

Churn Rate Marketing Strategy

By: Christopher Angeles



TABLE OF CONTENTS

01

Problem & Solution

Address Churn Rate on
Company Revenue By
Designing Intervention
Strategy

02

Customer Analysis & Target

Gather, Use, and Predict
Customer Segmentation for
Targeted Strategy

03

Prediction Model

Create and Design a
Prediction Model and
Evaluate Future Revenue

04

Strategy

Develop Intervention Model
and Implement Company
Strategy

FIRST NATIONAL BANK

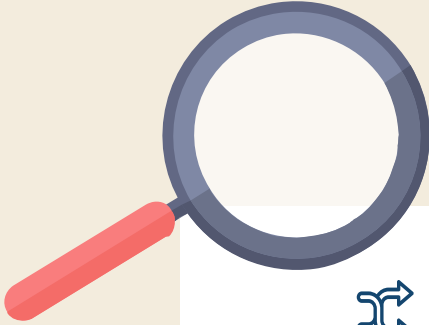
First National Bank is looking to address customer retention

Objectives :

- Reduce Account Closure
- Increase Customer / Service Ratio
- Reduce Bank Service Transfer



UNDERSTANDING THE PROBLEM



Churn Rate

Rate of customer attrition in a company, or the speed at which a customer leaves your company



Retention Costs

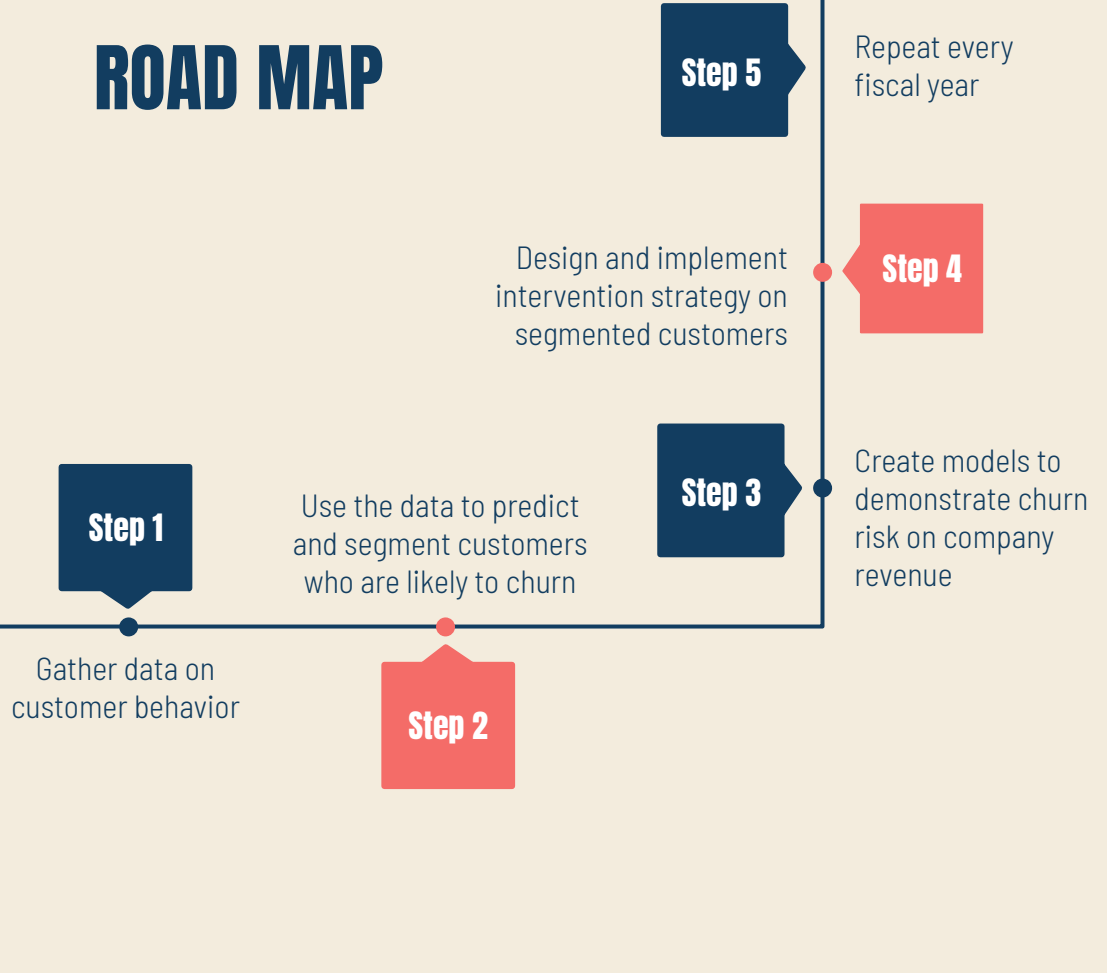
It's more expensive to acquire a new customer than it is to retain a current one



