Predicting Customer Churn with Machine Learning-

In a Bank

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GitHub repository link

https://github.com/sara-cloud/Project820

Project Abstract

Customer churn or customer attrition happens when the customers stop using the product or service of a business. It directly affects the company profitability. The success rate of selling to an existing customer is usually higher than the success rate of selling to a new customer. Also, it is estimated that acquiring a new customer can cost five times more than retaining an existing one. So, customer churn analysis is essential for any business or industry including banking. Customer churn prediction is one of the challenging issues, but it helps the business to identify the problems. Weather it is the poor quality product/service or wrong target market.

The goal of this project is to predict customer churn for a bank. In this dataset (churn_modeling.csv), we look at the "Exited" column to see if that customer is churned or not. We use the features such as Credit Score, Gender, Age, Tenure, Number of Products and … to predict customer churn.

The dataset includes 10,000 records and 13 columns (excluding row number), combination of numerical and non-numerical features. Fortunately, it doesn't contain missing entries.

We will initially perform EDA analysis and Data Pre-processing to identify and visualise the features contributing to customer churn. It's a classification task and we will use ML classifiers such as Logistic Regression, Random Forests, SVM and maybe other algorithms to compare the prediction performance.

The bank in this study has been gathering customer data for a while to identify potential churners. With analysing those customers who have already left the bank, we identify if they have some shared feature or behaviour patterns. Bank needs to identify customers at risk of churn before it is too late to take appropriate actions and optimize their strategic plans. Machine learning algorithms can help us here to resolve the below problems:

- Having the up-to-date list of potential churners, would greatly help sales and marketing to engage with customers differently. For example, customers who are currently at churn risk are not the good candidates to target in marketing campaigns to buy new products. When customers have already showed signs of churn, it is not a great time for sales department as well to reach out about additional services. Non-churn risk customers are probably better candidates to target at launching new service or product.

- Customer service management can use this study result to take appropriate actions, reach potential churners and understand their issues or pain points and gain back their trust. Customer satisfaction/success managers need this insight to know which customers they should contact. Successful customer interaction and retention strategy is related to speaking with the right customers at the right time.

- Identifying the features that contribute the most in customer churning help them address the specific and common issues the potential churners with those features might have. Implementing these insights is the opportunity to improve the product or service for growth and to reduce customer churn.

Literature Review

One of the main objectives of Churn prediction is finding the strategies for customer retention. The risk of customer churn in global markets and competition growth is always increasing. Hence, identifying early the churn signals for the customers that may leave voluntarily is becoming more and more necessary. Companies have realized keeping their existing customers is one of their most valuable assets (Lalwani, Mishra, Chadha & Sethi (2021).

This project aims to predict customers that are most likely to get churned in a bank using machine learning methods. The dataset in this study to create the churn models, is available in Kaggle. The dataset contains 10000 records of bank customers. The target or dependent parameter is a binary variable called “Exited”. It reflects whether the client has left this bank or not. Among 10000 customers, 7963 were retained and 2037 were exited. When the customer is retained, the target parameter reflects the binary flag 0 and when the customer has churned, the target parameter reflects the binary flag 1. The dataset includes 13 features or independent variables from customer data and transactions. This study considered various studies in this topic and in various industries with various dataset; however the main focus was on one study that have been conducted by Vasimalla & Rahman in 2020 (ML Based Customer Churn Prediction In Banking) with the same dataset. All attributes with the brief description are listed in the below table.

Feature Name	Feature Description
Row number	Row numbers from 1 to 10000.
Customer Id	Unique Ids for bank customer identification.
Surname	Customer’s last name.
Credit Score	Credit score of the customer.
Geography	The country from which the customer belongs.
Gender	Male or Female.
Age	Age of the customer.
Tenure	Number of years for which the customer has been with the bank.
Balance	Bank balance of the customer.
Num of Products	Number of bank products the customer is utilizing(savings account, mobile banking, internet banking etc.).
Has Cr Card	Binary flag for whether the customer holds a credit card with the bank or not.
Is Active Member	Binary flag for whether the customer is an active member with the bank or not.
Estimated Salary	Estimated salary of the customer in Dollars.
Exited	Binary flag 1 if the customer closed account with bank and 0 if the customer is retained.

Creating a Test Set

At first, will split our dataset into train and test with a function that implements random sampling.

EDA Analysis

Exploratory Data Analysis helps us understand our dataset better and get some insightful statistical information (like mean, max, and min) about the features and to perform initial investigations on data to discover patterns, spot anomalies and check assumptions with the help of summary statistics and visualizations. The statistical summary of the numerical features are provided in the below.

	count	mean	std	min	25%	50%	75%	max
CreditScore	10000.0	650.529	96.653	350.00	584.00	652.000	718.000	850.00
Age	10000.0	38.922	10.488	18.00	32.00	37.000	44.000	92.00
Tenure	10000.0	5.013	2.892	0.00	3.00	5.000	7.000	10.00
Balance	10000.0	76485.889	62397.405	0.00	0.00	97198.540	127644.240	250898.09
NumOfProducts	10000.0	1.530	0.582	1.00	1.00	1.000	2.000	4.00
HasCrCard	10000.0	0.706	0.456	0.00	0.00	1.000	1.000	1.00
IsActiveMember	10000.0	0.515	0.500	0.00	0.00	1.000	1.000	1.00
EstimatedSalary	10000.0	100090.240	57510.493	11.58	51002.11	100193.915	149388.247	199992.48
Exited	10000.0	0.204	0.403	0.00	0.00	0.000	0.000	1.00

In this data set, there was not any duplicates and missing (null) values. Continuous variables are Age, CreditScore, Balance, EstimatedSalary and Categorical variables are Geography, Gender, Tenure, NumOfProducts, HasCrCard, IsActiveMember (After dropping the irrelevant data/attributes which is explained in Pre-processing section.)

From conducting the exploratory data analysis some initial insights are reached. For example, we understand only a small percentage leaves within the first year; The bank kept 80% of its clientele and our dataset is skewed/imbalanced since the number of instances in the 'Retained' class outnumbers the number of instances in the 'Churned' class by a lot.

