Explanations Based on Item Response Theory (\textit{eXirt}): A Model-Specific Method to Explain Tree-Ensemble Model in Trust Perspective

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Abstract

Solutions based on tree-ensemble models represent a considerable alternative to real-world prediction problems, but these models are considered black box, thus hindering their applicability in problems of sensitive contexts (such as: health and safety). Explainable Artificial Intelligence (XAI) aims to develop techniques that generate explanations of black box models, since these models are normally not self-explanatory. Methods such as \textit{Ciu}, \textit{Dalex}, \textit{Eli5}, \textit{Lofo}, \textit{Shap} and \textit{Skater} emerged with the proposal to explain black box models through global rankings of feature relevance, which based on different methodologies, generate global explanations that indicate how the model’s inputs explain its predictions. This research aims to present an innovative XAI method, called \textit{eXirt}, capable of carrying out the process of explaining tree-ensemble models, based on Item Response Theory (IRT). 

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In this context, 41 datasets, 4 tree-ensemble algorithms (*Light Gradient Boosting*, *CatBoost*, *Random Forest*, and *Gradient Boosting*), and 7 XAI methods (including *eXirt*) were used to generate explanations. In the first set of analyses, the 164 ranks of global feature relevance generated by *eXirt* were compared with 984 ranks of the other XAI methods present in the literature, being verified that the new method generated different explanations from other existing methods. In a second analysis, exclusive local and global explanations generated by *eXirt* were presented that help in understanding the model trust, since in this explanation it is possible to observe particularities of the model regarding difficulty (if the model had difficulty predicting the test dataset), discrimination (if the model understands the test dataset as discriminative) and guesswork (if the model got the test dataset right by chance). Thus, it was verified that *eXirt* is able to generate global explanations of tree-ensemble models and also local and global explanations of models through *IRT*, showing how this consolidated theory can be used in machine learning in order to obtain explainable and reliable models.

**Keywords:**
Global Explanation, Item Response Theory, Explainable Artificial Intelligence, Black box, Model-Specific, *eXirt*;

1. **Introduction**

Technology has been evolving and today artificial intelligence is already a reality in the daily life of society. There are many real-world problems that machine learning algorithms solve, making human life more automated and intelligent (*Shalev-Shwartz and Ben-David* 2014; *Ghahramani* 2015).

Machine learning models based on tree-structured bagging and boosting algorithms are known to provide high performance and high generalization capabilities, and thus being widely used in intelligent systems embedded in real-world problems (*Maclin and Opitz* 1997; *Haffar et al.* 2022).

Even though they are popularly used in problems of the most different natures, tree-ensemble-based algorithms do not have a high number of XAI methods capable of creating explanations of their predictions, as well as neural networks, for example (*Ibrahim and Shafiq* 2023; *Samek et al.* 2021).

Tree-ensemble algorithms are not considered transparent\(^1\), their predictions

\(^1\)Transparent Algorithms: Algorithms that naturally generate explanations of how a
are not self-explanatory, thus being considered black box algorithms and, therefore, less used in problems related to sensitive contexts, such as health and safety, for example (Shojai et al., 2023; Ghosh et al., 2023; Ribeiro et al., 2022).

With the increasing need for high-performance models — which implies low transparency (Arrieta et al., 2020) — in sensitive contexts, there is currently a growing need to develop methods or tools that can provide information about local explanations (feature relevance explanation generated around each data instances) and global explanations (when it is possible to understand the logic of all instances of the model generating in global way) as a means to make predictions more easily interpretable and also more trustworthy by humans (Guidotti et al., 2018; Gunning and Aha, 2019; Lundberg et al., 2020a; Ribeiro et al., 2016; Wang et al., 2021).

In this regard, methods such as Ciù (Främling, 2020), Dalex (Biecek and Burzykowski, 2021), Eli5 (Korobov and Lopuhin, 2021), Lofo (Roseline and Geetha, 2021), Shap (Lundberg et al., 2020a) e Skater (Oracle, 2021a) have emerged to promote the creation of model-agnostic and model-specific explanations. Note, a model-agnostic is a XAI method that it does not depend on type of model to be explained (Arrieta et al., 2020), and a model-specific is a XAI method that apply to a specific type of machine learning model (Khan, 2022).

The main advantage of methods that use the model-agnostic approach is related to its independence related the type of model to explained. In other way, the main advantage of the model-specific approach is related the possibility of developing specific explanations for certain types of algorithms or even certain problems (Khan, 2022; Molnar, 2020).

It should be noted that each of the methods mentioned above is capable of explaining models using different techniques and methodologies, but one fact they have in common is that they all generate global relevance rankings of features related to the explanation of a model. And, therefore, are likely to have their results compared in quantitative way (Ribeiro et al., 2021).

The terminologies Feature Relevance Ranking and Feature Importance Ranking are widely used as synonyms in the computing community, but

\footnote{particular output was produced. Such examples include Decision Tree, Logistic Regression, and K-Nearest Neighbors.}

\footnote{Black box algorithms: machine learning algorithms that have the steps of classification or regression decisions hidden from the user.}
have different definitions herein, as shown in (Arrieta et al., 2020). Since feature rankings are regarded as ordered structures whereby each feature of the dataset used by the model appears in a position indicated by a score. The main difference being that, in relevance ranking, the calculation of the score is based on the model output, whereas to calculate the importance ranking of features, the correct label to be predicted is used (Arrieta et al., 2020; Molnar, 2020).

Global feature relevance ranking represents a significant part of this study because they allow for general analyses of how a given model generalizes a specific problem, along with analyses of how a given methodology explains a specific model, without the need for a preliminary understanding of the context in which the model is embedded (Ribeiro et al., 2021).

Despite being limited, the global feature relevance ranks carry general explanations about the analyzed model, and for this reason they were selected as a basic structure of explanation to compare results of different XAI methods in a quantitative way, without the need to use knowledge of a human expert of the context of each analyzed problem (Molnar, 2020). Because, in XAI there is no baseline definition for good or bad model explanations (Linardatos et al., 2021).

As shown in previous study (Ribeiro et al., 2021), explanations originating from different XAI methods may present specific similarities between themselves or also significant differences. This, considering the properties of the model to be explained and the particularities existing in each XAI method used. Given this fact, when there are several explanations for a set of models, the question naturally arises “Which model and explanation should I trust?”.

In addition to global explanations, there are local explanations that are created at the model dataset instance level, allowing a greater level of understanding of how a model performs predictions (Arrieta et al., 2020).

Explanation-by-example is a type of model explanation technique focused on local instances of significant examples from a dataset, which through specific techniques produce explanations that help in the process of interpreting model predictions by a human (Molnar, 2020). It is worth noting that this method is a viable way to create explanations that provide insights into how a human can trust a model prediction, or even the model as a whole (Ribeiro et al., 2016; Cardoso et al., 2022).

Focusing on tree-ensemble algorithms, this research identifies the need and opportunity to create a model-specific method, capable of generating global and local explanations aiming for greater reliability in the
parmpas et al., 2020; Ribeiro et al., 2016) model. With this, there is a need to have a way of evaluating models that is different from other existing XAI methods.

The Item Response Theory, is a very widespread theory, generally used in the process of evaluating candidates in selection processes. The theory uses the properties “discrimination”, “difficulty” and “guessing” to enable evaluation of latent characteristics, which cannot be observed directly, of the responses of candidates in a selection process. This is intended to establish the relationship of hit probability to the candidate’s ability (Andrade et al., 2000).

This research proposes a new method for explaining tree-ensemble models based on Item Response Theory, called eXirt. Seeking to validate this method, global feature relevance ranks were generated for models created from 4 different algorithms (Light Gradient Boosting, CatBoost, Random Forest, and Gradient Boosting) and 41 different datasets (binary classification), which were compared to the results of 6 XAI methods already known in the literature, aiming to show similarities and differences in several contexts of problems. Then, analyzes of local explanations uniquely generated by the eXirt method are also presented, which provide insights on how to trust the analyzed models.

This research is the continuation of previous studies carried out in: “Explanation-by-Example Based on Item Response Theory” (Cardoso et al., 2022), “Does Dataset Complexity Matters for Model Explainers?” (Ribeiro et al., 2021) and “Decoding Machine Learning Benchmarks” (Cardoso et al., 2020), which have already been duly published.

The main contributions to the studies in Explainable Artificial Intelligence that this research generates are as follows:

• An innovative XAI method, called eXirt, which is based on Item Response Theory, an interesting theory still under-explored in machine learning;

• Innovative explanations of tree-ensemble models generated by the eXirt method, capable of generating global feature relevance ranks based in IRT, along with local information on model discrimination, difficulty and guessing, enabling unique insights into its reliability;

• Comparisons of the features relevance ranks generated by the eXirt method with the results generated by the Ciu, Dalex, Eli5, Lof, Shap
This article is organized in follows sections: Section 2 presents work related to this research; Section 3 introduces key background concepts about XAI and IRT; Section 4 presents the methodological and conceptual part on which the experiments and the central proposal of the article are based; Section 5 results of analysis involving identification of dataset profiles, and the production of global and local explanations; Section 6 Conclusions of paper; Section 7 Presentation of future works.

2. Related Works

This section will present: The research-related works that support the comparative analyzes carried out between the different XAI methods (subsection 2.1); And references regarding the taxonomy used, and a bibliographical survey will be presented on the main XAI methods present in the literature (subsection 2.2).

2.1. Analysis involving XAI methods

In recent years, there has been a growing interest in the topic of Explainable Artificial Intelligence among society, proof of this is the growing number of publications on these topics in research repositories such as (Vince, 2006; Hunter, 1998; Durniak, 2000) or even volumes of internet searches on the topic (Trends Developers, 2023).

One of the reasons for the interest in this area of research is the increasing presence of intelligent systems in everyday human life, such as systems aimed at: Smart Cities, Smart Homes, Traffic Control, Human Health Control, Public Security, Education, Economy, among others (Shalev-Shwartz and Ben-David, 2014; Ghahramani, 2015).

