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# THE GRAMMAR OF INTERACTIVE EXPLANATORY MODEL ANALYSIS

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## ABSTRACT

The growing need for in-depth analysis of predictive models leads to a series of new methods for explaining their local and global properties. Which of these methods is the best? It turns out that this is an ill-posed question. One cannot sufficiently explain a black-box machine learning model using a single method that gives only one perspective. Isolated explanations are prone to misunderstanding, which inevitably leads to wrong or simplistic reasoning. This problem is known as the Rashomon effect and refers to diverse, even contradictory interpretations of the same phenomenon. Surprisingly, the majority of methods developed for explainable machine learning focus on a single aspect of the model behavior. In contrast, we showcase the problem of explainability as an interactive and sequential analysis of a model. This paper presents how different Explanatory Model Analysis (EMA) methods complement each other and why it is essential to juxtapose them together. The introduced process of Interactive EMA (IEMA) derives from the algorithmic side of explainable machine learning and aims to embrace ideas developed in cognitive sciences. We formalize the grammar of IEMA to describe potential human-model dialogues. IEMA is implemented in the human-centered framework that adopts interactivity, customizability and automation as its main traits. Combined, these methods enhance the responsible approach to predictive modeling.

**Keywords** Explainable AI · Model-agnostic explanation · Black-box model · Interactive explainability · Human-centered XAI

## 1 Introduction

Complex machine learning predictive models, aka black-boxes, demonstrate high efficiency in a rapidly increasing number of applications. Simultaneously, there is a growing awareness among machine learning practitioners that we require more comprehensive tools for model interpretability and explainability. There are many technical discoveries in the field of explainable and interpretable machine learning (XIML) praised for their mathematical brilliance and software ingenuity (Baehrens et al., 2010; Ribeiro et al., 2016; Lundberg and Lee, 2017; Biecek, 2018; Alber et al., 2019; Apley and Zhu, 2020). However, in all this rapid development, we forgot about how important is the interface between human and model. Working with models is highly interactive, so the data scientist’s tools should support this way of operation. Interactive interpreters, so-called REPL (read-eval-print-loop) environments, available in R or Python tools, significantly facilitated the data analysis process. Another breakthrough was notebooks that speed up the feedback loop in the model development process (Xie, 2017; Kluyver et al., 2016). Not only is the process of building the model interactive, but, naturally, so is the process of analyzing and explaining the black-box. While Roscher et al. (2020) surveys XIML use for knowledge discovery, Lipton (2018) and Miller (2019) point out that there is a huge margin for improvement in the area of human-centered XIML.

People must trust models predictions to support their everyday life decisions and not harm them while doing so. Because of some spectacular black-box failures, even among the most technologically mature entities (Yu and Ali, 2019; Rudin, 2019), governments and unions step up to provide guidelines and regulations on machine learning decision systems to ensure their safeness, robustness and transparency (ACM US Public Policy Council, 2017; European Commission, 2020). The debate on the necessity of XIML is long over. With a *right to explanation* comes great responsibility for everyone creating algorithmic decision-making to deliver some form of proof that this decision is fair (Goodman and Flaxman, 2017). Constructing and assessing such evidence becomes a troublesome and demanding task. Surprisingly we have a growing list of end-to-end frameworks for model development (Nguyen et al., 2019), yet not that many complete and convenient frameworks for model explainability.

We agree with Gill et al. (2020) that in practice, there are three main approaches to overcoming the opaqueness of black-box models: evading it and using algorithms interpretable by design (Rudin, 2019), bias checking and applying mitigation techniques (Feldman et al., 2015), or using post-hoc explainability methods (Miller, 2019). Although the first two are precise, the last solution is of particular interest to ours in this paper. We base our contribution on the philosophies of Exploratory Data Analysis (EDA) (Tukey, 1977), which presents tools for in-depth data analysis, Explanatory Model Analysis (EMA) (Biecek and Burzykowski, 2021), which presents tools for in-depth model analysis, and The Grammar of Graphics (Wilkinson, 2005), which formalizes and unifies language for the visual description of data. Although the objective is set to bridge the research gap concerning opaque predictive models developed for *tabular data*, the introduced concept can be generalized to other tasks, specifically in deep learning.

## 1.1 Objectives

Wang et al. (2019) posits that we can extend XIML designs in many ways to embrace the human-centered approach to XIML, from which we distinguish the needs to (1) provide contrastive explanations that cross-compare different model’s aspects, (2) give exploratory information about the data that hides under the model in question and its explanations, (3) support the process with additional beneficial factors, e.g. explanation uncertainty, variable correlation, (4) integrate multiple explanations into a single, more cohesive dashboards.

In this paper, we meet these objectives through a sequence of single aspect model explanations aiming to significantly extend our understanding of black-box models. Interactivity always involves a sequence of operations; thus, explanatory model analysis can be seen as a dialogue between the operator and the explanatory interface (Kuzba and Biecek, 2020). For this reason, in this work, we formally describe the language in which this communication is possible. The introduced grammar of Interactive Explanatory Model Analysis (IEMA) focuses on a multifaceted look at the various possible explanations of the model’s behavior. We adhere to the *Rashomon effect* (Breiman, 2001) by juxtaposing complementary explanations, whereas conventionally it is used to denote analyzing diverging models. Moreover, we overview the challenges in providing meaningful insights on black-box predictive models for various stakeholders at once. This leads to implementing the open-source framework that allows utilizing IEMA in practice.

The paper is organized as follows. We introduce the grammar of IEMA which bases on the new taxonomy of explanations (Section 2) and present its use on two approachable predictive tasks (Section 3). Then, we overview the practical challenges of human-centered XIML (Section 4) and briefly preview the open-source modelStudio framework (Section 5). We discuss how our approach relates to the novel concept of responsible machine learning and conclude the paper (Section 6). To our knowledge, this is the first paper that formalizes the grammar of dialogue between the human and the predictive model.

## 1.2 Related work: a theory-practice mismatch in XIML

**Theory.** Research in cognitive sciences shows that there is a lot to be gained from the interdisciplinary look at XIML. Miller et al. (2017) and Miller (2019) continuously highlight that there is room for improvement in existing solutions, as most of them rarely take into account the human side of the black-box problem. While developing human-centered XIML frameworks, we should take into consideration the needs of multiple diverse stakeholders (Barredo Arrieta et al., 2020; Bhatt et al., 2020; Sokol and Flach, 2020; Kuzba and Biecek, 2020), which might require a thoughtful development of the user interface (Eiband et al., 2018). It is a different approach than in the case of machine learning frameworks, where we mostly care about the view of machine learning engineers. Hohman et al. (2018) comprehensively surveys research in the human-centered analysis of deep learning models. Srinivasan and Chander (2020) recommend further adoption of a human-centered approach in generating explanations, as well as understanding of the explanation context. Fürnkranz et al. (2020) perform user studies to analyze the plausibility of rule-based models that show that there is no negative correlation between the rule length and plausibility. We relate to these findings in proposing long sequences of explanations to analyze black-box models.

