

Exploring Shapley Values of Bank Customer Churn

This report is extracted from the notebook "1.1-exploring-shapley-values.ipynb" under /notebooks/ in the repository.

After exploring 5 different machine learning logistic regression models in notebook **1.0-initial-data-exploration.ipynb** we have decided to go for the a LinearRegression model, with varying alphas (C) which is the model that we will be using to investigate the shapley values.

The model chosen is not the best performing model, the best performing model is a complex linear regression with features to the power of 3. This made it very difficult to analyze the most impactful features in our model. We know it is a regression problem, so we decided to scale it back to a standard linear regression to aid our analysis.

The performing metrics for this model is the following:

	precision	recall	f1-score	support
0	0.90	0.70	0.79	796
1	0.37	0.69	0.48	204
accuracy			0.70	1000
macro avg	0.63	0.69	0.63	1000
weighted avg	0.79	0.70	0.72	1000

Figure 1- Performance metrics of simple logistic regression binary classifier

With 0 and 1 representing churn.

Shapley values are useful to see the impact of each feature, and to break down how a prediction is made. We will be using the `shap` library to implement this.

It is important to note this datasets have been concatenated after being transformed. The shap plots will output the features with names such as: Feature 0, Feature 1, Feature 2... but they preserve the order from the original input. Hence we can simply map them here:

Feature Description

Feature 0: "Credit Score"

Feature 1: "Age"

Feature 2: "Tenure"

Feature 3: "Balance"

Feature 4: "products_number"

Feature 5: "credit_card"

Feature 6: "active_member"

Feature 7: "estimated_salary"

Feature 8: "Credit Card"

Feature 9: "Gender (M)"

Feature 10: "Gender (F)"

Feature 11: "Country: France"

Feature 12: "Country: Germany"

Feature 13: "Country: Spain"

If we visualize the shapley values for one prediction of the dataset we can see:

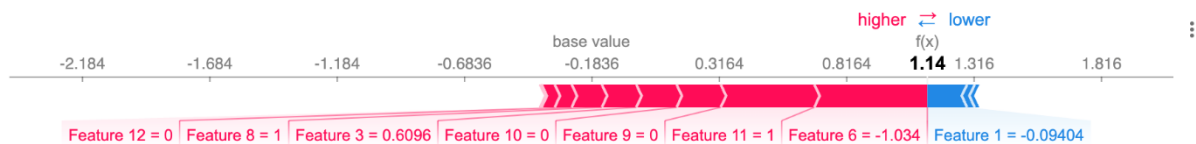


Figure 2- Shapley values for one prediction

Here we can see that for this particular instance, *Feature 6: "active member"* was the leading factor in deciding customer churn, in addition to the country they belonged to (*Feature 11 [France]*), indicating the bank can perform better in some countries, or has less competition in certain countries increasing their churn rate. It seems like the bank balance, or the amount of money in the bank (*Feature 3*) also increased the churn rate. Also seems like in this particular case, age negatively impacted customer retention (*Feature 1*).

If we continue and visualize for all points against dataset, we can also detect what appears to be the most meaningful feature, and that is '*Feature 1*' which is 'Age', and we can clearly see that the older a customer is, the more likely he/she is on staying a loyal customer of the bank. While the reverse is true, the younger the customer, the more likely they are of switching banks.

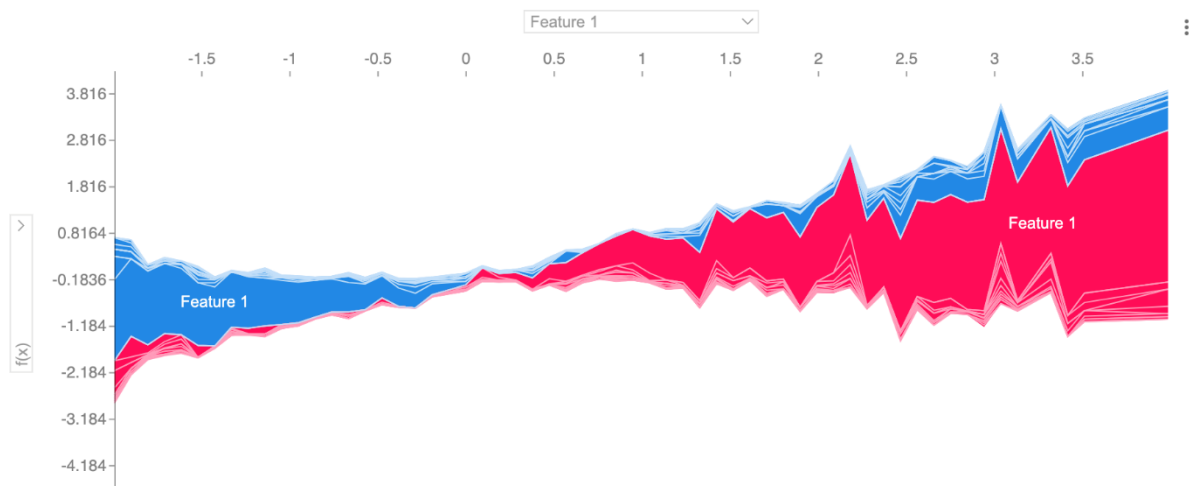


Figure 3 - Impact of most dominant feature (age) in customer churn. Blue represents negative impact (no customer retention), red is positive impact (customer retention)

If we plot a summarized plot for each class on the whole dataset, we can see which features are the most relevant, and how their values (negative to positive) impact the final prediction.