As a result, the area of XAI is gaining more attention, creating an increasing need to explain the aforementioned systems, mainly due to the fact that in most cases, these systems are based on black box algorithms, due their high performances (Arrieta et al., 2020).

With the rapid rise of the XAI area, the taxonomic differences used by different works are notable. Seeking to standardize the understanding of the taxonomic terms used here, we chose to adopt the taxonomy used in the work Arrieta et al., 2020 as the main basis for this research.
With the increasing emergence of new proposals that seek to explain black box models, a need arises in this context, which is the quantitative comparison between these XAI methods, due to the need to understand whether such explanations are different between the models or even similar (Sahatova and Balabaeva, 2022; Chadaga et al., 2023; Hariharan et al., 2023; Jouis et al., 2021).

Defining whether a model’s explanation is good or bad is a complicated task, as discussions in the area of XAI already show that there is no explanation that can meet the expectations of all individuals involved in a context/problem, that is, there is no baseline as to the ideal explanation that can be generated from a model (Sokol and Flach, 2020).

In this sense, research that seeks to propose new XAI methods, most of the time does not compare the results of their proposed methods with the results of other methods, most often focusing on descriptions of the theoretical basis of which their methods are based on (Lundberg et al., 2020b; Roseline and Geetha, 2021; Korobov and Lopuhin, 2021; Biecek and Burzykowski, 2021).

Research that seeks to compare different XAI methods, based on relevance ranking, is something new and still little explored by the machine learning community (Holzinger et al., 2020; Krishna et al., 2022). Therefore, the challenges involved in comparing methods are significant and the lack of a baseline makes the problem even greater, as seen in (Ribeiro et al., 2021). Even so, research involving comparisons has been emerging, but with restrictions on a single dataset and a few models that can be created from this data (Sahatova and Balabaeva, 2022; Chadaga et al., 2023; Hariharan et al., 2023; Jouis et al., 2021).

For example, in Sahatova and Balabaeva (2022) visual comparisons are made of the local explanations produced by the methods Shap and Lime (Ribeiro et al., 2016) under a machine learning model aimed at detecting objects in images of tumorography. The main comparisons made between the methods are visual in nature, as the model input data is in image format.

In the study Chadaga et al. (2023), a decision support system is created based on the methods Šhap, Eli5, QLattice, Anchor, and Lime with the aim of creating explanations of a machine learning model aimed at diagnosing COVID 2019. Here different types/formats of explanations are generated and are used to discuss different perspectives of the proposed problem.

In the research Hariharan et al. (2023) the methods of Permutation Importance, Šhap, Lime, and Ciu are used under a machine learning model aimed at the problem of Intrusion Detection focused on cybersecurity. In
this study, comparisons of explanations are made using accuracy, consistency and stability.

In Jouis et al. (2021) the Anchors and Attention methods are used under a job offer prediction model. In the study, different types and formats of explanations are used, duly compared in a quantitative and qualitative way.

Differentiating itself from existing research in the current literature, this research uses descriptions of theoretical concepts and quantitative comparison of results, to present and validate a new XAI method called eXirt. To this end, the main concepts surrounding XAI and the main concepts of Item Response Theory were described in the following sessions. Further on, results involving a large number of data and tree-ensemble models are presented.

2.2. XAI methods in the literature

This research carried out a second bibliographical search, focusing on identifying research focused on propositions of existing XAI methods, so it was possible to find the main XAI methods specifically aimed at generating global feature relevance rankings in a model-agnostic and model specific manner that support tabular data.

As a result, a total of six XAI methods were found to be properly validated and compatible with one another (at library and code execution dependencies level). These methods include: CIU (Främling, 2020), Dalex (Baniecki et al., 2021), EHi5 (Korobov and Lopuhin, 2021), Lofo (Roseline and Geetha, 2021), SHAP (Lundberg et al., 2020a) and Skater (Oracle, 2021a).

This survey found other tools aimed at model explanation, including: Alibi (Apley and Zhu, 2020), Lime (Ribeiro et al., 2016), IBM Explainable AI 360 (Arya et al., 2020), Anchor (Ribeiro et al., 2018), Attention (Lin et al., 2017) e Interpreter ML (Nori et al., 2019). However, due to incompatibilities and technical problems, they ended up not being used in this research.

The main problems and incompatibilities found were: No generation of global ranks; Rank generation based on another XAI method already existing in the pipeline; Non-compatibility with pipeline dependencies (at library version level); Lack of method library updates; No support for the Light Gradient Boosting, CatBoost, Random Forest and Gradient Boosting models.

Due to incompatibilities between XAI methods libraries and versions of machine learning model libraries and dependencies scikit-learn, only the Light Gradient Boosting, CatBoost, Random Forest and Gradient Boosting algorithms were used herein as models to be explained by the aforementioned methods. In other words, this problem is directly linked to the
way these tools were programmed rather than the methodologies they advocate.

Note that the six methods presented herein generate relevance rankings based on the same previously trained machine learning models (with the same training and testing split), manipulate their inputs and/or produce new intermediate models copies. Therefore, they are required to be compatible with each other so that a fair comparison of their final rankings of explanations can be made.

Table 1 shows a general comparison between the techniques found during bibliographic research.

| Name          | Base algorithm                        | Explanation technique                                  | Global explanation (by rank) | Local explanation | Model Specific or Agnostic? | Compatible? |
|---------------|---------------------------------------|-------------------------------------------------------|------------------------------|-------------------|----------------------------|-------------|
| Alibi         | Out-of-bag error                      | Feature Permutation and accuracy and fit               | Yes                          | Yes               | Agnostic                  | No          |
| Anchor        | if-Then Rules                         | Rules                                                 | No                           | Yes               | Agnostic                  | No          |
| Attention     | Structured Self-attentive embedding   | Multiple Vector Representations                        | No                           | Yes               | Specific                  | No          |
| CIU           | Decision Theory                       | Feature Permutation and Multiple Criteria Decision Making | Yes                          | No                | Agnostic                  | Yes         |
| Dalex         | Leave-one covariate out               | Feature Permutation                                   | Yes                          | Yes               | Agnostic                  | Yes         |
| Eli5          | Assigning weights to decisions        | Feature Permutation and Mean Decrease Accuracy         | Yes                          | Yes               | Specific                  | Yes         |
| eXirt         | Item Response Theory                  | Feature Permutation and Model Ability                 | Yes                          | Yes               | Specific                  | Yes         |
| IBM Explainable AI 360 | Same of Shap                  | Same of Shap                                          | Yes                          | Yes               | Specific                  | No          |
| Interpreter ML | Same of Lime and Shap                | Same of Lime and Shap                                 | Yes                          | Yes               | Specific and Agnostic     | No          |
| Lime          | local linear approximation            | Perturbation of the Instance                          | No                           | Yes               | Agnostic                  | No          |
| Lofo          | Leave One Feature Out                 | Feature Permutation                                   | Yes                          | No                | Specific                  | Yes         |
| Shap          | Game Theory                           | Feature Permutation                                   | Yes                          | Yes               | Specific                  | Yes         |
| Skater        | Information Theory                    | Feature Relevance                                     | Yes                          | Yes               | Agnostic                  | Yes         |

Note, the eXirt in table 1 explainable base in Item Response Theory, is the XAI method defended by this article, it appears prematurely here only at the level of global comparison with the other methods.
Still in table 1, it can be seen that most existing XAI methods use the “Feature Permutation” technique to perform the model explanation process. However, it should be emphasized at this moment, that the eXirt differs from other methods by having base in IRT.

An important detail, at the time of this article’s production, an XAI method capable of explaining machine learning models through global explanations based on attribute relevance ranking using Item Response Theory as a basis was not found.

3. Background

In this section, concepts, taxonomies and theories related to Explainable Artificial Intelligence (subsection 3.1) and Item Response Theory (subsection 3.2) are presented, which will be used throughout this work.

3.1. Explainable Artificial Intelligence

The so-called post-hoc explanation is the currently most widely used existing XAI method category in the computing community. The post-hoc techniques can be divided into different strategies: Text Explanations, Visual Explanations, Local Explanations, Explanation-by-simplification, Feature Relevance Explanations and Explanation-by-example. Among these six types of techniques, this research is based on the last two, Feature Relevance Explanation and Explanation-by-example, as they are properly used by the XAI method proposed here.

3.1.1. Feature Relevance Explanation

The CIU, DaleX, Eli5, Lofo, SHAP and Skater are capable of generating several types of model explanations — however, for quantitative comparisons, only the ranking generation processes are described. Thus, in order to facilitate the understanding of how each XAI method listed above generates the feature relevance explanations, descriptions about their basic operations are presented below.

The Contextual Importance and Utility (CIU) is a XAI method based on Decision Theory [Keeney et al. 1993] that focuses on serving as a unified metric of model-agnostic explainability based on the implementation of two different scores: Contextual Importance (CI) and Contextual Utility (CU) [Främling, 2020].
As verified in preliminary tests carried out by this research, these two indices generate equal ranks. Thus, it was decided to use the CI (Främling, 2020), since its definition shows that this score is more general to the context of the model data (Främling, 2020).

The method Dalex is a set of XAI tools based on the LOCO (Leave one Covariate Out) approach and can generate explainabilities from this approach. This method receives the model and the data to be explained, calculates model performance, performs new training processes with new generated data sets, and makes the inversion of each feature of the data in a unitary and iterative way, methods what features are important to the model, evaluates its performance obtained according to the inversions of the features (Baniecki et al., 2021; Biecek and Burzykowski, 2021).

A little less popular but very powerful is the Leave One Feature Out (Lofo), a XAI method with a similar proposal to that of Dalex, but no feature inversion is performed here, because in the Lofo metric the iterative step is based on iterative removal of the features to find its global relevance to the model. This method also analyzes the performance of the model (Roseline and Geetha, 2021).