**Practice.** Focusing on overcoming the opacity in black-box machine learning has led to the development of various model-agnostic explanations (Friedman, 2001; Ribeiro et al., 2016; Lundberg and Lee, 2017; Lei et al., 2018; Fisher et al., 2019; Apley and Zhu, 2020). There is a great need to condense many of those explanations into comprehensive frameworks for machine learning practitioners. Because of that, numerous technical solutions were born that aim to unify the programming language for model analysis (Biecek, 2018; Alber et al., 2019; Greenwell and Boehmke, 2020; Arya et al., 2020). They calculate various instance and model explanations, which help understand the model’s predictions next to its overall complex behavior. It is common practice to produce visualizations of these explanations as it is more straightforward to interpret plots than raw numbers. Despite the unquestionable usefulness of the conventional XI ML frameworks, they have a high entry threshold that requires programming proficiency and technical knowledge (Bhatt et al., 2020).

**Match.** We aim to (1) improve on the work related to more practical XI ML methods, (2) satisfy the desideratum of the aftermentioned theoretical contributions.

## 2 The Grammar of Interactive Explanatory Model Analysis

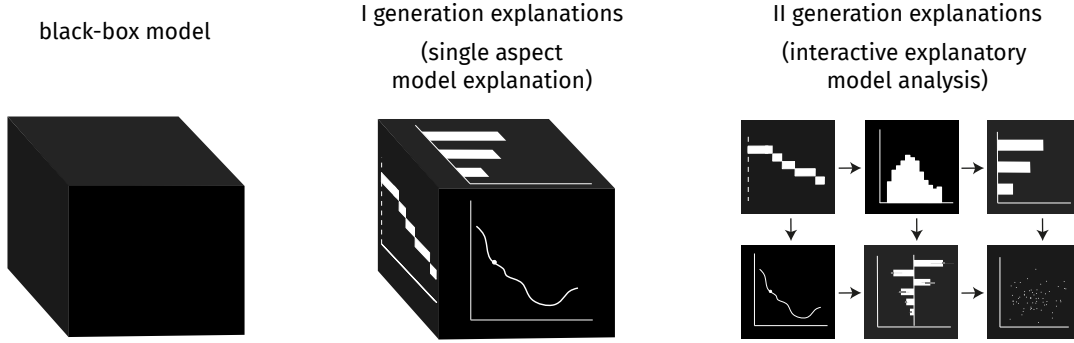


Figure 1: Increasing computing power and the availability of automated machine learning tools resulted in complex models that are effectively black-boxes. The first generation of model explanations aims at exploring individual aspects of model behavior. The second generation of model explanation aims to integrate individual aspects into a vibrant and multi-threaded customizable story about the black-box that addresses the needs of various stakeholders. We call this process Interactive Explanatory Model Analysis (IEMA).

Figure 1 shows how the perception of black-box machine learning changes with time. For some time, model transparency was not considered necessary, and the main focus was put on model performance. The next step was the first generation of explanations focused on individual model’s aspects, e.g. the effects and importances of particular variables. The next generation focuses on the analysis of various model’s aspects. The second generation’s requirements involve a well-defined taxonomy of explanations and a definition of the grammar generating their sequences. We first introduce a new taxonomy of methods for model analysis, and then, on its basis, we formalize the grammar of IEMA to show how different methods complement each other.

### 2.1 Taxonomy of explanations in IEMA

The taxonomy of explanations in IEMA consists of two dimensions presented in Figure 2. It is based on EMA (Biecek and Burzykowski, 2021) and accordant with the alternative XI ML taxonomies (Molnar, 2020; Lundberg et al., 2020; Barredo Arrieta et al., 2020; Arya et al., 2020). The first dimension categorizes single aspect explanations with respect to the question “*What to explain?*”. The second dimension groups the methods with respect to the question “*How to explain?*”. The proposed taxonomy distinguishes three key objects answering the “*What to explain?*” question.

1. **Data exploration** techniques have the longest history, see EDA (Tukey, 1977). They focus on the presentation of the distribution of individual variables or relationships between pairs of variables. Often EDA is conducted to identify outliers or abnormal instances; it may be interesting to every stakeholder, but most important is for model developers. Understanding data allows them to build better models. For semantic reasons and clarity in the grammar of IEMA, we further relate to these methods as *data explanations*.

2. **Global model explanation** techniques focus on the models' behaviour on a certain dataset. Unlike data explanations, the main focus is put on a particular model. We could have many differing models for one dataset, i.e. in the number of variables. Various stakeholders use global methods, but they are often of interest to model validators, which check whether a model behaves as expected. Examples of such methods are: model performance metrics, SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017), Permutational Importance (Fisher et al., 2019; Greenwell and Boehmke, 2020), Partial Dependence Plots (PDP) (Friedman, 2001; Greenwell, 2017), Accumulated Local Effects (ALE) (Apley and Zhu, 2020).
3. **Local instance explanation** techniques deal with the model's output for a single instance. This type of analysis is useful for detailed model debugging, but also to justify the decision proposed by the model to the end-users. Examples of such methods are: LIME (Ribeiro et al., 2016), SHAP (Lundberg and Lee, 2017), Break-down Attribution (Staniak and Biecek, 2018), Ceteris Paribus (CP) (Biecek and Burzykowski, 2021).

The second dimension groups the explainability methods based on the nature of the performed analysis. Similarly, we distinguish three types here.

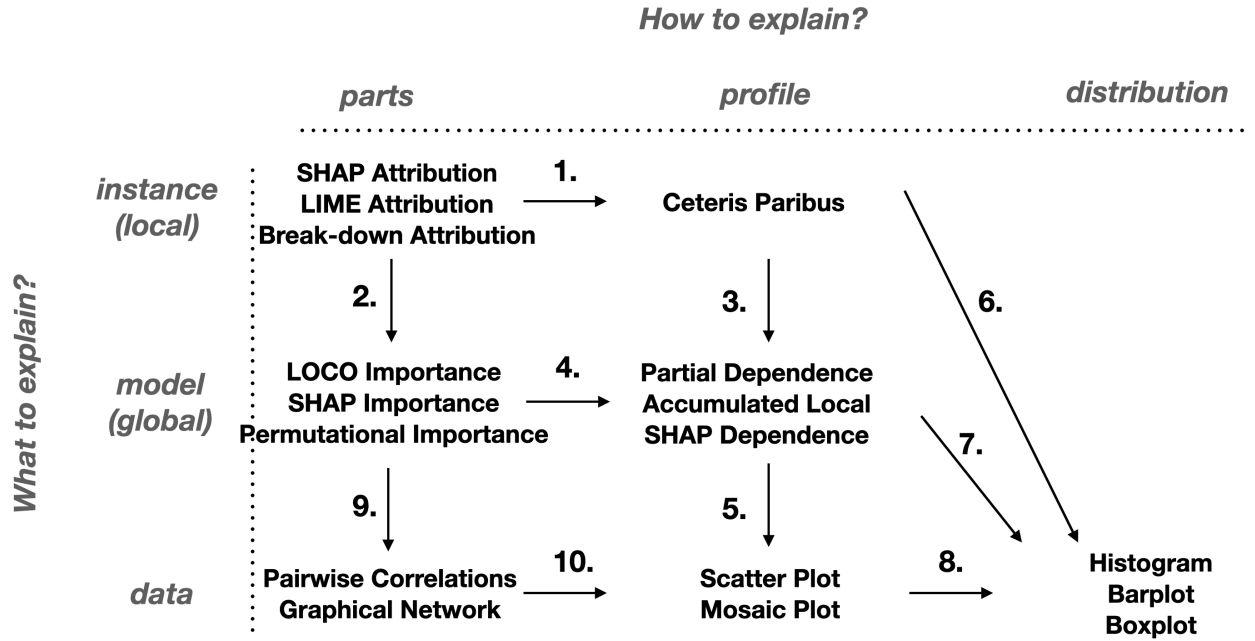


Figure 2: The concept of Interactive Explanatory Model Analysis shows how the various methods for model analysis enrich each other. Columns and rows span the taxonomy of explanations in IEMA, where names of well-known techniques are listed in cells. The graph's edges indicate complementary explanations.

