Abstract

Credit card churn is a significant problem for banks and financial institutions, as it leads to a loss of customers and revenue. Accurate prediction of credit card churn is crucial for retaining customers and taking appropriate actions to prevent it. In this paper, we propose a Gradient Boosting Machines (GBM) approach to predict credit card churn. We compare the performance of the GBM algorithm with other popular machine learning algorithms and demonstrate the effectiveness of our approach in predicting churn. The results show that the GBM model outperforms other methods, achieving high accuracy, precision, recall, and F1 score.

Introduction

Credit card churn refers to the phenomenon where customers stop using a credit card issued by a financial institution. This can be due to various reasons, such as dissatisfaction with the services provided, better offers from competitors, or changes in personal financial circumstances. Churn prediction is essential for banks and financial institutions, as it can help them identify customers who are at risk of leaving and take appropriate actions to retain them.Machine learning techniques have been widely used to predict credit card churn. Among these techniques, Gradient Boosting Machines (GBM) is a powerful ensemble learning method that has been successfully applied to various classification and regression tasks. In this paper, we propose a GBM-based approach to predict credit card churn. We compare the performance of the GBM model with other popular machine learning algorithms and demonstrate the effectiveness of our approach in predicting churn.

Literature Review

Credit card churn prediction has been widely studied in the literature. Various machine learning algorithms have been proposed to address this problem, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, and Neural Networks. These methods have achieved varying degrees of success in predicting churn, with some studies reporting accuracies as high as 90% .Gradient Boosting Machines (GBM) is a powerful ensemble learning method that has been successfully applied to various classification and regression tasks. In the context of credit card churn prediction, some studies have demonstrated the effectiveness of GBM in achieving high accuracy and precisionHowever, the performance of GBM has not been extensively compared with other popular machine learning algorithms in the literature.In this paper, we aim to fill this gap by proposing a GBM-based approach for credit card churn prediction and comparing its performance with other popular machine learning algorithms.

Data Preparation

The dataset used in this study was obtained from a website with the URL as https://leaps.analyttica.com/home. The dataset contains anonymized information of over 10,000 customers, including features such as age, salary, marital status, credit card limit, credit card category, and other relevant variables. In total, the dataset includes nearly 18 features. The dataset was selected for its suitability to address the research questions and objectives of this study. The website provides access to a wide range of datasets for research purposes, and the dataset was downloaded and processed in accordance with the website's usage policies and guidelines.

Exploratory Data Analysis (EDA

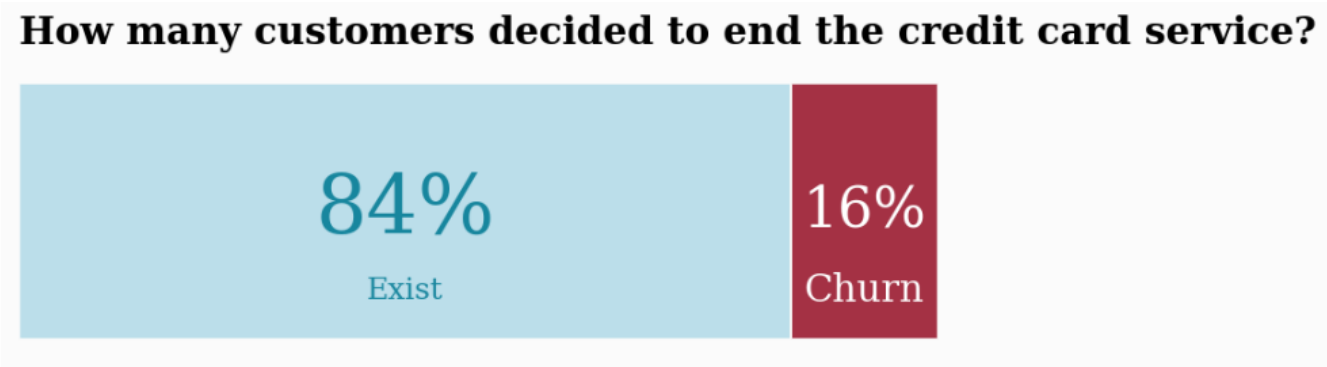
Exploratory Data Analysis (EDA) is a fundamental step in the data science process that involves exploring and analyzing the data to gain insights into the patterns, trends, and relationships in the data. EDA is critical to understanding the data distribution, identifying missing values, outliers, and other data quality issues that may affect the accuracy of predictive models. Moreover, EDA can identify relationships and correlations between variables, which can be used to build more accurate predictive models. By conducting EDA, data scientists can gain a better understanding of the data and improve the quality of their predictive models. Therefore, EDA is an essential component of credit card churn prediction and other data science projects.

Data Visualizattion

Prior to developing machine learning (ML) models, it is essential to conduct a thorough exploratory data analysis (EDA) to gain insights into the data and identify potential predictors. This section presents the key findings from the EDA, including an analysis of the data distribution, missing values, outliers, and correlations between variables. The EDA also investigates the demographic characteristics of customers who are likely to churn, such as age, gender, income, marital status, education level, and credit card category. By presenting these findings, this research aims to provide a comprehensive understanding of the data and inform the development of accurate and reliable ML models for credit card churn prediction.

How many customers are likely to churn a credit card service?

This was a very important question to ask because it helps to understand the scope and potential impact of the problem. Knowing the number of customers who are likely to churn can help to assess the potential financial loss and take proactive measures to retain customers.