Bottom Line

A small increase in customer retention equates to a large decrease in company costs

ROAD MAP



OUR PROCESS & TOOLS



Exploratory Data Analysis

Using python, pandas, and the collected data set, we will explore the data

Data Preprocessing

Reconfigure the data to reflect our analysis and model parameters

Model Building

Construct a model that predicts and segments customers that have highest churn risk

Model Evaluation & Optimization

Run evaluation analysis and optimization for the model

EXPLORATORY DATA ANALYSIS

Dataset

CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0
...
15606229	Obijaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0
15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

Interesting Factors

- Number of Products
- Age
- Credit Score
- Tenure
- Has a Credit Card

* The dataset was used from kaggle.com - churn prediction of bank customers

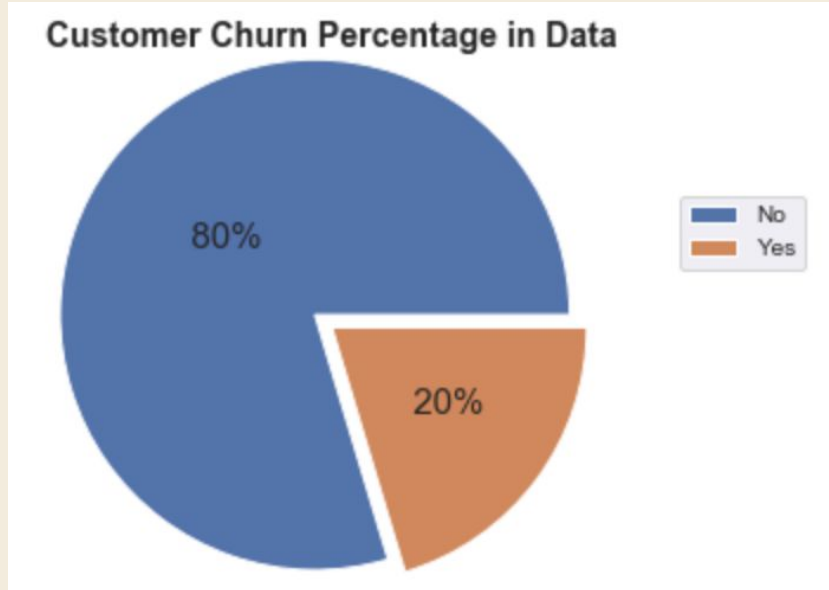
CLEANING & DATA PREPARATION

Categorizing Tenure and Credit Score will allow us to target the customer more effectively for our model and extract information