1. **Analysis of parts** focuses on the importance of the model's components – single variables or groups of variables. The model's output can be quantified by evaluating its quality or average prediction. Examples of such methods are: LOCO (Lei et al., 2018), LIME, Break-down, SHAP, Permutational Importance.
2. **Analysis of the profile** covers the effect of a target variable to changes in an explanatory variable. The typical result is a prediction profile as a function of the selected variable in the input data. Examples of such methods are: CP, PDP, ALE.
3. **Analysis of the distribution** shows the distribution of certain variables in the data. The results make it easier to understand how typical are certain values.

Figure 2 shows how EMA techniques fit the proposed taxonomy. These are 17 methods for explaining data, models and instances. The list might not be exhaustive, and more methods to explain particular aspects of the model will certainly be developed over time. We refer to the appropriate papers and books for explanations' definitions, as we focus on providing a level of abstraction over the well-known methods used in XIML practice. Nevertheless, we introduce the following notation to strengthen the intuition.

Global explanations operate on a dataset and a model. Let  $X^{n \times p}$  stand for a dataset with  $n$  rows and  $p$  columns. Here  $p$  stands for the number of variables while  $n$  stands for the number of instances. Let  $f : \mathcal{X} \rightarrow \mathcal{R}$  denote for the model of interest, where  $\mathcal{X} = \mathcal{R}^p$  is the  $p$ -dimensional input space. Local explanations additionally operate on a single instance. Let  $x^* \in \mathcal{X}$  stand for the instance of interest; often  $x^*$  is an observation from  $X$ .

When we refer to the analysis of an *instance profile*, we are interested in a function that summarises how the model  $f$  responds to changes in variable  $X_j$ . For local explanations such as CP, the profile  $g(z)$  for variable  $X_j$  and instance  $x^*$  is defined as

$$g_{x_j^*}(z) = f(x^* | x_j^* = z), \quad (1)$$

where  $x_j^* = z$  means that the value of variable  $X_j$  in an instance  $x^*$  is changed to  $z$ . When we refer to the analysis of *instance parts*, we are interested in the attribution of individual variables to some measure. For local explanations such as SHAP Attribution, we want the variable attributions  $h(x_j^*)$  of variables  $X_j$  that sum up to a model prediction for an instance  $x^*$

$$\sum_{j=1}^p h(x_j^*) = f(x^*). \quad (2)$$

Global explanations may be defined as some aggregation of the local explanations, e.g. over the whole dataset. For *model profile* explanations like PDP,  $G(z)$  is an average of CP over all instances  $x^i \in X$

$$G_{X_j}(z) = \frac{1}{n} \sum_{i=1}^n g_{x_j^i}(z). \quad (3)$$

For *model parts* explanations like SHAP Importance,  $H_X(X_j)$  is an average of absolute SHAP Attribution values over all instances  $x^i \in X$

$$H_X(X_j) = \frac{1}{n} \sum_{i=1}^n |h(x_j^i)|. \quad (4)$$

## 2.2 Context-free grammar of IEMA

In the previous section, we described the intuition behind the IEMA grammar. However, to be able to generate explanations, we need a formalised notation of this concept. In this section, we define the context-free grammar of IEMA to generate a language of explanations' sequences (Chomsky, 1956). A context-free grammar  $G$  is defined by the 4-tuple  $G = (N, T, R, S)$ , where:

- $N$  is a set of nonterminal symbols which correspond to the concepts in taxonomy of IEMA (Figure 2). These have names with only lowercase letters in Table 1, e.g. `model_explanation`, `model_parts_`.
- $T$  is a set of terminal symbols that correspond to the data, instance, and model explanations. These have names with uppercase letters in Table 2, e.g. `Histogram`.
- $R$  is a set of rules denoted with  $\rightarrow$  and  $|$  in Tables 1 and 2.
- $S$  is the start symbol denoted as `explanation` in Table 1.

Finally,  $\varepsilon$  stands for the *NULL* symbol. The presented rules are a formal way of understanding the grammar of IEMA. These allow for defining the process of black-box model analysis; however, they are not necessary in practice.

## 2.3 Complementary explanations in IEMA

The explanatory techniques presented in Figure 2 are focused on explaining only a single perspective of the instance, model or data; hence, these enhance our understanding of the black-box only partially. The main results of this paper are based on the observation that each explanation generates further cognitive questions. EMA adds up to chains of questions joined with explanations of different types. Juxtapositioning of different explanations helps us to understand the model's behavior itself better. Novel XIML techniques aim to provide various complementary perspectives because EMA is a process in which answering one question raises new ones. The introduced approach implies designing a flexible, *interactive* system for EMA in which we plan possible paths between the model's perspectives that complement each other.

We define interactions with the machine learning system as a set of possible paths between these complementary explanations. Figure 2 shows a proposed graph of interactions, which creates the grammar of IEMA. The edge in the graph denotes that the selected two explanations complement each other. For example Figure 3 shows an interaction for edge 1, Figure 4 shows an interaction for edge 6, while Figure 5 shows an interaction for edge 3.

Table 1: Rules defining the context-free grammar of IEMA. These start with nonterminal symbols; most notably explanation is the start symbol.

explanation	→	instance_explanation   model_explanation   data_explanation
instance_explanation	→	instance_parts · instance_parts_
instance_parts_	→	Select_Variable · instance_profile · instance_profile_ · instance_parts_   model_parts · model_parts_ · instance_parts_   ε
instance_profile_	→	data_distribution · instance_profile_   model_profile · model_profile_ · instance_profile_   ε
model_explanation	→	model_parts · model_parts_
model_parts_	→	Select_Variable · model_profile · model_profile_ · model_parts_   data_parts · data_parts_ · model_parts_   ε
model_profile_	→	data_profile · data_profile_ · model_profile_   data_distribution · model_profile_   ε
data_explanation	→	data_parts · data_parts_   ε
data_parts_	→	data_profile · data_profile_   ε
data_profile_	→	data_profile · data_parts_   data_distribution   ε

Table 2: Representation of possible terminal symbols in the context-free grammar of IEMA. These correspond to the taxonomy of explanations.

data_parts	→	Pairwise_Correlation   Graphical_Networks
data_profile	→	Scatter_Plot   Mosaic_Plot
data_distribution	→	Histogram   Boxplot   Barplot
model_parts	→	Permutational_Importance   LOCO_Importance   SHAP_Importance
model_profile	→	Partial_Dependence   Accumulated_Local   SHAP_Dependence
instance_parts	→	SHAP_Attribution   BD_Attribution   LIME_Attribution
instance_profile	→	Ceteris_Paribus

### 3 Exemplary use-cases of IEMA

We have already introduced the taxonomy of explanations and the grammar of IEMA. Now, we present these XI ML developments based on two predictive tasks.

