Operationalizing algorithmic explainability in the context of risk profiling done by robo financial advisory apps.

Research Paper | 8th December 2019

Sanjana Krishnan, Sahil Deo, Neha Sontakke

Abstract

Risk profiling of users is of functional importance and is legally mandatory for each robo financial advisor. Irregularities at this primary step will lead to incorrect recommendations for the users. Further, lack of transparency and explanations for automated decisions makes it tougher for users and regulators to understand the rationale behind the decisions made by the apps, leading to a trust deficit. Regulators closely monitor this profiling but possess no independent toolkit to "demystify" the black box or adequately explain the decision-making process of the robo financial advisor.

Our paper argues the need for such a toolkit and proposes an approach towards developing it. We use machine learning models to deduce an accurate approximation of the robo advisory algorithm and provide three levels of explanation. First, we reverse engineer the model to find the importance of inputs. Second, we infer relationships between inputs and with the output. Third, we allow regulators to explain decisions for any given user profile, in order to 'spot check' a random data point. With these three explanation methods, we provide regulators, who lack the technical knowledge to understand algorithmic decisions, a toolkit to understand it and ensure that the risk-profiling done by robo advisory apps comply with the regulations they are subjected to.

Keywords: Algorithmic decision-making systems (ADS), algorithmic regulation, algorithmic explainability and transparency, robo financial advisory apps, fintech, explainable AI, Machine Learning

Introduction

There is a growing ubiquity of decision-making algorithms that affect our lives and the choices we make. These algorithms curate our internet and social media feed, trade in the stock market, assess risk in banking, fintech and insurance, diagnose health ailments, predict crime prevention, and a lot more. Broadly, these are known as Algorithmic Decision-making Systems (ADS). Machine learning algorithms are the backbone of ADS and artificial intelligence (AI), and power the automated, independent decision making done by computers. Machines 'learn' by going through millions of data points and find associations and patterns in them. They then apply the learnt rules on new data to predict the outcomes. These algorithms have promised and delivered considerable gains in efficiency, economic growth, and have transformed the way we consume goods, services, and information.

However, along with the gains, these algorithms also pose threats. Several cases have come to light where algorithm powered decisions have given rise to undesirable consequences. An automated hiring tool used by Amazon discriminated heavily against women applying for software development jobs, because the machines learn from past data which has a disproportionate number of men in software positions (Dastin, 2018). Software used for crime prediction in the United States showed a machine bias against African-Americans, exacerbating the systemic bias in the racial composition of prisons (ProPublica, 2016). Google's online advertising system displayed ads for high-income jobs to men much more often than it did to women (Datta, Tschantz, & Datta, 2015). Social media algorithms are found to inadvertently promote extremist ideology (Costello, Hawdon, Ratliff, & Grantham, 2016) and affecting election results (Baer, 2019). Recently, researchers found that racial bias in the US health algorithms reduced the number of Black patients identified for extra care by more than half (Obermeyer, Powers, Vogeli, & Mullainathan, 2019) (Kari, 2019).

In effect, contrary to the promise of unbiased and objective decision making, these examples point to a tendency of algorithms to unintentionally learn and reinforce undesired and non-obvious biases, thus creating a trust deficit. This arises mainly because several of these algorithms are not adequately tested for bias and are not subjected to external due-diligence. The complexity and opacity in the algorithms decision-making process and the esoteric nature of programming denies those affected by it access to explore the rights-based concerns posed by algorithms.

However, if these algorithms are making decisions in the public sphere and affect an individual's access to services and opportunities, they need to be scrutinized. Over the last two years, there is a growing call to assess algorithms for concepts like fairness, accountability, transparency, and explainability and there has been an increase in research efforts in this direction.

Our research is situated in this context and we attempt to operationalize the concept of explainability in automated tools used in fintech. We have selected the case of robo financial advisory apps which conduct a risk profiling of users based on a questionnaire and use it to give them investment advice. These algorithms are subjected to regulations in India and several other countries. However, regulators without the technical knowledge possess no means to understand the algorithms and test it themselves. Our research explores various explainability methods and implements it to provide a customized toolkit for regulators to ensure that risk-profiling algorithms comply with the regulations that they are subject to.

What are robo financial advisors?