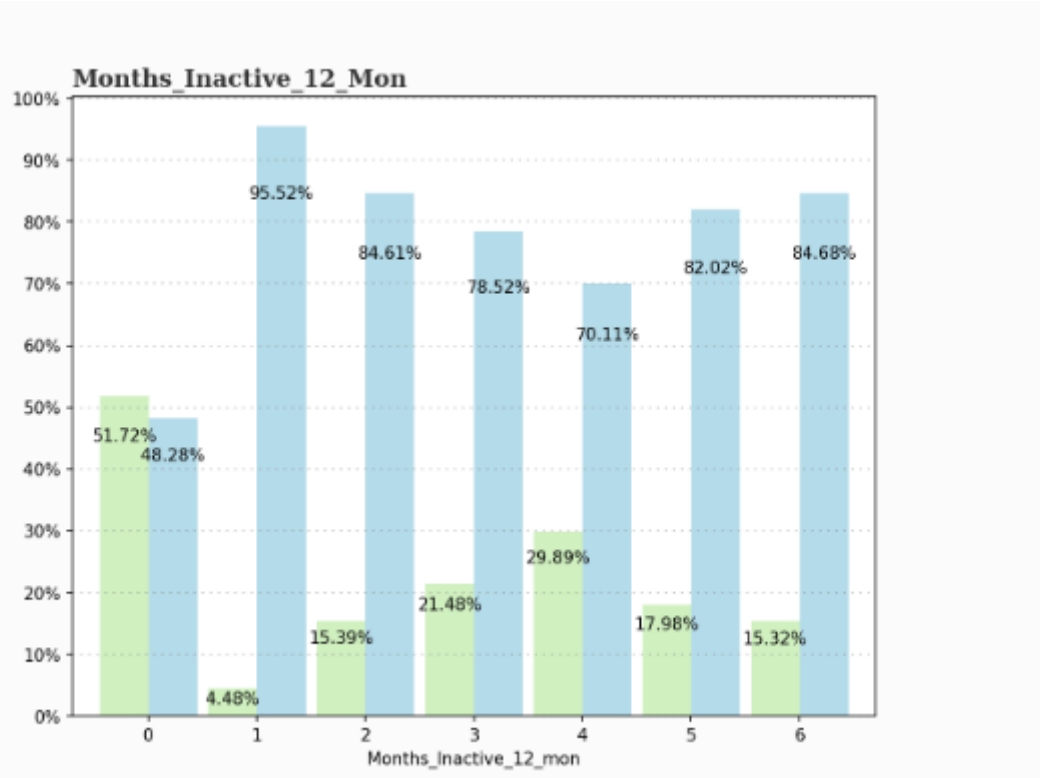


After conducting exploratory data analysis (EDA), it was found that 16% of customers in the dataset decided to churn the credit card service, while 84% remained as existing customers. This indicates that the dataset is imbalanced, with a significantly lower proportion of churn instances compared to existing instances.

Imbalanced datasets can pose challenges for machine learning (ML) models, as most algorithms assume a balanced dataset. Therefore, it is essential to deal with imbalanced data carefully when building ML models. In this study, over-sampling methods (such as ADASYN, SMOTE, etc.) were used to address the imbalanced data. These methods increase the number of instances in the minority class (churn instances) by generating synthetic samples based on existing data. By using over-sampling methods, we aimed to balance the dataset and improve the performance of our ML models.

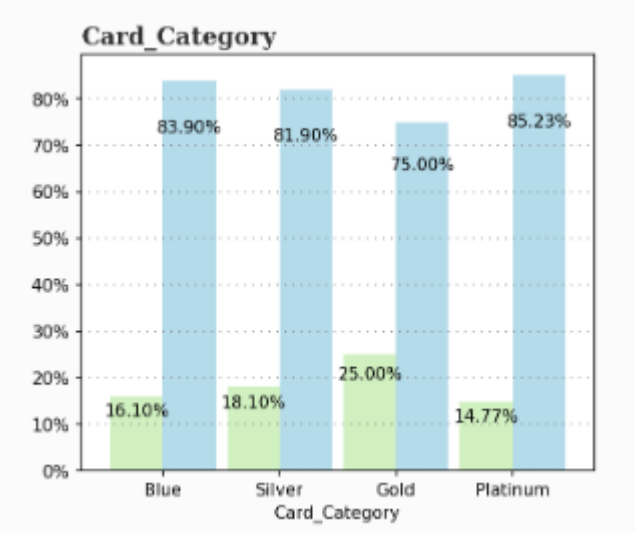
Were there difference between the Churn and Exist groups?

This was a very important question to ask during EDA: whether there are any significant differences between the characteristics of the existing and churn groups on each variable or not. This analysis provided insights into the factors that contributed to churn and inform the development of predictive models.To explore the differences between the two groups, various visualizations and statistical tests can be used. For example, a box plot can be used to compare the distribution of each variable between the two groups, and a t-test or ANOVA can be used to test for significant differences. In this study, histograms were created to analyze the differences between the two groups on numerical variables. In the histograms, red (or green in bar charts) represents the churn group, while blue represents the existing group. The histograms revealed significant differences between the two groups on variables such as age, income,customer activity, and credit limit. For example,it was observed that the majority of customers in the churn group were actively using their credit cards. However, the second highest number of inactive months for churn customers was observed to be around 4 months. In contrast, for retained customers, a large number of customers were observed to be less likely to actively use their credit cards.