### 3.1 Regression task of predicting FIFA-20 player’s value

**Setup.** In the first use-case, we apply the grammar of IEMA to the Gradient Boosting Machine (Friedman, 2001) model predicting player’s value based on the FIFA-20 dataset (Leone, 2020). We aim to show a universal example of knowledge discovery with explainable machine learning. We only use model-agnostic explanations; thus, the model’s structure is irrelevant – we refer to it as a *back-box* model. We construct the sequence of questions using the introduced grammar to provide a broad understanding of the black-box. We start with an analysis of the model’s prediction for a single instance, more precisely Cristiano Ronaldo’s<sup>1</sup>. The black-box model estimates CR7’s value at 38M Euro. Consider the following human-model dialogue:

**Q1: What factors have the greatest influence on the estimation of the worth of Cristiano Ronaldo?** In the taxonomy, this is the instance-level question about parts. To answer this question, we may present SHAP or Break-down Attributions as in Figure 3. The movement\_reactions and skill\_ball\_control variable increases worth the most, while the age is the only variable that decreases CR7’s worth.

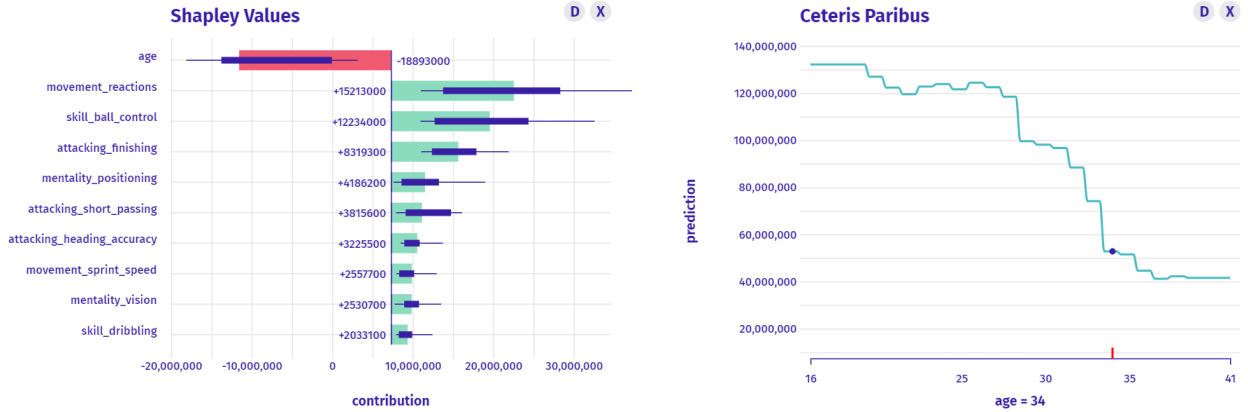


Figure 3: **Left:** SHAP Attributions to the model’s prediction shows which variables are most important for a specific instance. **Right:** Ceteris Paribus shows the instance prediction profile for a specific variable.

**Q2: What is the relationship between age and the worth of CR7? What would the valuation be if CR7 was younger or older?** This is an instance-level question about the profile which we answer with the Ceteris Paribus technique in Figure 4. Between the extreme values of the age variable, the player’s worth differs more than five times.

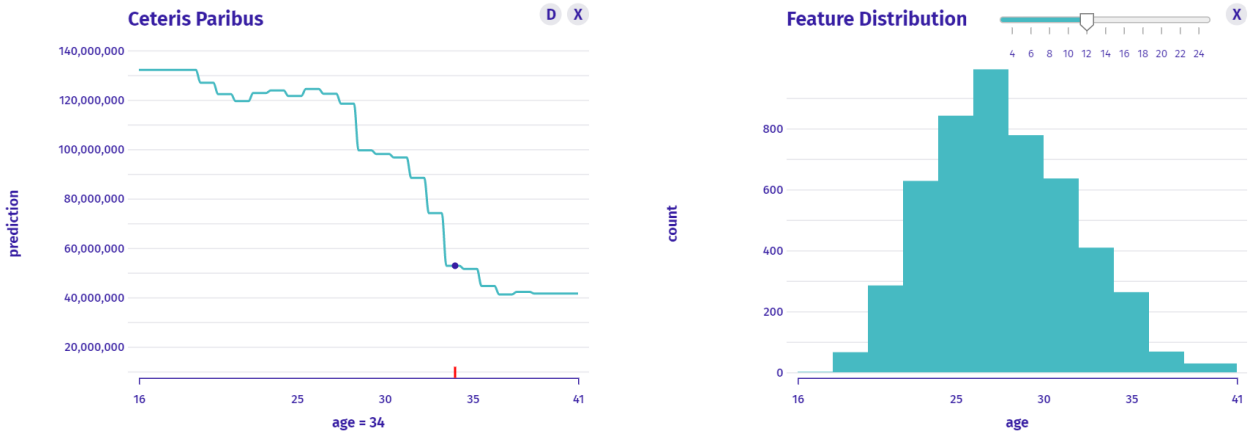


Figure 4: **Left:** Ceteris Paribus for the age variable shows the monotonicity of the instance prediction profile, for which values are large or small. **Right:** Histogram shows the distribution of the age variable’s values.

<sup>1</sup>Cristiano Ronaldo is one of the most famous footballers globally; hence, variables attributing to his worth may be of high interest.

**Q3: How many players are Cristiano Ronaldo’s age?** In the taxonomy, this is a model-level question about the distribution. Histogram answers the question as presented in Figure 4. We see that the vast majority of players in the data are younger than CR7; thus, his neighbourhood might not be well estimated by the model.

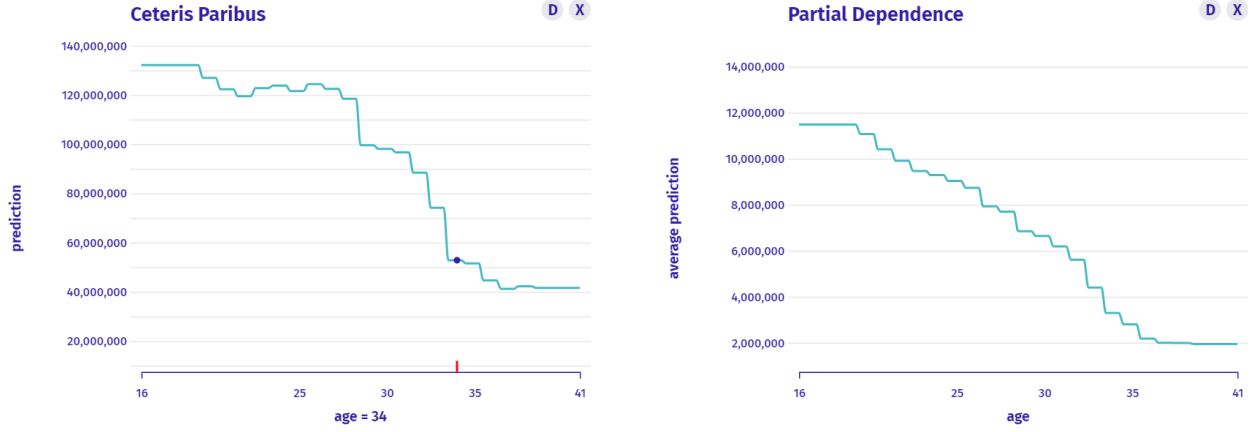


Figure 5: **Left:** Ceteris Paribus for a single instance shows how the model behaves in its neighbourhood. **Right:** Partial Dependence shows an average model prediction profile that agrees with instance analysis.