Robo advisory applications are automated web-based investment advisory algorithms that estimate the best plans for trading, investment, portfolio rebalancing, or tax saving, for each individual as per their requirements and preferences. Typically, it is done through a questionnaire or survey. Robo advisors open up the potential for finance to be democratized by reducing the financial barrier to entry and providing equal access to financial advice.

The first robo financial advisory app was launched in 2008, and the use of such tools has expanded with the increased use of internet-based technology and the sophistication of functionalities and analytics (Abraham, Schmukler, & Tessada, 2019) (Narayanan, 2016). In a 2014 report, the International Organization of Securities Commission (IOSCO) made a comprehensive effort to understand how intermediaries use automated advisory tools. They identified a spectrum of ‘Internet-based automated investment selection tools’ and classified them based on the complexity of the advice that it gives, from a basic level of risk categorization to a complex assessment of the customers age, financial condition, risk tolerance, capacity, and more to offer automated advice suited to their investment goals. The output is often a set of recommendations for allocations based on parameters like the size of funds (small, mid-cap), the type of investment (debt and equity funds), and even a list of securities or portfolios (IOSCO, 2014).

This risk profiling done by these robo-financial advisors is a crucial step to determine the risk category (the risk perception, capacity, and tolerance) of the user which determines the investment advice. Irregularities at this primary step will lead to incorrect recommendations for the users. Unlike human advisors, robo advisors provide no reasons or explanations for their decisions, and this shortcoming reduces trust in them (Maurell, 2019).

Two aspects would contribute to building trust in robo-advisors. First, building trust requires us to demystify why algorithms do what they do. Users exposed to these risks need to know the basis of the algorithms decision-making process in order to trust the system, especially in matters of personal wealth investment. Thus, firms need to be proactive and work on explaining the ADS. Second, for users to feel assured that firms are doing what they claim to be doing, a regulatory body that lays down rules and audits the algorithms would increase confidence in the system. This would give users the assurance that there is an external body that has provisions to ensure that their investment advisors are unbiased, are acting in their best interests, and do not face a conflict of interest.

Several robo financial advisory applications operate in India. Prominent ones include PayTM money, GoalWise, Artha-Yantra, Upwardly, Kuvera, Scripbox, MobiKwick, and Tavaga, among others.

In the next section we review literature to ground our research in theory and build on it. It covers two areas that are relevant to this study. The first part seeks to understand the regulatory landscape and the existing regulations on algorithms. In the Indian context, it looks at the guidelines that SEBI has on robo-advisory apps. The second part looks for technical solutions to the opaque algorithms by understanding the latest research on explainable Algorithmic Decision-making Systems (ADS).

In the third section, we list our research questions and define the scope of the study. In the fourth section we expound on our data and methodology. The final two sections detail the findings of our research and discusses the way forward.

Regulating ADS

The European Union General Data Protection Regulation (EU GDPR) adopted in 2016 lays down comprehensive guidelines for collecting, storing, and using personal data. While it is mainly aimed at protecting data, Article 22 speaks about “Automated individual decision making, including profiling”, specifying that *“data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her” (*subject to exceptions for contract enforcement, law and consent). It calls for consent, safeguarding the rights and freedoms, and further gives the subject the right to obtain human intervention, express their point of view and contest the decision (EU GDPR, 2016).

(Goodman & Flaxman, 2017) in their review of Article 22 of the GDPR reflect that this could necessitate a ‘complete overhaul of widely used algorithmic techniques’. They look at this provision as a ‘right to non-discrimination’ and a ‘right to explanation’ when read with other articles in the GDPR. On the contrary, (Wachter, Mittelstadt, & Floridi, 2016) argue that while the right to explanation is viewed as an ideal mechanism to enhance the accountability and transparency of automated decision-making, there is doubt about the legal existence and feasibility of such a right in the GDPR, owing to the lack of explicit, well-defined rights and imprecise language. They contest that Article 13-15 the GDPR, only mandates that 'data subjects receive meaningfully, but properly limited information', what they call the 'right to be informed'. They raise the need for a meaningful right to explanation to be added to Article 22, where data controllers need to give the rationale for decisions, evidence for the weighing of features and logic of decision making.

(Citron & Pasquale, 2014) argue that transparency and opening the black-box are crucial first steps and that oversight over algorithms should be a critical aim of the legal system. They argue for procedural regularity in assessing all publicly used algorithms to ensure fairness. Another approach to meaningfully govern algorithm decision-making proposes having a special regulatory or supervisory agency to audit algorithms, akin to the US National Transportation Safety Board (Shneiderman, 2017). Schneiderman proposes that such a body would have the power to license algorithms, monitor their use, and conduct investigations.

