# Bank Customers Churn Classification



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Introduction

#### Introduction

In this work the purpose is to build a model that predicts if a customer will churn form the bank (or not) given various data points and information from historical data:

#### Goals:

- Predicting if a customer will leave or not.
- Banks will be able to predict the risk of the customer on whether they will leave or not.



02

Methodology

## Methodology

#### **Data Extraction**

- -Data from Kaggle
- -10000 Row
- -14 Columns



#### **EDA**

- -Data Wrangling
- -Data Cleaning
- -Visualization

## Feature Engineering

- -Outliers
- -Dummy Variables





#### **Models**

- -Model Preprocessing
- -Building Models

### **Tools**

Jupyter Notebook

**Pandas** 

Seaborn

**Matplotlib** 

Sklearn

**NumPy** 

Dabl

## **Data Split**



## **Exploratory Data Analysis**

- Data Cleaning
- Same size after cleaning

- No extreme values
- Imbalanced data



## Heatmap

| 100               |           |          |         |        |        |         |        |         |        |         |        |        |         |         |
|-------------------|-----------|----------|---------|--------|--------|---------|--------|---------|--------|---------|--------|--------|---------|---------|
| France -          |           | -0.58    | -0.58   |        |        |         |        |         | -0.23  |         |        |        |         | -0.1    |
| Germany -         | -0.58     | 1        | -0.33   |        |        |         |        |         | 0.4    |         |        |        |         |         |
| Spain -           | -0.58     | -0.33    | 1       | -0.017 | 0.017  |         |        |         | -0.13  |         |        |        |         | -0.053  |
| Female -          |           |          |         | 1      | -1     |         |        |         |        |         |        |        |         |         |
| Male -            |           |          |         | -1     | 1      | -0.0029 |        |         |        |         |        |        |         | -0.11   |
| CreditScore -     |           |          |         |        |        | 1       | -0.004 |         |        |         |        |        |         |         |
| Age -             |           |          |         |        |        |         | 1      | -0.01   |        |         |        |        |         |         |
| Tenure -          |           | -0.00057 |         |        |        |         |        | 1       | -0.012 |         |        |        |         |         |
| Balance -         | -0.23     | 0.4      | -0.13   |        |        |         |        |         | 1      | -0.3    | -0.015 |        |         |         |
| NumOfProducts -   |           |          |         |        |        |         |        |         | -0.3   | 1       | 0.0032 | 0.0096 |         | -0.048  |
| HasCrCard -       |           |          |         |        |        |         |        |         |        |         | 1      | -0.012 |         |         |
| IsActiveMember -  |           |          |         |        |        |         |        |         |        |         |        | 1      | -0.011  | -0.16   |
| EstimatedSalary - |           |          |         |        |        |         |        |         |        |         |        |        | 1       | 0.012   |
| Exited -          | -0.1      |          | -0.053  |        | -0.11  |         |        |         |        | -0.048  |        | -0.16  |         |         |
|                   | - Jance - | many -   | - uieds | male - | Male - | Score - | Age    | enure - | lance  | ducts - | -Card  | mper - | alary - | - yited |

Features that has big correlation with exiting the bank:

• Age (29%)

--0.75

- Customers in Germany (17%)
- Female customers (11%)

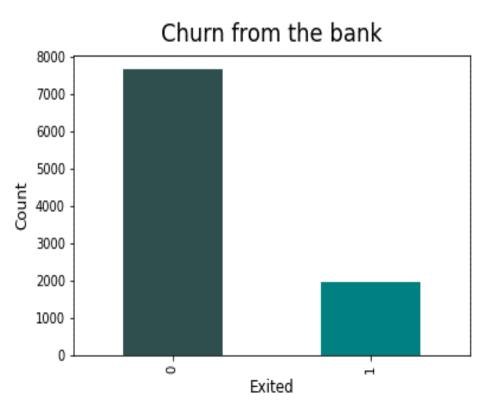
# 03 Data Preprocessing

## **Feature Engineering**

#### Steps:

- Feature selection using LASSO and Recursive Feature Elimination
- Dummy variables
- Outliers

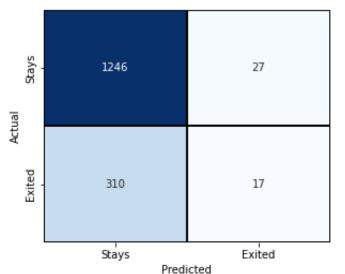
### **Data Imbalance**



**Solved using RandomOverSampler (ROS)** 

# 04 Models

# **Baseline Model: Logistic Regression**



| - 1200 |
|--------|
| - 1000 |
| - 800  |
| - 600  |
| - 400  |
| - 200  |
|        |

| 00 | Score     | Training | Validation |
|----|-----------|----------|------------|
| 0  | Accuracy  | 0.6659   | 0.6641     |
| 0  | Precision | 0.6636   | 0.6636     |
| 0  | Recall    | 0.6800   | 0.6801     |
|    | Fl        | 0.6717   | 0.6718     |