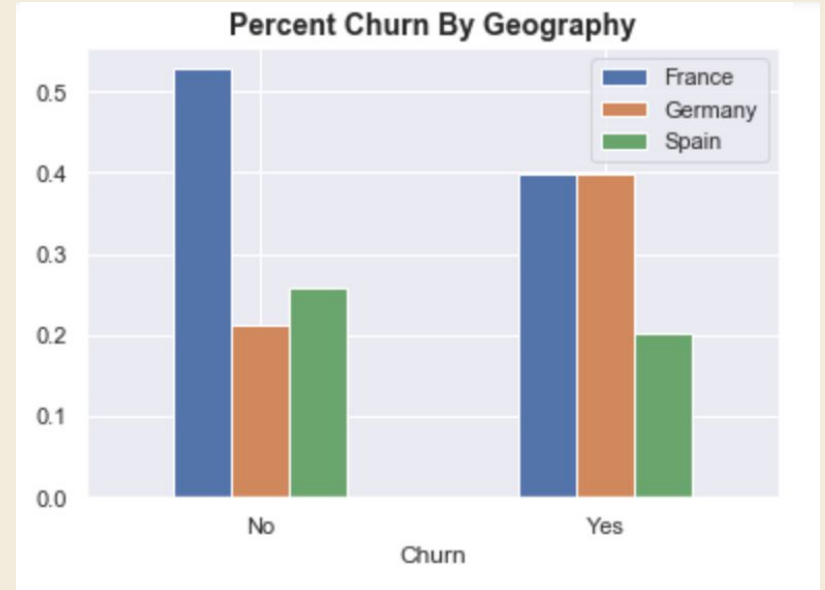
Churn	TenureGroup	CreditScoreGroup
Yes	Tenure 0-2 Years	Credit 600-700
No	Tenure 0-2 Years	Credit 600-700
Yes	Tenure 7+ Years	Credit 500-600
No	Tenure 0-2 Years	Credit 600-700
No	Tenure 0-2 Years	Credit 700+
...
No	Tenure 3-7 Years	Credit 700+
No	Tenure 7+ Years	Credit 500-600
Yes	Tenure 3-7 Years	Credit 700+
Yes	Tenure 3-7 Years	Credit 700+
No	Tenure 3-7 Years	Credit 700+