In the Indian context, (Kapur & Khosla, 2019) say that dealing with new technologies is one of the most demanding challenges facing regulatory design. (Padmanabhan & Rastogi, 2019) identify that the point of threat to individual and group rights has shifted from data gathering to data processing, and that the regulation of algorithms is unaddressed. The book also raises the point that there are no clear substantive safeguards against potential harm to social and individual rights, or regulatory mechanisms to mitigate against them in India.

While there are no explicit regulations on algorithms, in India, automated tools used in fintech are subject to regulations. The Securities Exchange Board of India (SEBI) is a statutory body that regulates the securities market in India. They came up with a consultation paper in 2016 (Consultation Paper on Amendments/Clarifications to the SEBI (Investment Advisers) Regulations, 2013) in which they lay rules for Online Investment Advisory and automated tools. In it, they clearly state that these automated tools need to comply with all rules under the SEBI (Investment Advisers) Regulations, 2013, over and above, which they are subjected to more compliances.

One primary function of an investment advisor under the Investment Advisors Regulations is to profile the risk of the user; it states, "risk profiling of investor is mandatory, and all investments on which investment advice is provided shall be appropriate to the risk profile of the client." Further, it also says that in the tools that are fit for risk profiling, the limitations should be identified and mitigated. There are further rules that require them to act in their best interests, disclose conflicts of interest, and store data on the investment advice given.

Under the specific rules for investment advisory automated tools, firms are required to have robust systems and controls to ensure that any advice made using the tool is in the best interest of the client and suitable for the clients; disclose to the clients how the tool works and its limitations of the outputs it generates; comprehensive system audit requirements and subjecting them to audit and inspection, among others. Finally, regulations also mandate that robo advisory firms need to submit a detailed record of their process to SEBI. This includes the firm's process of risk profiling of the client and their assessment of the suitability of advice given, which to be maintained by the investment adviser for a period of five years.

Explainable Algorithmic Decision Systems (ADS)

Algorithms are ‘black-boxes’ and users affected by it know little to nothing about how decisions are made. Being transparent and explaining the process helps build trust in the system and allows users to hold it accountable. With their growing ubiquity and potential impact on businesses, ‘explainable AI’(xAI) or more generally, ‘explainable algorithmic decision systems’ is more necessary than ever.

Explainability has been defined in various ways in research. The most prominent one, given by FAT-ML considers an algorithm explainable when it can *"Ensure that algorithmic decisions as well as any data driving those decisions can be explained to end-users and other stakeholders in non-technical terms".* (FAT ML) They identify 'Explainability' as one of the five principles for accountable algorithms. The other four are responsibility, accuracy, auditability, and fairness.

(Castelluccia & Le Métayer, March 2019) in their report identify three approaches to explainability. A black-box approach, white-box approach and a constructive approach. The black-box approach attempts to explain the algorithm without access to its code. In this approach, explanations are found by observing the relationship between the inputs and outputs. In the white-box approach, the code is available and can be studied to explain the decision making process. The constructive approach is a bottom-up approach that keeps explainability in mind before and while coding the ADS, thus building in 'explainability by design'.

Explainability is affected by the type of algorithm as well. While some models are easy to explain with or without access to the code, large and complex ML and neural network models are very difficult to explain to humans. For example in fintech, an ML model used to predict loan defaults may consist of hundreds of large decision trees deployed in parallel, making it difficult to summarize how the model works intuitively (Philippe Bracke, 2019). Several methods for explainability have been studied in research, and have been briefly covered in the methodology section

The quality of explanations are evaluated by several indicators such as their intelligibility, accuracy, precision, completeness and consistency. There can often be a trade-off between them. By focussing on completeness, the intelligibility of the explanation can be compromised.

Research statement

Our research looks at how an algorithm based decision making "black box" plays out in the fintech sector, specifically in determining the risk profile of users in robo financial advisory apps. **The objective of this paper is to demystify this "black box" by operationalizing algorithmic explainability. This is done from the perspective of the regulator.**

Questions

1. What methods from xAI can we use to explain the risk-category profiling done by a robo-financial advisor algorithms?
2. To what extent can these xAI methods be used to operationalize algorithmic explainability and fulfil the regulatory requirements that robo-financial advisors need to comply with? What are the limitations?
3. Can these xAI methods be streamlined or standardised for all regulators?

