Algorithmic encounters

Algorithmic Encounters: an interactional approach to the AI accuracy vs interpretability trade-off

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Abstract In this paper we attempt to provide a formal assessment of AI interpretability based on an observation of machine learning development sessions as 'algorithmic encounters'. We begin by considering the unbalance between the existing lacuna of metrics to assess AI interpretability in relation to the abundance of established approaches for measuring accuracy. To this respect, we introduce an approach based on interactional sociology to the study of AI interpretability as the patterning of talk between different forms of machine learning models utilisation: reproductive and consumptive utilisation. We then provide a detailed scenario of how this approach could be designed into a formal analysis of AI interpretability, based on the example of the testing of rival models to predict football player transfer value.

Index Terms— Accuracy, Interpretability, Symbolic Interactionism, Artificial Intelligence, gaming encounters

I. Introduction

IT is apparent even to its own proponents that Artificial Intelligence is at a point where a study of its own ways of working is desperately needed [1]. It is often stated that a unique feature of new intelligent machines is that the same scientists who have created artificial intelligent agents cannot fully anticipate their behaviours and that some of their attributes are impossible to formalise analytically. This lack of understanding has been identified as the 'AI Knowledge Gap': the number of unique AI systems grows faster than the number of studies that characterize these systems' behaviour [2] and it is suggested to be given to the interdisciplinary scholar to fill. By presenting an innovative approach based on interactional sociology theory and method to the study of AI interpretability, this paper is an attempt in this direction.

At present, the scientists who study the behaviours of these agents—in what has been named explainable AI or xAI—are predominantly the same scientists who have created the agents themselves. The results of engaging in evaluation activities called optimisation or meta-learning is more deep learning [3]. But methodologies aimed at maximised algorithmic performance are not optimal for conducting scientific observation of the properties and behaviours of AI agents. Even the leaders in the AI field recognise that different investigative approaches are needed.

As famously observed by Breiman [4] —a classical statistician turned data scientist—there seems to be in machine learning a trade-off between interpretability and accuracy. Traditional statistical methods such as linear regression provide a picture that can be understood by many outside the AI field of the relation between response and predictor variable. However, statistical methods are less accurate when it comes to identifying a good predictor. AI methods such as neural networks or random forests do not seem to provide a clear picture of the relation between response and predictor variable but appear to be much more accurate in identifying a good predictor [5]. In this paper we present a new approach to AI interpretability based on concepts and methods from interactionist sociology. As opposed to looking at social science as a resource aspect in the process, one good just to evaluate AI and the implications of algorithms after the fact, we discuss how sociological theory and method can take a foundational place in the very notion of algorithm design.

The starting point of our inquiry is that it is difficult to have a testing methodology for interpretability as we have for accuracy. There is a variety of accepted KPIs and performance benchmarks for accuracy in machine learning. These range from measures of the absolute difference between the predicted value and the actual/expected value such as Mean Absolute Error (MAE) to measures that by representing the proportion of variance explained by the independent variable show how well the model 'understands' the data i.e. R^2.

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There are no comparable established options to formally test interpretability. We therefore look at building a process to generate key metrics to benchmark machine learning models' interpretability against.

This paper proposes a study of AI whereby the interpretability of the various steps of model design is made visible through the naturalistic observation of the patterning of data scientists' talk to the screen, to each other and to an audience of data owners, domain experts and other interested parties.

This approach is demonstrated by offering a detailed description of a scenario where a panel of experts is invited to take part in a series of focus groups at each stage of problem development and their conversations in relation to the viability of the proposed models are recorded and analysed.

In this paper we describe how this naturalistic approach inspired by the social sciences can help assess interpretability of AI applications. Based on a detailed example of the development of predictive models to support football player investment, we describe when, how and by means of which artefacts such approach to assess AI interpretability alongside accuracy can be applied in practice.

II. Algorithmic Encounters: A Framework from the Study of Social Interaction

Talking about a real-world example analysing the speed of trials based on court data systems, Breiman [4:207] reports that when using decision trees—a highly interpretable form of machine learning— results are immediately apparent to the non-expert audience (in his case an assembly of judges). According to Breiman, the interpretability of the decision trees is in the fact that the assembly immediately starts to comment algorithmic results saying: 'I knew those guys were dragging their feet'.

In another note from the same paper when discussing another more inscrutable machine learning method called random forests, Breiman confirms that in his experience despite successes in prediction in the medical sector, given that doctors can interpret logistic regressions and not 50 decision trees hooked together in random forests, in a choice between accuracy and interpretability the medical professionals will always go for interpretability.