**Q4: Whether such relation between age and worth is typical for other players?** This is a model-level question about the profile that we answer with Partial Dependence as presented in Figure 5. We see a global pattern that age reduces the player’s worth about five times (with established skills). However, we suspect that younger players have lower skills, so another question arises.

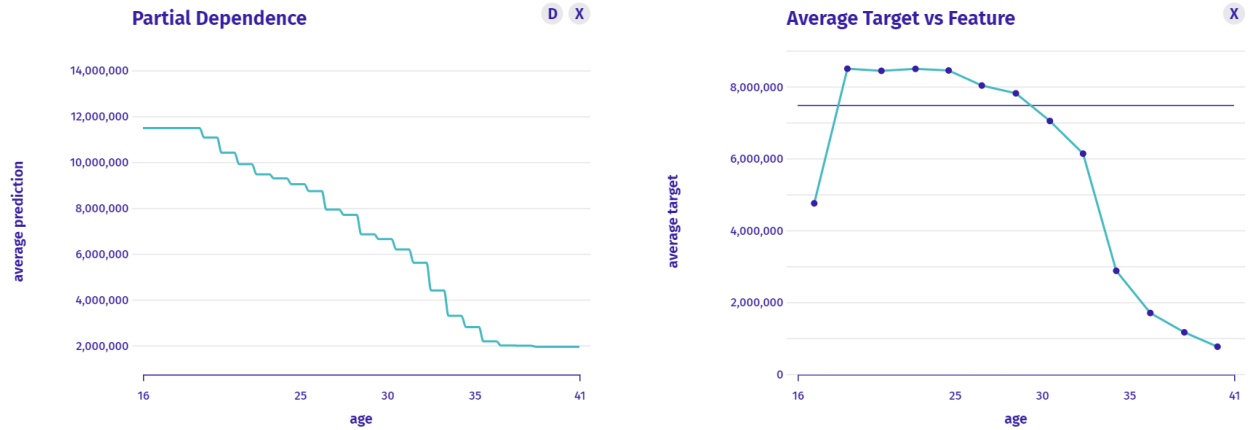


Figure 6: **Left:** Partial Dependence shows the explanation of average model’s prediction. **Right:** The average value of the target variable as a function of the selected variable shows the data explanation for comparison.

**Q5: What is the relationship between the valuation and age in the original data?** This is the data-level question about the profile answered by Figure 6. Finally, we might ask more questions concerning the overall model’s behavior.

**Q6: Which variables are the most important when all players are taken into account?** In the introduced taxonomy, this is a model-level question about the parts answered by Figure 7. There are three: `movement_reactions`, `age` and `skill_ball_control` variables are the most important to the black-box model with high certainty.

**Q1–Q6:** Figures 3-7 show the process of model analysis. No single explanation gives as much information about the model as the sequence of various model’s aspects. The grammar of IEMA allows for the prior calculation of potential paths between explanations summarised in Figure 8. To keep the thoughts flowing, the desired tool must provide interactive features, customizability and ensure a quick feedback-loop between questions. These functionalities are



available<sup>2</sup> in the open-source modelStudio framework (Baniecki and Biecek, 2019), which we briefly preview in Section 5. Figure 9 shows the parsing tree for the presented exemplary path.

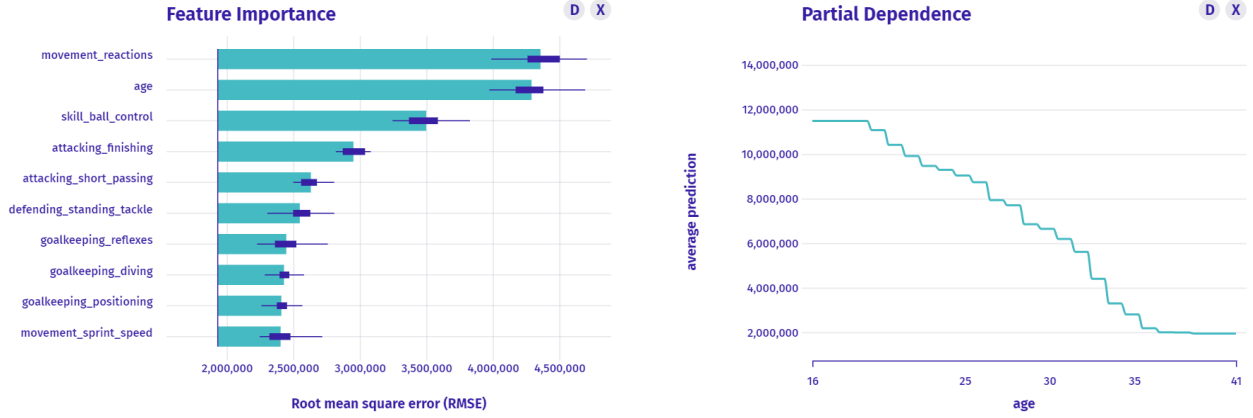


Figure 7: **Left:** Permutational Importance shows which variables influence the model prediction the most. **Right:** Partial Dependence may imply high variable importance by the model profile variability.

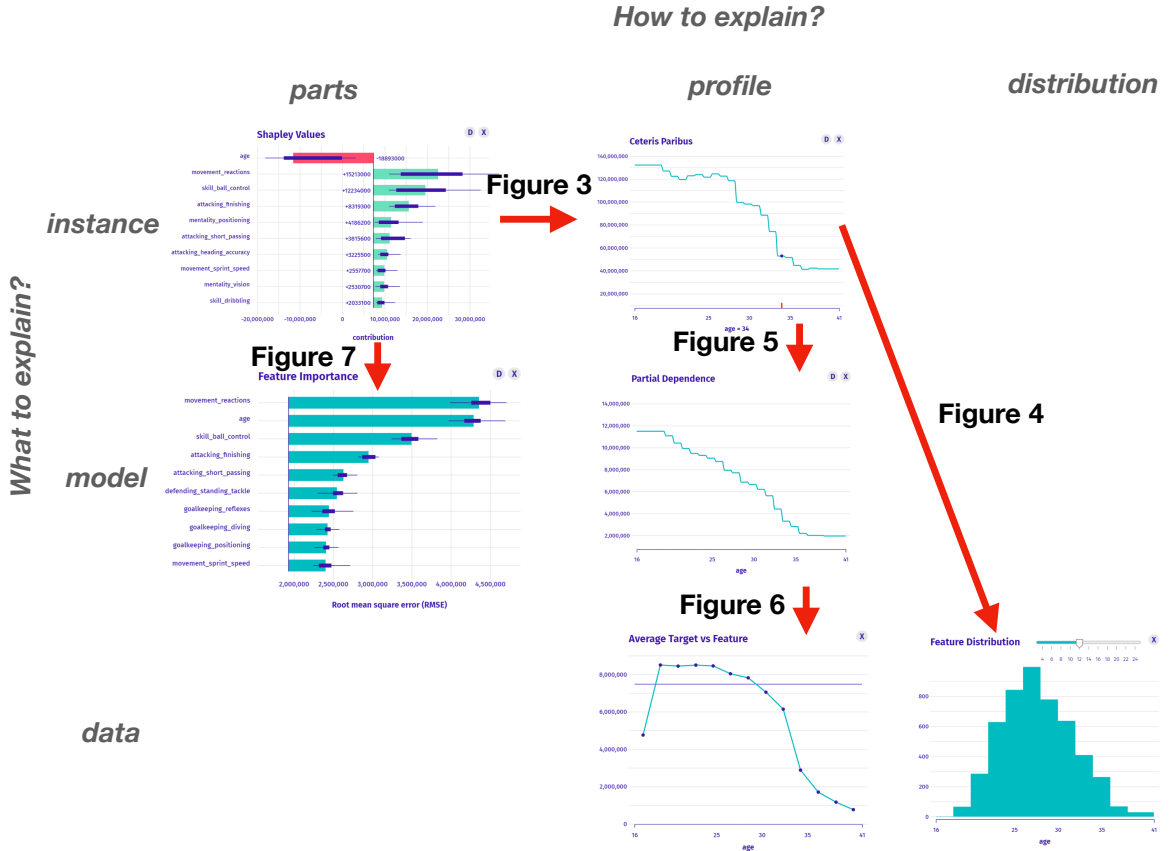


Figure 8: Summary of a single path in the Interactive Explanatory Model Analysis of FIFA-20 use-case. Different users may choose different orders to explore this graph using the introduced grammar of IEMA.