Different visualisation techniques are applied to different types of variables to differentiate between continuous and categorical variables and look at them separately. You can find further details in the links below for EDA analysis:

https://github.com/sara-cloud/Project820/blob/main/EDA_Analysis.ipynb

https://github.com/sara-cloud/Project820/blob/main/EDA_Analysis.pdf

Data Preprocessing

Preprocessing is an important phase to convert raw data into a suitable format for building and training ML models that can guarantee the model can make good prediction. During that, the tasks such as feature selection, data conversions and imbalanced data will be handled.

Feature Selection

Data or attributes which have no impact on our prediction are **irrelevant** and keeping them may negatively affect the performance of our classification models. Irrelevancy of some attributes including 'RowNumber', 'CustomerId', and 'Surname' are obvious as they are specific to each customer. These attributes can be dropped. In the similar study(Vasimalla & Rahman, 2020), they proposed that Geography too has nothing to do with the prediction and they dropped this in the initial phase. However, based on EDA analysis done, this feature is kept since it is observed that customers in Germany are more likely to churn than customers in the other two countries (the churn rate is almost double compared to Spain and France). So, this feature hasn't been neglected for this study.

Vasimalla & Rahman used mRMR (Minimum Redundancy Maximum Relevance) and Relief which are both Filter type feature selection methods. The Filter method in feature selection evaluates the significance of feature characteristics, such as the variance of feature and reaction relevance. In mRMR for classification problems, it ranks the features sequentially applying the Minimum Redundancy Maximum Relevance algorithm (Jiang and Li, 2015).

Relief rates features using the Relief algorithm. This method is more suitable to estimate the features significance for distance-based supervised models which apply pair distances between observations to predict the response. It ranks the predictors based on importance of specified numbers of nearest neighbors (Beretta and Santaniello, 2011).

Although the mentioned algorithms will be studied for any addition or advantage of application for this study, other Filter type feature selection methods(tests) such as Chi-square test for categorical variables and Anova for numeric variables can serve the purpose.

The Chi-square test is used for categorical features in a dataset. We calculate Chi-square between each feature and the target and select the desired number of features with the best Chi-square scores. ANOVA is used when one variable is numeric and one is categorical, such as numerical input variables and a classification target variable in a classification task.

Since EDA already revealed more features that can be dropped as they do not provide any value in predicting the target variable. Chi-square and Anova will be used only to confirm the initial hypothesis. Then we can use the drop method to remove the three variables from the train set. EstimatedSalary in continuous variables for both Churned and Retained shows a uniform distribution. And Tenure and HasCrCard in categorical features deemed redundant as they have a similar churn rate.

Encoding Categorical Features

Machine learning algorithms work with numeric features. So, categorical variables require to be transformed (encoded) to numeric values in Preprocessing steps.

In this dataset two variables require encoding requirement, Gender and Geography. For example, Gender can be transformed like Male --> 1 and Female --> 0. And the 3 categorical values in Geography as well will be manually mapped to numeric values. In the previous similar

study(Vasimalla & Rahman, 2020), they only encoded Gender and Geograpgy had been removed from the features list.

Scaling

Scaling is applied to normalise the range of variables in a dataset. Some machine learning algorithms are sensitive to feature scaling such as SVMs, while others like Random Forests are invariant. During this method the features will be standardised using mean and standard deviation. Feature scaling in this dataset will be applied for Age, CreditScore and Balance. Although Vasimalla & Rahman(2020) used SVMs as one of their ML algorithms, they skipped scaling.

Addressing Class Imbalance

As we have seen previously, the data is highly imbalanced(7963 Retained class and 2037 Churned class). If we apply Classifications on imbalanced data, the result will be biased in favour of the majority class. There are some techniques or strategies such as oversampling and undersampling that can address this problem and configure the class distribution.

Vasimalla & Rahman(2020) used typical random oversampling and they stated that didn't use undersampling because the size of data will decrease and there will not be enough data to build the model. Therefore, they used the random oversampling for the minority class. In this study however, SMOTE technique is considered due to the main disadvantage with oversampling that by making exact copies of existing examples, overfitting is more likely. This technique is suggested in the study of Paulose et al(2021) regarding Effective ML Techniques to Predict Customer Churn. Random oversampling just increases the size of the training data set through repetition of the original examples. Oversampling using SMOTE not only increases the size of the training data set, it also increases the variety by generating synthetic examples rather than by oversampling with replacement (Huang, 2015).

Building Machine Learning Models

Aljoumaa et al.(2019) applied decision tree, random forest, GBM tree algorithm, and XGBoost algorithms for the customer churn Prediction in telecommunication industry. XGBoost performed superior than others in terms of AUC accuracy. They also suggested accuracy can be improved further with the optimization feature selection algorithms.