In this paper we make the argumentative move that 'logistic regression' is a word, and that 'decision trees', 'random forests' are also words. By examining how 'AI' words are used in various situations of conduct - such as a focus group held by a carefully selected panel of domain experts, we make the helpful assumption that machine learning models such as random forests are as witness-able as the logistic regression and the decision trees mentioned in the earlier example.

The argumentative move we are making is based on a notational convention introduced by sociologists Harold Garfinkel [6] who bracketed the activities under study to remind themselves that mentioning them e.g. [random forests] leaves their identifying details unspecified and that an effort to specify their details may transform our initial sense of what doing [random forests] involves, as an activity.

From this perspective, making AI interpretable is a relational activity grounded in an orientation towards other actors such as peers, data owners, clients and commissioners. During the activity of making AI interpretable i.e. the effort of specifying what [random forests] involves, relevant social interactions occur which cannot be defined solely in terms of mathematical rules. Following Goffman notion of 'gaming encounters' [7], these interactions can be seen as the interplay between different frames of social action: the frame of mathematically relevant features and the frame of socially relevant attributes.

Taking the example of chess, Goffman [7:61] observes that as usually presented in chess manuals, glances, bodily movements and worded exchanges are left out, enabling the codification of chess encounters as plays of the game of chess, with the latter being analysable in terms of schematic visual representations of moves. A gaming encounter however can be also characterized by sanctioned displays of socially relevant attributes, such as dexterity, endurance, self-control and the like. Games, then, can be seen as arrangements or conventions for 'integrating into gaming encounters...socially significant externally based matters' [7:64].

Applying this approach to a study of AI interpretability would mean to consider that as in gaming encounters there is a patterning of play and reality, algorithmic encounters go beyond computer coding and that AI practice is negotiated in the interaction across multiple frames of interpretation. 'Keying', for Goffman, refers to the systematic process by which activities are transformed from one meaningful frame to another scheme of interpretation.

There are at least two distinctive frames in the AI situations which we call algorithmic encounters. One is the frame of the actual reproduction of machine learning models—which is the frame the accuracy debate refers to. This is the realm of the calculation, where numbers, computer code and mathematical formulations are produced. All that matters in this frame is the measure of the scoring ability of an algorithm in a classification task. In this framing, which Vollmer called reproductive [8:583], the reference of the inner workings of the algorithm to any reality external to the set of signs and operations defined by computational practices is bracketed.

Still, this is only one part of the story. As Domingos notes [9:84], first timers are often surprised by how little time in a machine learning project is spent actually doing machine learning. Participants will know that when calculating the highest scoring classifier, more is at stake than just optimization. Coming back to Breiman's examples, they will know that at some point the user of the algorithm, e.g. a doctor or a judge will look at these results and eclectically combine them with other sources including their domain expertise to sustain more esoteric claims about e.g. diagnosing cancer or reforming the judiciary system. This is the frame that Vollmer calls consumptive, that is, the frame in which people consume, mention, talk about and refer to AI.

This set of concepts make possible a study of the interpretability of AI as the patterning of shifts between negotiations *within* AI and speech *about* AI. These shifts of frame are coordinated across participants via discourse markers and distinct presentations of the self which include differences in comportment and facial expressions. As well as by the frequency of reference-shifting [10:534], interpretability can also be detected by attending to the directionality of reference-shifting from reproductive to consumptive.

For example, according to our framework when a prediction generated by the machine learning model is given to the panel of experts to assess, if the discussion lands on the viability of the data used as ground truth or the need to test the model against different data, comments such as these will be classified as an example of a *down-keying* from consumptive to reproductive utilisation, reflecting badly on model interpretability.

On the contrary, every time a panellist talks up the evidence and relates it back to their work experience without asking further clarifications on how the numbers have been produced in that particular case, this is an example of *up-keying* from reproductive to consumptive and it reflects positively on the interpretability score of the model.

III. The Case: Assessing Rival Models to Predict Transfer Value of Football Players

This section presents the case study to apply the above framework for the study of the accuracy vs interpretability trade-off. We begin the section by introducing the case, before moving to describe in details the various components of our approach to assess interpretability alongside accuracy.

The case is that of a model to predict transfer value of individual football players. The data is biometric and attribute data for players that have been traded over the summer 20/21. Transfer data is from transfermarkt.co.uk and player data is from the 180,000 players in the sofifa.com database. Both databases are built using crowdsourcing techniques.