<sup>2</sup>The modelStudio dashboard for the FIFA-20 use-case: <https://iema.drwhy.ai>.

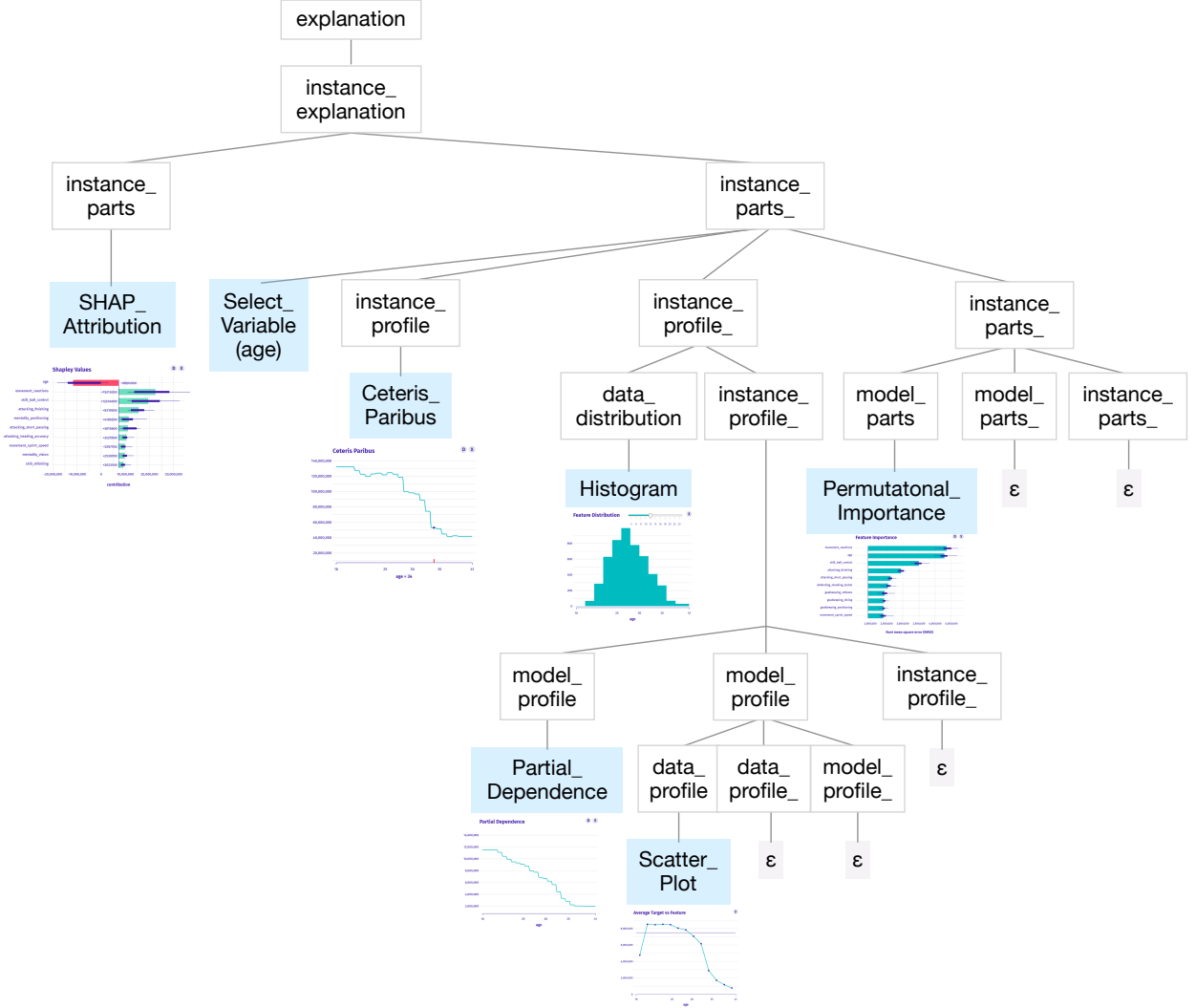


Figure 9: Parsing tree for the example from Figure 8. It represents the semantic information that symbols derived from the grammar of IEMA. Blue leaves indicate the terminal symbols, e.g. XIML methods.

### 3.2 Classification task of predicting COVID-19 patient’s mortality

In the medicine domain, machine learning supporting knowledge discovery and decision-making becomes more popular. Historically, interpretable white-box models were used to facilitate both of these tasks, as they provide transparent prediction attributions and variable importances (Rudin, 2019). Nowadays, black-boxes may provide better performance and robust generalization, but there is a vital necessity to explain their behavior; thus, XIML is a crucial factor in various predictive tasks concerning medical data (Lundberg et al., 2020; Bruckert et al., 2020). Schmid and Finzel (2020) showcase an interactive system for human-model dialogue that supports decision-making with a deep learning black-box in medicine.

Contrastively Yan et al. (2020) create an interpretable decision tree that supports decision-making in a hospital, concerning COVID-19 mortality. We applied IEMA to showcase the potential human-model dialogue with a machine learning black-box in this use-case (Baniecki and Biecek, 2021). It results in a list of potential questions that appear in explanatory model analysis, as well as the practical tool that could be used in place of a standard decision tree<sup>3</sup>.

<sup>3</sup>The modelStudio dashboard for the COVID-19 use-case: <https://rai-covid.drwhy.ai>.

## 4 Challenges in human-centered XIML

The issues for future human-centered XIML research presented by Choudhury et al. (2020) contain enhancing the technical view in black-box system design through a socio-technical one and lowering the entry threshold for different stakeholders, e.g. domain experts. Specifically, explaining complex predictive models has a high entry threshold, as it may require:

1. **Know-how:** We produce explanations using frameworks that involve high programming skills.
2. **Know-why:** We need to understand the algorithmic part of the model and heavy math behind explanations to reason properly.
3. **Domain knowledge:** We validate explanations against the domain knowledge.
4. **Manual analysis:** We need to approach various aspects of a model and data differently as *all valid models are alike, and each wrong model is wrong in its way*.

The idea of explainability scenarios introduced by Wolf (2019) may be a starting point for reinforcing our designs by showcasing these requirements. It is possible to enhance the model explanation process to lower the barriers and facilitate the analysis of different model’s aspects. In this section, we introduce three main traits that a modern XIML framework should possess to overcome some of the challenges in the human-model interface.