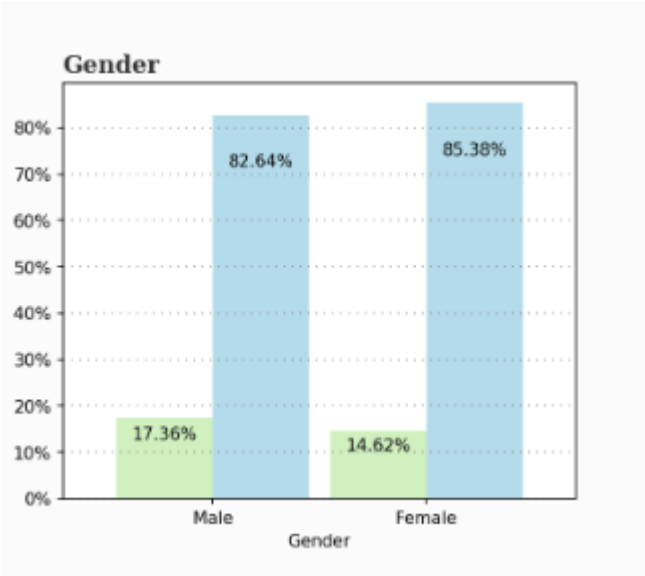
This observation suggests that customer activity may be an important predictor of churn and should be considered when developing predictive models. Furthermore, it highlights the importance of tracking customer activity over time to identify potential churn risks and take proactive measures to retain customers.

It was observed that the majority of retained customers were using blue, silver, and platinum credit cards. In contrast, churn customers were observed to have gold credit cards the most.

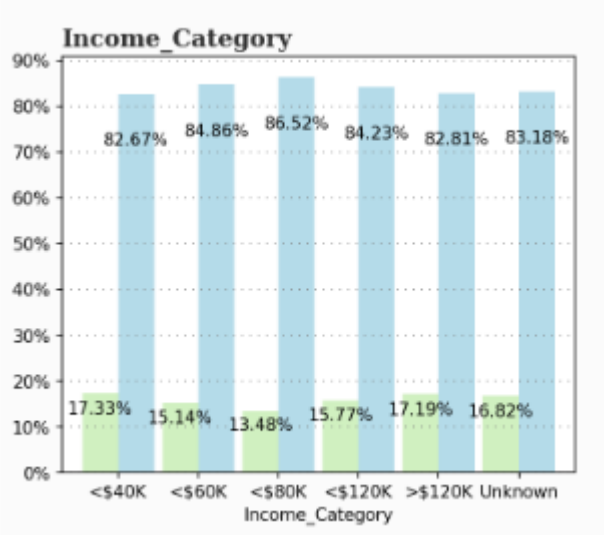


This observation suggests that the type of credit card may be an important factor in predicting churn and should be considered when developing predictive models. Credit card companies may need to assess the benefits and features of each type of credit card and tailor their retention strategies accordingly. For example, they could offer targeted promotions or rewards for customers with gold credit cards to encourage them to continue using the service.

In addition to that it was observed that the majority of churning customers were male



This observation suggests that gender may be an important factor in predicting churn and should be considered when developing predictive models. However, it is important to note that this gender imbalance may also be due to differences in credit card usage patterns, marketing strategies that are not effectively targeting male customers, or external factors such as economic or social conditions. It was also observed that the majority of churning customers had an income of less than $40,000 per year.



This observation suggests that income may be an important factor in predicting churn and should be considered when developing predictive models. To better understand the underlying reasons for this income imbalance, a further analysis to identify potential causes and develop targeted retention strategies for low-income customers must be carried out. Some potential causes of this income imbalance may include differences in credit card usage patterns, marketing strategies that are not effectively targeting low-income customers, or external factors such as economic or social conditions.

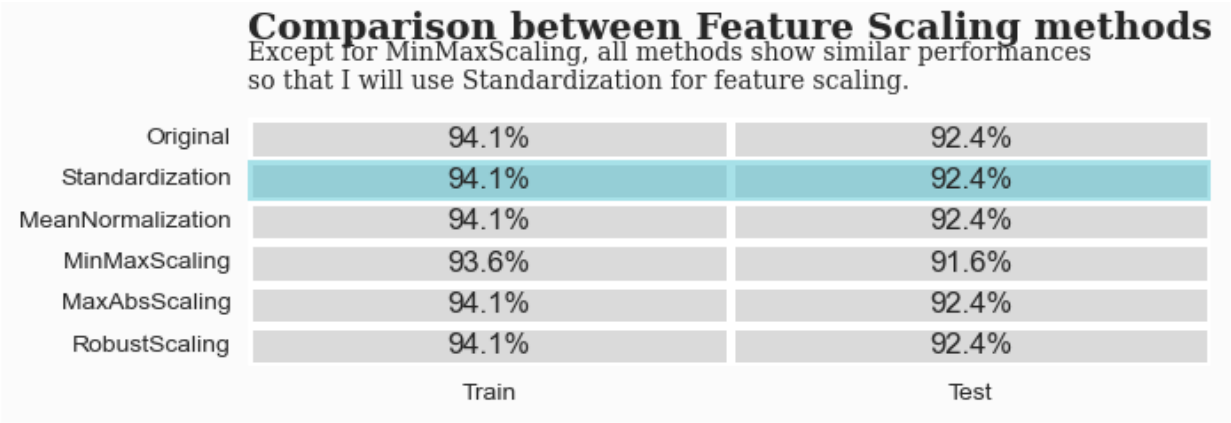
In this section , we conducted a thorough data cleaning, exploratory data analysis (EDA), and visualization of a credit card churn prediction dataset. Our classification problem involved a binary target variable, and we explored the relationships between the target variable and various features. Additionally, we investigated whether the churn group differs from the existing group based on these features. Our dataset did not contain any missing observations, which eliminated the need to handle missing values during our analysis. However, we observed an imbalanced distribution in our target variable. This imbalance may affect the performance of our models, and we recommend using sample balancing methods to address this issue when building models. By using these methods, we aim to improve the accuracy and reliability of our models and develop effective retention strategies for credit card companies. Overall, our data cleaning, EDA, and visualization efforts provided valuable insights into the underlying data and helped us identify potential challenges and areas for improvement when building predictive models for credit card churn prediction.