Despite the mushrooming amount of data on sport performance, the exponential growth in attendance of major sport analytics events [11] and the popularity of movies and books related to the topic [12], football operators remain divided between 'quants' and traditionalists over whether lesson learn from stop-start sport can apply to the fluidity of football.

The panel should therefore represent the diversity of views on machine learning applications within the industry. The sample of experts to involve is tentatively identified as being composed by representatives from data provider, transfer market operators and club representatives. Company representatives, scouts or content moderators will represent data providers such as transfermarkt.co.uk and sofifa.com. Another set of experts is recruited from transfer market intelligence firms such as https://www.playerlens.com and football player agencies. A third typology should be representative of clubs such as sporting directors and chief scouts as well as football analysts.

The focus group will be facilitated by a presenter who will go through the detailed explanation of the use case and a moderator who will manage turn taking in discussions. The meetings will address the usefulness of the proposed machine learning models to predict transfer value at various steps of its development. Also addressed will be whether participants agree to the various steps and/or at what stage the believe a lack of understanding of the model would most affect the uptake of results by domain experts in their respective fields.

These focus groups are organised according to a three-stage approach to research design in machine learning introduced by Domingos [9]. Following Domingos these are (i) problem representation, (ii) problem evaluation and (iii) problem optimisation.

An appropriate way of identifying the empirical underpinning of the 'algorithmic encounter' framework introduced in the above section is to observe closely how problem development unfolds in the live process of the focus group. Instead of asking domain experts if and how they understand what happens at the different stages of problem development, visual and audio recording of the discussion itself together with protocols of participant observation will be used. While a focus group cannot be regarded as naturally occurring data in the strict sense as professionals are not observed in their everyday environment, it can capture situation-relevant elements that resemble the decision-making set-up of club football, when different experts are summoned to discuss options regarding transfer market. Furthermore, participant observation has the potential for better data yields as some reference-shifting does not necessarily include verbalisation and is likely to involve gestures or facial expressions that are hardly retained by the restricted angle of an audio recording.

Building on Healy & Moody [13], reports to the panel should include visual representations. Adapting from 'photo-elicitation' techniques from visual anthropology and consumer research [14], Pollock & Campagnolo [15] found that using visual numbers can help informants articulate their views on complex problems.

A. *Problem Representation*

At the problem representation stage, panel participants are presented with a report summarising the steps taken to harvest and explore the data.

For example in our case, the report will include examples of the python libraries functions used to extract relevant records of transfer market data and of the shared identities established to smatch the two datasets i.e. in our case fuzzy matching on the player's full name. Discussed will be also the process by which the role of ground truth is assigned. In our case what counts as ground truth will be the actual transfer value that the player has last recorded.

For example in our case, a feature correlation matrix will be developed to show the player attributes in the dataset that have the strongest correlation with the ground truth transfer market valuation (see Fig.1 below).

Also to explore how well players can be modelled into different clusters based on the available attributes, a K means clustering graph will be presented such as the one in Figure 2 showing how different players can be modelled into different positions based only on their biometric attributes sourced from sofifa.com.

Figure 1 here

Discussions at this stage are expected to revolve around data quality and the viability of actual transfer market value as ground truth. One first topic for the focus group is to comment regarding the suitability of transfermarkt and sofifa data for the present task. Considerations over alternative datasets will be elicited. Panellists will be also asked to comment whether actual transfer value is the best value to optimise the predictions from the features in our dataset. A conversation regarding possible alternative 'ground truths' will be facilitated.

Figure 2 Here

B. *Problem Evaluation*

At the problem evaluation stage, the focus will be on the KPIs chosen as model performance benchmarks, the dummy estimator considered to compare model performance against and model selection. To support discussion, the accuracy scores of the five models considered will be given to panel participants in a tabular format such as that in Table 1 below.

TABLE 1
A COMPARATIVE VIEW ON ACCURACY PERFORMANCE ACROSS MODELS

Model	$\boxed{R^2}$ Score	MAE
Linear Regression	3%	£ 11,296,717.13
Decision Tree	2%	£ 8,364,641.46
Random Forest	6.7%	£ 4,517,431.27
XGboost	6.5%	£ 5,337,149.75
Rdm F & PCA	6.4%	£ 5,221,356.63

It is apparent that the R^2 score between anecdotally more interpretable models such as linear regression and decision tree is largely inferior to the R^2 score of Random forests, gradient boosted decision trees (XGboost) and random forest with principal component analysis: the last three anecdotally less interpretable models have a R^2 score that is nearly three times higher than the first two. The difference in MAE however is less apparent. At this stage, as well as addressing how practically relevant is the general difference in variance for R^2 and MAE values between models, discussion will be facilitated by the provision of specific cases of individual player valuation.

