Importing dependencies

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style = 'white')


from sklearn.preprocessing import MinMaxScaler

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score
```

Loading of Dataset and Initial Inspection

```
df = pd.read_csv('./drive/MyDrive/datasets/churn_bank.csv')

df.head()
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave          619    France  Female   42

1          2    15647311      Hill          608     Spain  Female   41

2          3    15619304      Onio          502    France  Female   42

3          4    15701354      Boni          699    France  Female   39

4          5    15737888  Mitchell          850     Spain  Female   43


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1
```

```
   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

```
df.describe()
```

```
         RowNumber    CustomerId   CreditScore           Age
Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000
10000.000000
mean    5000.50000  1.569094e+07    650.528800     38.921800
5.012800
std     2886.89568  7.193619e+04     96.653299     10.487806
2.892174
min        1.00000  1.556570e+07    350.000000     18.000000
0.000000
25%     2500.75000  1.562853e+07    584.000000     32.000000
3.000000
50%     5000.50000  1.569074e+07    652.000000     37.000000
5.000000
75%     7500.25000  1.575323e+07    718.000000     44.000000
7.000000
max    10000.00000  1.581569e+07    850.000000     92.000000
10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.530200      0.70550        0.515100
std     62397.405202       0.581654      0.45584        0.499797
min         0.000000       1.000000      0.00000        0.000000
25%         0.000000       1.000000      0.00000        0.000000
50%     97198.540000       1.000000      1.00000        1.000000
75%    127644.240000       2.000000      1.00000        1.000000
max    250898.090000       4.000000      1.00000        1.000000

       EstimatedSalary        Exited
count     10000.000000  10000.000000
mean     100090.239881      0.203700
std       57510.492818      0.402769
min          11.580000      0.000000
25%       51002.110000      0.000000
50%      100193.915000      0.000000
75%      149388.247500      0.000000
max      199992.480000      1.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
df2 = df.iloc[:, 3:]
```

RowNumber, CustomerId, and Surname are all irrelevant, thus, they will not be included.

```
df2.head()
```

```
   CreditScore Geography  Gender  Age  Tenure    Balance  
NumOfProducts  \
0          619    France  Female   42       2       0.00  
1   
1          608     Spain  Female   41       1   83807.86  
1   
2          502    France  Female   42       8  159660.80  
3   
3          699    France  Female   39       1       0.00  
2   
4          850     Spain  Female   43       2  125510.82  
1   

   HasCrCard  IsActiveMember  EstimatedSalary  Exited  
0          1               1        101348.88       1  
1          0               1        112542.58       0  
2          1               0        113931.57       1  
3          0               0         93826.63       0  
4          1               1         79084.10       0  
```

```
df2['Gender'].replace(to_replace = 'Female', value = 0, inplace = 
True)
df2['Gender'].replace(to_replace = 'Male', value = 1, inplace = True)
```

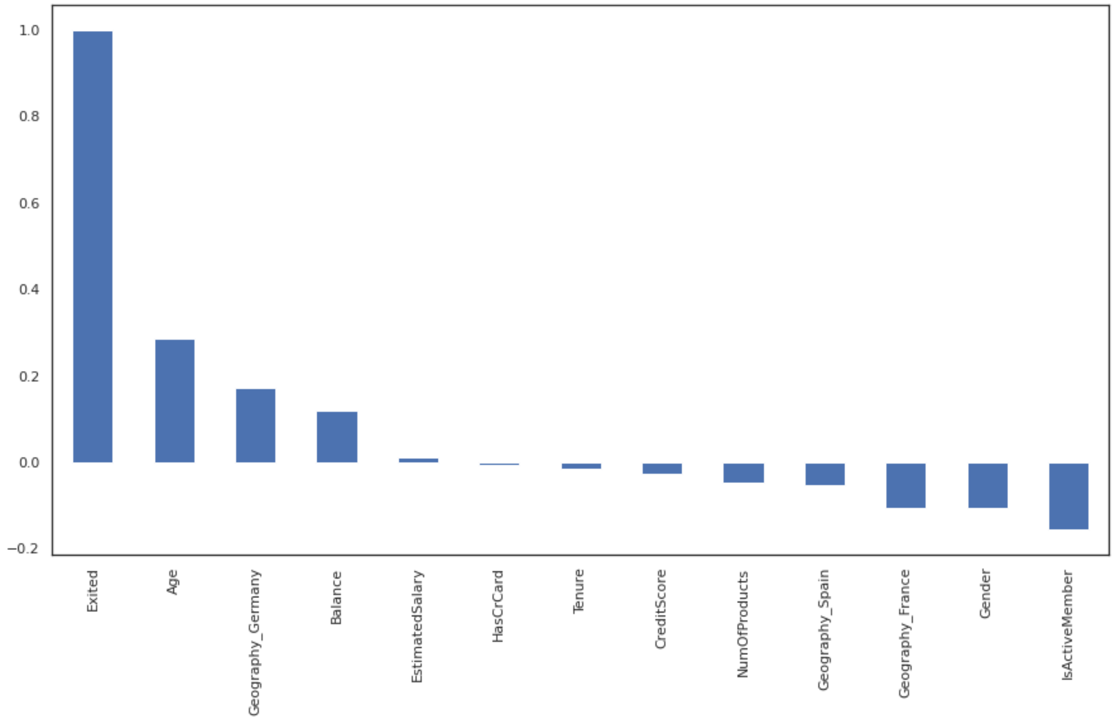
```
df2['Gender'].unique()
```

```
array([0, 1])
```

```
df_dummies = pd.get_dummies(df2)
df_dummies.head()
```

```
   CreditScore  Gender  Age  Tenure    Balance  NumOfProducts  
HasCrCard  \
0          619       0   42       2       0.00              1  
1
1          608       0   41       1   83807.86              1  
0
2          502       0   42       8  159660.80              3  
1
3          699       0   39       1       0.00              2  
0
4          850       0   43       2  125510.82              1  
1

   IsActiveMember  EstimatedSalary  Exited  Geography_France  \
0               1        101348.88       1                 1   
1               1        112542.58       0                 0   
2               0        113931.57       1                 1   
3               0         93826.63       0                 1   
4               1         79084.10       0                 0   

   Geography_Germany  Geography_Spain  
0                  0                0  
1                  0                1  
2                  0                0  
3                  0                0  
4                  0                1  
```

```
plt.figure(figsize = (15, 8))
df_dummies.corr()['Exited'].sort_values(ascending = False).plot(kind = 
'bar')
plt.show()
```