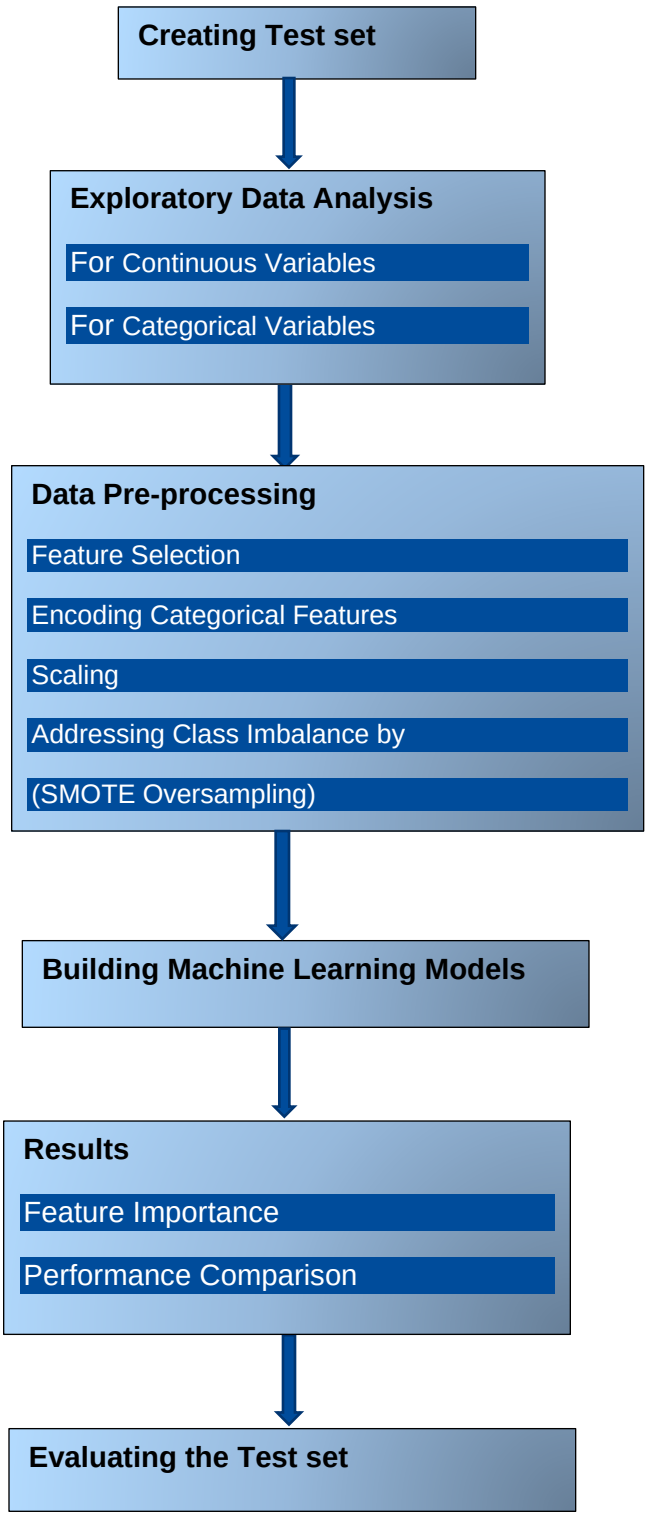
Huang et al.(2015) applied various classifiers for the customer churn Prediction and the results confirmed that random forest gives maximum accuracy compared to others in terms of AUC and PR-AUC analysis. They suggested that accuracy can be further improved applying the feature extraction optimization techniques.

Lalwani et Al. (2021) used the famous machine learning methods such as Logistic Regression, Naïve Bayes, SVM, Decision Trees, Random Forest, XGBoost and CatBoost Classifier, AdaBoost Classifier and Extra tree Classifier. The results reflect that the ensemble learning techniques, Adaboost and XGBoost classifiers performed superior than others in terms of AUC accuracy with the score of 84% for the churn prediction. They also performed superior compared to other algorithms in terms of all the performance measures including accuracy, precision, F-measure, recall and AUC score.

Vasimalla & Rahman (2020) applied KNN, SVM, Decision Tree and Random Forest classifiers and the result in different classifiers were compared over the selected features by various feature selection methods. As previously mentioned they used 2 different geature selection techniques mRMR and Relief. The best result was obtained from RF classifier together with oversampling with the score of 95.74% and Feature selection methods had nothing to do with RF and Decision Tree classifiers. It was observed that feature reduction in feature selection is decreasing the prediction score of tree classifiers. Another result achieved was that unlike other three classifiers, oversampling is decreasing the accuracy score in SVM.

In this study also the most common machine learning methods such as Logistic Regression, Random Forest, Support Vector Machines(SVM), … will be applied and they will be evaluated by performing k-fold cross-validation. Since correctly classifying the customers who will churn or positive class is more critical, so in this project, the focus will be more on recall for optimising our models as the scoring measure. Providing Confusion matrix and learning curves will help us visualise the training size impact on the errors.

Methodology Summary



Data Analysis procedures

Our data has 14 attributes and 10000 instances. The feature**, '**Exited**',** is the target variable indicating if the customer has churned or not (0 = No, 1 = Yes).

The attributes of 'RowNumber', 'CustomerId', and 'Surname' are specific to each customer and can be dropped:

The `info()` method can give us valuable information such as the number of non-null values and the type of each feature:

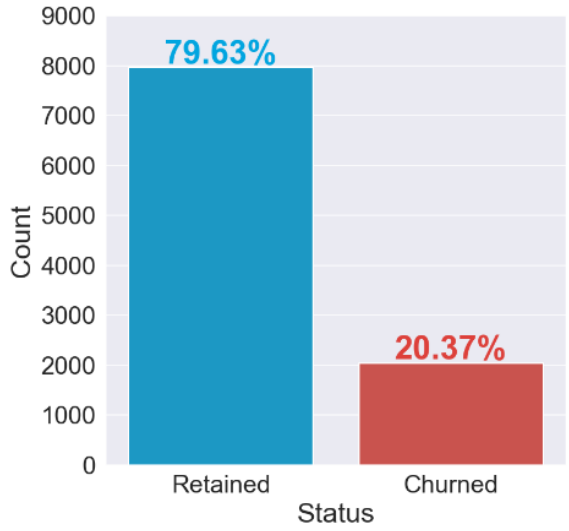
```
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: float64(2), int64(7), object(2)
```

There are no missing values in the DataFrame. The below gives us a statistical summary of the numerical features:

	count	mean	std	min	25%	50%	75%	max
CreditScore	10000.0	650.529	96.653	350.00	584.00	652.000	718.000	850.00
Age	10000.0	38.922	10.488	18.00	32.00	37.000	44.000	92.00
Tenure	10000.0	5.013	2.892	0.00	3.00	5.000	7.000	10.00
Balance	10000.0	76485.889	62397.405	0.00	0.00	97198.540	127644.240	250898.09
NumOfProducts	10000.0	1.530	0.582	1.00	1.00	1.000	2.000	4.00
HasCrCard	10000.0	0.706	0.456	0.00	0.00	1.000	1.000	1.00
IsActiveMember	10000.0	0.515	0.500	0.00	0.00	1.000	1.000	1.00
EstimatedSalary	10000.0	100090.240	57510.493	11.58	51002.11	100193.915	149388.247	199992.48
Exited	10000.0	0.204	0.403	0.00	0.00	0.000	0.000	1.00

Target Variable: Exited

- Zero (0) for a customer that has not churned, and
- One (1) for a customer that has churned.



