WEEK 11

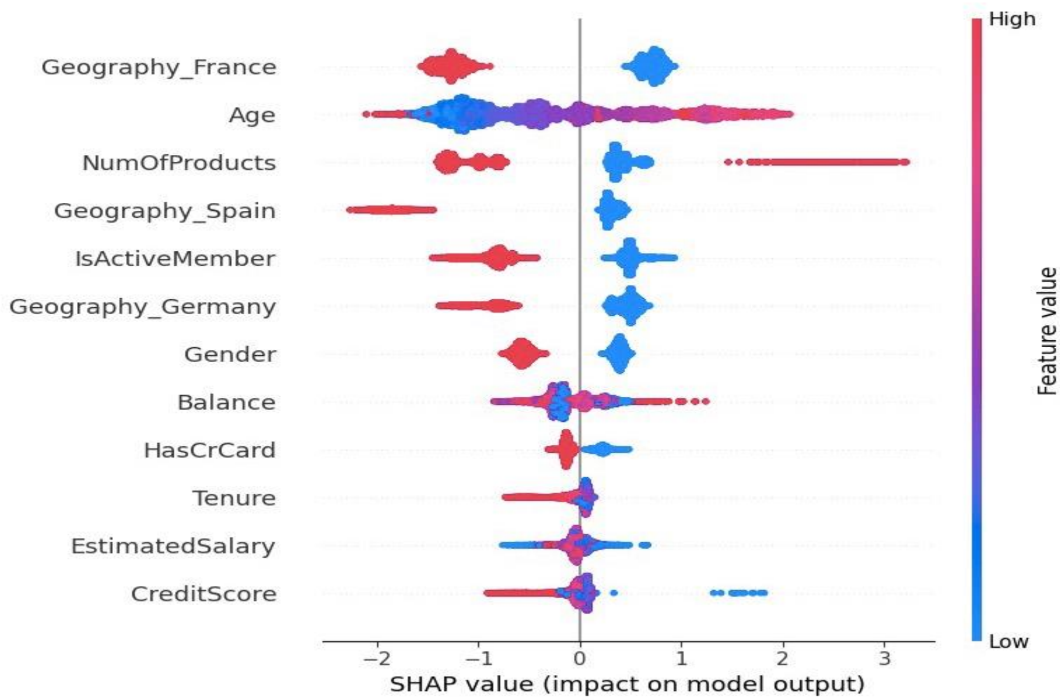
Introduction:

This week, we conducted a comprehensive analysis of potential risks and biases in our customer churn prediction dataset and model outputs. Our primary goal was to identify the most crucial features for predicting banking customer churn and assess the model's sensitivity to changes in these features. We also evaluated the impact of removing age and gender variables from our dataset on the model's accuracy and robustness.

Feature Importance:

To evaluate the feature importance for predicting banking customer churn, we utilized the SHAP value. The SHAP summary plot provides valuable information on the most important features and their range of effects over the dataset. Positive SHAP values are indicative of churning, while negative SHAP values are indicative of staying at the same bank. As demonstrated by the color bar, higher values are represented in red, while lower values are represented in blue. By analyzing the distribution of the red and blue dots, we can gain a general understanding of the directionality impact of features.

Based on our analysis, the top 10 features that impact customer churn are geography France, age, number of products, Geography Spain, active membership, geography Germany, balance, credit card status and tenure. Our analysis indicated that a higher value of geography France leads to lower chance of churn, while a higher value of gender (male) leads to lower chance of churn, and a higher value of active membership status leads to lower chance of churn.



Sensitivity Analysis

We evaluated the sensitivity of five features, namely geography (France and Spain), age, gender and active membership status. We investigated whether the prediction would change if we altered one feature at a time while keeping other features constant. We found that a 10-20% change in one feature could lead to around 10% predictions flip. For instance, when we exchanged the values for geography France and Spain, we observed that 198 predictions (9.9%) flipped after exchange, as 50% of the customer geography shifted to Spain and 25% to France. Regarding gender, when we increased the percentage of male customers from 55% to 70%, we noted that 216 predictions (10.8%) flipped. Furthermore, when we decreased each customer's age by 10 years, 203 predictions (10.15%) flipped, and when we increased the percentage of active members from 51.5% to 70%, we observed 245 predictions (12.25%) flipping. Our analysis indicated that the model's predictions are sensitive to these features.

Robustness and Bias Analysis

Age and gender are protected variables, and any bias in predicting churn based on these variables could have significant ethical and social implications. To assess the model’s bias and robustness, we evaluated its performance after removing age and gender variables from our dataset. We observed a significant decrease in accuracy, recall, and precision for both the training and validation sets. Furthermore, the model’s performance on the test set also decreased after removing age and gender variables, suggesting that these variables are essential for accurately predicting customer churn. The recall metric showed a decrease from 67% to 55% after removing age and gender variables form the dataset. To mitigate the potential bias associated with age, we could consider using age group instead of age as a feature.

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Training set: Accuracy: 0.8426126303364155, Recall: 0.8164469801298446, Precision: 0.86153207390492
Validation set: Accuracy: 0.80375, Recall: 0.5626911314984709, Precision: 0.5183098591549296
Test set: Accuracy: 0.8105, Recall: 0.55470737913486, Precision: 0.5165876777251185
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Risks

Apart from the potential bias, there are additional risks associated with using the model for predicting banking customer churn. One such risk is the possibility of false negatives, where the model fails to identify customers who are at risk of churning, resulting in the bank losing customers. This could lead to a decrease in revenue and market share for the bank. Another potential risk is the violation of customer privacy, as the model may require access to sensitive customer data to make accurate predictions. Any misuse or mishandling of such data could lead to legal and reputational issues for the bank.

Conclusion:

In conclusion, predicting churn customers is crucial for banks to take actions and prevent customer from churning. Our analysis revealed that the model is sensitive to changes in features, and age and gender variables are essential for accurately predicting customer churn. Therefore, banks and institutions must be cautious when interpreting the model’s predictions and consider the potential; biases associated with protected variables. Further work could involve exploring methods to mitigate such biases and improve the model’s robustness.