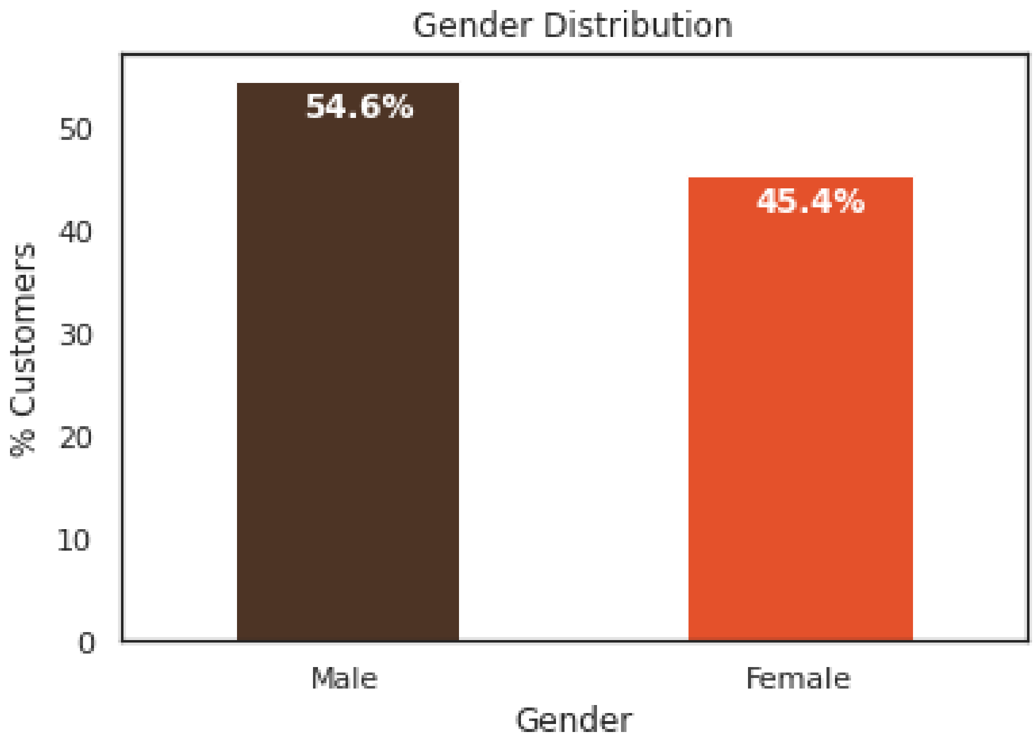
Age, Geography_Germany, and *Balance* all seem to be positively correlated to churning. On the other hand: *isActiveMember, Gender,* and *Geography_France* all seem to be negatively correlated. Exploration of the patterns is important before delving right into modelling.

EXPLORATORY DATA ANALYSIS

Distribution of customers based on their personal information

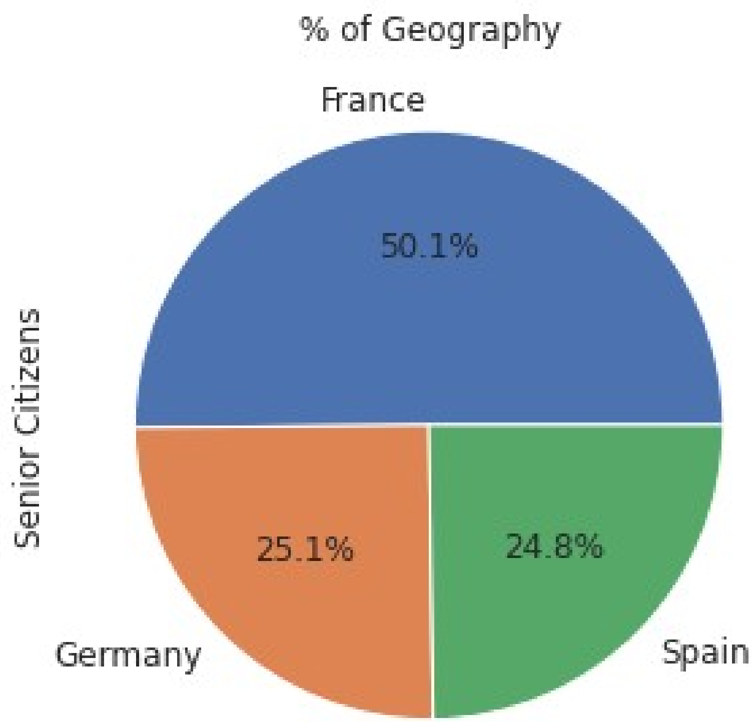
```
colors = ['#4D3425','#E4512B']
ax = (df['Gender'].value_counts()*100.0 /len(df)).plot(kind='bar',
stacked = True, rot = 0, color = colors)
ax.set_ylabel('% Customers')
ax.set_xlabel('Gender')
ax.set_ylabel('% Customers')
ax.set_title('Gender Distribution')

totals = []

for i in ax.patches:
    totals.append(i.get_width())

total = sum(totals)

for i in ax.patches:
    ax.text(i.get_x()+.15, i.get_height()-3.5, \
            str(round((i.get_height()/total), 1))+'%',
            fontsize=12,
```

```
            color='white',
           weight = 'bold')

plt.show()
```



The number of entries who are Male are greater in numbers compared to the Female entries, although not that significant.