The bank retained 80% of its customers.

Here we notice that our data is imbalanced since the number of instances in the 'Retained' class outnumbers the number of instances in the 'Churned' class by a lot. Therefore, accuracy is probably not the best metric for model performance.

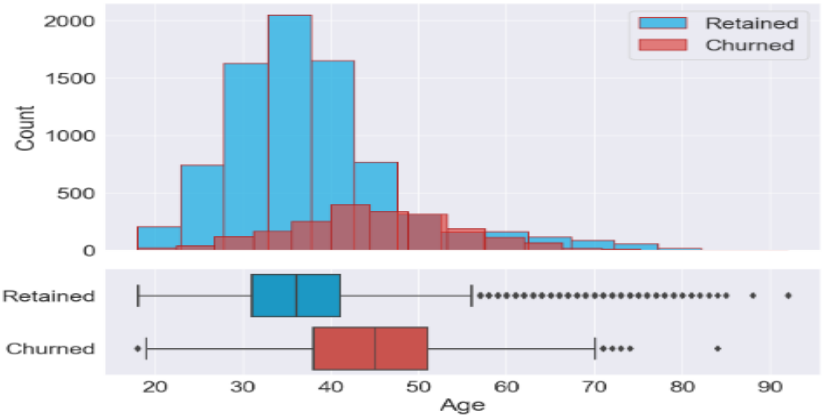
Different visualisation techniques apply to different types of variables, so it's helpful to differentiate between continuous and categorical variables and look at them separately.

Continuous Variables

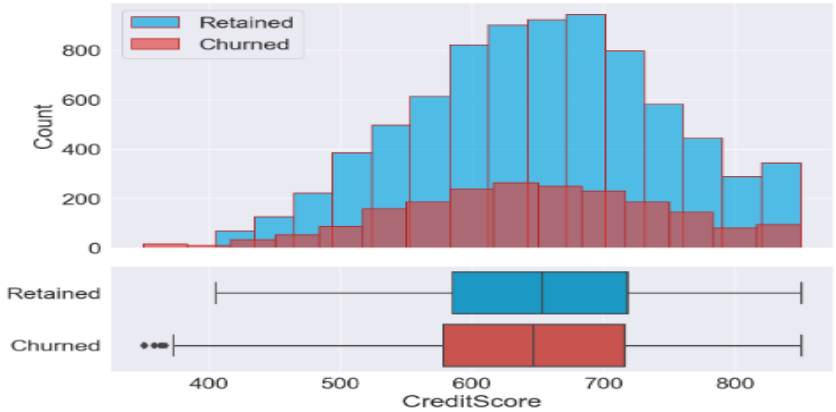
For the four continuous numeric features we observe that 'Age' is slightly skewed to the right of the median than to the left. If we ignore the first bin, 'Balance' follows a fairly normal distribution, and the distribution of 'EstimatedSalary' is more or less uniform and provides little information.

The standard correlation coefficient between every pair of (continuous) features is computed in below.

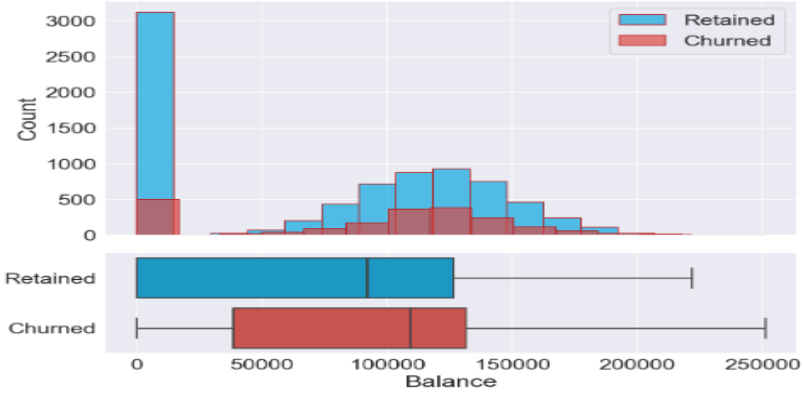
There is no significant intercorrelation between our features, so we do not have to worry about multicollinearity. In next steps, these features were analysed in greater detail.



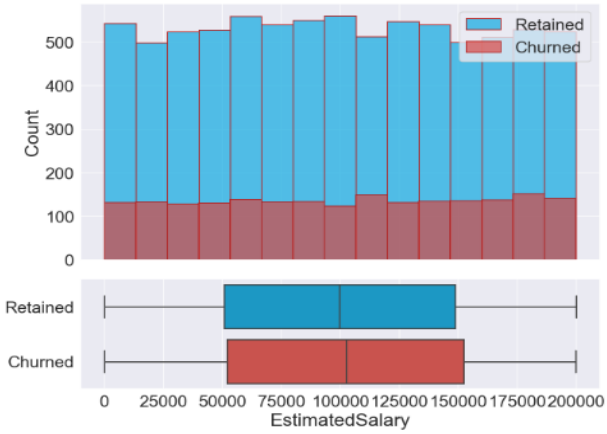
There is a clear difference between the age groups. As we see above, the older customers are more likely to churn. So, the bank should adapt its strategy to meet the requirements based on the preferences of customers at different ages.



There is no significant difference between retained and churned customers in terms of their credit scores.