Lofo initially evaluates the model’s performance with all input features included, then iteratively removes one feature at a time, retrains the model and evaluates its performance on a specific validation dataset. The mean and standard deviation of the relevance of each feature are then reported (Roseline and Geetha, 2021).

A very popular and quick method to be performed, the Explain Like I’m Five (Eli5) is a complete tool that helps explore machine learning classifiers and explains the predictions (Korobov and Lopuhin, 2021). Among the many different ways to explain a machine learning model, Eli5 is capable of executing the Mean Decrease Accuracy algorithm to generate an attribute relevance ranking (TeamHG-Memex, 2021).

The central idea of the algorithm is to calculate the relevance of the feature by observing how much the performance (accuracy, F1, R², etc.) decreases when a feature is not available for the model. Thus, each feature is removed (only from the test part of the dataset) and then the model’s performance is calculated without it using a specific feature (Korobov and Lopuhin, 2021).

One of the most popular and currently used methods is the SHapley Additive exPlanations (SHAP), proposed as a unified method of feature relevance that explains the prediction of an instance \( X \) from the contribution of an
feature, based in the game theory of *Shapley Value* (Roth, 1988; Lundberg et al., 2020b; Lipovetsky and Conklin, 2001).

For *Shap*, each feature is considered a player in a game and the objective of this game is to achieve the model’s output. In this way, in an iterative manner on feature subsets, new models are re-trained with and without the feature subsets and the *Shapley Values* of each feature are calculated, ultimately generating an attribute relevance ranking (Lipovetsky and Conklin, 2001; Lundberg, 2023).

Last but not least is the method *Skater*, a set of tools capable of generating ranks of the relevance of model features, differing from the other methods to calculate its explanation index based on Information Theory (Reza, 1994), through measurements of entropy in changing predictions through a disturbance of a certain feature (Oracle, 2021a).

Unlike other XAI methods, *Skater* was developed by a private initiative and is now closed source software. In-depth information about how this method works is very scarce, but it is still widely used by the XAI community (Oracle, 2021a,b).

### 3.1.2. Explanation-by-example

Methods based on *Explanation-by-example* select specific instances of the dataset in order to explain the behavior of the models or to explain the distribution of data through local explanations (Molnar, 2020).

There are explanations based on model-agnostic and also model-specific examples, the latter being generally aimed at neural networks. According to Molnar (2020), the main types of explanations for example are based on: *Counterfactual Explanations* (Wachter et al., 2017), *Adversarial Examples* (Biggio and Roli, 2018), *Prototypes* (Kim et al., 2016), and *Influential Instances* (Koh and Liang, 2017).

Each of these proposals seeks to carry out the process of identifying relevant instances of the analyzed dataset, which directly or even indirectly explain and justify the output of the model, whether it is correct or incorrect (Molnar, 2020).

Based on what was presented above, this research understands the under-need to compare the *Explanation-by-example* results presented in this article with results from tools that already exist today, because, as seen in Ribeiro et al. (2021), it is to be expected that the results of explanations are merely different in specific cases and when considering the number of comparisons...
to be performed (at the level of dataset instances) the conclusions would become imprecise.

Therefore, the results regarding Explanation by example are directly justified by the interpretations of the properties (guessing, discrimination and difficulty) of IRT, since the proposed method is based on this theory and how it can help in process of local and global explanation of the model, generating important information regarding model confidence.

3.2. Item Response Theory

The area of Item Response Theory (IRT) belongs to Psychometrics and offers mathematical models for estimating latent traits, relating the probability of an individual giving a specific response to an item with the characteristics of the items in the area of knowledge analyzed (Pasquali and Primi, 2003; Andrade et al., 2000).

Traditional assessment methods measure individuals’ performance on tests based on the total number of correct answers, but this approach has limitations. For example, how to deal with correct answers obtained by chance, or even how to evaluate the difficulty of each test question (Andrade et al., 2000).

Unlike traditional assessments, IRT focuses on test items, evaluating performance based on the ability to get specific items correct, not just the total count of correct answers (Hambleton et al., 1991).

IRT seeks to evaluate unobservable latent characteristics of an individual, providing the relationship between the probability of a correct answer and their latent traits, that is, the individual’s ability in the area of knowledge evaluated (Hambleton et al., 1991).

In summary, IRT consists of mathematical models that represent the probability of an individual getting an item correct, considering item parameters and the respondent’s ability. Different implementations of IRT exist in the literature, such as the “Rasch Dichotomous Model” (Kreiner, 2012) and the “Birnbaum Three-Dimensional Model” (Birnbaum, 1968). In this study, the latest implementation was used, known as the 3PL logistic model, which performs probabilistic calculations in two stages: Item Parameter Estimation and Skill Estimation.

In the two topics below, it will be described how the main processes of this theory can be understood and abstracted to the area of machine learning through a hypothetical example.
3.2.1. Estimation of Item Parameters

The calculation of item parameters (discrimination, difficulty, and guessing) in the 3PL is performed using estimation techniques, such as the Maximum Likelihood Estimation - MLE (Myung, 2003). In this technique, the objective is to find the values of the parameters that maximize the probability of observing the actual responses of individuals to the items. Each property has the following definition:

- **Discrimination:** consists in how much a specific item $i$ is able to differentiate between highly and poorly skilled respondents. It is understood that the higher its value, the more discriminative the item is. Ideally, a test should feature a gradual and positive discrimination;

- **Difficulty:** represents how much a specific item $i$ is hard to be responded correctly by respondents. Higher difficulty values represent more difficult items to answer;

- **Guessing:** representing the probability that a respondent gets a specific item $i$ right randomly. It can also be understood as the probability that a respondent with low ability will get the item right. It is also the smallest possible chance that an item will be correct regardless of the estimated ability of the respondent.

To facilitate the abstraction of the procedure performed, we will use a simple example as a small case study containing 6 individuals, 4 hypothetical questions and the answers of each one arranged in a response matrix presented in the table 2.

Note, in the hypothetical example the values presented are illustrative, because the results of the IRT are accurate when you have more than 100 individuals (Andrade et al., 2000; Prudêncio et al., 2015; Baylari and Montazer, 2009).

In the table 2 the number “1” indicates a correct answer and “0” indicates a wrong answer by the respondent (individual). From this response matrix, the parameter estimation can be done in 4 steps:

- **Parameter initialization:** Item parameters are initialized with arbitrary values.

- **Calculation of expected probabilities:** From the initial item parameters, the expected correct answer probabilities for each item are calculated for each individual.
Table 2: Simple example of a response matrix of 6 individual and 4 questions.

| Individual 1 | Question 1 | Question 2 | Question 3 | Question 4 |
|--------------|------------|------------|------------|------------|
| Individual 2 | 1          | 1          | 1          | 0          |
| Individual 3 | 1          | 1          | 0          | 0          |
| Individual 4 | 1          | 1          | 0          | 0          |
| Individual 5 | 1          | 0          | 0          | 0          |
| Individual 6 | 1          | 0          | 0          | 1          |

Parameters Update: Item parameters are updated iteratively, using the MLE to maximize the likelihood of the data, by comparing the observed responses of individuals with the expected probabilities calculated in the previous step.

Iterations: The previous two steps are repeated until the parameter estimates do not change significantly between iterations.

In the table 3 follow the hypothetically extracted item parameter values for the responses of individuals in the table 2.

Table 3: Hypothetical values of item parameters estimated by Table 2

| Question 1 | Discrimination | Difficulty | Guessing |
|------------|----------------|------------|----------|
| Question 2 | 0.19           | 0.36       | 0.00     |
| Question 3 | 0.58           | 0.39       | 0.00     |
| Question 4 | 0.86           | 1.28       | 0.25     |

The hypothetical example described in the Table 2 shows that a test with 4 questions was applied to a total of 6 individuals, through a simple counting of correct answers, it can be stated that individual 1 got more questions right (total from 4). It can also be said that candidate 5 was the one who got the fewest questions right (total of 1), while the others candidates had intermediate results.

When observing the hypothetical item parameter estimates presented in the Table 3 it is verified that discrimination, difficulty and guessing provide more specific information about each test question, such as below.

Discrimination: “Question 1” cannot be considered the best to discriminate individuals because the value 0 (discrimination null), this happened because all the respondents got the question right. “Question 4” can be
considered the most discriminating question, followed by “Question 3” and “Question 2” respectively.

**Difficulty**: higher difficulty values indicate more difficult questions, so “Question 4” is considered the most difficult, followed by 2, 3 (with very close values) and 1 (with value $-\infty$ due to all individuals having got it right).

**Guessing**: the question that presented significant value was “Question 4”, as it is observed that “Individual 6” even without correctly answering “Question 2” and “Question 3” (which present intermediate difficulties similar) correctly answered question 4 (considered the most difficult).

As noted above, the process of estimating item parameters provides important information about questions and individuals related to an evaluative test. Below are procedures for calculating the ability of individuals.

### 3.2.2. Estimation of ability

The logistic model 3PL, presented in the equation $P(U_{ij} = 1 | \theta_j)$ consists of a model capable of evaluating the respondents of a test from the estimated ability $(\theta_j)$, together with the correct answer probability $P(U_{ij} = 1 | \theta_j)$ calculated as a function of the individual skill $j$ and the parameters of the item $i$.

$$P(U_{ij} = 1 | \theta_j) = c_i + (1 - c_i) \frac{1}{1 + e^{-a_i(\theta_j - b_i)}} \quad (1)$$

The 3PL is used to model the relationship between individuals’ ability and the likelihood of correctly answering an item on a test. It assumes that the probability of a correct answer depends on three item parameters: item discrimination, item difficulty, and item guessing.

