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Predictive Performance and Interpretability: Glass Box Modeling with Explainable Boosting Machine

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Abstract – This study aims to perform a comprehensive comparative analysis of glass box modeling using Explainable Boosting Machine (EBM) and black box modeling with XGBoost in the context of telecom churn prediction. The primary focus is on evaluating predictive performance and interpretability, recognizing the trade-off between model complexity and explainability. The Explainable Boosting Machine (EBM) is chosen as a representative glass box model due to its intrinsic interpretability features, enabling us to gain insights into the decision-making process. On the other hand, XGBoost, a well-known black box model, is selected for its superior predictive capabilities, often at the cost of reduced interpretability. The study employs a Telecom Churn dataset, and both models are trained, evaluated, and compared in terms of accuracy, precision, recall, and F1 score. Interpretability is assessed through global and local explanations generated by EBM and LimeTabular for XGBoost. Results from this comparative analysis provide valuable insights into the balance between model performance and interpretability in the specific domain of telecom churn prediction. This exploration contributes to the ongoing discussion regarding the appropriate model choice, considering the diverse needs of stakeholders ranging from data scientists to business analysts.

Keywords: Explainable Boosting Machine, XGBoost, Glass Box Model, Black Box Model, Interpretability, Telecom Churn Prediction.

I. Introduction

In the realm of predictive modeling, striking a balance between model interpretability and predictive performance remains a crucial challenge[1]. This study delves into the comparative analysis of two distinct modeling approaches: the glass box model, represented by the Explainable Boosting Machine (EBM), and the black box model, exemplified by XGBoost. The focus of this investigation is on their application in Telecom Churn prediction, where accurate forecasts and transparent insights are paramount for strategic decision-making. Previous research has extensively explored the trade-off between model interpretability and complexity. Glass box models, such as decision trees and linear models, offer human-interpretable insights into the underlying decision-making process but may sacrifice predictive accuracy[2]. On the other hand, black box models, including ensemble methods like XGBoost, often provide superior predictive performance but at the cost of reduced interpretability[3].

In telecom churn prediction specifically, studies have employed various machine learning techniques to address this challenge. Some have favored interpretable models for the sake of transparency in decision-making, while others have leveraged the predictive power of complex black box models to optimize accuracy[2].

II. Materials and Method

A. Dataset

Level-2 and level-3 headings can be used to detail main headings.

Gender	Tenure	Contract	Churn	Payment Method
Female	1	Month-to-month	No	Electronic check
Male	34	One year	No	Mailed check
Male	2	Month-to-month	Yes	Mailed check
Male	45	One year	No	Bank transfer (automatic)
Female	2	Month-to-month	Yes	Electronic check

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Fig. 1 Small part of the dataset being used.

B. *Model Training*

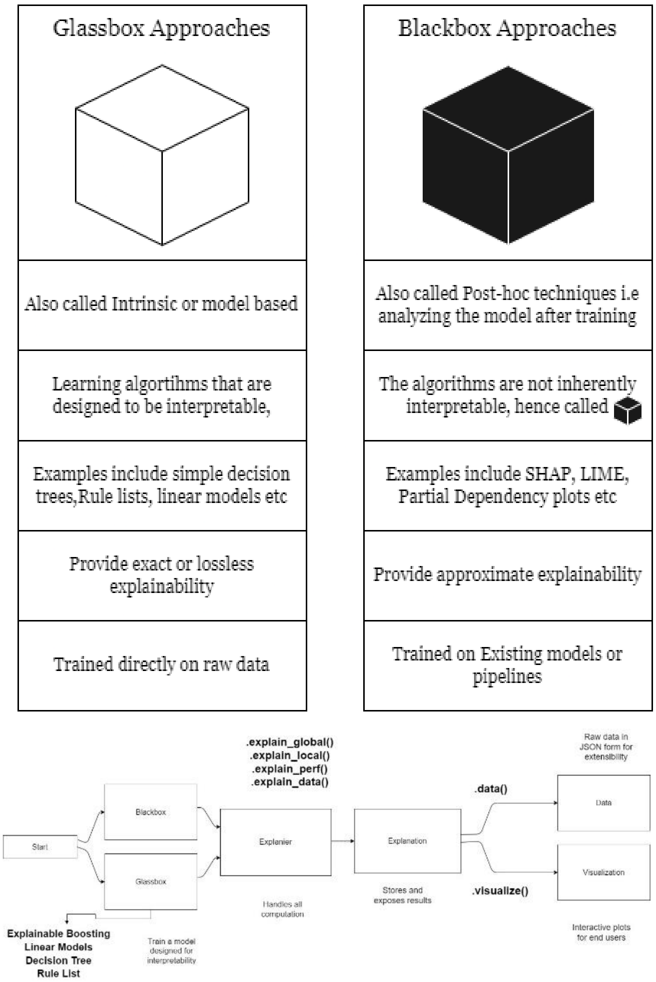

Fig. 2 Comparison between glassbox and blackbox models.