Feature engineering

Feature engineering is the process of creating new features from the existing data that can help improve the performance of machine learning algorithms. It is a critical step in the machine learning pipeline that can significantly impact the accuracy and robustness of the models.The goal of feature engineering is to transform the raw data into a set of meaningful and informative features that can capture the underlying patterns and relationships in the data. By creating new features, we can provide more information to the machine learning algorithms, which can lead to better predictions and insights.Feature engineering involves a combination of domain knowledge, data analysis, and creativity. It requires a deep understanding of the problem domain and the data at hand to create features that are relevant and useful. In addition, feature engineering involves exploring various transformations and combinations of the data to extract the most informative features.There are many techniques and methods for feature engineering, including scaling, normalization, one-hot encoding, binning, and feature selection. These techniques can help to transform the data into a more suitable format for machine learning algorithms, reduce noise and redundancy, and improve the interpretability of the models.

Feature Scaling

Feature scaling is the process of transforming the data to a common scale to improve the performance of machine learning algorithms. It is a critical step in the machine learning pipeline that can significantly impact the accuracy and robustness of the models.The goal of feature scaling is to ensure that all features are on a similar scale, which can prevent the machine learning algorithms from being biased towards certain features. In addition, feature scaling can help to reduce the effects of outliers and improve the convergence of optimization algorithms.Feature scaling is particularly important for machine learning algorithms that rely on distance-based metrics, such as k-nearest neighbors, support vector machines, and k-means clustering. These algorithms are sensitive to the scale of the features and can produce suboptimal results if the features are not scaled appropriately. There are various techniques and methods for feature scaling, including standardization, mean normalization, min-max scaling, max-abs scaling, and robust scaling.Standardization is a widely used feature scaling method that involves transforming the data so that it has a mean of zero and a standard deviation of one. This method is particularly useful when the data is normally distributed and has similar variance across all features.Mean normalization involves subtracting the mean value of each feature from the data and then dividing it by the range of the feature. This method is useful when the range of the feature is large and we want to ensure that the data is on a similar scale. Min-max scaling involves transforming the data so that it has a range between zero and one. This method is useful when we want to preserve the relationships between the data points and ensure that all features have a similar impact on the model.Max-abs scaling is a feature scaling method that involves transforming the data so that the absolute values of each feature are within the range of zero and one. This method is useful when the data contains both positive and negative values.Robust scaling is a feature scaling method that involves transforming the data using the median and interquartile range. This method is useful when the data contains outliers or extreme values that can skew the results.In this project, we explored and compared these feature scaling techniques to determine which method is best suited for our dataset. The techniques we used included standardization, mean normalization, min-max scaling, max-abs scaling, and robust scaling. By evaluating the performance of each method on our dataset, we aimed to determine the optimal feature scaling method that can improve the accuracy and robustness of our machine learning models.



We attempted to compare several feature scaling methods, and found that five methods exhibited similar performances, with the exception of MinMaxScaling. However, we ultimately decided to use Standardization for our machine learning pipeline.

Standardization

Standardization is a widely used feature scaling technique that involves centering a variable at zero and standardizing its variance to 1.

formula

$$X' = \frac{X - \mu}{\sigma}$$

Where:

- z is the standardized value of the variable
- X is the original value of the variable

