Interpreting Customer Churn Prediction : An Explainable AI approach for Enhancing Business Insights.\* (use style: *paper title*)

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*Abstract*—In today's highly competitive market, retaining customers and fostering business growth has become increasingly challenging. Consequently, the extensive utilization of machine learning models in developing churn prediction models has posed a challenge due to their opaque nature. As a result, understanding the reasoning behind their predictions can take time and effort. This research paper introduces a novel approach incorporating LIME (Local Interpretable Model-Agnostic Explanations) to address this issue to offer local interpretability for individual predictions. Additionally, SHAP (Shapely Additive Explanations) values are employed to quantify the contribution of each feature toward the final prediction. To evaluate the proposed approach, our study employed a real-world dataset obtained from a specific bank containing customer data from the European region. Various machine learning algorithms, such as KNN, SVM, Random Forest, ANN, and XGBoost, were utilized, and their accuracy and performance were compared. However, the primary focus of our paper is on the XGBoost model, known for its time efficiency and higher accuracy.

Keywords— Customer Churn prediction, Explainable AI, XGBoost, Machine learning Models, LIME

# Introduction

Customer churn, which refers to customers discontinuing their use of a product or service, is a significant concern for businesses across various industries, including banking. Understanding this phenomenon is crucial for businesses to take proactive measures in retaining customers, enhancing customer satisfaction, and ultimately boosting revenue. The rise of AI and machine learning has led to a remarkable increase in the use of these technologies for predicting customer churn.

However, one of the main challenges in using AI for customer churn prediction is the "black box" problem, which is not suitable for regulated financial services. Many AI models are complex and difficult to interpret, making it challenging to understand the reasoning behind their predictions. To overcome this limitation, Explainable AI (EXAI) models have emerged. These models provide transparency and interpretability, enabling businesses to comprehend why a model makes specific predictions and take appropriate actions accordingly. EXAI is currently applied in various industries, including sales, human resources, healthcare, disease diagnosis and classification, medicine distribution, and the financial sector.

To create and utilize these AI models, it is essential to understand what explainable AI means. The term was first used by [2] to describe how well a system could explain the actions of AI-controlled characters in simulation games. Although the phrase is relatively new, the need for explainability dates back to the mid-1970s when researchers began exploring explanations for expert systems. However, as AI progressed with the development of machine learning, the focus shifted towards creating models and algorithms that prioritize predictive capabilities, causing the progress in explainability to slow down.

According to the Bank of England [4], explainability means that stakeholders can comprehend the main drivers behind decisions made by model-driven systems. The concept of explainability (also referred to as interpretability) implies that a machine learning model and its output can be communicated to humans in a way that makes sense at an acceptable level. Miller defines interpretability as the extent to which a human can understand the cause of a decision [5]. Achieving interpretability with customers can promote transparency and confidence, allowing banks to reassure clients that decisions are not arbitrary and helping them understand the factors influencing their relationship with the bank, such as why a customer is likely to churn.

Regulated financial services, like the German Federal Financial Supervisory Authority [6], do not accept "black box excuses," emphasizing the importance of providing explanations. The General Data Protection Regulation (GDPR) of the European Union also requires businesses to use personal data for automated processing to explain how the system makes choices. Furthermore, the GDPR grants individuals in the European Union a "right to explanation" regarding automated decision-making. Hence, providing explanations for model outputs is essential, and advancements in understanding these systems can lead to wider acceptance of novel approaches in financial applications.

Linear and logistic regression models are considered more interpretable but have lower accuracy compared to artificial neural networks and tree models, which are deemed more accurate. To bridge this gap, we will utilize the XGBoost model in our study. XGBoost is highly precise and time-efficient and incorporates a cutting-edge technique for interpreting its final predictions. Additionally, we will evaluate various machine learning models and neural networks alongside our model. Our research goes beyond prediction and focuses on explaining the model's decisions.

Although Rahman's model [8] has shown high accuracy in predicting customer churn in banks, its lack of interpretability makes it challenging for bank management to understand the underlying causes of customer turnover. Caparrini [9] explores the explainability of machine learning models, providing grading for peer-to-peer models with a focus on Shapely Additive Explanations (SHAP). However, our study aims to investigate the usage of SHAP and Local Interpretable Model-Agnostic Explanations (LIME) [10] to offer more precise and understandable explanations of model predictions

The rest of the paper discusses about the related literature of credit scoring and reinforcement learning in section 2. In Section 3 the methodology presented in this paper is discussed followed by experimental results in section 4. Finally, conclusions from the work reported here are summarized in section 5 along with future directions.

# Related work

## Statistical Logistic Regression Model

A statistical logistic regression model is a type of regression analysis used to predict the probability of a binary outcome. It is commonly employed when the dependent variable, the response variable, has two possible outcomes (e.g., yes/no, success/failure). Logistic regression aims to estimate the relationship between the independent variables (also called predictors or explanatory variables) and the probability of a specific outcome occurring. And because our customer churn model relies on two assumptions to determine if a customer will leave, it can be used. These models have now been adopted by the scientific community in the fields of economics, finance, and other social and environmental sciences [12] [13].

Create a response variable, Yn, for each customer, n, to indicate whether the client has left the company or not; Yn is equal to 1 if the customer has left and 0 otherwise. Additionally, let Xn represent a vector of explanatory variables. A collection of predictors is employed in the Logistic Regression model to calculate the probability that an event will occur. Here is what the logistic regression predicts will happen.

Is a linear representation of the input variables in the equation, taking a value between -∞ and +∞, while taking a value between 0 and 1. Numerous statistical flaws exist in LR. Two of these are multi-collinearity and decreased performance precision.

Thammadi and Gangadharaiah (2019), in their study, focus on predicting customer churn in the banking industry using logistic regression and decision trees. It highlights the importance of logistic regression as a reliable and interpretable model for customer churn prediction.Deng et al. (2015) explore the use of deep learning techniques in customer churn prediction and highlight logistic regression's significance as a baseline model. In addition, it discusses the interpretability of logistic regression and its role in understanding the drivers of customer churn. Verbeke and Martens (2012) compare logistic regression performance with other classification techniques for customer churn prediction in the banking industry. It demonstrates the effectiveness of logistic regression and provides insights into its application in predicting customer churn. Ngai et al. (2009), in their work, provide a comprehensive literature review on the application of data mining techniques, including logistic regression, in customer relationship management. It discusses the use of logistic regression for customer churn prediction and highlights its advantages and limitations.

## Application of Machine Learning for customer Churn

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* Do not mix complete spellings and abbreviations of units: “Wb/m2” or “webers per square meter”, not “webers/m2”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.
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*a**b* 

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##### Acknowledgment *(Heading 5)*

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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