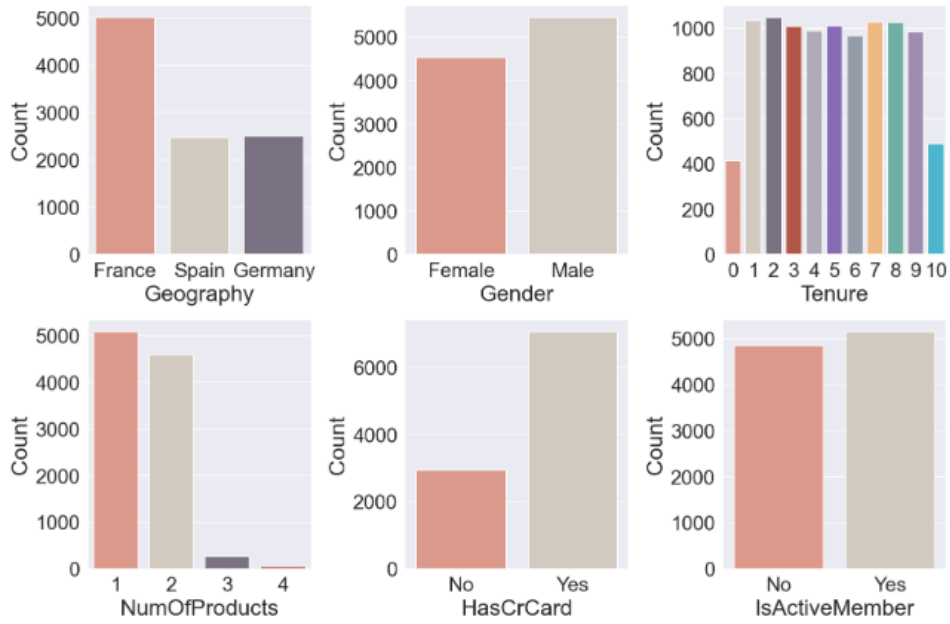


Again, the two distributions are quite similar.



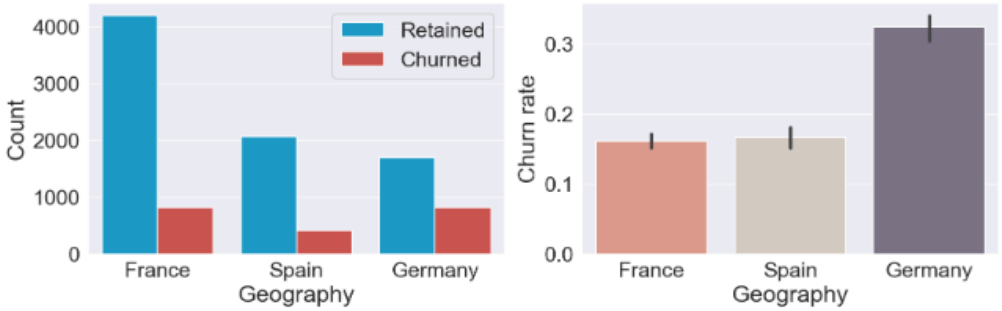
The churned and retained customers present a similar distribution in their salaries. So, we can conclude that salary doesn't have an important effect on the probability of churn.

Categorical Variables

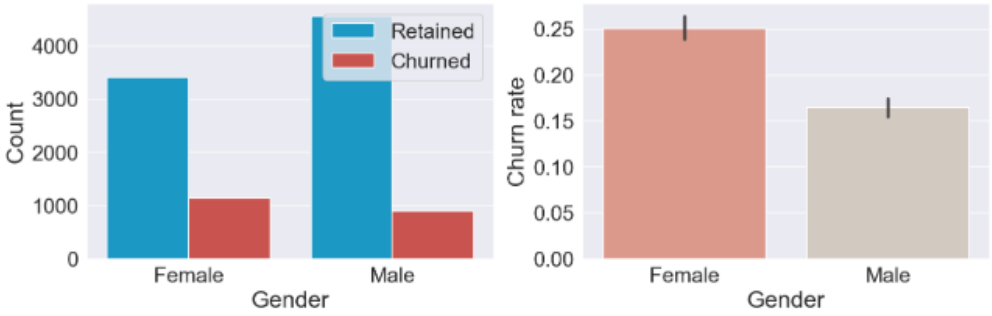


The customers are from the three countries and there are more customers are in France. There are more male customers than females. Only a small number of customers left within the first year. The count of customers in tenure years between 1 and 9 is almost the same, Most of the customers have 1 or 2 products, and a small portion has purchased 3 or 4 products. The majority of customers have a credit card, and almost half of customers are not active.

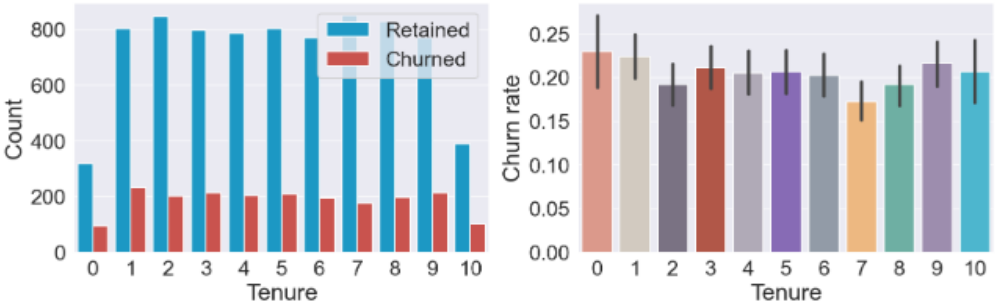
In the below these features were analysed in greater detail.



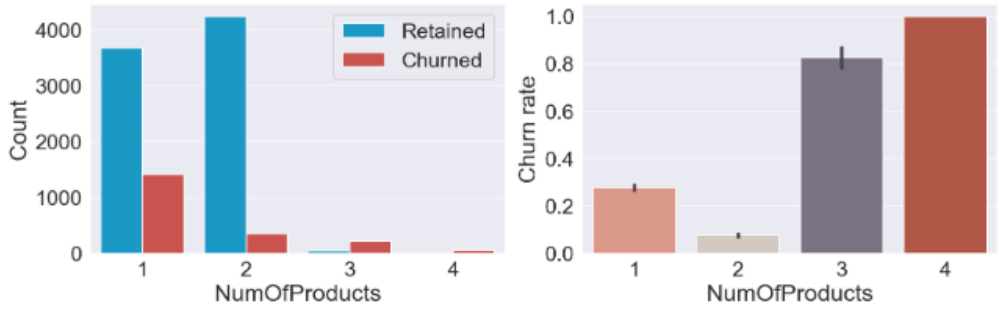
Customers from Germany churn almost double in rate compared to other countries. It can be due to higher competition or different preferences for customers.