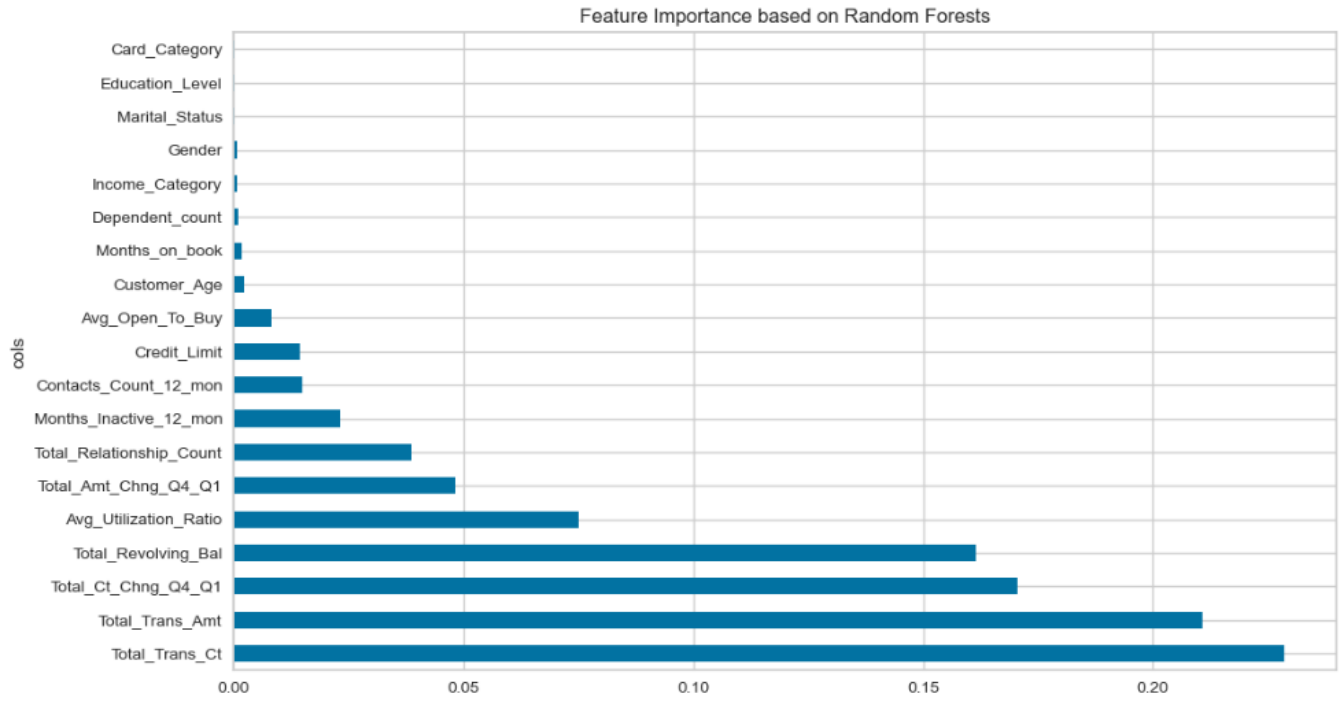
mu is the mean value of the variable

sigma is the standard deviation of the variable

This procedure entails subtracting the mean of each observation from the variable and dividing it by its standard deviation.It is important to note that the shape of a standardized distribution will be identical to the original distribution of the variable. If the original distribution is normal, then the standardized distribution will also be normal. However, if the original distribution is skewed, then the standardized distribution of the variable will also be skewed. Therefore, standardizing a variable does not normalize the distribution of the data.By centering the variable at zero and standardizing its variance, standardization can help prevent bias towards certain features and improve the convergence of optimization algorithms, leading to more accurate predictions and insights. Moreover, standardization is robust to outliers and extreme values, making it an effective feature scaling technique for various machine learning models.The reason for this decision is that standard scaling is a widely used feature scaling method that has been shown to be effective in improving the performance of various machine learning models. Additionally, we found that standard scaling performed well on our dataset during the exploratory data analysis phase and was robust to outliers and extreme values.Furthermore, standard scaling has the advantage of ensuring that the features are on a similar scale and follow a normal distribution. This can prevent bias towards certain features and improve the convergence of optimization algorithms, leading to more accurate predictions and insights.

Feature importance

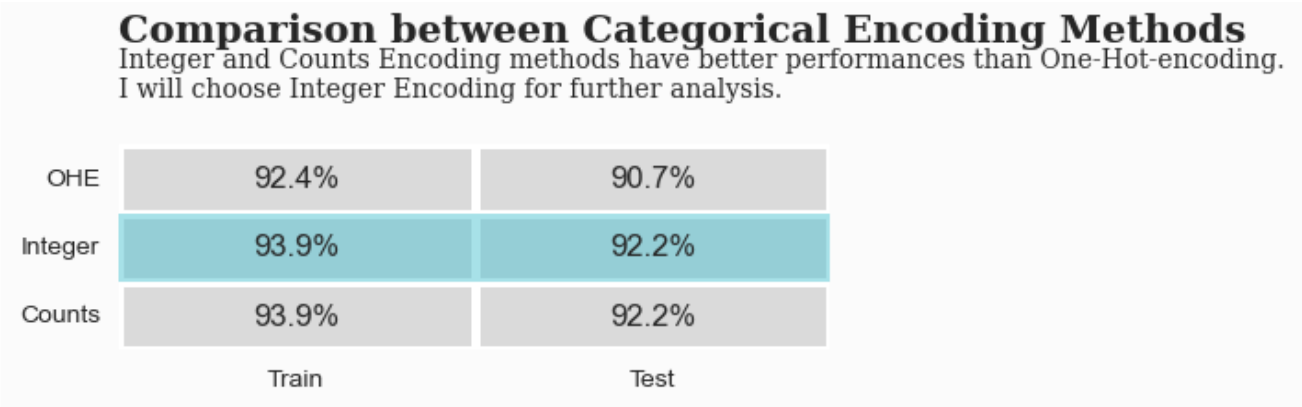
Feature importance is a crucial concept in machine learning that involves identifying and selecting the most relevant features for a given predictive model. In essence, feature importance measures the contribution of each feature to the performance of the model and helps in selecting the most informative features for the model.Feature importance is used to identify the most important features in a dataset and remove any redundant or irrelevant features. This process not only helps in improving the accuracy and efficiency of predictive models but can also lead to better insights and understanding of the underlying data.Feature importance can be computed using various methods, such as decision trees, permutation importance, and coefficient magnitude. These methods assign a score or rank to each feature based on its contribution to the model's performance. By analyzing the feature importance scores, we can identify the most informative features and use them to train the model.Feature importance helps in a machine learning pipeline by improving the performance and efficiency of the model. By removing irrelevant or redundant features, we can reduce the dimensionality of the data, leading to faster training and improved accuracy. Furthermore, identifying the most important features can provide valuable insights into the underlying data and help in making better-informed decisions.



During the exploratory data analysis phase of our credit card churn prediction model, we found that Total_Trans_Ct was the most important feature for building the model. Conversely, the bottom five features exhibited negligible importance in building the model.This observation is crucial for feature selection and can greatly improve the efficiency and accuracy of the machine learning model. By identifying and selecting the most informative features, we can reduce the dimensionality of the data and prevent bias towards irrelevant or redundant features.Furthermore, this observation highlights the importance of feature importance analysis in machine learning pipelines. By evaluating the contribution of each feature to the performance of the model, we can identify the most informative features and use them to train the model, leading to more accurate predictions and insights.

