and 1 for Churned Customers

1. Data normalization.

As we do not have negative values in our dataset, we rescaled the continuous variables applying MinMaxScaler in our data to a range between 0 and 1. Particularly, this method is useful to see all the variables from the same lens (same scale), in this way we will bring all values into the range [0,1].

When we Encode Categorical Data, we turned string variables into numerical variables, when we did that, we do not have to scale or normalized that data, it is not recommended to normalize or scale them because they are no longer continuous variables.

1. We need to separate and define the dataset into X (input features) and y (target variable) and then split the data into independent and dependent variable.

The main variable for predicting a customer churned or not is the target variable (dependant variable) ‘Attrition\_Flag’, which is a binary classification. Then the model evaluates ‘y’ depending on the banking data from the customers, such as age, marital status, income, education level and bank transaction history.

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