In the equation (1), the properties discrimination, difficulty, and guessing of the items $i$, are represented respectively by the letters $a_i, b_i,$ and $c_i$

The $\theta_j$ is the ability of the individual $j$, which is a continuous parameter representing the latent trait being measured. $P(U_{ij} = 1 | \theta_j)$ represents the probability of correctly answering item $i$ for an individual $j$ with ability $\theta$;

Now with the knowledge of the $PL3$ equation, we return to the hypothetical example showing the value of $\theta$ for each individual, table [4]

The value calculated in the $\theta$ ability estimation process, presented in the table [4], indicates individuals with greater ability (higher values) and individuals with lower abilities (lower values). Note that “Individual 1” is the most skilled among the respondents, followed respectively by “Individual 2”, “Individual 3”, “Individual 4”, “Individual 5” and “Individual 6”, these
Table 4: Result of $\theta$ estimation using the hypothetical example as a basis.

| Respondent | Ability ($\theta$) |
|------------|--------------------|
| Individual 1 | 0.905              |
| Individual 2 | 0.281              |
| Individual 3 | 0.195              |
| Individual 4 | 0.195              |
| Individual 5 | 0.091              |
| Individual 6 | 0.091              |

last two tied, as the question agreed by guessing (“Question 4” by “Individual 6”) was disregarded.

Thus, once the item parameters are estimated and the hit probability is calculated using the equation \[ P(\theta) = \frac{1}{1 + e^{-a\theta + b}} \] the Item Characteristic Curve (ICC) can be obtained. The ICC defines the behavior of an item’s hit probability curve according to the parameters describing the item ($a_i$, $b_i$, $c_i$) and the respondents’ skill variance, figure 1.

![Image of the Item Characteristic Curve (ICC)](image)

Figure 1: Example of the representation of the parameter values of an item arranged on the Item Characteristic Curve - ICC. The letters $a$, $b$ and $c$ represent the discrimination, difficulty and guessing properties, respectively.

As can be seen in figure 1 the hit probability on axis $y$ is calculated by adding the values of the properties $a_i$, $b_i$, $c_i$ found in an item and the variation of the skill $\theta$.

Thus, the property $a_i$ (discrimination) is responsible for the slope of the logistic curve; the property $b_i$ (difficulty) plots the curve as a function of skill.
in the logistic function; and the property $c_i$ (guessing) places the basis of the logistic function relative to the axis $y$.

As stated herein, the IRT emerges as a consolidated theory from the field of Psychometrics, which can be adapted to the field of Machine Learning (ML). Therefore, it is sufficient to consider that a “test” is a dataset, each “test item” is the instances of this dataset, “independent variables” are the questions and the “dependent variable” is the answer, “each answer” can be evaluated as right or wrong, and each “individual” is a separate machine learning model. This association can be better understood from figure 2.

![Figure 2: Associations of IRT terms and Machine Learning terms.](image)

That is, from this abstraction above, this important theory can be used to evaluate computational models, thus obtaining the evaluative benefits that IRT provides. Similar abstractions to this one have been made in machine learning research that uses this theory (Martínez-Plumed et al., 2016, 2019; Kline et al., 2021; Baylari and Montazer, 2009; Chen et al., 2006; Araujo Santos et al., 2023).
4. Materials and Methods

In this section, methodological aspects of the research will be presented, related to: Description of the developed pipeline (subsection 4.1); Definition of the datasets used and their preprocessing (subsection 4.2); Description of clustering (subsection 4.3); Description of MCA (subsection 4.4); Definition of the correlation measure (subsection 4.5); And finally, the definition of the XAI method eXirt (subsection 4.6).

4.1. Pipeline overview

A general view of the main methodological points addressed in this study (in pipeline format) can be seen from the figure 3, which is presented in order to facilitate the abstraction of the steps performed in a methodology.

The pipeline, figure 3 presents the steps: (A) Selection of 41 datasets referring to binary classification problems present in the OpenML platform (OpenML 2021); (B) Utilization of 15 property parameters from all 41 analyzed datasets (provided by OpenML OpenML platform); (C) Application of the K-means (Scikit-learn Developers 2021) clustering algorithm in the dataset properties table, followed by a Multiple Correspondence Analysis (Abdi and Valentin 2007); (D) Pre-processing of the 41 datasets selected in the initial step; (E) Use of 4 tree-ensemble algorithms in each of the 41 datasets to create black-box models; (F-G) Use of 6 XAI methods present in the literature and eXirt (method proposed in this article) to create global explanations based on feature relevance ranks; (H) Comparison of the feature relevance ranks found by eXirt with the ranks of the other XAI methods (considering the existing dataset clusters); (I) Use the item parameter estimates created by eXirt in step (F) and create local and global explanations of the analyzed models.

Detail, all processes carried out in the pipeline can be reproduced from its repository described in Supplementary Information (D).

4.2. Dataset’s Preprocess

Were used 41 datasets, selected from the OpenML (OpenML 2021) basis, while observing the fact that they refer to binary classification problems, without data loss and with a greater number of executions by the community, in order to contribute to research that already uses these datasets present in this repository, which is considered the gold standard of data quality (Cardoso et al. 2020).
The datasets used were as follows: *australian*, *analcatdata-lawsuit*, *phishing websites*, *spec*, *satellite*, *banknote authentication*, *blood transfusion service center*, *churn*, *climate model simulation crashes*, *credit-g*, *delta ailerons*, *diabetes*, *eeg-eye-state*, *haberman*, *heart-statlog*, *ilpd*, *ionosphere*, *jEdit-4.0-4.2*, *kc1*, *kc2*, *kc3*, *kr-vs-kp*, *mc1*, *monks-problems-1*, *monks-problems-2*, *monks-problems-3*, *mw1*, *mozilla4*, *ozone-level-8hr*, *pc1*, *pc2*, *pc3*, *pc4*, *phoneme*, *prnm crabs*, *qsar-biodeg*, *sonar*, *spambase*, *steel-plates-fault*, *tic-tac-toe* and *wdbc*.

In all the datasets mentioned above, the following pre-processing and/or coding were applied: conversion of independent variables from categorical to numeric, application of min-max normalization (using 0 as min and 1 as max by feature) of independent variables and coding of the target variable (dependent) in binary to “0” or “1”.

### 4.3. Dataset’s Clustering

Analyzing the characteristics of a dataset without taking into account the context (real world problem represented by the dataset) is not a trivial task, as it involves several technical properties of the data. Even because a dataset...
is made up of several properties that reflect how it was built (Oreski et al., 2017).

This research chose to avoid an individual and merely descriptive analysis of each of the 41 previously selected datasets, in order to make the results generic. Following this idea, it was decided to group such datasets through the clustering process using their properties, seeking at the end of the process to identify the profile of each dataset cluster through analysis of existing correlations.

The data related to the properties of the datasets were provided directly by the OpenML API, which for consistency reasons was limited to 15 properties. This properties, were consolidated into an intermediate dataset called “dataset properties”. On this dataset, the K-means (Scikit-learn Developers, 2021) algorithm was executed in order to identify how many clusters the data could be better grouped. In Supplementary information (B), it is possible to observe the visual of mentioned dataset.

Seeking to identify the optimal number of clusters to best separate the 41 datasets analyzed, the algorithm for interpretation and validation between data clusters was used, which is called Silhouettes (Rousseeuw, 1987), by varying the value $K$ (clusters) between 2 and 10. In the end, $K = 4$ was found with Average Silhouette Width = 0.353, figure 4.

Figure 4 shows the result of running the silhouette algorithm, where it can be seen that for $k = 4$ the distances between each cluster (0, 1, 2 and 3) are above the average (red line), so this is an appropriate value of $k$.

4.4. Dataset’s Multiple Correspondence Analysis

In the step presented in the section above, 4 groups of datasets were found that presented similar characteristics to each other and, therefore, were identified as belonging to the same cluster after the execution of the K-means algorithm. However, a deeper analysis was necessary in order to be able to define which profiles the existing datasets in each cluster had. With that, the need arose to use the Multiple Correspondence Analysis (MCA) (Abdi and Valentin, 2007).

In the MCA (Abdi and Valentin, 2007) analysis applied on the properties datasets, whereby the lines in this table are the observations or individuals ($n$) concerned — the datasets are here — and the columns are the different categories of nominal variables ($p$) — here are the properties of each dataset. In this analysis, the label of the cluster each dataset belongs to was taken into consideration.
The silhouette coefficient values
Cluster label
0
1
2
3
0.353
The silhouette plot for the 4 clusters.
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Average
Silhouette
Width

Figure 4: Silhouette coefficients for clustering, using the \textit{K-means} algorithm, for $K = 4$. Distance means (axis $x$) and label of clusters 0, 1, 2 and 3 (axis $y$).

For the \textit{MCA} analysis to be performed, there is a need to apply the binarization process to the dataset containing the 15 analyzed properties. For this, the binarization called “cut” (Pandas Developers, 2022), this function is also useful for going from a continuous variable to a categorical variable. Supports binning into an equal number of bins, or a pre-specified array of bins.

This function, “cut”, supports binning into an equal number of bins, or a pre-specified array of bins. Here we used the equal number of bins, calculated from the number of equal-width bins in the range of $x$ variable.

During the binarization process, the values presented in smaller bins were coded “s”, while the values in higher bins were coded “h”. The result of the binarization, on the dataset with the 15 properties, can be seen in the section \textit{Supplementary Information} (C).

Note, this research initially considered working with \textit{Principal Component Analysis - PCA} (Karamizadeh et al., 2013) instead of \textit{MCA}, but only this last technique allowed the identification of the dataset profile of each cluster, based on two ranges of bin values (low value “s” and high value “h”) for the
15 analyzed properties. Therefore, this is the technique responsible for the basis of the results that will be presented in section 5.1.

4.5. Rank Correlations

For all 41 datasets (clustered into 4 different clusters), 4 machine learning models were created, based on the Light Gradient Boosting, CatBoosting, Random Forest, and Gradient Boosting algorithms. In all, a total of 164 models and 1.148 ranks were generated.