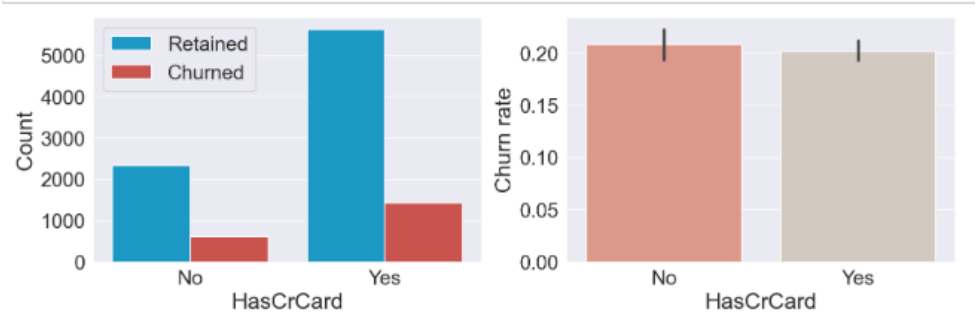
Female customers are more likely to churn.



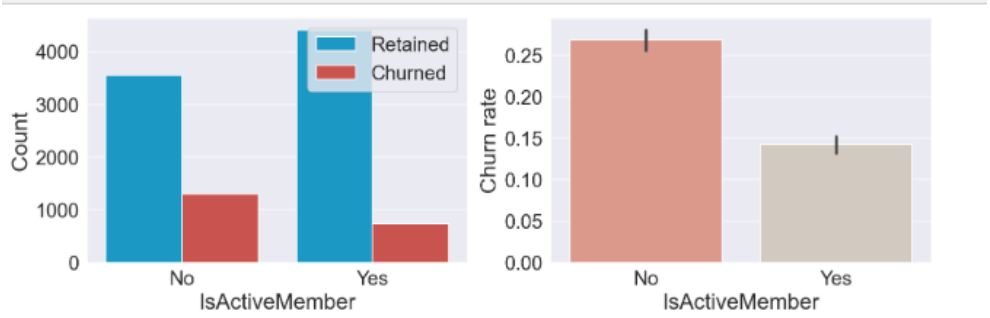
The number of customer tenure does not seem to affect the churn rate.



The customers with 3 or 4 products are more likely to churn. So, the bank should do a greater effort to support and satisfy the customers with more products.



Having a credit card similar to the tenure does not seem to affect the churn rate.



Inactive customers are more likely to churn. A great portion of the customers are inactive; so changing the policy to make more customers become active may affect the churn rate as well.

Data pre-processing and Feature Selection

Encoding and scaling are done at the first step in data pre-processing.

We have already dropped the features 'RowNumber', 'CustomerId', and 'Surname'. EDA also revealed more clear which features can be more effective in predicting our target variable. For example, 'EstimatedSalary', 'Tenure' and 'HasCrCard' display similar churn rate and are deemed redundant.

I used different approaches to test which features are the most significant in target prediction. In Wrapper feature selection, both forward and backward selection were implemented and in both we got quite similar results.

Sequential forward selection (SFS), in which features are sequentially added to an empty candidate set until the addition of further features does not decrease the criterion.

	feature_idx	cv_scores	avg_score	feature_names
1	(3,)	[0.08058955522086897, 0.08227376024621502, 0.0...	0.081	(Age,)
2	(3, 8)	[0.13538153836399136, 0.11308643046143596, 0.1...	0.113	(Age, IsActiveMember)
3	(1, 3, 8)	[0.14546484226502177, 0.1280060622036422, 0.13...	0.131	(Geography, Age, IsActiveMember)
4	(1, 2, 3, 8)	[0.15126131453420744, 0.14224830488845808, 0.1...	0.139	(Geography, Gender, Age, IsActiveMember)
5	(1, 2, 3, 5, 8)	[0.15676993786906002, 0.14287816634378248, 0.1...	0.144	(Geography, Gender, Age, Balance, IsActiveMember)
6	(0, 1, 2, 3, 5, 8)	[0.15793905064331581, 0.1430726887227125, 0.14...	0.144	(CreditScore, Geography, Gender, Age, Balance,...

Recursive feature elimination (RFE) is a backward selection of the predictors that fits a model and removes the weakest feature (or features) until the specified number of features is reached.

Backward method with 8 features:

Columns	Feature_names	Selected	RFE_ranking
0	CreditScore	True	1
1	Geography	True	1
2	Gender	True	1
3	Age	True	1
4	Tenure	True	1
5	Balance	True	1
6	NumOfProducts	True	1
7	HasCrCard	False	3
8	IsActiveMember	True	1
9	EstimatedSalary	False	2