DATA DEMOGRAPHIC

Total Percentage Churn

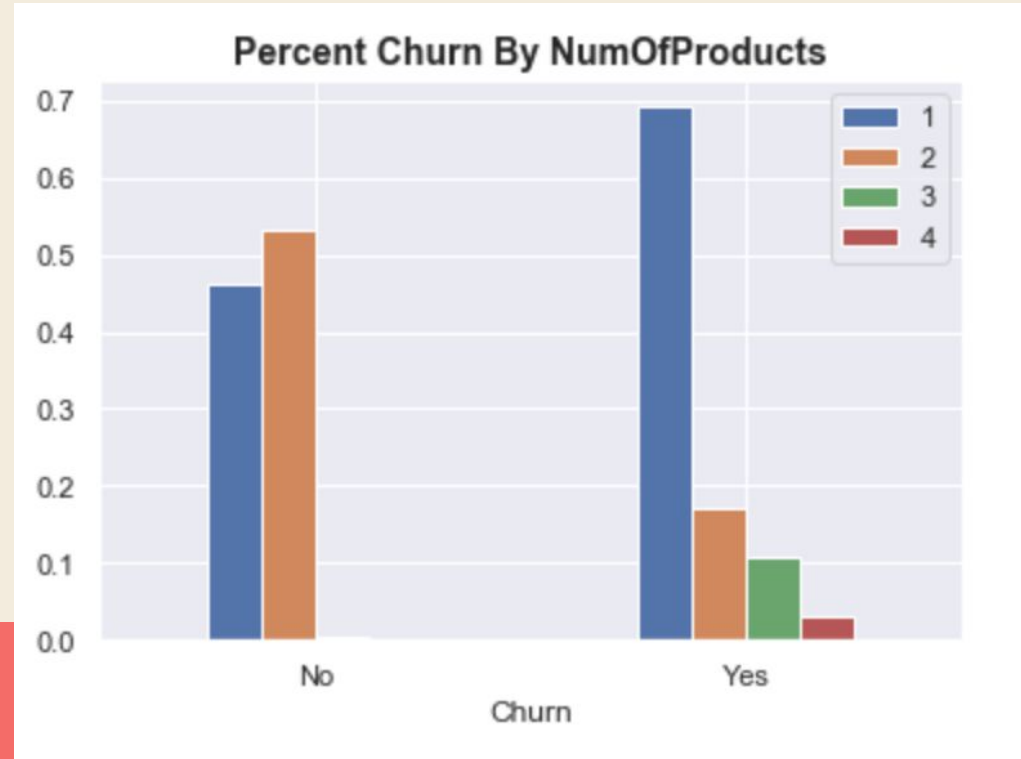


By Location

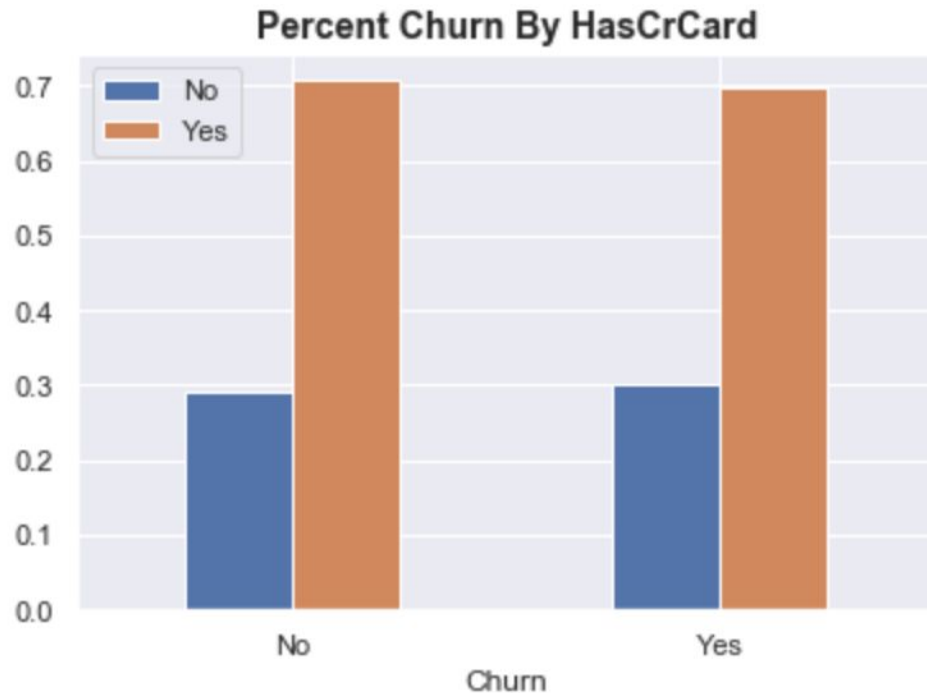


NUMBER OF PRODUCTS ON CHURN RATE

Here we can see that almost all our customers with 3+ services are not staying



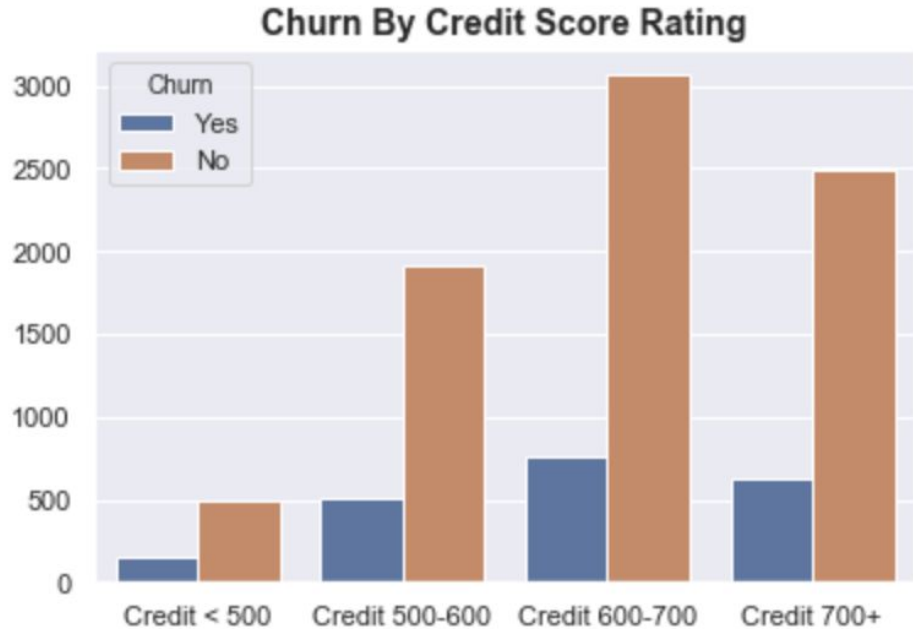
CREDIT CARD ON CHURN RATE



Customers with a credit card are just as likely to leave as customers who opt out of having a credit card