In order to calculate the correlation between eXirt ranks and ranks from others XAI methods (for each of the 4 models), the Spearman’s Rank Correlation Coefficient \( \text{Artusi et al., 2002} \) was selected. The reason for using this particular algorithm is that it measures the correlation between pairs of ranks considering the idea of ranks (positions) where different values (in this case, dataset features) may appear.

4.6. The eXirt Method

The method Explainable Based on Item Response Theory - eXirt is one of the XAI methods performed in the developed pipeline. This method is a new proposal to generate explanations for tree-ensemble models. It is able to perform explanations based on feature relevance rank (global) and based on item parameters and the Item Characteristic Curve (local and global), both based on IRT properties (discrimination, difficulty and guessing).

Just like other XAI methods, eXirt uses the training data, test data, the model itself together with its outputs, figure 5(A). In (B) the test data and a model are passed on to the eXirt. In (C-D) the method creates the so-called “Model Perturbation” (responsible for simulating the response of several respondents using only a single model). In (E-F) the creation of the response matrix used in the IRT run.

At the end of the process, about figure 5 in (G-K) a global explanations are generated based on relevance feature rank (calculated from the theta value). In (I-J) the local explanations are also created from the item parameters and also the curve characteristic of the item.

The “Model Perturbation” process, figure 5(D) is inspired on methods Dalex \( \text{Biecek and Burzykowski, 2021} \) and Lofo \( \text{Roseline and Geetha, 2021} \), for in this process iterative perturbations are performed on all features of the model (iteratively, one feature at a time), and at each iteration the answers of the model prediction are collected and, thus, it is possible to have a high
Perturbations: 7 different ways to perturb the attributes of the model (only 1 model is used). Note, in this illustrative example, the model has 4 inputs and 7 perturbations were applied to these. So number of respondents is $4^7 + 1 = 29$ (number 1 is the original model without perturbation).

The lowest total score indicates the best attribute to explain the model.

Number of responding candidates (since a high number of respondents is a necessity for the IRT).

Still referring to the “Model Perturbation”, 7 different ways to perturb input features of model have been used, figure 5 (C). Each of these perturbations are applied to each input of the model (individually). These perturbations can be divided into three types: Feature Perturbation, Single Value Perturbation and Permutation Perturbation.

The Feature Perturbation is a technique used to evaluate the relative importance of the inputs features in machine learning model, testing the model’s tolerance to different values of data perturbations. This technique involves perturbing all instances of an feature by changing values or adding noise (Molnar [2020], Robnik-Sikonja and Bohanec [2018]). The perturbations implemented were: sign inversion (multiplies all values by -1), application of binning (divides feature values into fixed-width bins), and application of standardization (modifies the feature value using z-score standardization).

Single Value Perturbation is a technique used to evaluate the machine learning model’s sensitivity to specific changes in the input data. In this
technique, a single specific value is assigned to all instances of an feature, allowing to investigate the impact of this perturbation on the model results (Chang et al., 2018). The perturbations implemented were: zeros (value 0 in all instances) and standard deviation (standard deviation value in all instances).

Lastly, the Permutation permutation is a most common perturbation technique used to evaluate the feature importance in bagging machine learning models. This technique involves random (or non-random) permutation of the values in specific feature (Breiman, 2001; Scikit-learn Developers, 2022). The perturbations implemented were: ascending ordering (orders the values of a feature in ascending order) and inversion (modifies the values of a parameter by inverting the feature vector from top to bottom).

The creation of the response matrix, figure 5 (E) and (F), contains the answers of all iterations of model (understood as different IRT respondents). The columns refer to the instances of the dataset that was passed on, while the rows refer to the different answers.

The implementation of the IRT used was Cardoso et al. (2020), called decodIRT, in a code developed exclusively for the purpose of this paper, as the code first receives the answer matrix, performs the calculations to generate the item parameter values — different algorithms can be used to calculate the IRT (such as: ternary, dichotomous, fibonacci, golden, brent, bounded or golden2) (Magis and Raïche, 2012) — and, after this step, generates the rank of most skilled classifiers, figure 5 (G).

Among the new features of decodIRT is a new score calculation that involves the calculated ability of all respondents and their respective hits and misses, called Total Score. This score can be understood as an adaptation of the True-Score (Lord and Wingersky, 1984), whereby the score is calculated by summing up all the hit probabilities for the test items. However, in cases where respondents have a very close ability, the True-Score result can be very similar or even equal, since only the hit chance is considered. To avoid equal score values and to give more robustness to the models’ final score, the Total Score also considers the respondent’s probability of error, given by: $1 - P(U_{ij} = 1|\theta_j)$. By rewarding the model when it gets the classification right and penalizing every time it misses the classification of an instance, the objective is to show when the disturbance in a certain feature impacted the classification.

Thus, every time the model gets it right, the hit probability is added, and if the model gets it wrong, the error probability is subtracted. The calculation
of the Total Score $t$ is defined by the Equation 2, where $i'$ corresponds to the set of items answered correctly, and $i''$ corresponds to the set of items answered incorrectly.

$$t = \sum_{i=1}^{i'} P(U_{ij} = 1|\theta_j) - \sum_{i=1}^{i''} 1 - P(U_{ij} = 1|\theta_j)$$ \hspace{1cm} (2)

In this regard, a skilled model with high hit probability that ends up getting an item wrong will not have its score heavily discounted. However, for a low ability model with low hit probability, the error will result in a greater discount of the score value. For, it is understood that the final score value should consider both the estimated ability of the respondent and his own performance on the test.

The Total Score resulting from the execution of decodIRT is not yet the final rank of explainability of the model, because in this case it is necessary to calculate the average of the skills found for each feature, figure 5 (H), involving the different perturbations of features used in the previous steps.

Ultimately, figure 5 (H) and (K), an explanation rank is generated where each feature appears with a skill value. In this case, the lower the ability values, the more the feature explains the analyzed model. Equation $T_{(f,r)}$ is presented, which represents the processes performed by eXirt, equation 3.

$$T_{(f,r)} = \sum_{j=1}^{(v*f)+1} e_j \sum_{i=1}^{r} (I_{ji} + p_{ji}) + \sum_{i=1}^{f} t$$ \hspace{1cm} (3)

Where $v$ refers to the number of perturbation used. The value of $j$ represents the respondent’s index of the iteration in model perturbation. While $f$ represents the total input features of the model, where $(v*f)$ the total number of respondents with perturbations and +1 is the respondent without perturbation (original model response).

While $e_j$ represents the process of building the response matrix, which is used in the following estimation of item parameter $I_{ji}$, where $j$ is the analyzed respondent and $i$ is the analyzed instance, and $r$ is the quantity of items to be considered in the estimation. In this step, item parameter estimates are already considered local explanations of the analyzed model.

The calculation of the ability is performed in $p_{ji}$, where $j$ is the analyzed respondent and $i$ is the analyzed instance. Finally, there is the iterative process for calculating the Total Score in $t$, where $f$ is the quantity of input
features of the model. In this step, the global feature relevance rank is created.

Important note, all processes involving IRT calculations are performed based on responses from the respondent population used in eXirt. As the response of the original model without perturbation is in the population, this is used as a baseline for the responses generated through perturbation. Therefore, eXirt will always consider the response of the original model without perturbation as the best population response. Thus allowing the results of the item parameter estimation process to be used as valid local explanations for the analyzed model, as well as global rank of feature relevance.

Based on the above, it can be seen that the execution of the method eXirt depends directly on the number of respondents in the iteration “perturbation of model” and also on the number of instances in the dataset. For this reason, 7 different ways of perturbing the inputs of the machine learning model were used, which already makes it possible to create a considerable number of respondents, figure 5 (C).

Since eXirt uses only 1 model, and applies iterative perturbations to it in order to create “virtual respondents”, it can be considered that the perturbations increase the complexities (in the sense of difficulty) of the input instances of the analyzed model. That is, in the real world this process can be seen as if the complexities of the questions of a test could be gradually increased in several tests, which are then applied to a single individual who will have their stability evaluated from each test applied.

With the above, since the operation of eXirt is based on the estimation of IRT properties (discrimination, difficulty and guessing), on the estimation of ability values, and on model perturbations, further processes will help: Identifying features that best explain how the model works in a global way; Identifying instances that explain how stable and reliable the model is, in a local and global way.

This research declares that all processes performed by the proposed method, eXirt, are compatible with the methodological steps performed by XAI model-agnostic methods. However, because the analyzes presented in this article are focused on tree-ensemble models, eXirt is initially considered model-specific. More information about eXirt in the section Supplementary Information (F).
5. Results and Discussion

This section presents the results divided into three different moments: A study on the used dataset profiles is presented (subsection 5.1); The results of comparisons of the global features relevance ranks generated by eXirt with the results of the other XAI methods (subsection 5.2); And a specific results of the eXirt method, related to local and global explanations of models (subsection 5.3).

5.1. Dataset’s Profile

The first step to better understand the results is observe clustering and multiple correspondence analysis processes being used. In clustering, 4 clusters were found, with the dataset arrangements presented:

- **Cluster 0**: “Australian”, “credit-g”, “haberman”, “monks-problems-1”, “monks-problems-2”, “monks-problems-3”, and “tic-tac-toe”;
- **Cluster 1**: “analcatdata-lawsuit”, “churn”, “climate-model-simulation-crashes”, “kc1”, “kc2”, “kc3”, “mc1”, “mw1”, “ozone-level-8hr”, “pc1”, “pc2”, “pc3”, “pc4”, and “Satellite”;
- **Cluster 2**: “kr-vs-kp”, “PhishingWebsites”, and “SPECT”;
- **Cluster 3**: “banknote-authentication”, “blood-transfusion-service-center”, “delta-aileron”, “diabetes”, “eeg-eye-state”, “heart-statlog”, “ilpd”, “ionosphere”, “jEdit-4.0-4.2”, “mozilla4”, “phoneme”, “prnm-crabs”, “qsar-biodeg”, “sonar”, “spambase”, “steel-plates-fault”, and “wdbc”.