**Interactivity.** Interactive dashboards are popular in business intelligence tools for data visualization and analysis due to their ease of use and instant feedback loop. Decision-makers can work in an agile manner, avoid producing redundant reports and need less know-how to perform demanding tasks. Unfortunately, this is not the case with XIML tools, where most of the current three-dimensional outputs are mainly targeted at machine learning engineers or field-specialists as oppose to nontechnical users (Miller et al., 2017). As an alternative, we could focus on developing interactive model explanations that might better suit wider audiences. Such a fourth dimension helps in the interpretation of raw outputs because users can access more information. Additionally, the experience of using interactive tools is far more engaging.

**Customizability.** Interactivity provides an open window for customization of presented pieces of information. In our means, customizability allows modifying the explanations dynamically, which means that all interested parties can freely view and perform the analysis in their way (Sokol and Flach, 2020). This trait is essential because human needs may vary over time or be different for different models. With overcoming this challenge, we reassure that calculated XIML outputs can be adequately and compactly served to multiple diverse consumers (Bhatt et al., 2020). Furthermore, looking at only a few potential plots or measures is not enough to grasp the whole picture. They may very well contradict each other or only together suggest evident model behavior; thus, the juxtaposition of model explanations with EDA visualizations is highly beneficial.

**Automation.** A quick feedback loop is desirable in the model development process. However, an endless, manual and laborious model analysis may be a slow and demanding task. For this process to be successful and productive, we have developed fast model debugging methods. By fast, we mean easily reproducible in every iteration of the model development process. While working in an iterable manner, we often reuse our pipelines to explain the model. This task can be fully automated and allow for more active time in interpreting the explanations. Especially in XIML, analyzing the results should take most of the time instead of producing them.

**Dashboard-like XIML frameworks.** Automation and customizability make the framework approachable for diverse stakeholders apparent in the XIML domain. Interactivity allows for a continuous model analysis process. Standard and well-established libraries for model interpretability and explainability documented by Adadi and Berrada (2018) are not entirely going out towards emerging challenges. Although some ideas are discussed by Liu et al. (2017); Hohman et al. (2018), we relate to open-source tools that recently appeared in this area, especially new developments used in machine learning practice. These are mostly dashboard-like XIML frameworks that aim to implement the introduced traits (Wexler et al., 2019; Spinner et al., 2019; Baniecki and Biecek, 2019; Hall et al., 2019; Nori et al., 2019; Google and Tang, 2020; Hoover et al., 2020; Golhen et al., 2021). We further discuss and compare them in Appendix A.

## 5 Human-centered framework for performing IEMA

### Interactive Studio for GBM model on FIFA-20 data

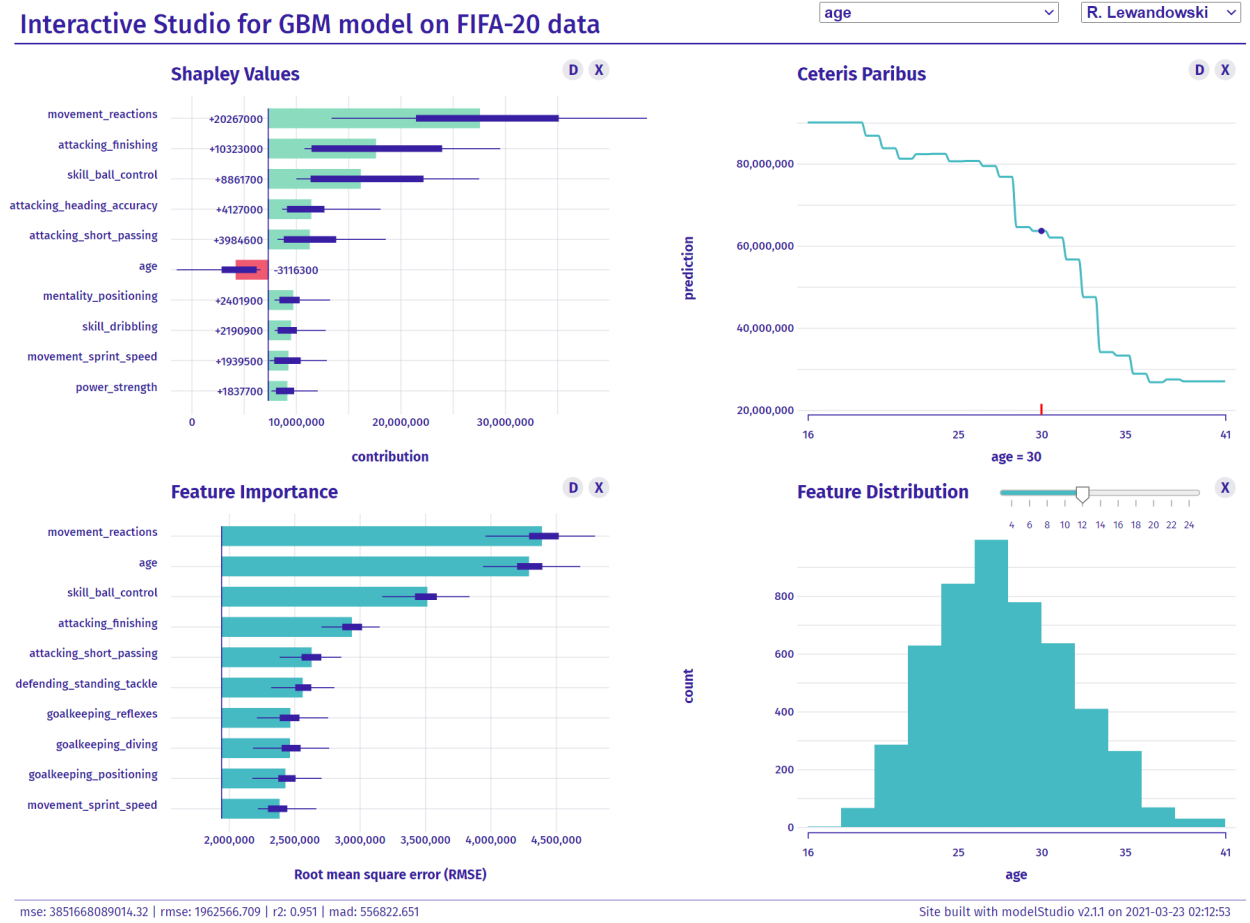


Figure 10: modelStudio automatically produces an HTML file - an interactive and customizable dashboard with model explanations and EDA visualizations. Here, we present a screenshot of its exemplary layout for the black-box model predicting a player’s value on the FIFA-20 data, see <https://iema.drwhy.ai>.

The modelStudio framework (Baniecki and Biecek, 2019) allows performing Interactive Explanatory Model Analysis. It automatically computes various (data, instance and model) explanations and produces a customizable dashboard consisting of multiple panels for plots with their short descriptions. These are model-agnostic explanations and EDA visualizations. Such a serverless dashboard is easy to save, share and explore by all the interested parties. Interactive features allow for full customization of the visualization grid and productive model examination. Different views presented next to each other broaden the understanding of the path between the model’s inputs and outputs, which improves human interpretation of its decisions.