To design a study that can explain the questionnaire based risk profiling done by robo-advisors, the boundaries of the study have to be defined. Four methodological considerations have been discussed in this section.

Defining the boundaries of the study

The first consideration for operationalizing is deciding the depth at which the review/assessment looks at the decision-making process; this depends on the availability of required inputs for assessment. As mentioned, there is a white-box and a black-box approach. For the white-box approach, it is essential to know how the computer makes decisions. This necessitates the third party assessing the algorithm to be given access to the algorithm. While this would greatly aid transparency, they are mostly built by firms and hence are considered as intellectual property. This is also the case for robo-financial advisory apps. Thus, in the absence of the code, the second “black-box” approach is used. Given the "black-box" nature of algorithms, alternate methods are used to check if inputs give the intended outputs, to check the representation of training data, identify the importance of features, and find the relationship between them. Robo-financial advisors would not disclose their code or algorithm used for predictions, and hence, we will use black-box explainable methods. In the absence of the algorithm, the firm would have to provide a dataset with a sample of its input criteria and corresponding predicted output to the regulator.

Second, there is a limitation to the level to which a black box algorithm can be simplified. As mentioned, there is a trade-off between complexity, completeness, and accuracy of the system and its explainability. Explainability is easier in parametric methods like linear models (where feature contributions, effects, and relationships can be easily visualized), their contribution to a model's overall fit can be evaluated with variance decomposition techniques (Ciocca & Biancotti, 2018). However, that task becomes tougher with non-parametric methods like support vector machines and Gaussian processes and especially challenging in ensemble methods like random forest models. The newer methods of deep learning or neural networks pose the biggest challenge, they are able to model complex interactions but are almost entirely uninterpretable as it involves a complex architecture with multiple layers (Thelisson, Padh, & Celis, 2017) (Goodman & Flaxman, 2017). Currently, there is a significant academic effort in trying to demystify these models. As it gets increasingly complex, there is also a call to avoid altogether using uninterpretable models because of their potential adverse effects for high stakes decisions, and preferably use interpretable models instead (Rudin, 2019). In our study, we do not know the methods used by the robo-advisor. Hence, our explanation methods need to account for all options and will seek to explain parametric and non-parametric methods used by robo-advisors to profile users. For this, we will employ methods from Machine Learning.

Third, we have global and local explanations. Global methods aim to understand the inputs and their entire modelled relationship with the prediction target or the output. It considers concepts such as feature importance, or a more complex result, such as the pairwise feature interaction strengths (Hall & Gill, 2018). Most feature summary statistics can also be visualized by using partial dependence plots or individual conditional plots. Local explanations in the context of model interpretability try to answer questions regarding specific predictions; why was that particular prediction made? What were the influences of different features while making this specific prediction? The use of local model interpretation has gained increasing importance in domains that require a lot of trust like medicine or finances. Given the independent and complimentary value added by both methods, we will include both global and locally interpretable explanations in our study.

Finally, there is a challenge in communicating the results. This depends mainly on the end-user— the person who will view the assessment report. The report would have to be designed based on why they want to see the findings, and what their technical capability, statistical, and domain knowledge is. If the end-user is a layperson wanting to understand how the algorithm makes decisions at a broad level, the tool would need to be explained in a very simplified and concise manner. In contrast, if the end-user is a domain expert or a regulator who is interested in understanding the details and verifying it, the findings reported would have to reflect that detail. In addition to this, there is a branch of study called Human-Computer Interface (HCI) that focuses specifically on choosing the best communication and visualization tools. Our current study does not focus on this aspect, but rather confines itself to employing appropriate explainable methods for a regulator. In our study, we have chosen three explainable methods, the details follow in the next section.

Hence, our tool narrows the scope of the study to the following- explaining the robo advisors black-box algorithm (that could you parametric or non-parametric models) using global and local explanations to a regulator.

Methodology

The research aims to answer how the questionnaire based risk profiling done by any robo-advisors can be explained. To study this in the absence of the algorithm, we need the questionnaire, and a sample of the responses given by users and the corresponding risk category predicted by the algorithm.