In model training there is variety of interpretability techniques.

Comparison of Interpretability Techniques: Explainable Boosting (EBM):

Type: Glassbox Model Strengths: Offers explicit interpretability through an additive model of interpretable components. Provides transparent insights into decision rules and feature importance weights. Well-suited for scenarios where model transparency is crucial.

Decision Tree:

Type: Glassbox Model Strengths: Naturally interpretable due to its hierarchical structure of decision nodes. Offers a clear visualization of decision-making processes. Effective in capturing non-linear relationships.

Decision Rule List:

Type: Glassbox Model Strengths: Presents decision rules in a human-readable format. Facilitates straightforward interpretation of how input features influence predictions. Suitable for scenarios requiring explicit, rule-based explanations.

Linear/Logistic Regression:

Type: Glassbox Model Strengths: Provides simple, interpretable relationships between input features and output. Allows for a clear understanding of the impact of each feature on the prediction. Particularly effective when relationships are linear.

SHAP Kernel Explainer:

Type: Blackbox Explainer Strengths: Enables the interpretation of complex, black box models like ensemble methods.

Utilizes Shapley values to attribute contributions of each feature to model predictions. Suitable for a wide range of machine learning models.

LIME (Local Interpretable Model-agnostic Explanations):

Type: Blackbox Explainer Strengths: Generates local, interpretable explanations for individual predictions. Model agnostic approach allows it to be applied to various types of models. Useful for understanding the behavior of black box models on specific instances.

Morris Sensitivity Analysis:

Type: Blackbox Explainer Strengths: Assesses the sensitivity of a model’s output to variations in input features. Provides insights into the relative importance of features. Applicable to models with complex, non-linear relationships.

Partial Dependence:

Type: Blackbox Explainer Strengths: Illustrates the relationship between a subset of features and the model’s predicted outcome. Captures the average effect of specific features while holding others constant. Useful for identifying trends and understanding feature interactions. Considerations:

Glassbox models offer explicit, rule-based interpretability but may sacrifice predictive performance in complex scenarios.

Blackbox explainers provide insights into the behavior of complex models but may lack the simplicity and directness of glassbox models. The choice between techniques depends on the specific goals of the analysis, the nature of the data, and the balance between interpretability and predictive accuracy required for the task at hand.

XGBoost Classifier:

Type: Blackbox Model Strengths: An ensemble learning algorithm known for high predictive accuracy. Operates as a complex black box model without explicit interpretability.

Superior at capturing intricate relationships within the data.

C. *Model Selection for Comparison*

For the purpose of our comparative analysis, we have chosen the Explainable Boosting Machine (EBM) as a representative of glassbox models and the XGBoost Classifier as an exemplar of blackbox models. This selection is driven by specific considerations that align with the objectives of our study.

Reasons for Choosing EBM (Glassbox Model):

Interpretability:

EBM is explicitly designed as a glassbox model, offering human-understandable insights into the decision-making process. This transparency is critical for scenarios where the interpretability of model predictions is of utmost importance.

Decision Rules and Feature Importance:

EBM provides clear decision rules and feature importance weights, facilitating a straightforward interpretation of how input features influence the model's predictions. This makes it an ideal choice for applications where stakeholders require a detailed understanding of the underlying logic. Global Explanation:

EBM inherently provides global explanations, allowing us to comprehend the overall behavior of the model across the entire dataset. This is essential for gaining insights into broader patterns and trends.

Reasons for Choosing XGBoost (Blackbox Model):

Predictive Power:

XGBoost is renowned for its high predictive accuracy and performance, particularly in complex scenarios. Its ensemble learning architecture enables it to capture intricate relationships within the data, making it a suitable benchmark for predictive modeling tasks. Handling Complex Patterns:

In scenarios where the relationships between features and the target variable are nonlinear and complex, XGBoost excels. Its ability to construct powerful decision trees and combine them in an ensemble makes it well-suited for capturing intricate patterns. Competitive Performance:

XGBoost has consistently demonstrated competitive performance in various machine learning competitions and real world applications. Choosing XGBoost as a blackbox model ensures that we assess our glassbox model (EBM) against a robust and widely-used counterpart. Rationale for Comparison:

By selecting EBM as a glassbox model and XGBoost as a blackbox model, our aim is to evaluate and contrast the trade-offs between interpretability and predictive performance. This comparison will provide valuable insights into the strengths and limitations of each approach, aiding in the understanding of when and where to deploy glassbox or blackbox models based on specific project requirements and constraints.

```
Classification Report for EBM Model:
              precision    recall  f1-score   support

          No       0.84      0.91      0.87      1036
         Yes       0.67      0.54      0.60       373

    accuracy                           0.81      1409
   macro avg       0.76      0.72      0.73      1409
weighted avg       0.80      0.81      0.80      1409

Confusion Matrix for EBM Model:
 [[938  98]
 [173 200]]
EBM Model Accuracy: 0.8076650106458482
```

Fig. 3 Train output from explainable boosting machine.

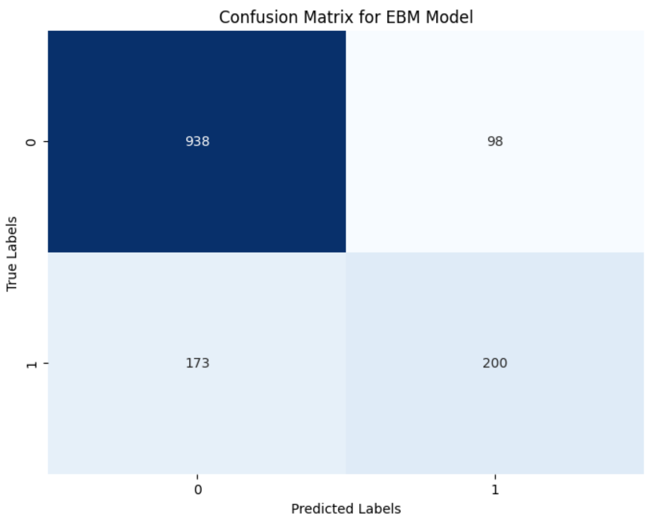

Fig. 4 EBM confusion matrix.

1) Glass Box Model: Explainable Boosting Machine

(EBM): Explainable Boosting Machine (EBM) serves as a representative glass box model, prioritizing interpretability without compromising predictive power [4]. EBM constructs an additive model comprising interpretable components, facilitating the generation of global explanations for model predictions. The interpretability of EBM stems from its explicit formulation, enabling the elucidation of decision rules and feature importance weights. You can see the result of the EBM on Fig.3 and Fig.4

```
Accuracy: 0.7778566359119943

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.87      0.85      1036
           1       0.59      0.52      0.55       373

    accuracy                           0.78      1409
   macro avg       0.71      0.70      0.70      1409
weighted avg       0.77      0.78      0.77      1409
```

Fig. 5 Train output from XGBoost.

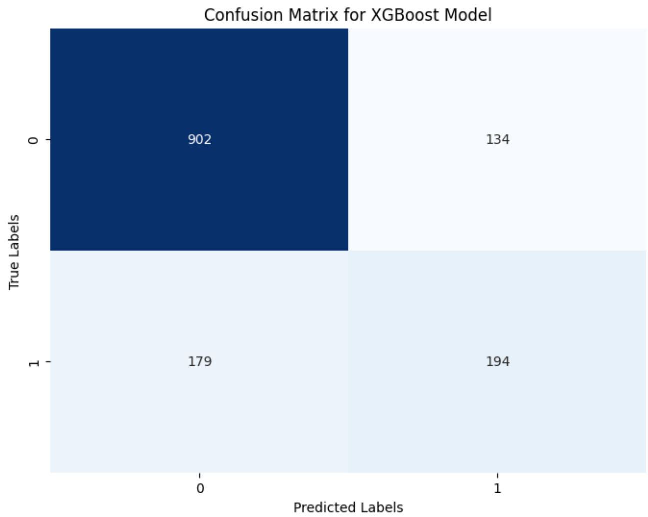

Fig. 6 XGBoost confusion matrix.

2) Black Box Model: XGBoost: XGBoost, a well-established black box model, was employed as a benchmark for predictive performance[5]. Characterized by its ensemble learning architecture, XGBoost excels in capturing complex relationships within the data but inherently lacks the trans-parency associated with glass box models. The trade-off between interpretability and accuracy becomes apparent in scenarios where model predictions necessitate scrutiny.

You can see the result of the XGBoost on Fig.5 and Fig.6

Evaluation Metrics

Performance assessment involved standard classification metrics, including accuracy, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC).