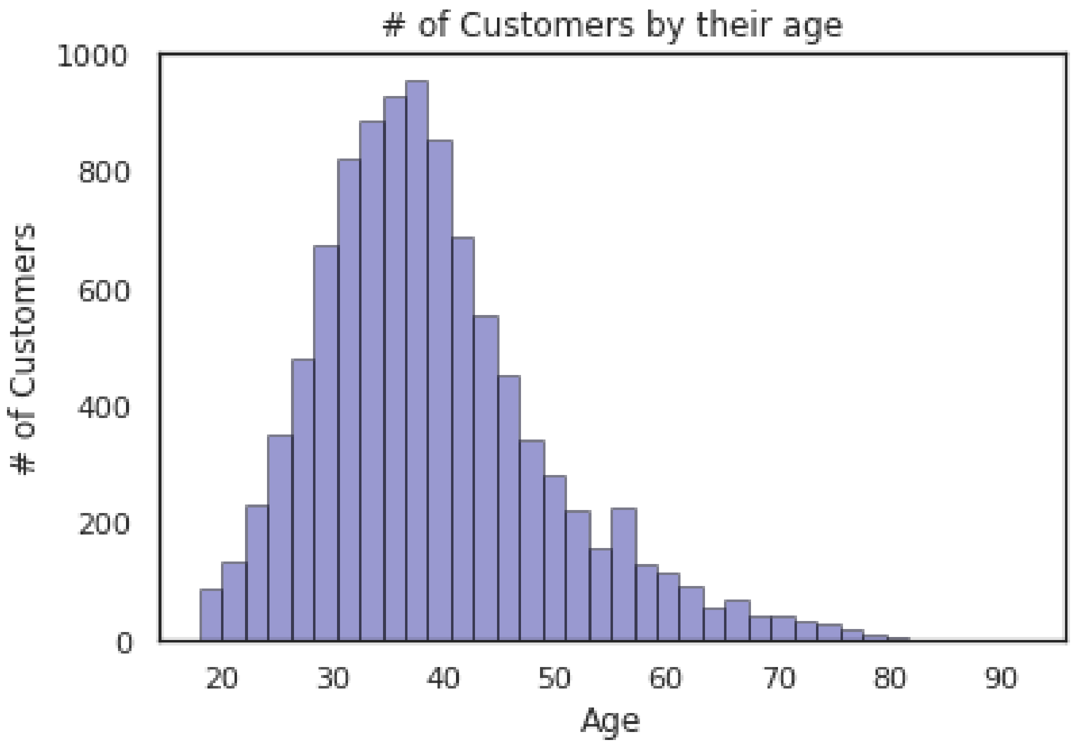
```
ax = (df['Geography'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%.1f%%',figsize =(5,5), fontsize = 12 )

ax.set_ylabel('Senior Citizens',fontsize = 12)
ax.set_title('% of Geography', fontsize = 12)
plt.show()
```



The number of people living in France largely dominates the dataset, having more entries than both Germany and Spain combined.

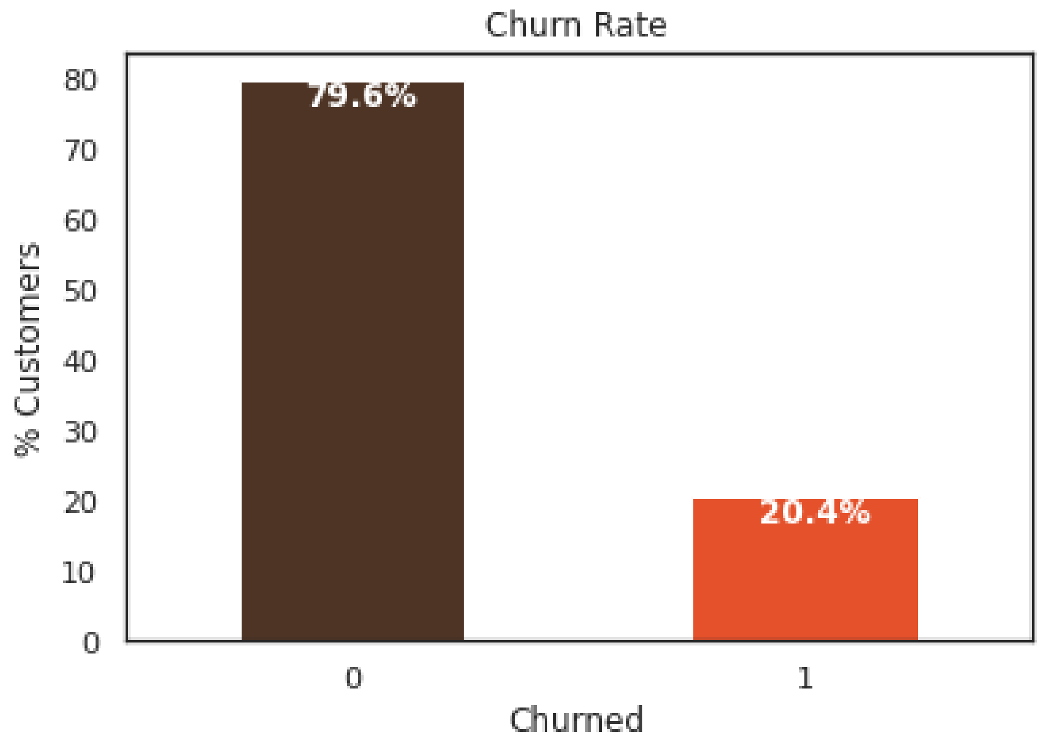
```
ax = sns.distplot(df['Age'], hist=True, kde=False,
             bins=int(180/5), color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
ax.set_ylabel('# of Customers')
ax.set_xlabel('Age')
ax.set_title('# of Customers by their age')

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



Most of the customers are aged around 40 years old. Significant decrease in distribution follows thereafter, with 80 years old and above having the least amount.