In order to consolidate the cluster profile analysis, a MCA was performed, as advocated in the literature [Abdi and Valentin 2007], and the relationship between the datasets in each cluster and the value ranges of the 15 properties analyzed was verified, figure 6.

Based on the inspection of the MCA result, shown in figure 6, one can notice different relationships and/or influences of specific properties (colored circles) analyzed in relation to the spread of datasets of each cluster (blue, red, orange, and green triangles). From this analysis, one can better understand which properties are most significant in each cluster, that is, which properties best differentiate the datasets from one cluster to another.

To characterize the profile, an equal number of properties were not fixed for each cluster, but the properties that most influenced the position of the
Figure 6: Multiple Correspondence Analysis - MCA with rows (data sets) and columns (properties) the axis $x$ and $y$ are respectively the 0 and 1 components of the analysis.
datasets on the ordinates of components 0 and 1 were used. The identified profiles were:

- **Cluster 0 profile:** datasets with higher class balances ("MajorityClassPercentage" = "s" and "MinorityClassPercentage" = "h"), lower autocorrelations ("AutoCorrelation" = "s"), higher entropy in the target class ("ClassEntropy" = "h"), and fewer numerical features ("NumberOfNumericFeatures" = "s");

- **Cluster 1 profile:** datasets with larger class imbalances ("MajorityClassPercentage" = "h" and "MinorityClassPercentage" = "s"), smaller class entropy values ("ClassEntropy" = "s"), many features ("NumberOfFeatures" = "h"), and many numeric features ("NumberOfNumericFeatures" = "h");

- **Cluster 2 profile:** datasets with the largest non-numeric features values ("PercentageOfBinaryFeatures" = "h", "NumberOfBinaryFeatures" = "h", and "NumberOfSymbolicFeatures" = "h");

- **Cluster 3 profile:** few datasets with non-numeric features and few instances ("NumberOfFeatures" = "s", "NumberOfSymbolicFeatures" = "s", "NumberOfBinaryFeatures" = "s", and "NumberOfInstances" = "s").

It is worth noting that some properties were not mentioned above because they appear at very similar distances for the four clusters.

### 5.2. The eXirt vs XAI Methods

The results presented below show the comparisons of the ranks generated by eXirt with the ranks generated by the other XAI measures, this taking into account the different clusters datasets “C0”, “C1”, “C2”, and “C3”. Note, without the process of clusterization and identification of datasets profiles, it would be difficult to evaluate the correlations of the models based on the 41 datasets through boxplots, as the scattering and outliers would prevent any analysis.

The idea is to show the stability of feature relevance ranks generated by eXirt, against different dataset profiles and also different machine learning algorithms. Also showing that the results generated by eXirt are not replications of results found by other existing XAI methods, even in conditions
where the other XAI methods agree with each other, as seen in [Ribeiro et al., 2021]. For this, each of the 4 models were created using their default settings indicated by their documentation, the models are: “M1” is Light Gradient Boosting (Microsoft, 2021), “M2” is CatBoost (Yandex, 2021), “M3” is Random Forest (Breiman, 2001), and “M4” is Gradient Boosting (Natekin and Knoll, 2013).

To facilitate the analyses, the Spearman correlation ($sp$) scale will be considered: 0 — 0.19 (very weak), 0.20 — 0.39 (weak), 0.40 — 0.59 (moderate), 0.60 — 0.79 (strong), and 0.8 — 1.0 (very strong). In order to evaluate the statistical validity of the results, the $p$-values generated in the correlation calculations will also be considered, since from this $p$-values it becomes possible to identify Confidence Intervals $ic$ statistics of a given statement in percentage, $ic = (1 − p$-value$)*100$.

At specific times, performance measures such as accuracy, precision, and recall will be used in order to present evidence that shows the model with the best performances. On the results of these three model performance measures, the Friedman Test (Demšar, 2006) will be carried out in order to verify the statistical significance of the different model performances.

5.2.1. Model performance

Taking as a basis the models “M1”, “M2”, “M3”, and “M4” from different clusters, analyzes of their performances were carried out, finding values of accuracy, precision, and recall. In the values found, the Frieman test was performed in order to find the differences between the models, indicating whether these are statistically significant. The result of this analysis is shown in figure 7.

The analysis of the models in the “C0” cluster begins (A-C), observing the accuracy, precision, and recall values displayed, making it evident that the “M2” model was the one that presented the best performance.

As shown in figure 7 (A-C), accuracy values fluctuate between $\approx 0.99$ and $\approx 0.68$, considering the lower and upper limits of each boxplot. Showing that all models present considerable performance. However, observing the intervals in which the precision and recall values fluctuate, between $\approx 0.99$ and $\approx 0.74$, it is noted that the models presented difficulties in correctly predicting the positive class (1).

Seeking to provide a statistical basis for comparing the models, figure 7 (D), the Friedman test was carried out and it was found that the “M2” model presented differences with high confidence intervals for the models ‘M3’ (p-
Figure 7: Accuracy, precision, Recall and p-values (Friedman Test) of the models “M1”, “M2”, “M3”, and “M4” for all clusters.

value = 0.02 ; ic = 98%) and “M4” (p-value = 0.08 ; ic = 92%). It can be stated that the difference in performance between the “M1” model and the “M1” model is not significant, as for the differences between the model “M2” for models “M3” and “M4” are statistically significant.
Based on the results presented in figures 7 (A-D), the next subsections analyzes referring to the models belonging to the cluster “C0” will focus on the models “M1” and “M2”, since these present the best performances on the datasets used.

In figure 7 (E-G), the accuracy values fluctuate between $\approx 0.99$ and $\approx 0.81$, considering the lower and upper limits of each boxplot. Which shows that all models present high performance. However, observing the intervals in which precision and recall values fluctuate, between $\approx 0.99$ and $\approx 0.0$, it is noted that some of the models presented problems in correctly predicting the positive class (1). This was already expected, as the datasets in the “C1” cluster have high imbalance.

By inspecting the figure 7 (H), it is not possible to notice a difference between the models, and when applying the Friedman test, it was proven that there was no statistically significant difference between the models. Therefore, the next subsections analyzes of the models belonging to the “C0” cluster will address models “M1” to “M4”.

Analyzing 7 (I-L), it can be seen that models “M1”, “M2” and “M3” present similar results to each other, while the Model “M4” presents a slightly lower performance than the others. However, when analyzing the p-values from the Friedman Test, it is noted that the difference between the models in question is not statistically significant (note the p-values between 0.31 and 1).

In figure 7 (I-K), the accuracy, precision and recall values fluctuate between $\approx 0.86$ and $\approx 0.99$, considering the lower and upper limits of each boxplot. This shows that all models present high performance regarding the problems to which they are applied in both classes (0 and 1).

Considering the accuracy, precision and recall values calculated for each of the “C3” models, figure 7 (M-O), similar accuracy values can be seen in the models “M1”, “M2” and “M3” (higher medians), as well as slightly lower values in “M4”. Precision and recall, on the other hand, showed greater differences in the performance of the models, again presenting the lowest values for “M4”.

In figure 7 (M-P), the accuracy, precision and recall values fluctuate between $\approx 0.6$ and $\approx 0.99$, considering the lower and upper limits of each boxplot. Although the visual difference in the boxplots is minimal, the statistical analysis based on the Friedman Test was able to highlight statistically significant differences between the models “M2” and “M4”.

Observing the p-values presented in figure 7 (P), it is clear that the mod-
els “M1” ($p$-value $= 0.14 \therefore ic = 86\%$), “M3” ($p$-value $= 0.35 \therefore ic = 65\%$) do not present a statistically significant difference ($p$-value $< 0.05$) in relation to the model “M2”. Therefore, “M4” ($p$-value $= 0.02 \therefore ic = 98\%$) presents a statistically significant difference compared to the model “M2”. Therefore, observing the results of the Friedman Test and the superiority (even if minimal) of performance of “M1”, “M2”, and “M3”, these models are defined as those that presented better performances on data from the “C3” cluster.

5.2.2. Models by cluster “C0”

Before analyzing the results of the pipeline for the “C0” cluster, it should be considered that the models based on these datasets tend to present more accurate predictions based on two main characteristics of the cluster profile, which is the fact of these datasets they will present: more balanced class values and also present high class entropy (Zhou, 2021).

The figure 8 on the left shows the fluctuations in the Spearman correlation values found from the comparisons of the ranks created by eXirt and the other XAI methods. On the right, the fluctuations in the $p$-values found in each comparison are shown, indicating whether certain comparisons are statistically significant.

It is possible to notice, figure 8 on the left, that eXirt presented correlations above 0.4 (dashed red line) in some ranking comparisons (boxplots that exceed the red dashed line). However, observing the figure 8 on the right, the medians of the $p$-values (green lines of the boxplots) point to comparisons with more significant results, within specific confidence intervals, which are:

- “M2”: skater (medians of $sp = 0.44$ and $p$-value $= 0.11 \therefore ic = 88\%$).
- “M1”: shap (medians of $sp = 0.38$ and $p$-value $= 0.14 \therefore ic = 86\%$);

The correlation values 0.38 and 0.44 are considered respectively “weak” and “moderate”, following the Spearman correlation scale, showing that eXirt was able to generate explanations of the machine learning models belonging to the “C0” cluster in a moderately correlated way to the explanations of the other existing XAI methods — in other words, the explanations of eXirt are different from the explanations generated by the other methods of XAI, observing models from the “C0” cluster.

It is evident, looking at the boxplots in figure 8, that the results of the explanations generated by all the XAI methods tested are different, even when dealing with computational models that do not present a statistically
significant difference in performance. The proof of this statement is that the
boxplots arranged in “C0 and M1” and “C0 and M2” are different from each
other.

