The Dataset: Bank Customer Churn Modeling

The dataset you'll be using to develop a customer churn prediction model can be downloaded from this KAGGLE LINK. Be sure to save the CSV to your hard drive.Taking a closer look, we see that the dataset contains 14 columns (also known as features or variables). The first 13 columns are the independent variable, while the last column is the dependent variable that contains a binary value of 1 or 0. Here, 1 refers to the case where the customer left the bank after 6 months, and 0 is the case where the customer didn't leave the bank after 6 months. This is known as a binary classification problem, where you have only two possible values for the dependent variable—in this case, a customer either leaves the bank after 6 months or doesn't.

It's important to mention that the data for the independent variables was collected 6 months before the data for the dependent variable, since the task is to develop a machine learning model that can predict whether a customer will leave the bank after 6 months, depending on the current feature values.

Here's an overview of the steps we'll take in this article:

1. Importing the libraries
2. Loading the dataset
3. Selecting relevant features
4. Converting categorical columns to numeric ones
5. Preprocessing the data
6. Training a machine learning algorithm
7. Evaluating the machine learning algorithm
8. Evaluating the dataset features

9. All right, let's begin!

Step 1: Importing the Libraries

The first step, as always, is to import the required libraries. Execute the following code to do so:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Step 2: Loading the Dataset

The second step is to load the dataset from the local CSV file into your Python program. Let's use the read_csv method of the pandas library. Execute the following code:

```
customer_data = pd.read_csv(r'E:/Datasets/Churn_Modelling.csv')
```

If you open the customer_data dataframe in Spyder's Variable Explorer pane, you should see the columns as shown below:

Step 3: Feature Selection

As a reminder, there are 14 columns total in our dataset (see the screenshot above). You can verify this by executing the following code:

```
columns = customer_data.columns.values.tolist()
print(columns)
```

In the output, you should see the following list :

['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited']

Not all columns affect the customer churn. Let's discuss each column one by one:

1. ***RowNumber****—corresponds to the record (row) number and has no effect on the output. This column will be removed.*
2. ***CustomerId****—contains random values and has no effect on customer leaving the bank. This column will be removed.*
3. ***Surname****—the surname of a customer has no impact on their decision to leave the bank. This column will be removed.*
4. ***CreditScore****—can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank.*
5. ***Geography****—a customer's location can affect their decision to leave the bank. We'll keep this column.*
6. ***Gender****—it's interesting to explore whether gender plays a role in a customer leaving the bank. We'll include this column, too.*
7. ***Age****—this is certainly relevant, since older customers are less*

likely to leave their bank than younger ones.

8. ***Tenure****—refers to the number of years that the customer has been a client of the bank. Normally, older clients are more loyal and less likely to leave a bank.*

9. ***Balance****—also a very good indicator of customer churn, as people with a higher balance in their accounts are less likely to leave the bank compared to those with lower balances.*

10. ***NumOfProducts****—refers to the number of products that a customer has purchased through the bank.*

11. ***HasCrCard****—denotes whether or not a customer has a credit card. This column is also relevant, since people with a credit card are less likely to leave the bank.*

12. ***ActiveMember****—active customers are less likely to leave the bank, so we'll keep this.*

13. ***EstimatedSalary****—as with balance, people with lower salaries are more likely to leave the bank compared to those with higher salaries.*

14. ***Exited****—whether or not the customer left the bank. This is what we have to predict.*

After careful observation of the features, we'll remove the **RowNumber, CustomerId**, and **Surname columns** from our feature set. All the remaining columns do contribute to the customer churn in one way or another.

To drop these three columns, execute the following code:

```
dataset = customer_data.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1)
```

Notice here that we've stored our filtered data in a new data frame

named dataset. The customer_data data frame still contains all the columns. We'll reuse that later.

Step 4: Converting Categorical Columns to Numeric Columns

Machine learning algorithms work best with numerical data. However, in our dataset, we have two categorical columns: **Geography and Gender**. These two columns contain data in textual format; we need to convert them to numeric columns.

Let's first isolate these two columns from our dataset. Execute the following code to do so:

```
dataset =    dataset.drop(['Geography', 'Gender'], axis=1)
```

One way to convert categorical columns to numeric columns is to replace each category with a number. For instance, in the Gender column, female can be replaced with 0 and male with 1, or vice versa. This works for columns with only two categories.