```
colors = ['#4D3425','#E4512B']
ax = (df['Exited'].value_counts()*100.0 /len(df)).plot(kind='bar',
stacked = True, rot = 0, color = colors)
ax.set_ylabel('% Customers')
ax.set_xlabel('Churned')
ax.set_ylabel('% Customers')
ax.set_title('Churn Rate')

totals = []

for i in ax.patches:
    totals.append(i.get_width())

total = sum(totals)

for i in ax.patches:
    ax.text(i.get_x()+.15, i.get_height()-3.5, \
            str(round((i.get_height()/total), 1))+'%',
            fontsize=12,
            color='white',
           weight = 'bold')
```

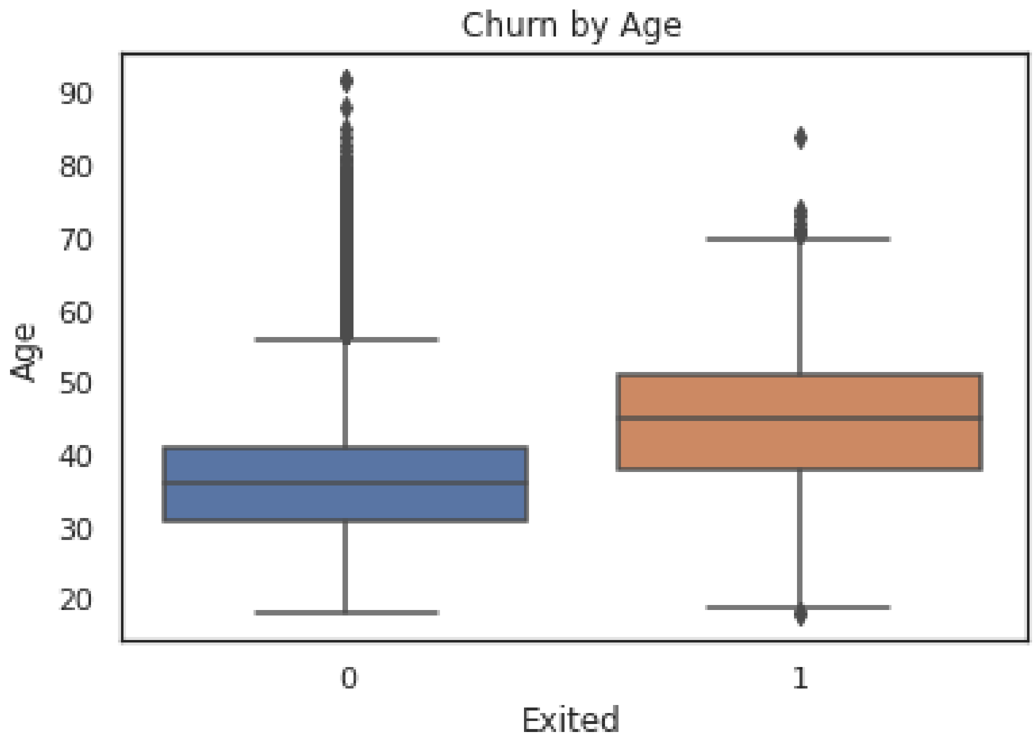


As visualization suggests, the dataset largely consists of more customers who have not churned rather than those who have churned, thus, it is expected that the data is skewed as the distribution between the two are far from equal. This is key in understanding the amount of false negatives.

Personal Information vs Churn Rate

```
plt.title('Churn by Age')
sns.boxplot(x = df['Exited'], y = df['Age'])
```

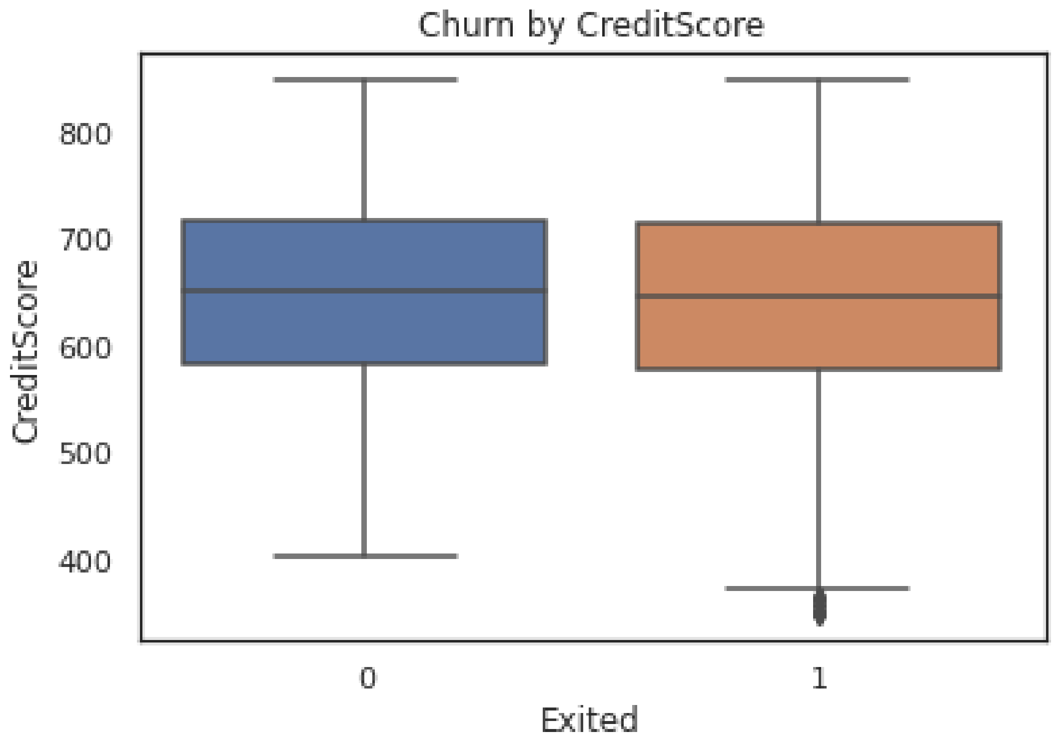
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe4dce3da50>
```