Model Interpretation

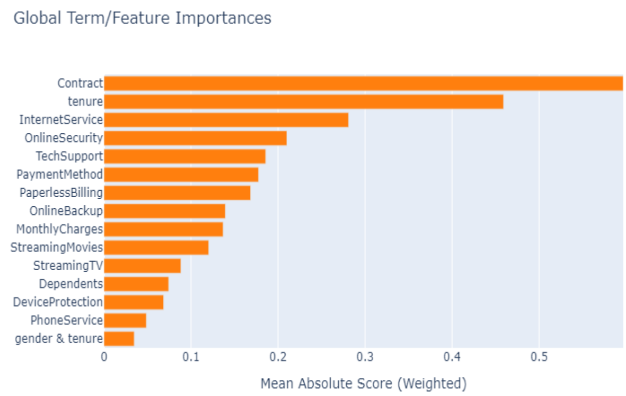

Fig. 7 Average impact on model output magnitude.

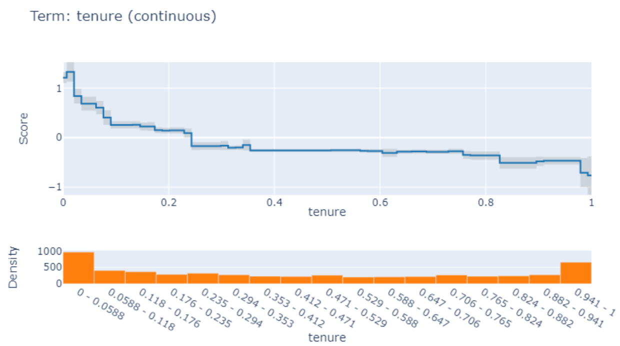

Fig. 8 The impact of tenure to outcome of the model.

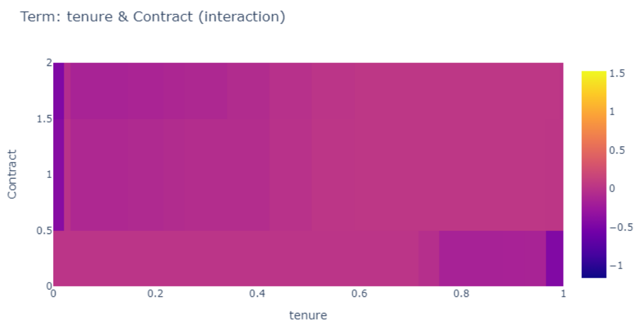

Fig. 9 The interaction between tenure and contract.

1) EBM Model Interpretation: The interpretability of the EBM model was evaluated through global explanations provided by the interpret library [4]. These

insights included feature importance and the rationale behind model decisions, allowing for a nuanced understanding of the underlying decision-making process.

As it seen on the Fig.7,8,9 because of the EBM we have an better analysis on the outcome of our trained model.

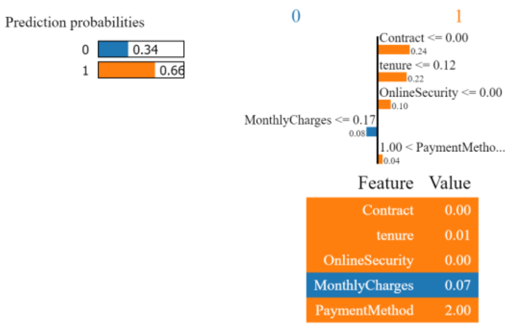

Fig. 10 Explanation of XGBoost model with LIME.

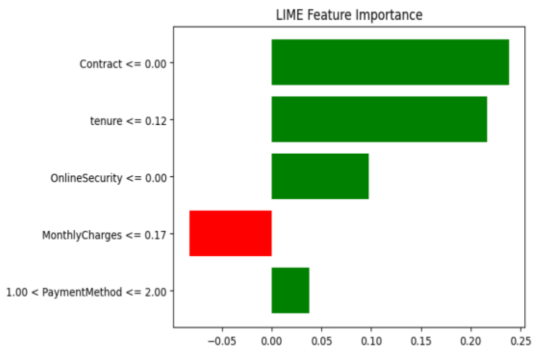

Fig. 11 Feature Importance of XGBoost model.

2) XGBoost Model Interpretation: LimeTabular explainer from the interpret library facilitated the interpretation of the XGBoost black box model [6]. LimeTabular provides local, interpretable explanations by perturbing instances and analyzing the impact on model predictions. While offering transparency at the instance level, it doesn't provide a global view as inherently present in glass box models.