The different correlation values and also different sizes of boxplots, figure
8 on the left, indirectly show that the XAI methods present in the literature
explained the models in the “C0” cluster using different ranks from each
other. Because, when comparing two boxplots for example, the greater the
differences (size and position) between them, the greater the differences in
the explanations of the methods. This can be better observed when analyzing
all the ranking comparisons generated in the research, section Supplementary
information (E).

The fact that each XAI method explains the same model and thus gener-
ates different explanations has a direct impact on its reliability, because if
several different explanations are generated for the same problem, it becomes
difficult for a human to trust a given explanation. This shows how complex
the mission of explainers of black box machine learning models is.
5.2.3. Models by cluster “C1”

Before analyzing the results of the pipeline for the “C1” cluster, it should be taken into consideration that naturally the models that are based on datasets of this cluster tend to present forecast trends for a specific class, because they are datasets with high imbalance, as well as a low class entropy ([Zhou, 2021]). Another characteristic of the datasets of this cluster, is the high number of features, which directly impacts the process of calculating the correlations between the ranks of feature relevance, since having more features has more possibilities of explanations of the model (higher possible combination of ranks).

The results shown in figure 9 are generated from models that use datasets from cluster “C1”, and show “weak” or even “very weak” correlations for most of the ranks generated by the eXirt compared to the other XAI methods. Which means that for this cluster of models, eXirt generated extremely different ranks of explanations from the other methods (except for a few outliers).

Figure 9: Results of Spearman correlations for models “M1”, “M2” “M3”, and “M4” based on the datasets cluster “C1”. The dashed red line divides the correlations between above and below “moderate”.

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A particularity of the figure 9 is the high number of outliers, which indicates that in at least 1 execution of each boxplot, a “moderate” or even “strong” correlation (positive or negative) different from the others was identified.

As the results presented in figure 9 point to fluctuations in correlations with strength around “very weak” ($sp < 0.19$), there is no need to evaluate the $p$-values since they will only show statistical significance for positive or negative correlations. Even so, the analyzes involving $p$-values can be seen in section *Supplementary information* (E).

In the results referring to the models in the “C1” cluster, it is evident that the explanations generated by eXirt are extremely different from the explanations generated by other XAI methods. It is also evident that the current XAI methods generated different explanations (note the difference in the sizes of the boxplots).

Once again, the results show that even for machine learning models with similar performance (without statistically significant differences) the explanations generated by the XAI methods are different from each other.

### 5.2.4. Models by cluster “C2”

Before starting the analysis of the models created from the datasets of the “C2” cluster, it should be considered that this is the cluster with the smallest number of datasets (3 in total), and these datasets have a high number of features non-numeric (mostly binary). Detail, the fact of having a small $n$ does not prevent the execution of the pipeline, however the boxplots will be more sensitive to changes in correlations.

The results previously presented in figure 9 referring to “C1” are similar to those presented in figure 10 but without the existence of outliers, which indicates that in all comparisons carried out, textiteXirt presented results that were extremely different from other XAI methods.

The correlations presented in figure 10 point to fluctuations in correlations with strength around “very weak” ($sp < 0.19$), the need to evaluate the given $p$-values is not identified that they will only show statistical significance for positive or negative correlations. Even so, the analyzes involving $p$-values can be seen in section *Supplementary information* (E).

Based on the results generated in the analyzes of the “C1” and “C2” models, the models from these two clusters can be considered as the most difficult to explain, as in general, the XAI methods used (including eXirt) generated different explanations from each other.
Figure 10: Results of Spearman correlations for models “M1”, “M2”, “M3”, and “M4” based on the datasets cluster “C2”. The dashed red line divides the correlations between above and below “moderate”.

5.2.5. Models by cluster “C3”

Before analyzing the results of the pipeline for the “C3” cluster, an important characteristic of this cluster must be taken into account, which is that it is made up of datasets with smaller numbers of instances. This lower number of instances should have an impact on the eXirt results, as fewer instances reflect a “minor test” applied to the model, therefore no type of negative impact was noted on the results.

The following analyses, from figure [11] onwards, will focus on the results of models “M1”, “M2” and “M3”, as these presented greater performances as seen above.

The results presented in figure [11] show correlations with strengths lower than “weak” \((sp < 0.39)\) in most of the results (note red dashed line). However, the third quartiles of some comparisons exceeded the red dashed line, which indicates moderate correlation. Therefore, for a better understanding of the correlations presented, we use the \(p\)-values generated in each comparison, figure [12]
Observing the lowest medians of the \textit{p-values} presented in figure 12, the following correlations in figure 11 can be highlighted as most significant within a specific confidence interval:

- “M1”: \textit{shap} (medians of $sp = 0.29$ and $p-value = 0.19$ : $ic = 81\%$);
- “M3”: \textit{shap} (medians of $sp = 0.2$ and $p-value = 0.21$ : $ic = 79\%$).
- “M1”: \textit{ci} (medians of $sp = 0.20$ and $p-value = 0.24$ : $ic = 76\%$);
- “M2”: \textit{ci} (medians of $sp = 0.07$ and $p-value = 0.29$ : $ic = 71\%$).

Observing the results listed above, it is clear that the confidence interval ($ic$) are not as expressive, showing that even in comparisons where \textit{eXirt} presented the highest correlations with the other XAI methods, the correlations did not present significant strengths.

As seen in figures 8 to 11, the results found by \textit{eXirt} in the process of creating explanations based on feature relevance rank are different from...
Figure 12: Results of $p$-values calculated in Spearman correlations for models “M1”, “M2”, and “M3” based on the datasets cluster “C3”. Note, values close to 0.05 are more significant.

the results found by other XAI methods in the literature, even in the face of models (dataset + algorithm) that represent problems with different profiles. In the results presented here, the focus was on comparing the feature relevance ranks generated by eXirt with the ranks of existing methods in the literature, but a complete comparison of all pairs of ranks generated can be accessed in the part Supplementary Information (E).

Indirectly, the results also show the difficulties surrounding research and evaluation of methods that propose to explain tree-ensemble black-box models using global feature relevance ranks, as one cannot simply emphasize that an “A” method is worse or better than another “B” method. Since this could only be done by specialists, external to the computing area, knowledgeable about each of the analyzed problems/datasets.

The results also show the problems and challenges that XAI methods generate when explaining tree-ensemble black-box models, since the methods present in the literature do not generate identical explanations, leaving the human user with doubts about which explanation to trust.
5.2.6. Details of eXirt global explanations

At this time, we have presented results referring to correlations of feature relevance ranks found from 4 different models based on 41 datasets of different problems. Therefore, seeking to present more detailed results, on how the eXirt ranks can be similar or even different in relation to the ranks generated by other XAI methods, we have chosen 2 models with explanations more reliable, from the previous stage of results in order to be presented in a manner visual as the ranks are composed.

For this, the “M2” model was selected which is based on the “credit-g” dataset of the “C0” cluster and also the “M1” model which is based on the “diabetes” dataset of the cluster “C3”, because they presented more reliable explanations (according to previous analyses).

Figure 13 presents a visual comparison of feature relevance ranks generated from the application of XAI methods eXirt, skater, loto, shap, eli5, dalex, and ci in model “M2” which is based on dataset “credit-g” (cluster “C0”). On the “x” axis, methods are presented in ascending order of correlation with the eXirt (using results presented in figure 8 model “M2”). On the “y” axis, the positions of each feature in the generated ranks are presented.

![Figure 13: Comparisons of feature relevance ranks generated by each XAI method from the “M2” model and “credit-g” dataset (cluster “C0”).](image)

In general, at least two features appear among the first positions in each
of the generated ranks, they are: “duration” and “check-status”, figure 13 thicker lines. These results show that these two features are more capable of explaining the analyzed model, given that all XAI methods point to these as relevant (positions closer to 0).

Figure 14 presents a visual comparison of feature relevance ranks generated from the application of the XAI methods eXirt, skater, lofo, shap, eli5, dalex, and ci to the “M1” model which is based on the “diabetes” dataset (cluster “C3”). On the “x” axis, methods are presented in ascending order of correlation with eXirt (using results presented in figure 11 model “M1”). On the “y” axis, the positions of each feature in the generated ranks are presented.

Even in the case of a model with fewer features, figure 14 thick lines, it can be noted again that two features stand out constantly appearing among the main positions of all ranks generated, the features are: “plas” and “mass”. This portrays the challenges in carrying out similar explanations, even for models that have a low number of entries.

![Figure 14: Comparisons of feature relevance ranks generated by each XAI method from model “M1” and dataset “diabetes” (cluster “C3”).](image)

In both cases, it can be noted that the eXirt was able to identify the features with greater relevance, pointed out by the existing methods. Showing that this method presents solid explanation generation processes and that the generated explanations are similar (but not identical) to the existing methods in the literature.

5.3. The eXirt exclusive local and global explanations to trust

Until now, results of the global explanations generated by eXirt and the other methods present in the literature have been presented, along with insights on which explanations would be more reliable. However, now detailed
results will be presented on the eXirt differentials, which are the local explanations based on the Item Response Theory property.

It was decided to select 2 datasets (randomly, one from each cluster) in order to diversify the results (in view of the different properties of each dataset). The chosen datasets were “credit-g” and “diabetes”.

As a first analysis aimed at identifying more stable and reliable models, we can present the percentages of discrimination, difficulty and guesswork found in the instances of the models, Table 5.

