ENSSEA

Data Mining & Machine Learning for Customer Churn Prediction Case: Telecom Company

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Presentation Plan

1. CONCEPTUAL FRAMEWORK

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CONCEPTUAL FRAMEWORK

Introduction

"Acquiring a new customer is anywhere from five to 25 times more expensive than retaining an existing one"

—Amy Gallo, Harvard Business Review

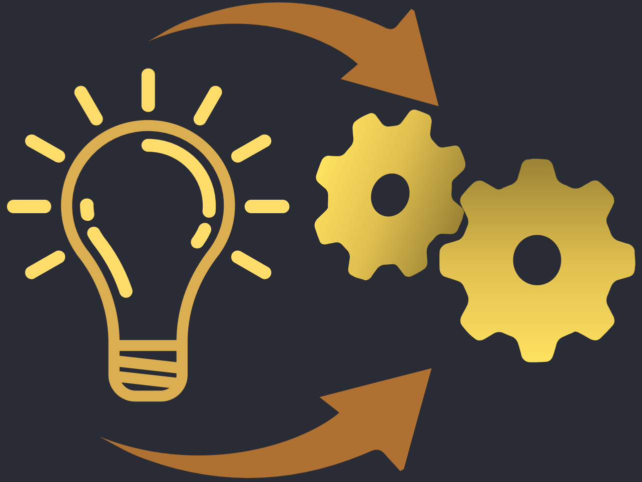
Objectives of the study

01 Build a precise predictive model for churn prediction

02 Determine the primary factors of customer churn

03 Give recommendations to the company to reduce churn

Research questions and Hypotheses



01

- ❑ Can data mining techniques accurately forecast customer behaviour?
- ➢ We can rely on data mining to anticipate client behaviour.

02

- ❑ What algorithms are most effective in customer churn prediction?
- ➢ Ensemble Learning methods are the most suited algorithms to predict customer churn.

03

- ❑ What is the most crucial variable in predicting the customer churn given the dataset?
- ➢ The customer last account balance is the most crucial variable for predicting customer churn,

Literature review

CRM

Is an essential business strategy that seeks to establish and maintain profitable relationships with customers

Churn

Is a marketing term that refers to a customer who switches from one company to another.

RFM

Stands for Recency, Frequency and Monetary, it is a three-dimensional method of categorizing or evaluating clients in order to discover the best customers.

Ensemble Learning

is a technique that combines many simple models to create a single, potentially highly powerful model

Methodology

PHASE 1
Data Exploration

PHASE 2
RFM Clustering

PHASE 3
Data Preprocessing

PHASE 4
Classification

PHASE 5
Evaluation & Interpretation

PHASE 6
Recommendations

Tools and programs

Numpy
LightGBM
Scipy
Python
Optuna
Pandas
Sklearn
Seaborn
Kaggle
Shap
Matplotlib
XGBoost

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EMPERICAL STUDY

Dataset overview

The dataset we used in this study is a public dataset about customers of an anonymous telecommunications company, It was collected from Kaggle, an open-source platform that hosts datasets and data science projects.

- This dataset is composed of:

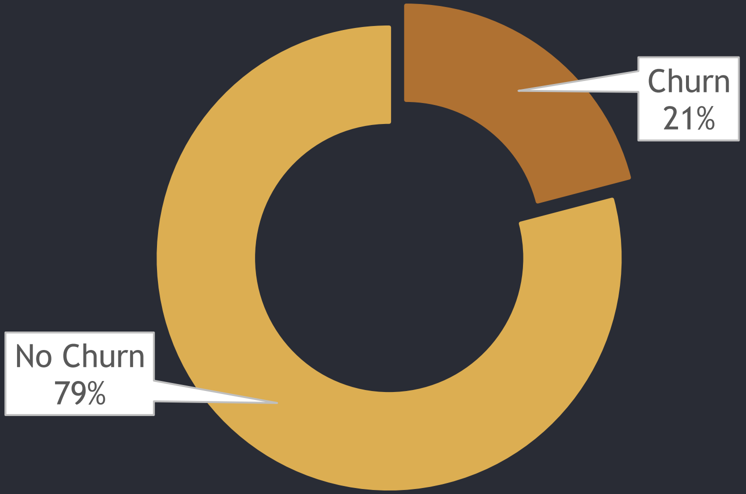
66,469
Customer

66
Variables

Exploratory Data Analysis

Before starting the study, we did some preliminary steps as follows:

- Dropped the Year and user_id columns
- Dropped the users with no activity for more then 1 year
- Dropped 17 variables that had correlations greater than 85%



Non churned customers:

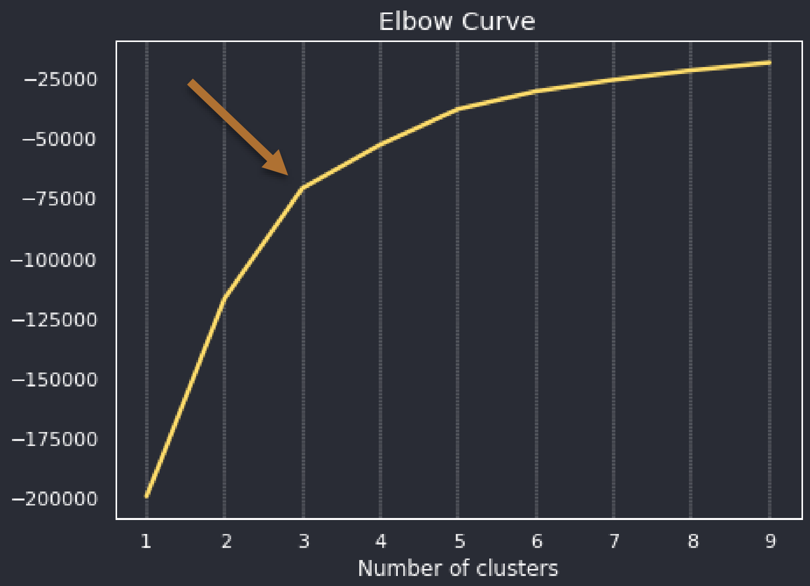
52,562

Churned customers:

13,907

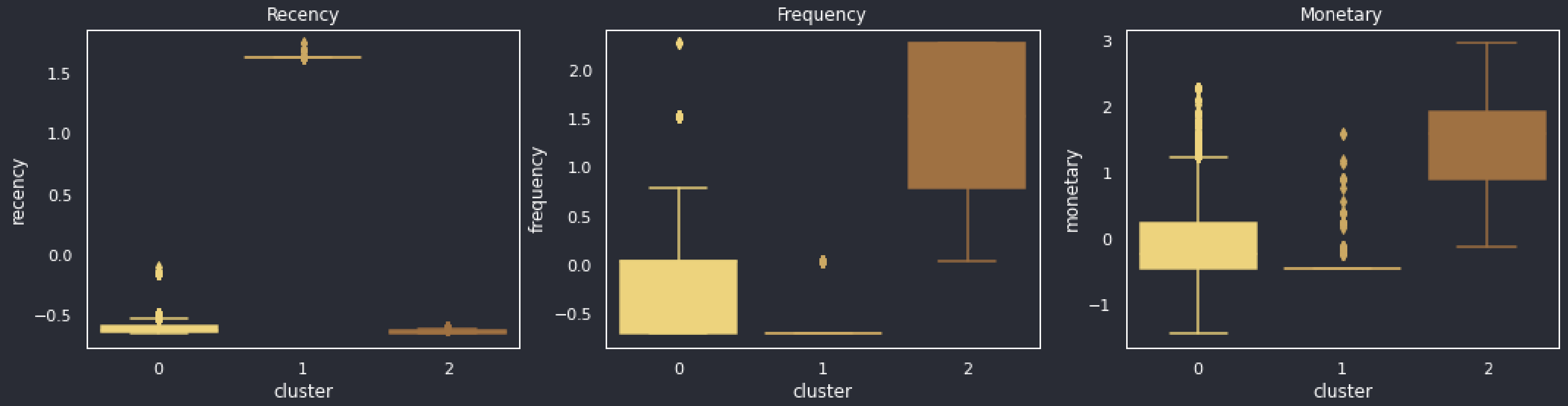
Clustering by RFM

- We note that k = 3 is the ideal number of clusters according to the elbow method,