For example, in the table below changes in the predicted value for the player Arthur and for the player Hakimi are compared across models.

TABLE 2
VALUES IN £ FOR THE PREDICTED TRANSFER OF PLAYERS ARTHUR AND HAKIMI AGAINST THE 'ACTUAL' TRANSFERMARKT VALUE

	Arthur	Hakimi
Transfermarkt	72,280,000	39,600,000
Linear R	95,621,974	4,942,266
Decision T	19,800,000	7,920,000
R Forests	46,000,601	14,362,121
XGboost	46,000,601	14,362,121

This table begs the question why linear regression and decision tree perform so poorly. The expert panel will be questioned on whether transfer market prediction where very talented young players can potentially break any previous relationship that have existed can be considered as a completely linear problem.

However, the above table of individual player cases also highlights that despite the higher accuracy scores random forest and XGboost prediction are still far from the 'actual' transfer value. This observation is expected to trigger further discussion among domain experts on the viability of the transfermarkt dataset for use as ground truth similar to that had in the problem representation focus group. Participants could react with a request for running these models with a different dataset.

According to our framework, comments such as these will be classified as an example of a down-keying from consumptive to reproductive utilisation, reflecting badly on interpretability. The focus group on problem optimisation described in the following section will be devoted to respond to suggestions from participants to improve the best performing model, run additional models on the same dataset or the same model with a different dataset.

For each case presented at this stage, an effort will be explicitly made to describe to the panel how the model makes decisions and the role that data plays in it. In the case of random forest, one possibility to describe this is retrieving what the model considers to be the most important features to support the prediction (see Table 3).

TABLE 3
RANDOM FORESTS MOST SALIENT FEATURES

	feature	importance
2	overall	0.07
38	movement_reactions	0.06
34	skill_ball_control	0.06
30	skill_dribbling	0.06
10	movement_reactions	0.05
16	dribbling	0.05
5	release_clause_eur	0.05
9	skill_moves	0.05
7	potential	0.04
0	wage_eur	0.04

For example in our case a table will be presented and participants will be asked to comment on the evidence that the overall player rating and biometric factors such as ball control and dribbling are deemed by the model as more important in determining player transfer value than e.g. player wage.

Every time a panellist talks up the evidence and relates it back to their work experience without asking further clarification on how the numbers have been produced in that particular case, this is an example of up-keying from reproductive to consumptive and it will be considered as reflecting positively on the interpretability score of the model.

Similar efforts to visually describe how the model makes decisions will be made with the other models. For example, a single decision tree will be returned from the final model to usefully explore how the model is assessing the prediction.

C. Problem Optimisation

At this stage, the panel will be asked to pick the 'winning model' in terms of the combined assessment of accuracy and interpretability – read the Data Analysis section below for how we generate the interpretability score.

Several different types of feature engineering will be then considered from evidence that seemed to emerge from the problem evaluation stage. For example, it is anticipated that in previous focus groups panel participants would have identified reliance on the relatively small amount real and recent transfer value ground truth as the largest flaw in the model. If this is the case, during this focus group the problem could be restructured to model on different data.

For example in our case we could look a transfermarkt crowdsourced transfer market values, a database that contains details for more than 800,000 professional footballers. In order to give a sense of the magnitude in the difference between the two datasets, the crowdsourced trasfermarkt value gives access to 50% times the amount of data than using the real market value. Outputs can be compared and contrasted to the largest errors generated by earlier analyses and new features created to ensure the model had the best possible chance to prioritise them when considering player transfer value.

Another evidence that seemed to emerge from looking at the features picked up by the random forests model (see Fig. 3) was that performance data such as ball control and dribbling are among the most important in determining player transfer value. This could be further investigated at the problem optimisation stage by focussing on a sub-set of data that the panel members know better (e.g. premier league data for the 2019/20 season).

Comparisons between results using old and new list of features will be discussed using accuracy measures such as MAE and R^2 as well as interpretability measures. To elicit further evidence on the interpretability at the problem optimisation stage, artefacts such as feature importance tables (see Figure 3) and individual player valuations such as those presented in Table 2 will be presented for comparison to the panel.