There is alot of variance in age of customers who have not churned, even reaching the ages of approximately 90 years old

```
plt.title('Churn by CreditScore')
sns.boxplot(x = df['Exited'], y = df['CreditScore'])
```

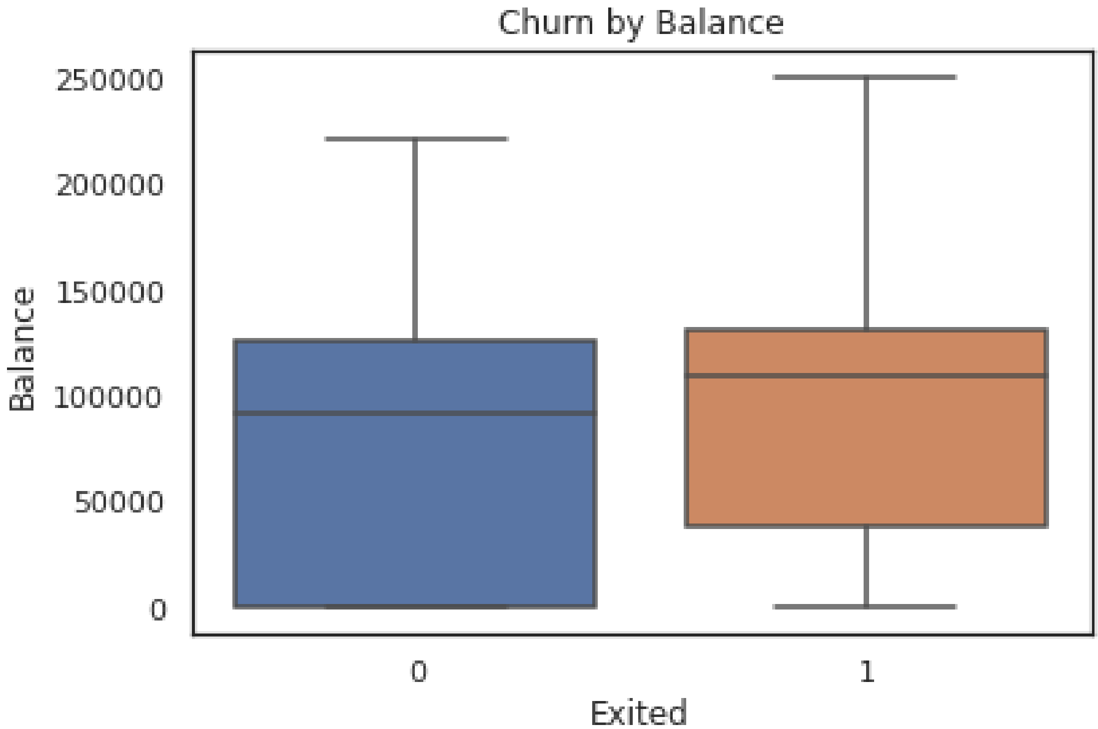
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe4dc638e90>
```



There isn't much to explain between a customer churning and their credit score, thus having little to no relevance.

```
plt.title('Churn by Balance')
sns.boxplot(x = df['Exited'], y = df['Balance'])
```

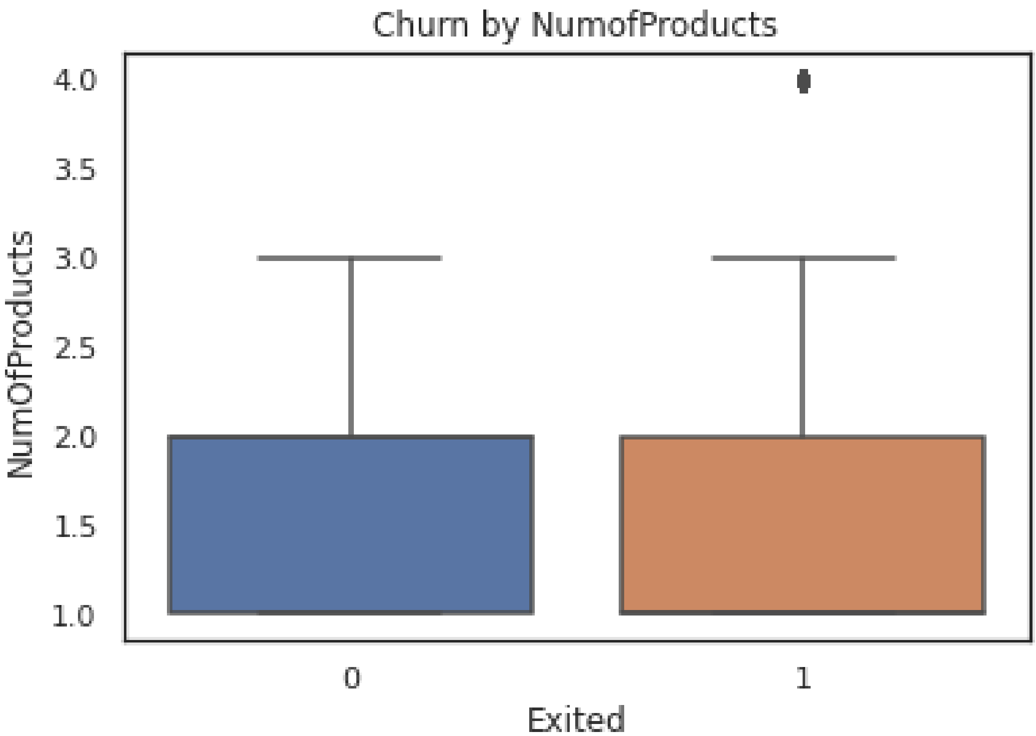
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe4dc5b8490>
```



Customers who have more in their balance tend to churn compared to those who have less in their balance.