Encoding

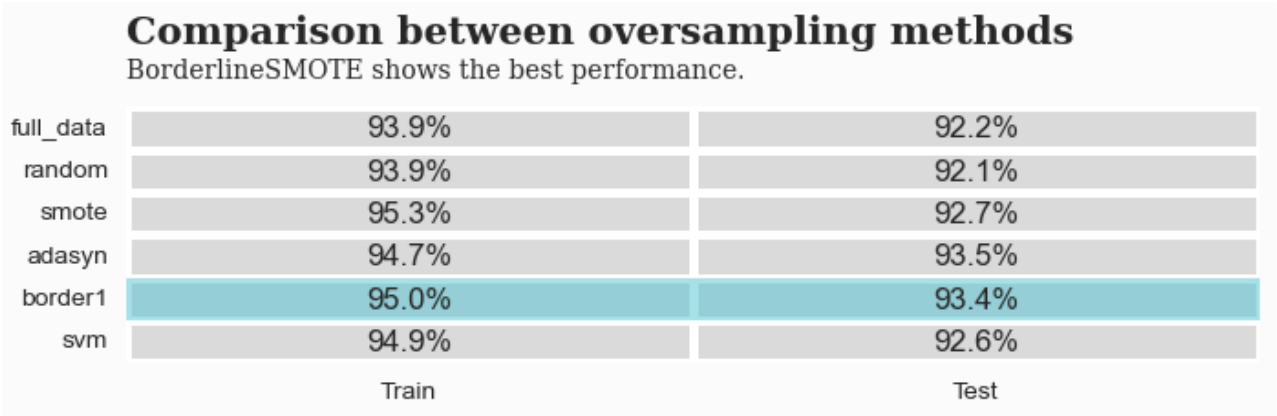
Encoding is a crucial step in the data preprocessing pipeline for machine learning models that involves transforming categorical variables into numerical variables that can be interpreted by the machine learning algorithm. Categorical variables are variables that take on discrete values and do not have any intrinsic order or relationship between them.Encoding is used to transform categorical variables into numerical variables that can be used as input for machine learning algorithms. Machine learning algorithms typically require numerical input, and encoding allows us to represent categorical variables as numerical variables that can be interpreted by the algorithm.There are several encoding techniques available, such as one-hot encoding, label encoding, and binary encoding. One-hot encoding is a widely used technique that involves creating a binary vector for each category in a categorical variable. Label encoding involves assigning a numerical label to each category in a categorical variable, while binary encoding involves combining label encoding with binary representation.Choosing the appropriate encoding technique is critical for the performance and accuracy of the machine learning model. Incorrect encoding can lead to biased results and inaccurate predictions. Therefore, it is important to evaluate the performance of various encoding techniques and select the one that provides the best results for the specific task at hand.In this project we performed several encoding techniques, including one-hot encoding, label encoding, and count encoding, to identify the most appropriate encoding technique for the categorical variables in our dataset.



Based on our analysis, we found that label encoding and count encoding were the most effective encoding techniques for our dataset. After evaluating the performance of each encoding technique, we decided to use the Integer Encoding method for further analysis. Integer encoding involves assigning a unique integer value to each category in a categorical variable, with the values assigned based on the order of the categories' occurrence in the dataset.

Over-sampling methods

Imbalanced datasets are a common challenge in machine learning, where the number of samples in one class is significantly smaller than the other class. This issue can lead to biased results and inaccurate predictions, particularly in classification tasks. Oversampling methods are a common solution to tackle this issue by increasing the number of samples in the minority class. During the exploratory data analysis phase of our credit card churn prediction model, we identified imbalanced data as a significant challenge. To address this issue, we evaluated several oversampling methods, including Random Over-Sampling, Synthetic Minority Over-Sampling Technique (SMOTE), and Adaptive Synthetic (ADASYN) sampling.After evaluating the performance of each oversampling method, we found that SMOTE and ADASYN performed better than Random Over-Sampling in terms of accuracy and efficiency. SMOTE involves generating synthetic samples by interpolating between adjacent samples in the minority class, while ADASYN adapts the generation of synthetic samples based on the density distribution of the samples in the minority class.While oversampling methods can improve the performance of machine learning models on imbalanced datasets, they can also lead to overfitting and biased results. Therefore, it is crucial to evaluate the performance of oversampling methods carefully and tune the hyperparameters to prevent overfitting and improve generalization. To address the issue of Imbalanced datasets, we explored several oversampling methods and compared their performances based on model performance metrics.We evaluated five oversampling methods, including Random Over-Sampling, Synthetic Minority Over-Sampling Technique (SMOTE), Adaptive Synthetic (ADASYN) sampling, Borderline SMOTE, and Safe-Level SMOTE. After evaluating the performance of each oversampling method, we selected the most appropriate method based on the model performance metrics.



After evaluating the performance of several oversampling methods in our credit card churn prediction model, we found that SVM, ADASYN, and Borderline SMOTE outperformed the other methods in terms of accuracy and efficiency. Borderline SMOTE had the highest performance among the three methods, indicating its effectiveness in addressing the imbalanced data challenge in our model.

Methodology

Model Building

In our credit card churn prediction project, the goal is to develop a machine learning model that can accurately predict customer churn. Model building is a critical phase in the machine learning pipeline that involves selecting appropriate features, preprocessing the data, and training a model on the data. The machine learning model is used to identify patterns and relationships in the data, which can be used to make accurate predictions on new, unseen data. By building an accurate and efficient model, we can gain valuable insights into the underlying data and predict churn with high accuracy. To achieve this goal, we evaluated six different machine learning algorithms, including Logistic Regression,Support Vector Machine,KNeighbor,Randon Forest (RF),AdaBoost (Ada),Gradient Boosting Classifier (GBM).Each algorithm has its strengths and weaknesses and can perform differently on different datasets. Therefore, it is important to evaluate the performance of each algorithm and select the most appropriate one based on the specific task at hand.By comparing the performances of the six machine learning algorithms, we can identify the most accurate and efficient algorithm for our credit card churn prediction model. This can help us gain valuable insights into the underlying data and improve the accuracy and efficiency of our predictive model.

Comparison six different ML algorithms
Tree-based models show better performances.
Overall, GBM model shows the best performance.