IV. DATA ANALYSIS

Drawing on a method adopted by Pollock & Hyysalo [16], the body of data deriving from the transcription of the three 3h focus groups at 9,000 words per hour will be compiled and inductively analysed adhering to the principles of naturalistic inquiry and constant comparison techniques [17]. The accumulating focus group and interview data will be coded based on in vivo phrases, terms, and labels offered by the informants.

These will be clustered under recurrent topics, again using in vivo categories such as frequency and directionality of reference-shifting from reproductive to consumptive e.g. whether domain experts are able to immediately draw the implications of the model for their work practice and whether evidence is used to mobilise socially significant externally based matters e.g. the hierarchy between different forms of professional expertise in football decision-making.

When these or other related recurring topics emerge during a focus group, purposive sampling related to key terms [17]-[18] will begin. This involves identifying those segments of the adjoining transcriptions that are related to reference shifting, up-keying and down-keying or reference to socially significant externally based matters i.e. matters referred to professional expertise. Purposive sampling will inform the set-up of the remaining focus groups as well as the inclusion of direct questions to understand different aspects of what they meant when in the focus group they sought clarifications regarding the reproductive use of the model or when they referred to its consumptive use and how this related to other cases they encountered in their work as data providers, transfer market agents or club representatives.

The in vivo entries and categories will be further compared in a second phase of coding to gain a sense of the variation within the frequency and directionality of reference shifting at the various stages of problem development (representation, evaluation and optimisation) and to clarify emerging trends.

As the links and interrelations between these categories became clearer we will collapse these into researcher-induced themes cast at a more abstract level, yet still informed by our informants' own terminology. This more logically ordered set of categories will provide an output in terms of degree of interpretability for each decision at the different stage of problem development.

An aggregate assessment of the interpretability of each model based on the frequency and directionality of reference-shifts will be produced according to the above process and casted against the accuracy score in a tabular form side by side to the accuracy scores discussed in the problem evaluation section. Anecdotally it is argued that e.g. linear regression models and decision trees are more interpretable than e.g. random forests and their variations. Assumptions such as these will be tested through the development of an interpretability score. Findings from our framework will address the following points:

(i) how the interpretability score adds to the accuracy variables and
(ii)in relation to the problem context and lived work experiences of our informants

By introducing this new framework to assess AI interpretability, our aim is that decisions regarding the size of the increase in accuracy that warrants the adoption of a less interpretable model could be made in a more informed and balanced way. Similarly to KPIs for accuracy, our approach to test interpretability is not meant to be exclusive. On the contrary we would promote additional approaches to interpretability valuation to be included as these would make decision-making on the accuracy interpretability trade-off more robust.

V. Conclusions

In this paper we attempted to provide a detailed description of what it takes to generate an assessment of AI interpretability based on the observation of machine learning development sessions as algorithmic encounters. We began by observing the unbalance between the existing lacuna of metrics to assess AI interpretability in relation to the abundance of approaches available for measuring accuracy. We looked at the existing debate in the field of explainable AI (xAI) to find that it is apparent even to its own proponents that a study of AI's own ways of working is desperately needed. To this respect, we introduced an approach based on interactional sociology to the study of AI interpretability as the patterning of different forms of utilisation of machine learning models: reproductive and consumptive utilisation. We then provided a detailed plan of how this framework could be designed into an analysis of AI interpretability, based on the example of the development of a research design based on the testing of rival models to predict player transfer value.

Performing machine learning is not solely about doing it correctly. There are so many more occasions in which deep machine learning is utilised which have nothing to do with producing or working out any new algorithm. Instead, these are situations that mobilise algorithms produced earlier or by others in conversations regarding for example areas of application. The ability of AI scholars and practitioners to use machine learning in social situations depends on their understanding of the circulation, provision, and reception of their algorithms by others.

This is especially true for machine learning where re-embedding is constitutive of its very nature. As described by Cardon et al. [19] algorithms are designed to produce outputs for the only purpose of maximising the predictive performance of the programme. Taking them to mean something in any other area of human activity is to de-contextualise them. As sociology points out, meaning making is intrinsically indexical [20]. The information produced by algorithms does not come in association with any given meaning. It is the context in which the output is put to use that decides what meaning to assign to it.

With this paper we hope to have contributed to show how social science theory and method can lend AI the tools to attend to this meaning-making process.

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