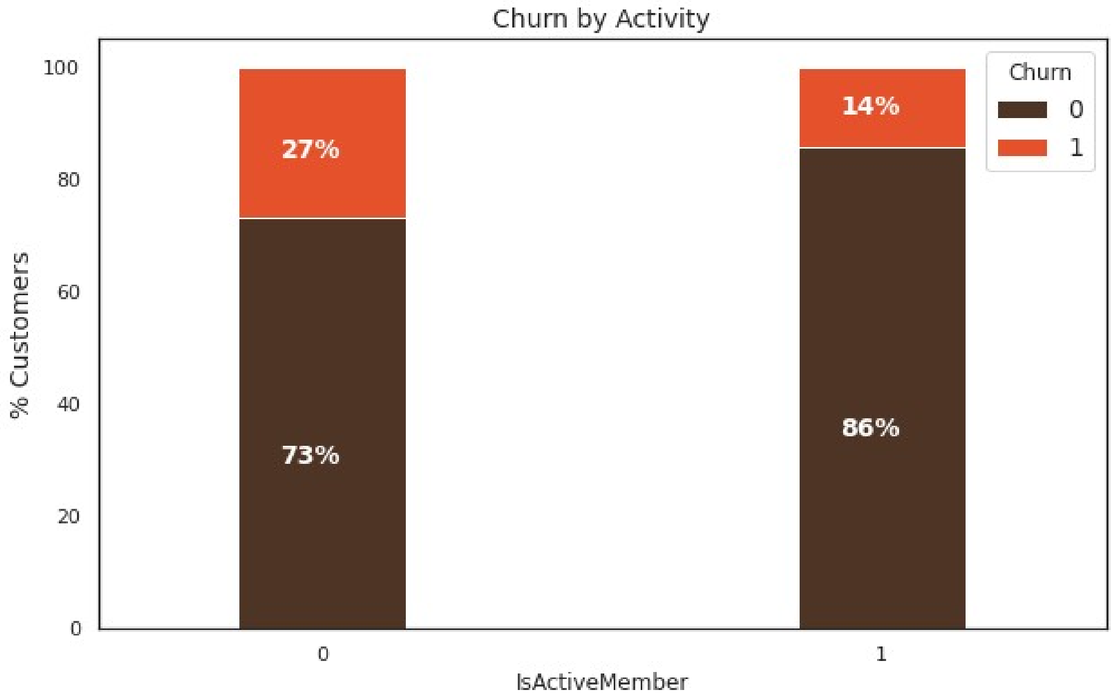
```
plt.title('Churn by NumofProducts')
sns.boxplot(x = df['Exited'], y = df['NumOfProducts'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe4dc5350d0>
```



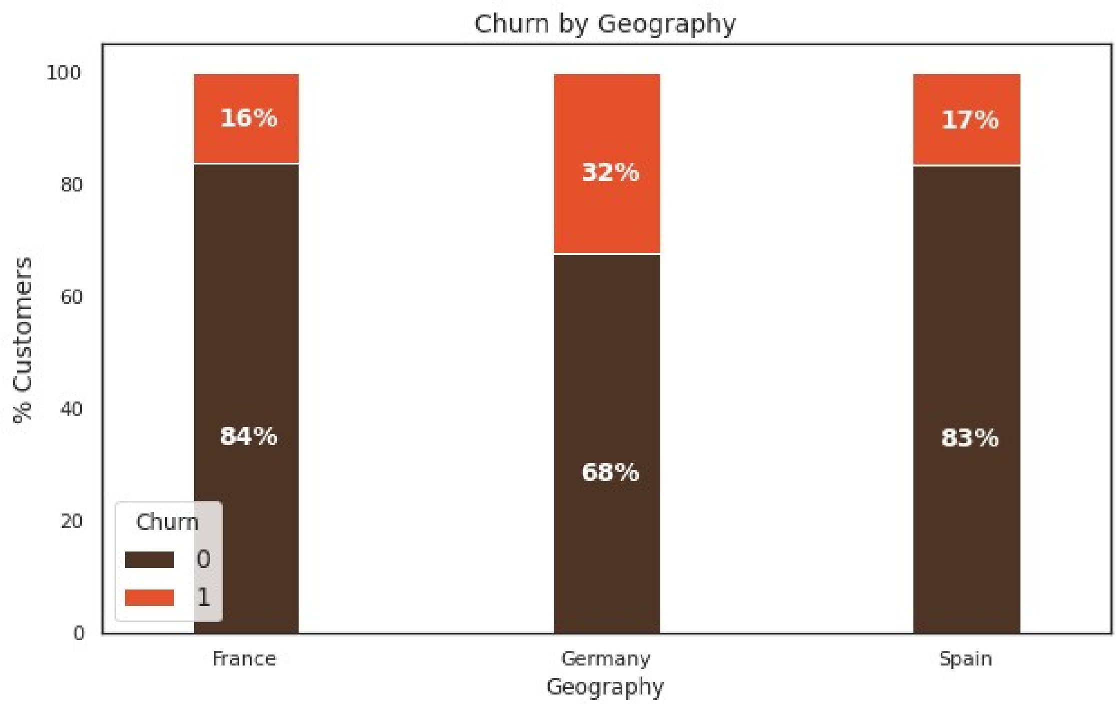
Customers who have 1-3 in number of products have the same probability of churning, but customers who have 4 products are more likely to churn.

```
colors = ['#4D3425','#E4512B']
contract_churn =
df.groupby(['IsActiveMember','Exited']).size().unstack()

ax = (contract_churn.T*100.0 /
contract_churn.T.sum()).T.plot(kind='bar', width = 0.3, stacked =
True, rot = 0, figsize = (10,6), color = colors)

ax.legend(loc='best',prop={'size':14},title = 'Churn')
ax.set_ylabel('% Customers',size = 14)
ax.set_title('Churn by Activity',size = 14)

for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x()+.25*width,
p.get_y()+.4*height),
                color = 'white',
               weight = 'bold',
               size = 14)
```