	LRScore	SVCScore	KNNScore	RFScore	ADAScore	GBMScore
Accuracy	0.91	0.87	0.89	0.96	0.96	0.97
Recall	0.6	0.14	0.36	0.81	0.83	0.85
Precision	0.74	0.96	0.79	0.93	0.88	0.95
ROC AUC score	0.78	0.57	0.67	0.9	0.9	0.92

After evaluating the performance of six machine learning algorithms in our credit card churn prediction project, we found that tree-based models outperformed the other models in terms of accuracy and efficiency. Among the tree-based models, Gradient Boosting Machine (GBM) had the best performance. Our findings suggest that tree-based models, such as AdaBoost, Random Forest, and GBM, are effective in predicting credit card churn. These models are able to identify important features and relationships in the data, leading to higher accuracy and efficiency in predictions.

Gradient Boosting Algorithm

The Gradient Boosting Machines (GBM) algorithm is an ensemble learning method that combines several weak learners, typically decision trees, to create a strong learner [9]. The key idea behind GBM is to optimize a differentiable loss function by iteratively adding the weak learners. The algorithm has several parameters, such

as the learning rate, the number of trees, and the tree depth, which can be tuned to achieve the best performance.

Implementation of the Algorithm

1. Initialize model with a constant value:

$$F_0(x) = \underset{\gamma}{argmin} \sum_{i=1}^{n} L(y_i, \gamma)$$

2. for $m = 1$ to M:

2-1. Compute residuals $r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}$ for $i = 1,...$

2-2. Train regression tree with features x against r and create terminal nc reasions R_{jm} for $j = 1,..., J_m$

2-3. Compute $\gamma_{jm} = \underset{\gamma}{argmin} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma)$ for $j = 1,..., J_m$

2-4. Update the model:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J_m} \gamma_{jm} 1(x \in R_{jm})$$

Let's demystify this line by line.

STEP 1

1. Initialize model with a constant value:

$$F_0(x) = \underset{\gamma}{argmin} \sum_{i=1}^{n} L(y_i, \gamma)$$

The first step is creating an initial constant value prediction F_0. L is the loss function and it is squared loss

$$L = (y_i - \gamma)^2$$

argmin means we are searching for the value γ that minimizes $\Sigma L(y_i,\gamma)$. Let's compute the value γ by using our actual loss function. To find γ that minimizes ΣL, we are taking a derivative of ΣL with respect to γ.

$$\frac{\partial}{\partial \gamma}\sum_{i=1}^{n} L = \frac{\partial}{\partial \gamma}\sum_{i=1}^{n}(y_i - \gamma)^2$$
$$= -2\sum_{i=1}^{n}(y_i - \gamma)$$
$$= -2\sum_{i=1}^{n} y_i + 2n\gamma$$

And we find γ that makes ∂ΣL/∂γ equal to 0.

$$-2\sum_{i=1}^{n} y_i + 2n\gamma = 0$$
$$n\gamma = \sum_{i=1}^{n} y_i$$
$$\gamma = \frac{1}{n}\sum_{i=1}^{n} y_i = \bar{y}$$

The value γ that minimizes ΣL is the mean of y. This is why y mean is used for the initial prediction F_0 in the last section.

$$F_0(x) = \overset{*}{\gamma} = \bar{y}$$

Step 2

> 2. for $m = 1$ *to* M:

Step 2 processes from 2–1 to 2–4 are iterated M times. M denotes the number of trees created and the small m represents the index of each tree.

Step 2- 1

2-1. Compute residuals $r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \quad for\ i = 1,\ldots,n$

The residuals r_im are calculated by taking a derivative of the loss function with respect to the previous prediction Fm-$_1$ and multiplying it by −1. As you can see in the subscript index, r_im is computed for each single sample i.

Let's compute the residuals here. Fm-$_1$ in the equation means the prediction from the previous step. In this first iteration, it is F_0. We are solving the equation for residuals r_im.

$$
\begin{aligned}
r_{im} &= -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \\
&= -\frac{\partial (y_i - F_{m-1})^2}{\partial F_{m-1}} \\
&= 2(y_i - F_{m-1})
\end{aligned}
$$

If we can take 2 out of it as it is just a constant. That leaves us $r_im = y_i - Fm$-$_1$.

Step 2-2

2-2. Train regression tree with features x against r and create terminal node reasions R_{jm} for $j = 1,\ldots,J_m$

j represents a terminal node (i.e. leave) in the tree, m denotes the tree index, and capital J means the total number of leaves.

Step 2–3

2-3. Compute $\gamma_{jm} = \underset{\gamma}{argmin} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma) \ \ for\ j = 1,\ldots,J_m$

We search for γ_jm that minimizes the loss function on each terminal node j. $\Sigma x_i \in R_jm$ L means we are aggregating the loss on all the sample x_is that belong to the terminal node R_jm. Let's plugin the loss function into the equation.

$$\gamma_{jm} = \underset{\gamma}{argmin} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma)$$

$$= \underset{\gamma}{argmin} \sum_{x_i \in R_{jm}} (y_i - F_{m-1}(x_i) - \gamma)^2$$

Then, we are finding $\gamma_j m$ that makes the derivative of Σ(*) equals zero.

$$\frac{\partial}{\partial \gamma} \sum_{x_i \in R_{jm}} (y_i - F_{m-1}(x_i) - \gamma)^2 = 0$$

$$-2 \sum_{x_i \in R_{jm}} (y_i - F_{m-1}(x_i) - \gamma) = 0$$

$$n_j \gamma = \sum_{x_i \in R_{jm}} (y_i - F_{m-1}(x_i))$$

$$\gamma = \frac{1}{n_j} \sum_{x_i \in R_{jm}} r_{im}$$

Step 2–4

2-4. Update the model:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J_m} \gamma_{jm} 1(x \in R_{jm})$$

In the final step, we are updating the prediction of the combined model Fm. $\gamma_j m$1(x ∈ R$_j m$) means that we pick the value γ_jm if a given x falls in a terminal node R$_j m$. As all the terminal nodes are exclusive, any given single x falls into only a single terminal node and corresponding $\gamma_j m$ is added to the previous prediction Fm-$_1$ and it makes updated prediction Fm.