Comparison of Glass Box and Black Box Models

Glass box models, such as EBM, offer transparency and interpretability by design. They operate on explicit rules and are easily understandable, providing insights into decision-making processes. In contrast, black box models like XGBoost, while achieving superior predictive performance, lack explicit interpretability. The trade-off lies in the ability to uncover intricate patterns versus maintaining a clear understanding of individual predictions.

Comparison of EBM and XGBoost

EBM:

Constructed as an additive model of interpretable components. Explicitly represents decision rules and feature importance weights. Offers global explanations for model predictions.

XGBoost:

An ensemble learning algorithm known for its predictive power. Operates as a complex black box model without explicit interpretability. Superior at capturing intricate relationships within the data.

III. DISCUSSION

The comparative analysis presented in this paper focuses on evaluating two distinct approaches to predictive modeling in the context of telecom churn prediction. The glass box modeling approach, represented by the Explainable Boosting Machine (EBM), and the black box modeling approach, exemplified by XGBoost, are assessed based on their predictive performance and interpretability.

The choice between these modeling approaches is often dictated by the specific requirements of the task at hand, recognizing the inherent trade-off between model complexity and explainability. Glass box models, such as EBM, prioritize interpretability by providing explicit decision rules and feature importance weights. On the other hand, black box models like XGBoost excel in predictive power, capturing complex relationships within the data but sacrificing explicit interpretability.

The telecom churn prediction scenario serves as an illustrative case where transparent insights into decision-making processes are crucial for strategic decision-making. The study employs a Telecom Churn dataset and evaluates both models in terms of standard classification metrics, including accuracy, precision, recall, and F1 score.

The interpretability of the models is assessed through global and local explanations generated by EBM and LimeTabular for XGBoost. EBM inherently provides global explanations, allowing for an understanding of the overall model behavior, while LimeTabular provides local, interpretable explanations for individual predictions in the case of XGBoost.

The results of the comparative analysis shed light on the balance between model performance and interpretability in the specific domain of telecom churn prediction. The findings contribute to the ongoing discussion regarding the appropriate choice of models, considering the diverse needs of stakeholders ranging from data scientists to business analysts.

Glass box models, with their transparent and rule-based nature, offer insights into decision-making processes but may sacrifice predictive performance in complex scenarios. Black box models, with their superior predictive power, provide insights into complex relationships but may lack the simplicity and directness of glass box models. The choice between these techniques depends on the specific goals of the analysis, the nature of the data, and the balance between interpretability and predictive accuracy required for the task at hand.

By selecting EBM as a glass box model and XGBoost as a black box model, the study aims to provide a nuanced understanding of the trade-offs between interpretability and predictive performance. This comparison offers valuable insights into the strengths and limitations of each approach, aiding in the decision-making process for deploying either glass box or black box models based on project-specific requirements and constraints.

IV. CONCLUSION

In conclusion, our comparative analysis of glass box modeling using Explainable Boosting Machine (EBM) and black box modeling with XGBoost in the context of telecom churn prediction has provided valuable insights into the intricate balance between predictive performance and interpretability.

The results indicate that the choice between glass box and black box models is contingent on the specific requirements of the task and the preferences of stakeholders. Glass box models, exemplified by EBM, offer explicit interpretability through clear decision rules and feature importance weights. These models are particularly advantageous when transparency and a detailed understanding of decision-making processes are paramount.

On the other hand, black box models, represented by XGBoost, demonstrate superior predictive power, excelling in capturing complex relationships within the data. While lacking the explicit interpretability of glass box models, black box models like XGBoost are crucial in scenarios where intricate patterns and high predictive accuracy are prioritized.

Our exploration contributes to the ongoing dialogue about model selection, acknowledging the diverse needs of stakeholders ranging from data scientists to business analysts. The telecom churn prediction scenario served as a relevant use case, emphasizing the importance of transparent insights in strategic decision-making.

Ultimately, the choice between glass box and black box models should be driven by a careful consideration of project-specific goals, data characteristics, and the desired balance between interpretability and predictive accuracy. Our findings empower practitioners and decision-makers to make informed choices in deploying models that align with the unique requirements and constraints of their projects.

As the field of machine learning continues to evolve, the discussion around interpretability and model performance remains critical. Future research endeavors should delve deeper into refining the interplay between these factors, exploring novel techniques that offer a harmonious blend of interpretability and predictive prowess. Through such advancements, we can strive for models that not only deliver accurate predictions but also provide meaningful insights into the decision-making processes, fostering trust and informed decision-making in various domains.

ACKNOWLEDGMENT

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