Active members are less likely to churn than those who aren't active.

```
colors = ['#4D3425','#E4512B']
contract_churn = df.groupby(['Geography','Exited']).size().unstack()

ax = (contract_churn.T*100.0 /
contract_churn.T.sum()).T.plot(kind='bar', width = 0.3, stacked =
True, rot = 0, figsize = (10,6), color = colors)

ax.legend(loc='best',prop={'size':14},title = 'Churn')
ax.set_ylabel('% Customers',size = 14)
ax.set_title('Churn by Geography',size = 14)

for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x()+.25*width,
p.get_y()+.4*height),
                color = 'white',
               weight = 'bold',
               size = 14)
```



While most of the customers are based in France, it relatively has the least amount of customers who have churned, while Germany who has roughly half the amount of customers from France, has the most amount of customers who have churned thus far.

Model Training and Evaluation

1. Logistic Regression

1A. **MODEL TRAINING**

```
y = df_dummies['Exited'].values
X = df_dummies.drop(columns = ['Exited'])

features = X.columns.values
scaler = MinMaxScaler(feature_range = (0, 1))
scaler.fit(X)
X = pd.DataFrame(scaler.transform(X))
X.columns = features

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random_state = 26)

model_logreg = LogisticRegression()
model_logreg.fit(X_train, y_train)
y_pred = model_logreg.predict(X_test)
```

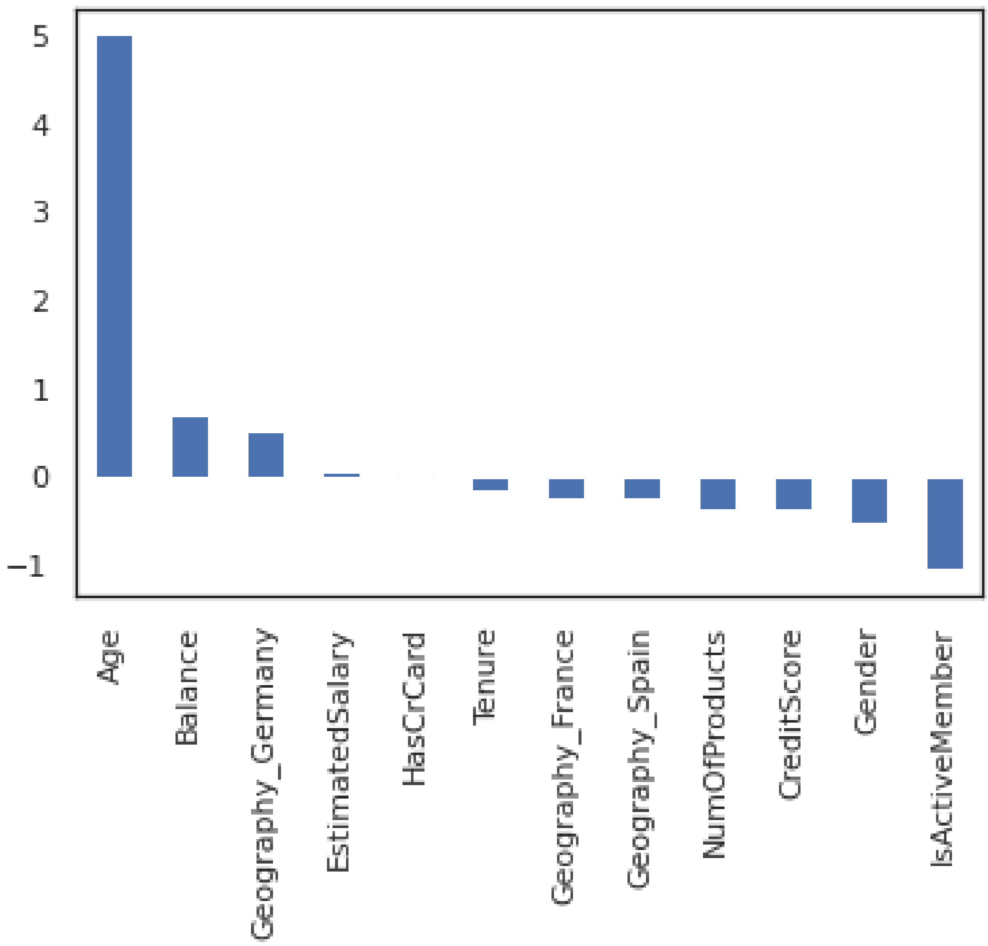
1B. **MODEL EVALUATION**

```
print('Logistic Regression Score:', accuracy_score(y_test, y_pred))
```

```
Logistic Regression Score: 0.817
```

```
weights = pd.Series(model_logreg.coef_[0], index = X.columns.values)
print(weights.sort_values(ascending = False).plot(kind = 'bar'))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```



Observations made with Logistic Regression:

- Age is positively correlated with churning, therefore the probability of churning increases with the age of the customers
- Amongst all the features, being an active member is the most negatively correlated with churning, therefore active members are the least likely to churn

2. Random Forest Classifier

2A. **MODEL TRAINING**

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 26)

model_rfc = RandomForestClassifier(n_estimators = 1000, oob_score =
True, n_jobs = -1, random_state = 26, max_features = 'auto',
max_leaf_nodes = 30)
model_rfc.fit(X_train, y_train)

y_pred1 = model_rfc.predict(X_test)
```