Clustering by RFM

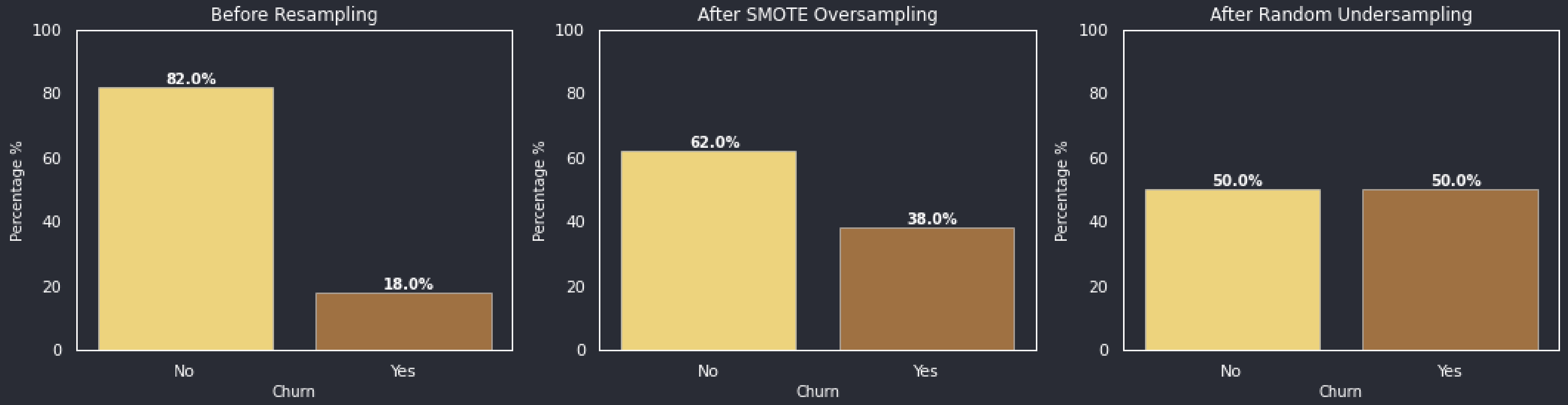
We fitted a K-means algorithm with k = 3 on the RFM table an had the following results:



We concluded to drop cluster 1,Thus, 17,949 customers were excluded from the study.

Data Preprocessing

To address class imbalance, we applied resampling techniques as follows:



We also applied a feature selection method, and found that 37 is the ideal number of variables to keep.

Model selection

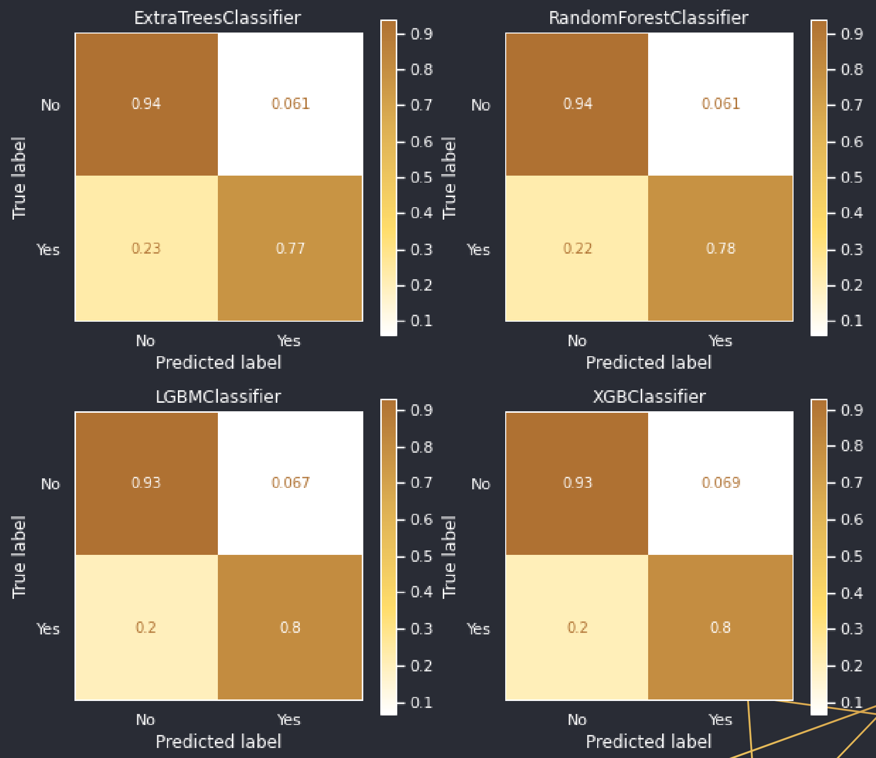
We applied various algorithms on the dataset and received the following results