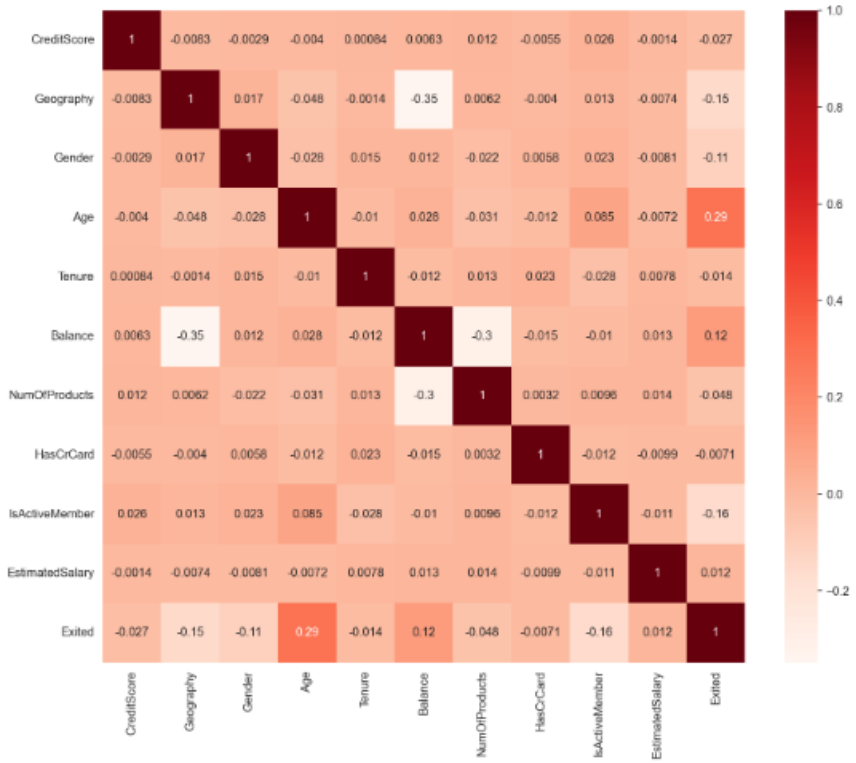
Backward method with 7 features:

Columns	Feature_names	Selected	RFE_ranking
0	CreditScore	True	1
1	Geography	True	1
2	Gender	True	1
3	Age	True	1
4	Tenure	False	2
5	Balance	True	1
6	NumOfProducts	True	1
7	HasCrCard	False	4
8	IsActiveMember	True	1
9	EstimatedSalary	False	3

For Categorical value, I also tried to confirm the result from a chi-square test and in continuous variables, I focused more on tested correlation with the target variable.

	Variable	Chi-square	p-value
3	NumOfProducts	1503.629	0.000e+00
0	Geography	301.255	3.830e-66
5	IsActiveMember	242.985	8.788e-55
1	Gender	112.919	2.248e-26
2	Tenure	13.900	1.776e-01
4	HasCrCard	0.471	4.924e-01

Both 'Tenure' and 'HasCrCard' have a small chi-square and a p-value greater than 0.05. About the continuous variables, ‘age’, ‘balance’, ‘Creditscore’ and 'EstimatedSalary have the highest to the lowest absolute value of correlation.



Embedded selection didn't give any good results to identify the significance among the features.

So, based on all of these, the 2 variables in categorical features and 2 in continuous are the candidates to be dropped if we conclude that we are getting the better result of the models.

Train-Test Splitting and Balancing

We will split our dataset into a train and test set which implements random sampling.

```
Train set: 8000 rows
 Test set: 2000 rows
```

By calling y_train.value_counts() , we get the imbalance result of:

```
0     6356
1     1644
```

Therefor, we need to handle it to avoid biased predictions. By calling the SMOTE method, not only we increased the size of the training data set, but also we increased the variety by generating synthetic examples.

```
0     6356
1     6356
```

Building Machine Learning Models

Logistic Regression, KNN, SVM, CART, Random Forests, XGBoost, LightGBM, CatBoost are the classifiers used as machine learning models and recall will be used as one of the the main scoring metrics for comparing and optimising our models to choose the best performed model. The reason is that minimizing the false negatives is critical here in this scenario. False negatives are the customers who are likely to be churned but we mis-predict them as un-churned or retained customers.

For the first stage of developing the machine learning models, I created the models without dropping any feature and then tunned some better performed models. However, I couldn't see any significant progress after obtaining the best estimators or hyperparameter optimization applying the GridSearchCV. GridSearchCV evaluates the performance by performing k-fold cross-validation.

So in the next approach, I decided to remove the first 2 least significant features in predicting target variable identified in the feature selection and EDA analysis ('HasCrCard' and 'EstimatedSalary'). And in the next level, I dropped the 3 variables of HasCrCard' , 'EstimatedSalary' and 'Tenure'.

The below are the tables that compare the models regarding effectiveness, efficiency and stability. The first three tables compare the performance measures in 3 different approaches with focusing on recall. (Apart from the confusion matrix, AUC score is calculated and AUC curve is also plotted for different classifiers in notebook.)

Evaluation: Effectiveness

SVM and GBC have always better predictive performance when our scoring metric is recall and it improves when we remove the redundant or ineffective features.

Without removing the least significant features				
Model	**Accuracy**	**precision**	**recall**	**f1-score**
LR	72%	38%	67%	49%
KNN	76%	43%	67%	52%
DT	76%	42%	54%	47%
RF	84%	59%	61%	60%
SVM	79%	48%	74%	58%
GBC	83%	56%	72%	63%
XGB	85%	65%	54%	59%
LightGBM	86%	67%	59%	63%
CatBoost	86%	66%	57%	61%

HasCrCard' and 'EstimatedSalary' are dropped				
Model	**Accuracy**	**precision**	**recall**	**f1-score**
LR	72%	38%	69%	49%
KNN	77%	45%	69%	55%
DT	78%	45%	59%	51%
RF	84%	59%	60%	60%
SVM	79%	48%	77%	59%
GBC	83%	56%	73%	63%
XGB	86%	67%	55%	60%
LightGBM	86%	66%	58%	61%
CatBoost	86%	68%	56%	62%

HasCrCard' , 'EstimatedSalary' and 'Tenure' are dropped				
Model	**Accuracy**	**precision**	**recall**	**f1-score**
LR	72%	38%	69%	49%
KNN	78%	46%	71%	55%
DT	77%	43%	56%	49%
RF	83%	56%	63%	59%
SVM	80%	49%	77%	60%
GBC	82%	53%	75%	62%
XGB	86%	66%	60%	63%
LightGBM	86%	65%	64%	64%
CatBoost	86%	66%	61%	63%

Evaluation: Stability

Stability is measured based on the standard deviation calculated in cross validation performed for 10 times (cv=10 in this project) for each model. For comparing purpose the 4 different measures are listed in below. The last column shows the stability when our scoring metric in cross validation is recall and as we see, XGB, LightGBM and CatBoost are the least reliable models compared to others.