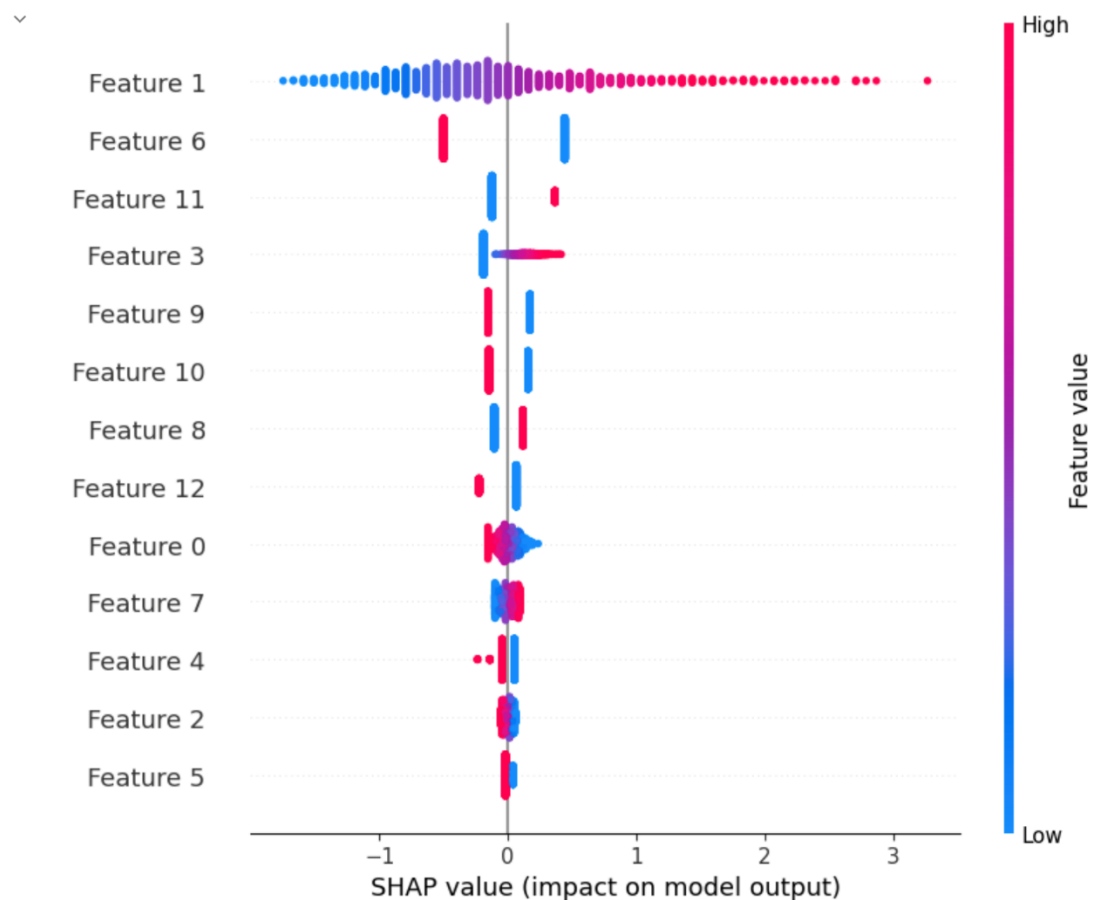


Figure 4- Summarized Plot for all features. We can see age (Feature 1), customer activity (Feature 6), and if they are based in France (Feature 11) are key contributors for churn. Additionally we can see expected human behaviour on churn prediction, for example on Feature 0 (Credit Score) we can see that customers with lower credit scores are more likely to stay as customers with the bank, likely because it is harder for them to open new accounts.

Shapley values were invaluable to find the factors that led to customers trends, not only that it also helped detect in which countries were performing better, in this case France. This analysis could allow the company to dictate region level policy, and target specific customer groups to increase its services. It would also be very valuable to conduct a Shapely value analysis per country, and discover what features are the most impactful at a regional level, as customer culture will affect the churn, which can help scope the bank's strategy for the country.

In conclusion, we can see here that the implementation of machine learning, and extracting understanding of what is influencing customer churn could be a great asset to define corporate strategy, and would provide great ROI to the company.