For a column like Geography with three or more categories, you can use the values 0, 1, and 2 for the three countries of France, Germany, and Spain. However, if you do this, the machine learning algorithms will assume that there is an ordinal relationship between the three countries. In other words, the algorithm will assume that 2 is greater than 1 and 0, which actually is not the case in terms of the underlying countries the numbers represent.A better way to convert such categorical columns to numeric columns is by using one-hot encoding. In this process, we take our categories (France, Germany, Spain) and represent them with columns. In each column, we use a 1 to designate that the category exists for the current row, and a 0 otherwise.

In this case, with the three categories of France, Germany, and Spain,

we can represent our categorical data with just two columns (Germany and Spain, for example). Why? Well, if for a given row we have that Geography is France, then the Germany and Spain columns will both have a 0, implying that the country must be the remaining one not represented by any column. Notice, then, that we do not actually need a separate column for France.

Let's convert both the Geography and Gender columns into numeric columns. Execute the following script:

```
Geography = pd.get_dummies(customer_data.Geography).iloc[:,1:]
```

```
Gender = pd.get_dummies(customer_data.Gender).iloc[:,1:]
```

*The get_dummies method of the pandas library converts categorical columns to numeric columns. Then, .iloc[:,1:] ignores the first column and returns the rest of the columns (Germany and Spain). As noted above, this is because we can always represent "n" categories with "n - 1" columns.*Now if you open the **Geography** and **customer_data** data frames in the Variable Explorer pane, you should see something like this:

Geography - DataFrame

Geography	Index	Germany	Spain
France	0	0	0
Spain	1	0	1
France	2	0	0
France	3	0	0
Spain	4	0	1
Spain	5	0	1
France	6	0	0
Germany	7	1	0
France	8	0	0
France	9	0	0
France	10	0	0
Spain	11	0	1
France	12	0	0
France	13	0	0

customer_data:

Next, we need to add the Geography and Gender data frames back to the data set to create the final dataset. You can use the concat function from pandas to horizontally concatenate two data frames as shown below:

```
dataset = pd.concat([dataset,Geography,Gender], axis=1)
```

Our data is now ready, and we can train our machine learning model. But first, we need to isolate the variable that we're predicting from the dataset.

```
X =    dataset.drop(['Exited'], axis=1),y = dataset['Exited']
```

Here, X is our feature set; it contains all the columns except the one that we have to predict (Exited). The label set, y, contains only the Exited cloumn

from sklearn.model_selection import train_test_split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, ra
```

Step 6: Machine Learning Algorithm Training

Now, we'll use a machine learning algorithm that will identify patterns or trends in the training data. This step is known as algorithm training. We'll feed the features and correct output to the algorithm; based on that data, the algorithm will learn to find associations between the features and outputs. After training the algorithm, you'll be able to use it to make predictions on new data.

There are several machine learning algorithms that can be used to make such predictions. However, we'll use the RANDOM FOREST ALGORITHM, since it's simple and one of the most powerful algorithms for classification problems.

```
from sklearn.ensemble import

 RandomForestClassifier

classifier = RandomForestClassifier(n_estimators=200, random_state=0)

classifier.fit(X_train, y_train)

predictions = classifier.predict(X_test)
```

Step 7: Machine Learning Algorithm Evaluation

Now that the algorithm has been trained, it's time to see how well it performs. For evaluating the performance of a classification algorithm, the most commonly used metrics are the F1 MEASURE, PRECISION, RECALL, AND ACCURACY. In Python's scikit-learn library, you can use built-in functions to find all of these values. Execute the following script:

```
from sklearn.metrics import classification_report, accuracy_score

print(classification_report(y_test,predictions ))

print(accuracy_score(y_test, predictions ))
```

The output looks like this:

	precision	recall	f1-score	support
	0.89	0.95	0.92	1595
	0.73	0.51	0.60	405
avg / total	0.85	0.86	0.85	2000

0.8635

The results indicate an accuracy of **86.35%,** which means that our algorithm successfully predicts customer churn 86.35% of the time. That's pretty impressive for a first attempt!

Step 8: Feature Evaluation

As a final step, let's see which features play the most important role in the identification of customer churn. Luckily, **RandomForestClassifier** contains an attribute named **feature_importance** that contains information about the most

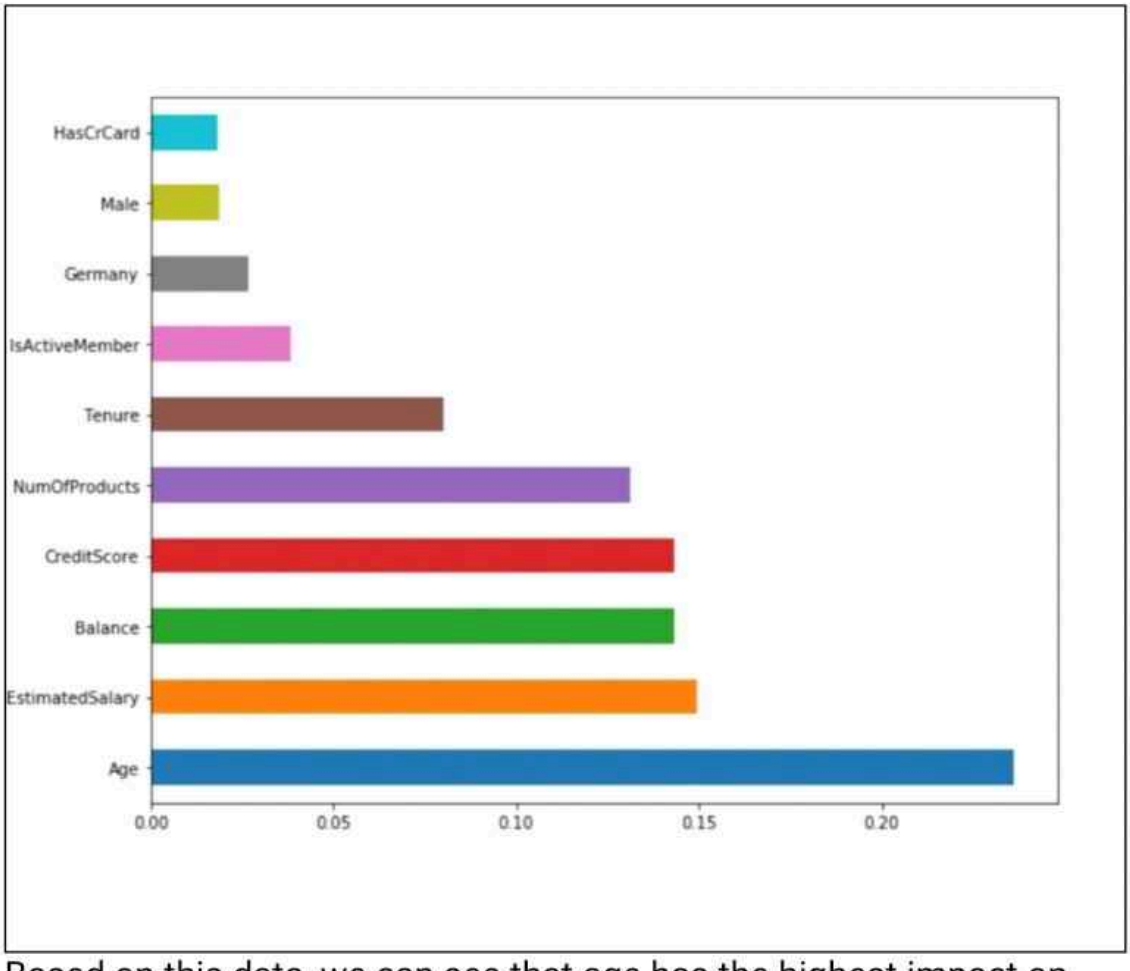
important features for a given classification.

The following code creates a bar plot of the top 10 features for predicting customer churn:

```
feat_importances = pd.Series(classifier.feature_importances_, index=X.columns)
feat_importances.nlargest(10).plot(kind='barh')
```

And the output looks like this:

output



Based on this data, we can see that age has the highest impact on customer churn, followed by a customer's estimated salary and account balance.