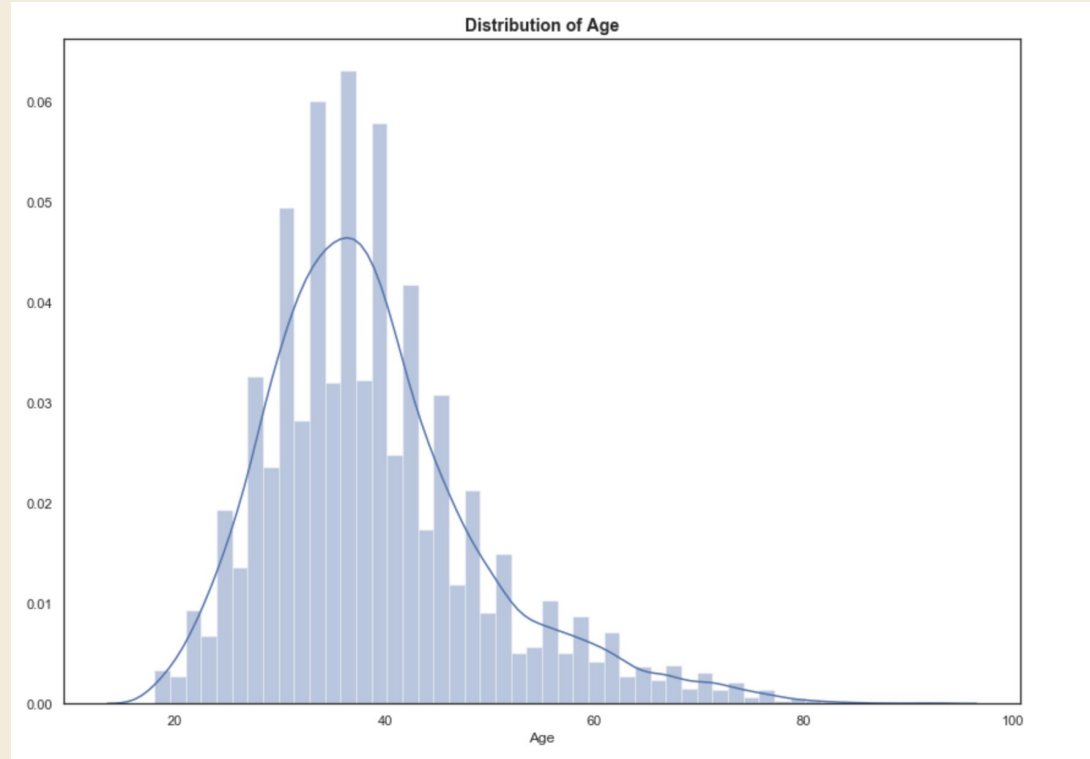
CREDIT SCORE RATING ON CHURN RATE

Customers with a credit score 500 or less are most likely to leave our service compared to higher credit score groups



DATA NORMALIZATION

Normalization of data is an integral part of machine modeling as it allows the transformation of numerical data values while keeping a common scale