Model	Stability in accuracy	Stability in f1-score	Stability in roc_auc	Stability in recall
LR	std 0.03	std 0.03	std 0.03	std 0.05
KNN	std 0.02	std 0.02	std 0.02	std 0.03
DT	std 0.04	std 0.05	std 0.04	std 0.09
RF	std 0.03	std 0.04	std 0.02	std 0.06
SVM	std 0.02	std 0.02	std 0.02	std 0.04
GBC	std 0.04	std 0.05	std 0.04	std 0.09
XGB	std 0.08	std 0.11	std 0.05	std 0.19
LightGBM	std 0.08	std 0.1	std 0.04	std 0.17
CatBoost	std 0.08	std 0.1	std 0.04	std 0.17

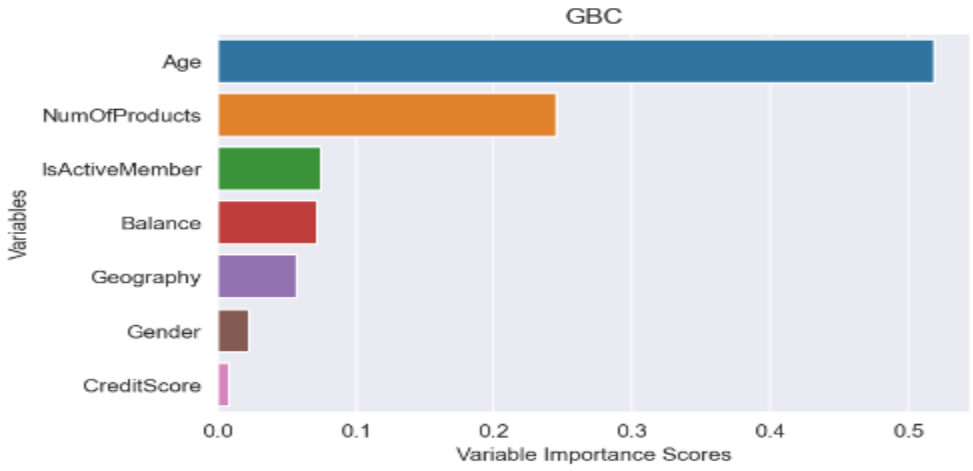
Evaluation: Efficiency

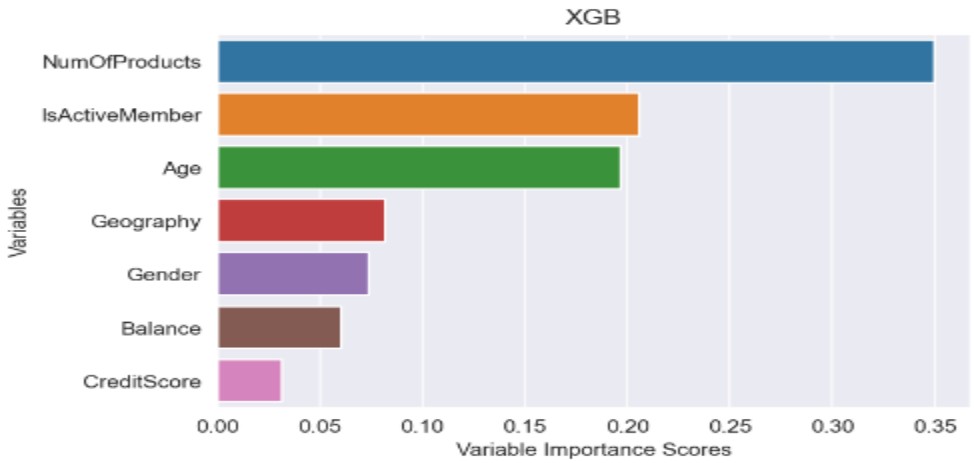
SVM and CatBoost are the least efficient models.

Model	Efficiency (Time)
LR	0,04
KNN	0,30
DT	0,08
RF	1,79
SVM	5,29
GBC	1,69
XGB	1,03
LightGBM	0,18
CatBoost	7,46

Feature Importance in different models

The below graphs visualise the feature importance in some classifiers We notice that Age, NumberOfproducts and IsActiveMember play the important predictive roles in these models and among the top 3 important features. However these features in other classifiers can be placed in different ranking order. The coefficient value for the features in the classiers are also provided in the notebook.





Study contribution

This study tried to conduct a very detailed EDA analysis and experiment different approaches (including different feature selection methods) and variety of classifiers with variety of strengths. Unlike other studies which Accuracy score is the main focus of model prediction performance, this study emphasizes on recall metric which is lower than other metrics probably due to imbalanced target variables, however it is critical for the aim of this study and business and worth investing.

Future Development

For the future development, a more exploratory feature engineer

I also tried to conduct some kind of feature engineering by combining existing features, but it didn't increase the predictive performance of the models in this study. It's still worth exploring it.

Also a more progressive model tunning with searching the best Hyperparameters is also suggested. In this study I tried to reach the best Hyperparameters with the help of GridSearchCV; however, I still see a capacity to improve.

Conclusions

The best models are GBC and SVM based on the recall score (77% and 75%), however GBC is a more efficient model. Most of the models have very high accuracy and AUC scores (Higher than 80%). The recall scores achieved can still be improved by model tunning.

The results reveal that the most significant features are age, number of products and IsActiveMember. It means older customers are more likely to churn, having more products increases the customers' likelihood to churn and active customers are less likely to churn.

The bank should take some measures to customize the service or products for the older customers as well as customers with more products. It is also beneficial to apply some methods to keep the customers engaged. It probably will increase the satisfaction for those targeted customers who are more likely to churn.

Adding more features and records also can improve the power or prediction. So gradually if the bank gathers more data with expanded features, it can improve the predictive performance.

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Dataset Reference

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