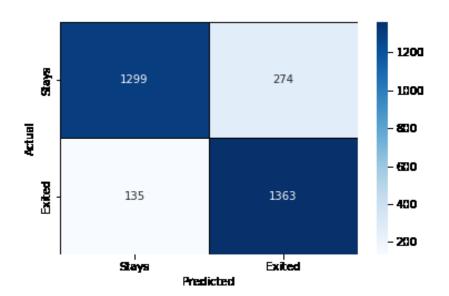
### **DABL Modeling**

```
In [116]: survivor classifier = dabl.SimpleClassifier(random state=42).fit(X train, y train)
          Running DummyClassifier()
          accuracy: 0.502 average precision: 0.498 roc auc: 0.500 recall macro: 0.500 f1 macro: 0.334
          === new best DummyClassifier() (using recall macro):
          accuracy: 0.502 average_precision: 0.498 roc auc: 0.500 recall macro: 0.500 f1_macro: 0.334
          Running GaussianNB()
          accuracy: 0.719 average precision: 0.776 roc auc: 0.792 recall macro: 0.719 f1 macro: 0.719
          === new best GaussianNB() (using recall macro):
          accuracy: 0.719 average precision: 0.776 roc auc: 0.792 recall macro: 0.719 f1 macro: 0.719
          Running MultinomialNB()
          accuracy: 0.637 average precision: 0.687 roc auc: 0.702 recall macro: 0.637 f1 macro: 0.637
          Running DecisionTreeClassifier(class_weight='balanced', max depth=1)
          accuracy: 0.700 average precision: 0.632 roc auc: 0.700 recall macro: 0.700 f1 macro: 0.697
          Running DecisionTreeClassifier(class weight='balanced', max depth=5)
          accuracy: 0.766 average precision: 0.819 roc auc: 0.846 recall macro: 0.766 f1 macro: 0.766
          === new best DecisionTreeClassifier(class weight='balanced', max depth=5) (using recall macro):
          accuracy: 0.766 average precision: 0.819 roc auc: 0.846 recall macro: 0.766 f1 macro: 0.766
          Running DecisionTreeClassifier(class weight='balanced', min impurity decrease=0.01)
          accuracy: 0.725 average precision: 0.730 roc auc: 0.779 recall macro: 0.725 f1 macro: 0.723
          Running LogisticRegression(C=0.1, class weight='balanced', max iter=1000)
          accuracy: 0.725 average precision: 0.765 roc auc: 0.209 recall macro: 0.725 f1 macro: 0.725
          Running LogisticRegression(class weight='balanced', max iter=1000)
          accuracy: 0.725 average precision: 0.765 roc auc: 0.209 recall macro: 0.725 f1 macro: 0.725
          Best model:
          DecisionTreeClassifier(class weight='balanced', max depth=5)
          Best Scores:
          accuracy: 0.766 average precision: 0.819 roc auc: 0.846 recall macro: 0.766 f1 macro: 0.766
```

## **Classification Models**

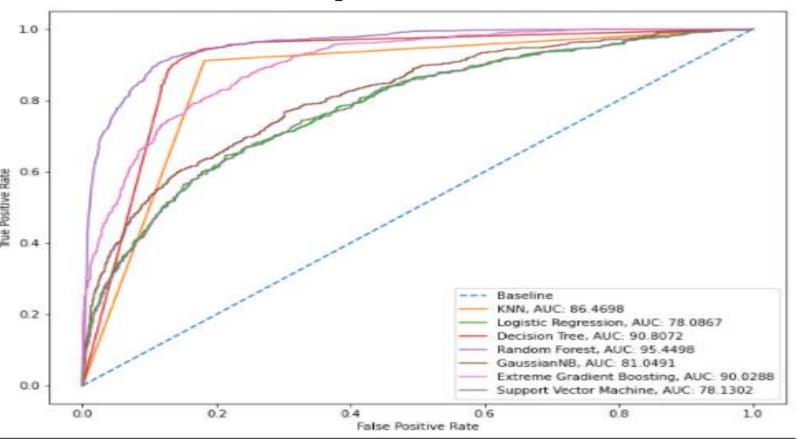
| Model                   | Accuracy | F1-Score |  |  |
|-------------------------|----------|----------|--|--|
| Logistic Regression     | 0.7468   | 0.7461   |  |  |
| KNN                     | 0.8702   | 0.8781   |  |  |
| Random Forest           | 0.8812   | 0.8881   |  |  |
| Gaussian Naïve<br>Bayes | 0.7444   | 0.7411   |  |  |
| SVM                     | 0.7424   | 0.7372   |  |  |
| Decision Tree           | 0.8751   | 0.8830   |  |  |
| XGB                     | 0.8221   | 0.8236   |  |  |

## **Ensemble: Max Voting Classifier**

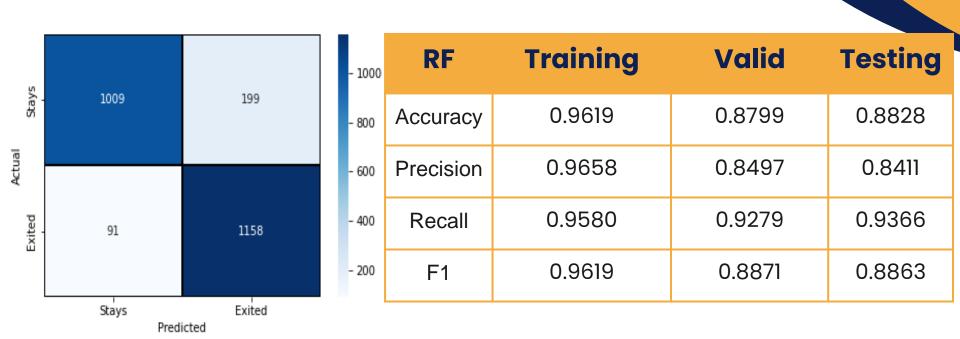


Training Accuracy: 0.9438 Testing Accuracy: 0.8668

#### **ROC Curve Graph**



#### **Best Model: Random Forest**





# Conclusions

- The best model to predict is Random Forest.
- Highest validation accuracy.

# Thanks!

Do you have any questions?

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