VARIABLE CORRELATIONS

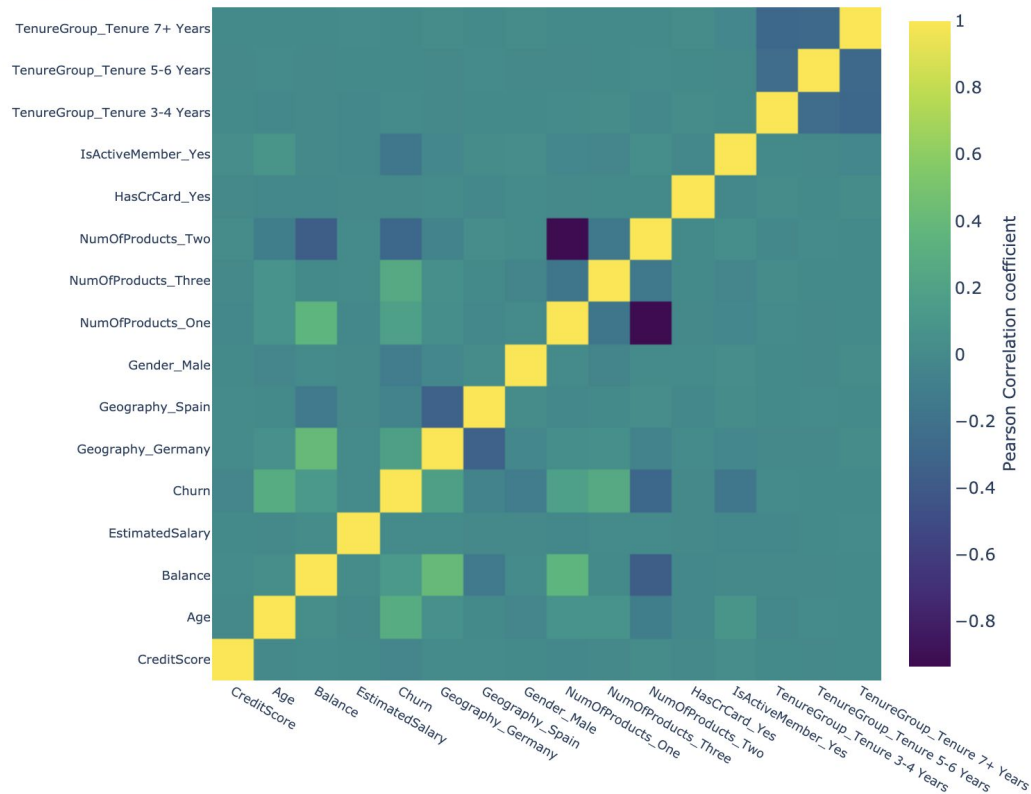
Age	3.966205
EstimatedSalary	3.383194
Balance	3.018990
HasCrCard_Yes	2.953638
Gender_Male	2.075848
IsActiveMember_Yes	2.009471
NumOfProducts_Two	1.925861
Geography_Germany	1.791260
TenureGroup_Tenure 7+ Years	1.613641
TenureGroup_Tenure 5-6 Years	1.481551
TenureGroup_Tenure 3-4 Years	1.479715
Geography_Spain	1.451756
NumOfProducts_Three	1.060019
CreditScore	1.001141

Variance Inflation Factor (VIF)

VIF provides a measurement on how much variance increases due to collinearity

CORRELATIONS MATRIX

Correlation Matrix for variables



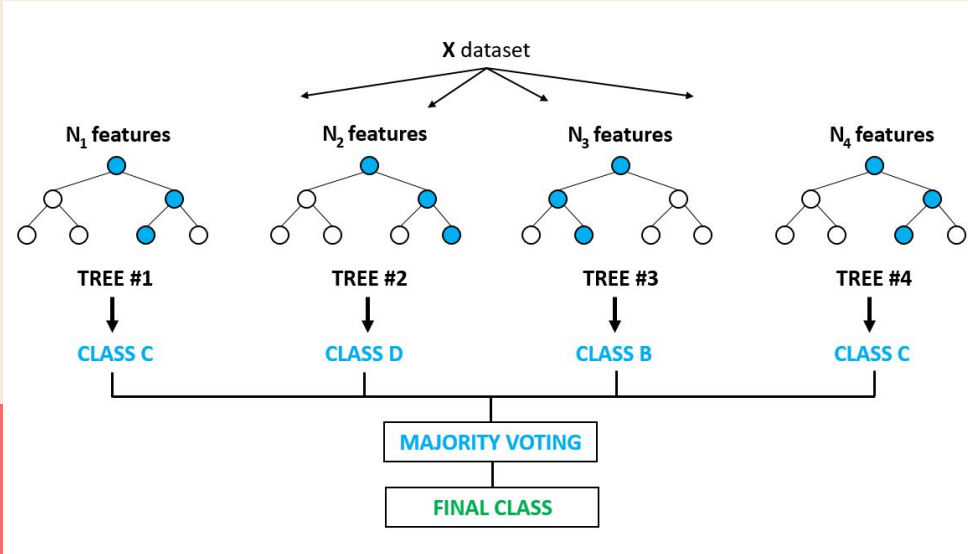
By reducing multicollinearity in our model, we are able to reduce variation and increase accuracy of our model