The key feature of the output produced with modelStudio is its interface. It is constructed to be user-friendly so that non-technical users have an easy time navigating through the process. There is a possibility to investigate a myriad of instances for local model explanations at once by switching between them freely with a drop-down box. The same goes for all of the variables present in the model. Additionally, one can choose a custom grid of panels and change their position at any given time. In Figure 10, we present an example of the modelStudio dashboard grid, which consists of SHAP Attribution, Ceteris Paribus, Permutational Importance and Histogram plots.

This solution puts a vast emphasise on implementing the grammar introduced in Section 2, performing IEMA like in Section 3, and overcoming the challenges discussed in Section 4. Overall, working with the produced dashboard is very engaging and effective. modelStudio lowers the entry threshold for all humans that want to understand the black-box predictive models. Due to the automated nature of dashboard generation, no sophisticated technical skills are required to produce it. Additionally, it shortens the human-model feedback loop in the machine learning development stage; thus, engineers may efficiently debug and improve models.

**Responsibility.** Recently, a responsible approach to machine learning is being brought up as a critical factor, and the next step for a successful black-box adoption (Barredo Arrieta et al., 2020; Gill et al., 2020). An interesting proposition concerning model transparency, fairness and security is the Model Cards framework introduced by Mitchell et al. (2019). It aims to provide complete documentation of the model in the form of a short report consisting of various information, e.g. textual descriptions, performance benchmarks, model explanations, and valid context. We acknowledge that apart from the introduced advantages of the `modelStudio` framework, its output serves as a supplementary resource, generated after model development, for documenting black-box predictive models (Baniecki and Biecek, 2021). The idea of responsible and reproducible research is important now more than ever (King, 1995; Baker, 2016). Roscher et al. (2020) discusses the use of XIML for knowledge discovery, especially in scientific domains. We believe that researchers should be able to easily support their contributions with explanations, which would allow others (especially reviewers) to analyze the model’s reasoning and interpret the findings themselves. The `modelStudio` framework allows for that because its serverless output is simple to produce, save and share as model documentation. The same principle stays for responsible machine learning used in the commercial domain. Decision-making models could have their reasoning put out to the world, making them more transparent for interested parties.

## 6 Conclusion

The topic of explainable machine learning brings much attention recently. However, related work is dominated by contributions with a very technical approach to XIML or works focused on providing a list of requirements for its better adoption.

In this paper, we introduce a third way. First, we argue that explaining a single model’s aspect is incomplete. Second, we introduce a taxonomy of explanations that focuses on the needs of different stakeholders apparent in the lifecycle of machine learning models. Third, we describe that XIML is an interactive process in which we analyze a sequence of complementary model’s aspects. Therefore, the appropriate interface for unrestricted model analysis must adopt interactivity, customization, and automation as the main traits. The introduced grammar of Interactive Explanatory Model Analysis has been designed to allow for effective adoption of a human-centered approach to XIML. Its practical implementation is available through the open-source `modelStudio` framework. To our knowledge, this is the first paper to formalize the process of interactive model analysis.

The main limitation of this contribution is its foundation on related work and our research neighbourhood’s experiences in the explanatory analysis of black-box machine learning predictive models. The domain-specific observations might influence both practical and theoretical insight; thus, in the future, we would like to perform human-centric experiments, using the defined grammar and telemetry possibilities of the framework, to study how possibly unidentified stakeholders analyze models. Additionally, the aggregation of raw telemetry gathered by the `modelStudio` framework used by dozens is of particular interest, as a large scale, real-world data may be more authentic than simulated tests.

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## A Comparison of dashboard-like XI ML frameworks

Here we present work related to the modelStudio framework (Baniecki and Biecek, 2019) previewed in Section 5. We explicitly omit standard and well-established libraries for model interpretability and explainability as it is a widely documented ground (Adadi and Berrada, 2018). As discussed in Section 4, they are not entirely going out towards emerging challenges. Although some ideas are discussed by Liu et al. (2017); Hohman et al. (2018), we are looking at tools that recently appeared in this area, especially new developments used in the machine learning practice. These are mostly interactive dashboard-like frameworks that focus on treating the model analysis as an extended process and take into account the human side of the black-box problem.

Driverless AI (Hall et al., 2019) is a comprehensive state-of-the-art commercial machine learning platform. It automates variable engineering, model building, visualization, and explainability. The last module supports some of the instance and model explanations and, most importantly, does not require the user to know how to produce them.



While doing a great job at that, it also delivers documentation that describes the complex explainable machine learning nuances. The main disadvantages of this framework are its commercial nature and lack of customization options.

InterpretML (Nori et al., 2019) provides a unified API for model analysis. It can be used to produce explanations for both white-box and black-box models. The ability to create a fully customizable interactive dashboard, that also compares many models at the same time, is a crucial advantage of this tool. Unfortunately, it does not support automation, which, especially for inexperienced people, could be a helpful addition to such a complete package.

TensorBoard (Google and Tang, 2020) is a dashboard that visualises model behavior from various angles. It allows tracking models structure, project embeddings to a lower-dimensional space or display audio, image and text data. More related is the What-If Tool (Wexler et al., 2019) that allows machine learning engineers to explain algorithmic decision-making systems with minimal coding. Using it to join all the metrics and plots into a single, interactive dashboard embraces the grammar of IEMA. What differentiates it from modelStudio is its sophisticated user interface that becomes a barrier for non-technical users. explainer (Spinner et al., 2019) is similar to What-If Tool adaptation of the TensorBoard dashboard. It focuses on explainable and interactive machine learning, contributing a more conceptual framework to perform user-studies on these topics.

exBERT (Hoover et al., 2020) is an interactive tool that aims to explain the state-of-the-art Natural Language Processing (NLP) model BERT. It enables users to explore what and how transformers learn to model languages. It is possible to input any sentence which is then parsed into tokens and passed through the model. The attentions and ensuing word embeddings of each encoder are then extracted and displayed for interaction. This example shows a different proposition adapted for the NLP use case but still possesses key traits like automation and interactivity of the dashboard.

Finally, the most recent contributions are Arena (Piatyszek and Biecek, 2021) and shapash (Golhen et al., 2021). In Table 3, we present a brief comparison of relevant, meaning such as discussed at the start of this Section, XI ML frameworks. All of them take a step ahead to provide interactive dashboards with various complementary explanations that allow for a continuous model analysis process. Most of these frameworks produce such outputs automatically, which is a high convenience for the user. As stated before, the ultimate XI ML framework should be customizable and interactive to suit different needs and scenarios. What distinguishes the modelStudio dashboard is its serverless architecture; other mentioned frameworks utilize a server architecture that we perceive as an inconvenience in several applications.

Table 3: Comparison of the relevant XI ML frameworks. Interactive, customizable, and automated tools become more approachable for diverse stakeholders, apparent in the XI ML domain.

	instance explanation	model explanation	EDA	interactive	automated	customizable
modelStudio (Baniecki and Biecek, 2019)	✓	✓	✓	✓	✓	✓
Driverless AI (Hall et al., 2019)	✓	✓	✓	✓	✓	
InterpretML (Nori et al., 2019)	✓	✓	✓	✓		✓
What-If Tool (Wexler et al., 2019)	✓	✓	✓	✓	✓	✓
Tensorboard (Google and Tang, 2020)	✓		✓	✓	✓	
exBERT (Hoover et al., 2020)	✓			✓	✓	
Arena (Piatyszek and Biecek, 2021)	✓	✓	✓	✓	✓	✓
shapash (Golhen et al., 2021)	✓	✓	✓	✓	✓	