Name	Accuracy	Recall	Precision	F1_score	Fit Time	Recall_STD
XGBClassifier	**0.922**	**0.917**	0.926	**0.921**	105.999	0.003
LGBMClassifier	0.920	0.914	0.926	0.920	**236.458**	0.003
RandomForestClassifier	0.912	0.896	0.927	0.911	7.872	0.005
ExtraTreesClassifier	0.912	0.894	**0.927**	0.910	4.383	0.004
GradientBoostingClassifier	0.907	0.894	0.918	0.906	12.285	**0.002**
BaggingClassifier	0.905	0.889	0.920	0.904	3.863	0.004
DecisionTreeClassifier	0.874	0.895	**0.859**	0.877	**0.609**	0.005
AdaBoostClassifier	0.873	0.843	0.898	0.870	2.966	**0.005**
LogisticRegressionCV	**0.857**	**0.803**	0.902	**0.849**	18.035	0.003

With ● being the highest value in the columns and ● being the lowest value

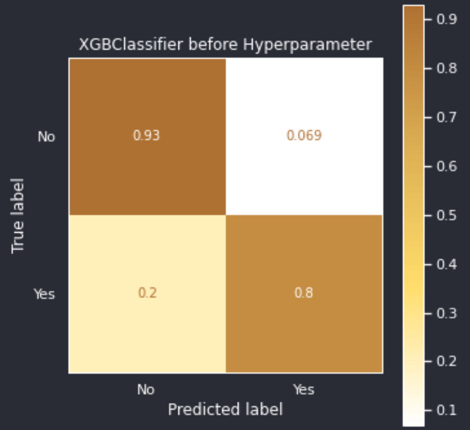
Model selection

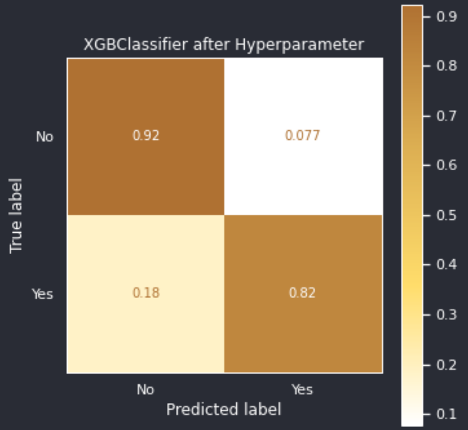
- From the previous and the present charts, we choose XGBClassifier for validation.