Here we can visualize the correlations

RANDOM FOREST MODEL

To predict and classify our customers, we used the random forest algorithm model

Random Forest classifier consists of many individual decision trees that all work in tandem



MODEL PREDICTION & CLASSIFICATION

How well does our first model classify our customers?

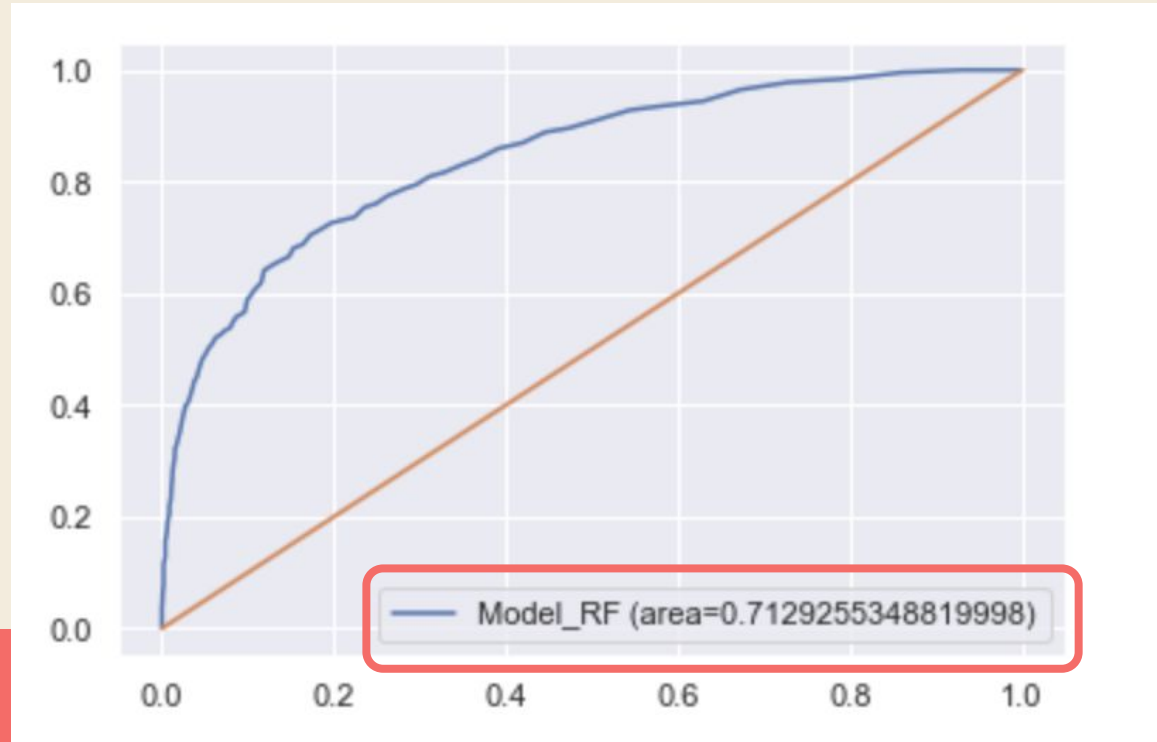
Using a confusion matrix, we are able to see our prediction accuracy

Churn	Predicted: NO	Predicted: YES
Actual: NO	2534	117
Actual: YES	362	321

MODEL AUC ROC CURVE ANALYSIS

How well does our first model classify our customers?