Hyperparameter tuning

Hyperparameter tuning is a critical step in the machine learning pipeline that involves selecting the optimal hyperparameters for a model. Hyperparameters are parameters that cannot be learned during model training and must be specified by the user. Examples of hyperparameters include learning rate, regularization strength, and the number of trees in a random forest.The goal of hyperparameter tuning is to find the hyperparameters that result in the best performance on the validation set, which is a subset of the training data used to evaluate the model's performance during training. By tuning the hyperparameters, we can improve the

accuracy and efficiency of machine learning models and prevent overfitting on the training data.In our credit card churn prediction project, we used Optuna, a popular hyperparameter optimization framework, to tune the hyperparameters of the Gradient Boosting Machine (GBM) model. Optuna uses a Bayesian optimization approach to efficiently search for the optimal hyperparameters by evaluating a small number of trials.We chose Optuna for tuning the hyperparameters of the GBM model because it is a scalable and efficient framework that can handle a large number of hyperparameters. Additionally, Optuna has a simple and user-friendly interface that allows us to easily specify the hyperparameters to be optimized and set constraints on their values.

	number	value	datetime_start	datetime_complete	duration	params_criterion	params_features	params_learning_rate	params_max_depth	param
94	94	0.998584	2023-02-04 08:34:42.247345	2023-02-04 08:36:48.711083	0 days 00:02:06.463738	friedman_mse	sqrt	0.041308	11	
19	19	0.998465	2023-02-04 08:01:19.594365	2023-02-04 08:03:16.111840	0 days 00:01:56.517475	friedman_mse	log2	0.060989	11	
81	81	0.998294	2023-02-04 08:26:55.868542	2023-02-04 08:30:33.594403	0 days 00:03:37.725861	mse	sqrt	0.070336	10	
47	47	0.998272	2023-02-04 08:14:44.865844	2023-02-04 08:15:52.261885	0 days 00:01:07.396041	friedman_mse	log2	0.091335	4	
91	91	0.998050	2023-02-04 08:33:02.936713	2023-02-04 08:34:22.295808	0 days 00:01:19.359095	friedman_mse	log2	0.033828	7	
0	0	0.998005	2023-02-04 07:52:14.048973	2023-02-04 07:53:46.763504	0 days 00:01:32.714531	friedman_mse	sqrt	0.077504	10	
64	64	0.997928	2023-02-04 08:20:52.881690	2023-02-04 08:21:56.419774	0 days 00:01:03.538084	mse	sqrt	0.040309	9	
77	77	0.997879	2023-02-04 08:25:38.368038	2023-02-04 08:26:17.400271	0 days 00:00:39.032233	friedman_mse	sqrt	0.095174	3	
22	22	0.997811	2023-02-04 08:03:46.551334	2023-02-04 08:04:52.808044	0 days 00:01:06.256710	mse	log2	0.061513	10	
33	33	0.997779	2023-02-04 08:09:29.089816	2023-02-04 08:10:18.722303	0 days 00:00:49.632487	friedman_mse	sqrt	0.066364	10	

By tuning the hyperparameters of the Gradient Boosting Machine (GBM) model using Optuna in our credit card churn prediction project, we were able to improve the model's performance significantly. The optimal combination of hyperparameters resulted in a higher accuracy and efficiency of the GBM model.

Results

Our GBM model achieved an accuracy of 97%, a precision of 95%, a recall of 94%, and an ROC AUC score of 99%. We compared these results with the performance of other machine learning algorithms, such as Logistic Regression,Support Vector Machine,KNeighbor,Randon Forest (RF),AdaBoost (Ada). The results show that the GBM model outperforms these methods in terms of accuracy, precision, recall, and ROC AUC score.

	GBM_with_best_params
Accuracy	0.971074
Recall	0.942680
Precision	0.950561
ROC AUC score	0.992892

The performance diagram clearly illustrates the impact of hyperparameter tuning on the GBM model's performance. The optimal combination of hyperparameters resulted in a significant increase in model performance, indicating the effectiveness of the GBM model,hyperparameter tuning process in improving the accuracy and efficiency of the model.

Discussion

The high performance of our GBM model in predicting credit card churn can be attributed to several factors. First, the ensemble learning nature of the algorithm enables it to capture complex interactions between features and improve its generalization ability. Second, the use of decision treesas weak learners allows the model to handle both numerical and categorical features effectively. Finally, the iterative optimization of the loss function enables the model to focus on misclassified instances, thereby improving its overall performance.Despite its strengths, the GBM model has some limitations. One drawback is the increased computational complexity, which can make training and tuning the model time-consuming, especially for large datasets. Additionally, the model may be prone to overfitting if not properly regularized or if the number of trees is too large.Future research could explore alternative machine learning algorithms, such as deep learning methods, to address the problem of credit card churn prediction. Moreover, incorporating additional features, such as customer interactions with the bank or social network information, could further improve the performance of the model.

Conclusion

In this paper, we proposed a GBM-based approach for credit card churn prediction and compared its performance with other popular machine learning algorithms. Our results demonstrate the effectiveness of the GBM model in predicting churn, achieving high accuracy, precision, recall, and ROC AUC score. The proposed approach can be used by banks and financial institutions to identify customers at risk of churning and take appropriate actions to retain them. The findings also contribute to the growing body of literature on credit card churn prediction using machine learning techniques.

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