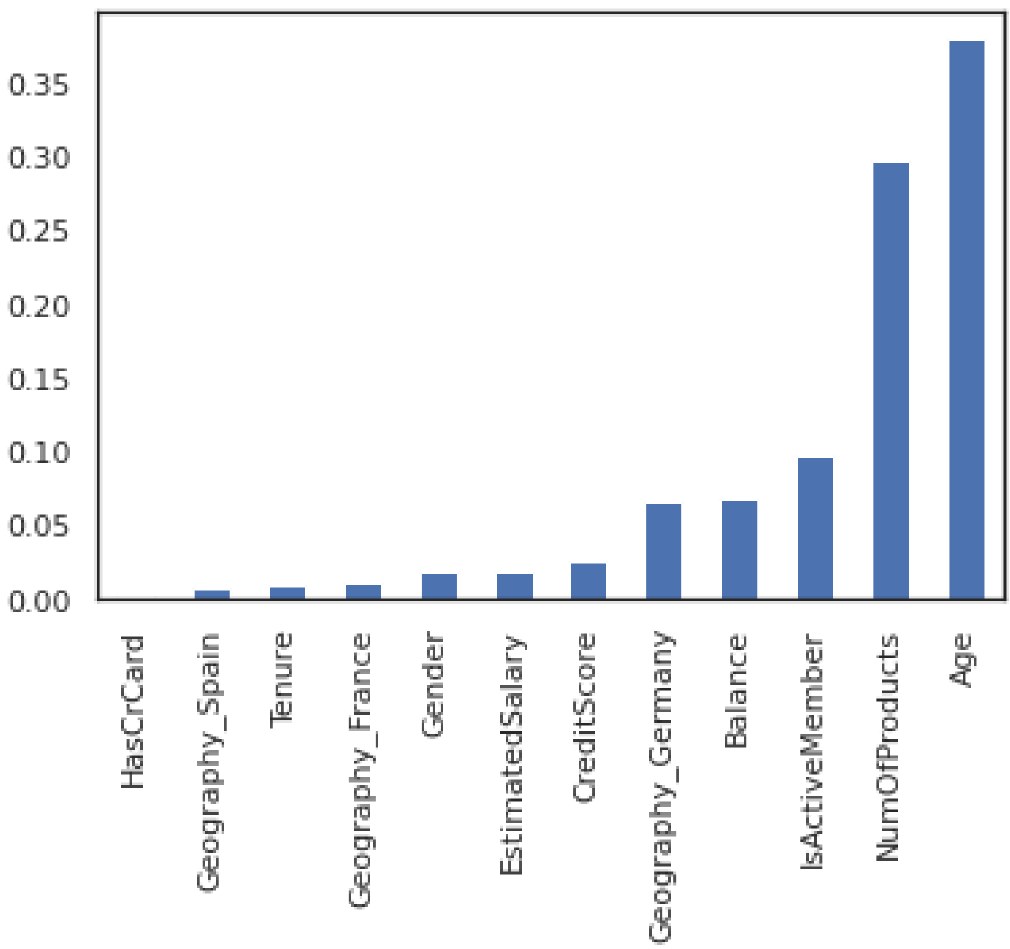
2B. **MODEL EVALUATION**

```
print("Random Forest Classifier:", accuracy_score(y_test, y_pred1))
```

```
Random Forest Classifier: 0.8685
```

```
impt = model_rfc.feature_importances_
weights_rfc = pd.Series(impt, index = X.columns.values)

weights_rfc.sort_values().plot(kind = 'bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe4dc7ec2d0>
```



In terms of Random Forest Classifier, the most important feature remains to be the Age, however, this time NumOfProducts exponentially arose in relevance, while HasCrCard remains to be irrelevant/unimportant.

3. Support Vector Classifier

3A. **MODEL TRAINING**

```
model_svc = SVC(kernel = 'poly')
model_svc.fit(X_train, y_train)
y_pred2 = model_svc.predict(X_test)
```

3B. **MODEL EVALUATION**

```
print('Support Vector Classifier:', accuracy_score(y_pred2, y_test))
```

```
Support Vector Classifier: 0.862
```

4. ADA Boost Classifier

4A. **MODEL TRAINING**

```
model_ada = AdaBoostClassifier()

model_ada.fit(X_train, y_train)
y_pred3 = model_ada.predict(X_test)
```

4B. **MODEL EVALUATION**

```
print('ADA Boost Classifier:', accuracy_score(y_pred3, y_test))
```

```
ADA Boost Classifier: 0.858
```

5. XGBoost Classifier

5A. **MODEL TRAINING**

```
model_xgb = XGBClassifier()
model_xgb.fit(X_train, y_train)
y_pred4 = model_xgb.predict(X_test)
```

5B. **MODEL EVALUATION**

```
print('XGBoost Classifier:', accuracy_score(y_pred4, y_test))
```

```
XGBoost Classifier: 0.8705
```

XGBoost has the highest accuracy among all the techniques demonstrated above, albeit being retrospectively expensive. It achieves this accuracy relatively faster, because of its parallel computing capabilities.

Out of all the models, the XGBoost provided the highest accuracy, while, in contrast, Logistic Regression had the lowest score.