Table 5: Discrimination, Difficulty and Guessing values for models “M1” to “M4” generated from 2 selected datasets.

| Model          | Discrimination | Difficulty | Guessing |
|----------------|----------------|------------|----------|
| Credit-g + M1  | 64%            | 37%        | 38%      |
| Credit-g + M2  | 96%            | 5%         | 15%      |
| Credit-g + M3  | 96%            | 6%         | 15%      |
| Credit-g + M4  | 97%            | 2%         | 22%      |
| Diabetes + M1  | 45%            | 16%        | 14%      |
| Diabetes + M2  | 16%            | 29%        | 8%       |
| Diabetes + M3  | 13%            | 31%        | 13%      |
| Diabetes + M4  | 38%            | 42%        | 19%      |

In this Table 5, the percentages presented were calculated based on the item parameters estimations calculated by eXirt in each execution of the pipeline. The percentages presented refer to the number of instances with high values considering the thresholds: discrimination > 0.75, difficulty > 1, and guessing > 0.2, as done in (Cardoso et al., 2020).

Observing the Table 5 rows referring to the models based on the “credit-g” dataset, the “M2” and “M3” models are identified as being the most stable and reliable, since they present: a high number of discriminative instances (meaning: the perturbations applied to them were sufficient to distinguish skilled models from non-skilled models among the respondents), few difficult instances (meaning: the models had difficulty in answering only 5% of 6% of the instances submitted to them), and smaller amounts of instances correct by guessing (meaning: these models guessed at least 15% of the instances submitted to them). That is, it is easier for a human user to trust a model that presents little difficulty in responding to dataset instances and low guessing successes.
The results of the models based on the “diabetes” dataset, Table 5, are presented. In them, the model “M1” as the most stable and reliable, as this model obtained the highest percentages of discrimination (45%), lower percentages of difficulty (16%) and intermediate values of guessing (14%).

Note, high guessing values should not always be understood as bad, because depending on the problem to be solved by the model, the act of the model guessing some instances may be desirable. However, this research points out that high guessing values (close to 50%, for example) can mean problems with existing biases in the model.

Although analyzes of item parameter percentages help to identify more reliable models, table 5, this type of analysis has limitations that are overcome through analyzes involving Item Characteristic Curves, which will be presented below.

5.3.1. The eXirt ICC local and global explanations

Seeking to go even deeper in relation to the local explanations that eXirt is able to generate, the Item Characteristic Curves (ICC) are presented below, at the instance level, with the discrimination, difficulty and guessing values for the models “M1” to “M4” based on dataset “credit-g”, figures 15 and 16.

The aforementioned views show in detail (instance level) how each model responds to dataset instances. This level of explanation is the most detailed possible that eXirt can provide, as it allows the user to know: If the model considers the instance discriminative or not; Whether or not the model had difficulty responding to the instance; Or if the model simply guessed a certain instance. Allowing with this, a greater understanding of the confidence that the user can employ in the model.

In figure 15, four different ICCs are presented, one for each model “M1” to “M4”, of a random instance of the test set (this specific instance is the same for all models). Based on the concepts of IRT, one can identify how each model predicted this instance, as follows.

Model “M1” (blue line), guessed the instance (higher values to the left of the ICC line), not presenting significant difficulty values, and presenting negative discrimination values (decreasing values to the right), indicating that the model hit the instance due to the presence of some existing bias in it, which only this model (among the others) identified;

Model “M2”, (orange line), was the model with one of the lowest guessing values (lower values to the left of the ICC line), required less skill for
the model to achieve the maximum probability of success and thus presents less difficulty (line quickly reaches the top of the “y” axis), and presented a significant value of positive discrimination (angle of upward inclination of the ICC line);

Model “M3”, [15] (green line), was the model with the lowest guessing value (lower values to the left of the ICC line), needed higher skill values to achieve the maximum probability of success and therefore, it presents greater difficulty (line reaches the top of the “y” axis more slowly), and presented one of the highest values of positive discrimination (steepest angle of upward slope of the ICC line);

Model “M4”, [15] (red line), was the model with the highest guess value after “M1”, required one of the highest skill values to achieve maximum probability (line slowly reaches the top of the “y” axis), and presented discrimination values very close to the values found by the “M3” model.

As can be seen above, the instance-level explanations that eXirt is able to generate insights that show latent characteristics of the analyzed model,
mainly regarding its stability and reliability. Since such explanations, because they are at the instance level, can be evaluated for an entire dataset (or even splits such as training and testing).

That is, it is up to the human user to decide which model is more stable and reliable, based on the results of local explanations generated by eXirt.

It is known that human judgment, in the process of choosing a model, is often guided by the performance of this model, however in situations where the performance values of the models are close, it is a difficult task for a human to be able to distinguish which is the most reliable model among those tested.

Aiming to present an alternative to this problem, eXirt is capable of calculating the averages of the discrimination, difficulty and guessing values generated during the model explanation process (over the test set) and thus presenting a global explanation, based on ICC capable of providing global information to a human individual about the reliability of each model.

To illustrate this eXirt explanation format, we can use the “diabetes” dataset, this dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases, the objective is to predict based on diagnostic measurements whether a patient has diabetes. The numbers of features and instances are 9 and 768 respectively. The performances of the models “M1”, “M2”, “M3” and “M4” created from this dataset (using a split 70%—30% of test training) are shown in the table 5.3.1.

Table 6: Accuracy, precision and recall data for models M1 to M4 based on the diabetes dataset.

| Model | Accuracy | Precision | Recall |
|-------|----------|-----------|--------|
| M1    | 0.71     | 0.59      | 0.59   |
| M2    | 0.74     | 0.64      | 0.60   |
| M3    | 0.75     | 0.69      | 0.59   |
| M4    | 0.74     | 0.64      | 0.60   |

According to the table 5.3.1, the accuracy, precision and recall values are relatively close, showing a minimal difference between the machine learning models “M1” to “M4”. However, when analyzing the data generated by eXirt, figure 16, it is possible to better understand how each model predicts the test dataset, allowing the definition of which one is more reliable.

As can be seen in figure 16, the most reliable model is “M1”, since it presented the lowest mean difficulty = −1.48, the highest mean discrimination
= 0.96, along with one of the lowest guessing averages = 0.1. In other words, this is the model that had the lowest average difficulty in answering the predictions, on average it is the one that best discriminates the instances of the test set, and gets the easy instances of the test set right (missing only some more difficult ones), showing that your learning is solid.

As the second most reliable model, “M4” is pointed out, since it presented the second lowest average of difficulty = −0.93, the second highest average of discrimination = 0.72, together with one of the lowest averages of guess = 0.1.

The models “M2” and “M3” are the least reliable models for the dataset in question, since they present the highest averages of difficulty with respective values equal to −0.69 and 0.59, they also present discrimination average values respectively −0.63 and −0.89 and guessing averages equal to 0.1 and 0.12 respectively. In other words, despite having presented relatively low difficulty in carrying out the prediction process, the negative discrimination

Figure 16: Item Characteristic Curve (ICC) for all instances of the “diabetes” dataset. The gray lines are the local explanations and the black lines (thicker) are the global explanations for each model.
values indicate the possible presence of bias in both models, as negative
discrimination means models with lower abilities had a greater chance of
getting the predictions right.

Local and global explanations based on Item Characteristic Curve and
Explainable-by-Example provide model information that no other XAI method
can generate. Therefore, these two formats of explanations are the main dif-
fferences of this new method in relation to the others, in addition to expla-
nations based on the relevance ranking of attributes proven to have different
values.

The results presented in this section reinforce the challenges that the Ex-
plainable Artificial Intelligence area faces with the difficult task of explaining
locally the black-box tree-ensemble models, since each model is capable of
generalizing the data/problem from a different perspective, whether this per-
spective is local or global.

6. Conclusions

In view of all the analyzes carried out, this research achieves its objec-
tive by presenting an innovative proposal for an XAI method, called eXirt,
which is capable of carrying out the process of explaining tree-ensemble ma-
chine learning models in a globally based on feature relevance ranks and lo-
cally/globally using Item Characteristic Curve and Explainable-by-Example,
all based on Item Response Theory.

As seen, we used comparisons of attribute relevance ranks generated by
eXirt and other XAI methods, aiming to quantitatively measure how similar
explanations based on IRT are to existing explanations in current literature.
It is evident that eXirt generated considerably different explanations from
the Ciut, Dalex, Eli5, Lofo, Shap and Skater methods in a significant part of
the experiments.

The fact that eXirt shows different and innovative ways of explaining tree-
ensemble black box models, shows that IRT was able to allow the proposed
method to explain models through a perspective that has not yet been used
by other current XAI methods.

This research motivates the use of eXirt by the machine learning commu-
nity, as feature relevance ranks provide an overview of how input features are
relevant to the proposed model and local and global explanations based on in
Item Characteristic Curve and Explainable-by-Example provide information
that helps a human individual choose which model and even which instances of predictions are most reliable.

7. Future works

- Develop an interface for the eXirt seeking the interaction of the human with its explanations, thus enabling the creation of a collaborative explanation between man and machine.

- Expand the analyses with eXirt for other types of algorithms, which are not exclusively tree-ensemble by analyzing the potential of this measure to become Model Agnostic, since the whole methodology proposed by eXirt is compatible with the nature of this type of measure.

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CRediT author statement

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Ethics approval

Not applicable.

Consent for publication

All individuals and institutions involved in the research in question are in agreement with the publication of this article in the journal.

Supplementary information

A - General repository of research:

- https://github.com/josesousaribeiro/eXirt-XAI-Pipeline;

B - Dataset properties with normalized values:

- https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/data/df_dataset_properties_norm.csv;

C - Dataset properties with binarized values:

- https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/data/df_dataset_properties_binarized.csv;
D - Repository for reproducibility of pipeline:

- [https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/code/pipeline_xai.py](https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/code/pipeline_xai.py)

E - Extra analysis illustrations:

- [https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/doc/Supplementary%20Material%20Based%20on%20Illustrations.pdf](https://github.com/josesousaribeiro/eXirt-XAI-Pipeline/blob/main/doc/Supplementary%20Material%20Based%20on%20Illustrations.pdf)

F - The eXirt distribution:

- [https://github.com/josesousaribeiro/eXirt](https://github.com/josesousaribeiro/eXirt)

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