AUC ROC Curve tells us how well our model can distinguish between the different categories



MODEL PERFORMANCE MEASURES

Accuracy

Correctly prediction observations out of the total number of observations

0.86

Precision

Correctly prediction positive observations out of total positive observations

0.76

F1-Score

The weighted average of precision and the ratio of correct positives to all positive observations, correct or not

0.58



MODEL OPTIMIZATION WITH CATBOOST

By optimizing our model,
we are able to reduce
false negative
predictions, increasing
our models effectiveness

Categorical Boost is a
machine learning
algorithm that works by
converting categorical
values to numerical ones
based on statistical
combinations

CATBOOST MODEL PREDICTION & PARAMETERS



ACCURACY + **0.011**



PRECISION + **0.045**



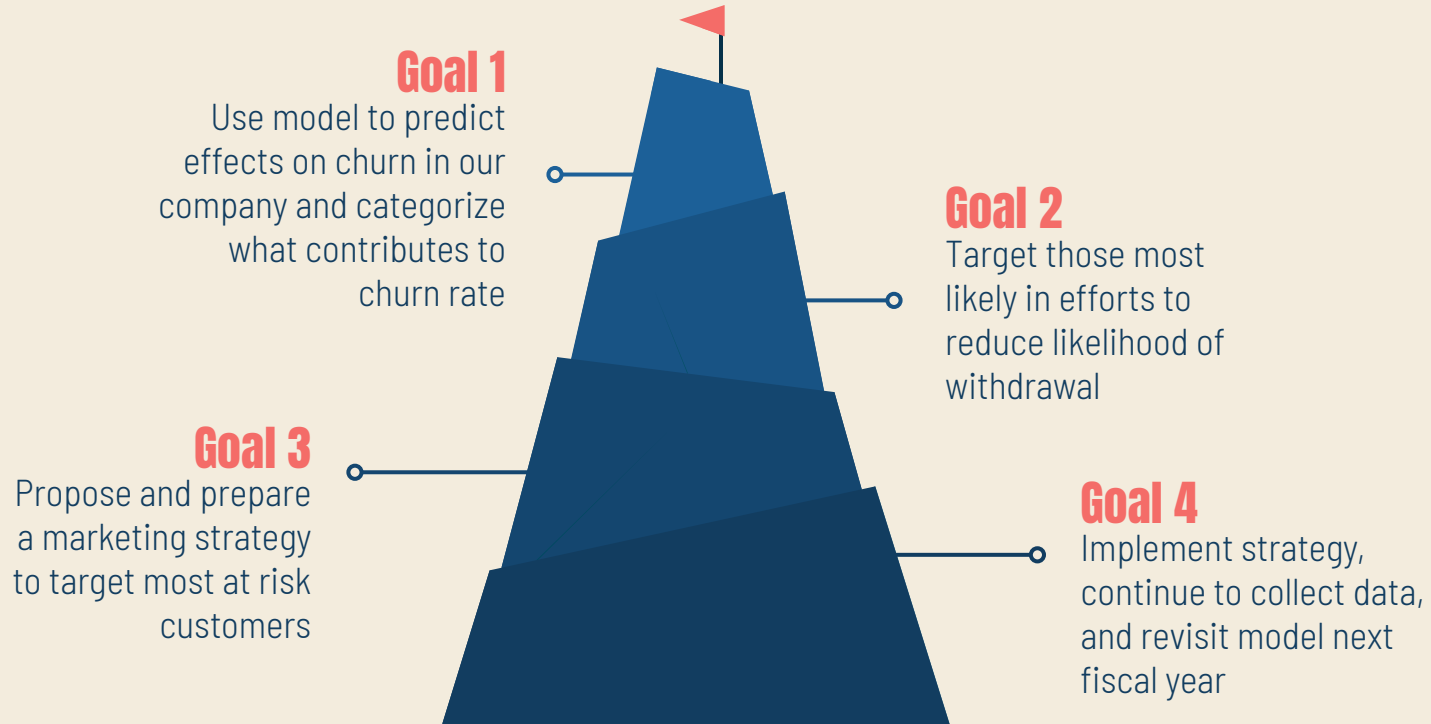
F1-SCORE + **0.058**

AUC ROC CURVE : 0.740

*Up from 0.71

Churn	Predicted: NO	Predicted: YES
Actual: NO	2545	83
Actual: YES	328	344

PROCEEDING WITH A STRATEGY



THANKS