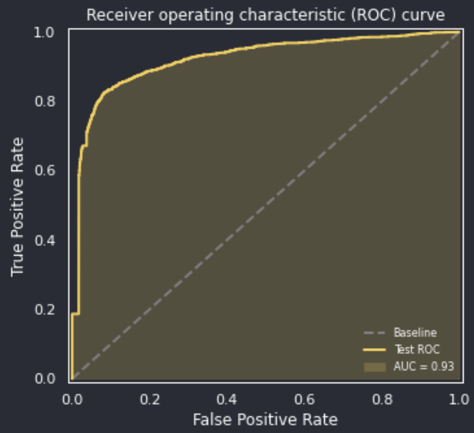
Model validation

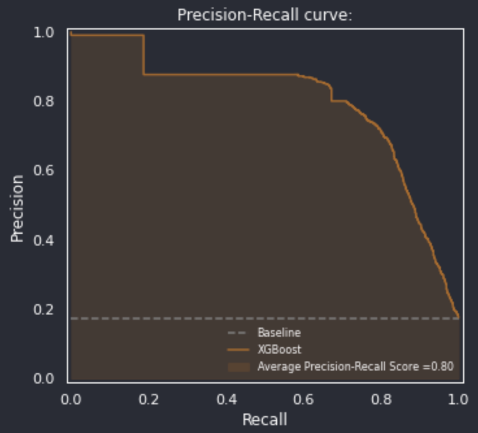
Hyperparameter optimization





ROC & Precision – Recall curve





The new model has improved in the Recall score of the positive class 'Yes'

The two curves satisfy our business requirement

Model evaluation

The results of the final model on the test set are as follows:

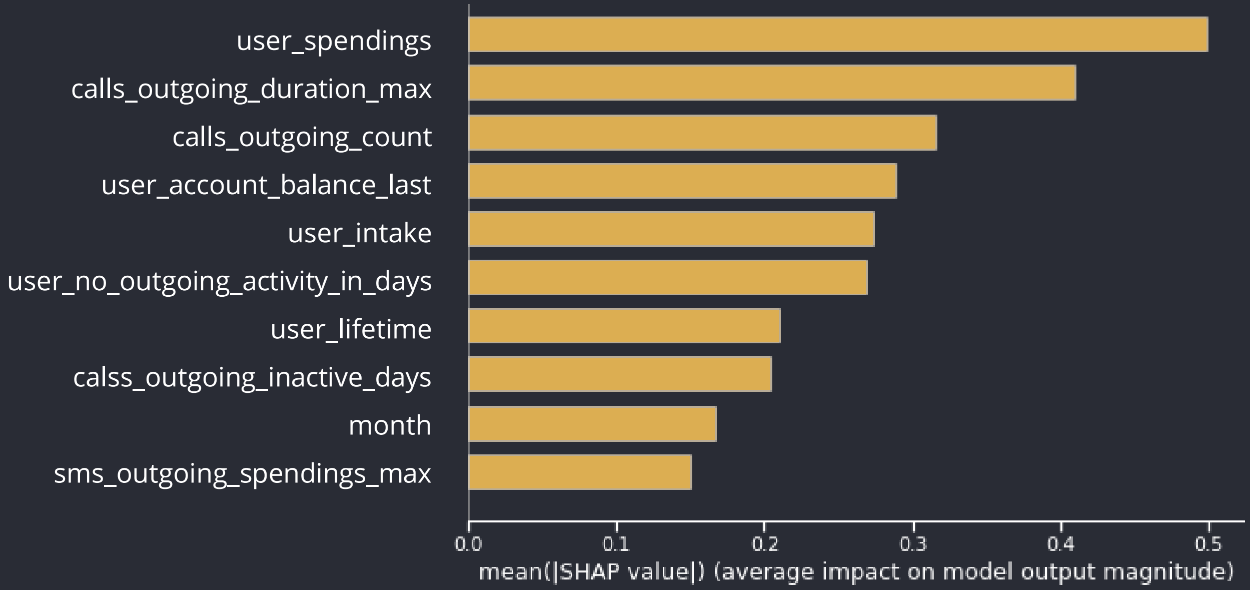
90% Accuracy

91% Precision

82% Recall

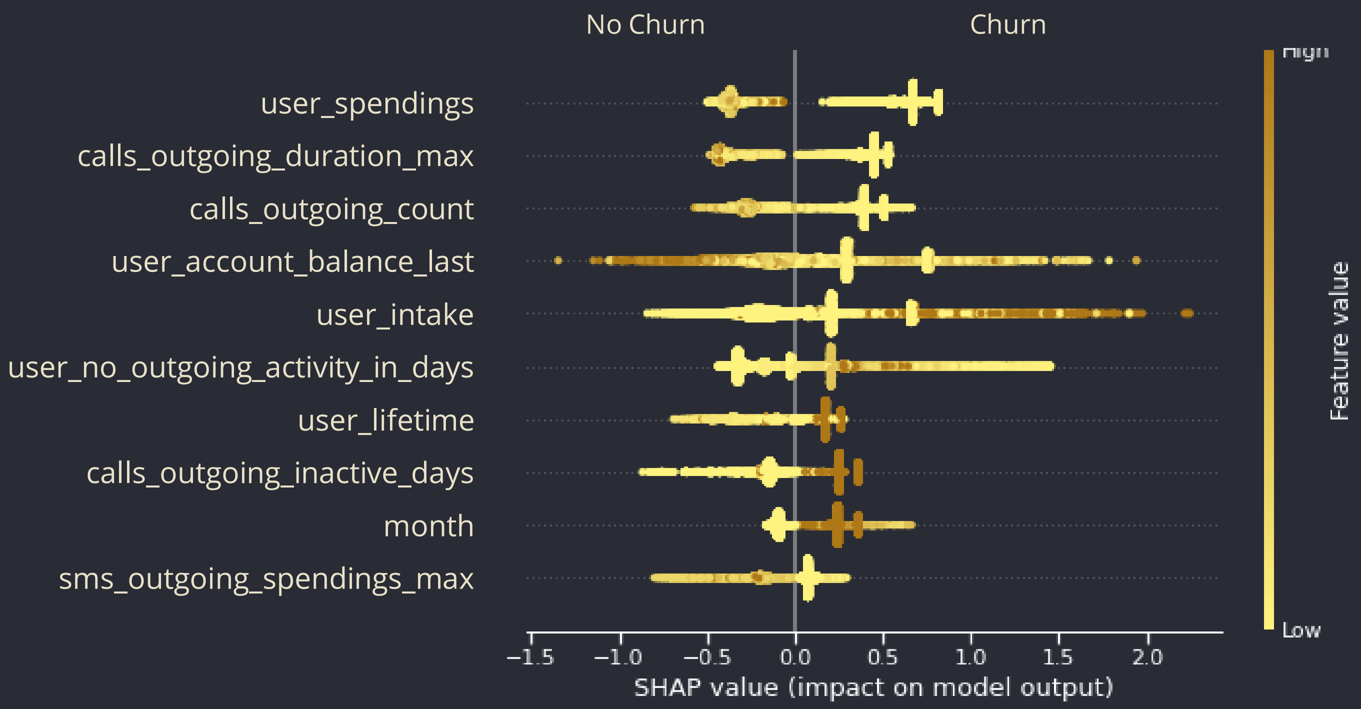
Model Interpretation

Feature importance plot



Model Interpretation

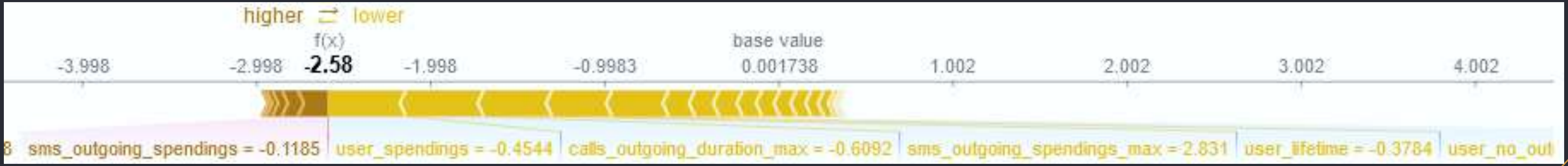
Summary plot



Model Interpretation

Individual 1 (Churn)

Individual (Did not Churn)



Conclusion

Based on the summary of findings, the following conclusions were derived:

01 Ensemble learning algorithms such as Extreme Gradient Boosting (XGBoost) performed the best on the datasets.

02 XGBoost performed better than other models, with an accuracy of 90%.

03 The most significant feature in predicting customer churn is user_spendings.

Recommendations

01 Integrate churn prediction results into the customer relations and marketing departments' IT tools

02 Bring the marketing department closer to CRM and synchronize future actions (retention, promotion, . . .).

03 Valorising projects based on data mining to allow the company to align itself with the other competitors

THANKS!

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