The methodology is divided into three parts. The first part talks about how the sample dataset required for the study was generated. To ensure that the results of the study are replicable given any input conditions, we used several different methods to generate this sample dataset on which the explanation methods could be tested. The second part looks at the information that our study needs to provide in order to make the robo advisors decision explainable to the regulator. Data about how much each response contribute to the decision and how they relate with each other have been addressed in this section. In the third and final section, we explore the global and local explainability methods and measures that are needed to explain the robo advisory ADS. We describe the methods we studied and the methods shortlisted.

Before proceeding, we clarify the meaning of three terms that are commonly used in ML and data analysis, and explain what they mean in the context of our study (see diagram in Appendix 1)

- Each question in the questionnaire is a 'feature' in the dataset. The weights associated with each feature contributes to the decision made by the ADS.
- The risk categories (no risk to high risk) that robo advisors assign to a user are 'classes'. There are 5 classes in this study.
- 'Category' refers to the option for a question (or equivalently, the response given to a question)

The other definitions and terms from ML and statistics that have been used in the methodology and findings are explained in Appendix 1.

Generating the dataset for the study

To conduct this study, we need to generate a sample data set that can adequately represent the real world. The reliability would have to be such that it can work for input-output data from any robo advisory app. In other words, the analysis should be able to handle any number of questions, any type of question (ie questions with categorical or continuous variables as its options), and any number of options

For our study, we use the questionnaire from PayTM money to create a data set with all possible user profiles.

Step 1- The robo advisory questionnaire is used to model an equation by giving weights to each question (i.e. feature). It is converted to a format such that output is a function of the features and weights. For example- =f(w1x1, w2x2, w3x3..), where xi represents the answer for question 1 and wi is any real number that represents the weight given to question1. If the questionnaire has two questions and question 1 is about the age of the respondent and question 2 about the salary of the respondent, the output risk category could be modelled by an equation like risk category= w1(age)+w2(salary).

Step 2- A score is assigned to each option (‘category’) in each question. For example, within the question about age, the option with age group 18-25 could have a score of 1, age-group 26-35 a score of 0.7 and so on.

Step 3- Using the questions and options, all possible combinations of user profiles are generated

Step 4- Using the values from step1 and step2, the output score is calculated for every user profile. The entire range of scores is divided into five risk categories in order to put each user in one of five categories— no risk, low risk, medium risk, likes risk, and high risk. Each of these risk categories (no risk-high risk) is called a ‘class’

Thus the dataset generated has all possible user profiles with a risk category. For all the analysis, a stratified sample of this dataset was used. The detailed process, equations used for this study and profile of the selected dataset can be found in Appendix 2.

Validity and reliability checks-

- In order to ensure that the dataset is an accurate representation of reality, data from PayTM was used. Because the process we use is independent of the number or type of features and categories, it can be replicated for any robo-advisory aps.
- In order to ensure replicability and reliability of results, in step1, several types of input models were used. For our study, we replicated the results for four types of possible models- a limear model, polynomial, quadratic and logarithmic model. The details pf it are in Appendix 2, the results for all types have been reported in the findings
- The process we use is also independent of the weights associated with features or the score associated with options. Hence, the study is valid for any values.

Information that needs to be explained by the robo-advisory

To explain the internal mechanics and technical aspects of an ADS in non-technical terms, we need to first identify the instances of decision-making which are opaque and in order to make them transparent and explain them.

Robo advisors conduct a complex assessment of the customers age, financial condition, risk tolerance, capacity, and more to categorize the customer in to a risk category and use it to offer automated advice suited to their investment goals using algorithms. In contrast, with human advisors, the users can ask the investment advisor why they have been given a certain advice. Further, there is no way to ascertain that the advice given is not unwittingly biased, has unintended correlations or is giving undue importance to certain undesirable features (for example, the scrutiny that Apple credit cards are currently facing because the algorithm gave a 20 times higher credit limit to a man as compared to his wife; both with the same financial background (Wired.com, 2019))

Thus, there is a need to explain the rationale for the risk categorization and show that there is no undesirable importance given to certain features. For example, if they have questions on age and salary, the explanation would need to tell which is more important and by how much. If there are questions about gender, we need to know that they do not have an undue influence on the output. Apart from these two "global" explanations, we also need to give the regulators the ability to spot check the advice. For any randomly selected user profile, a "local" explanation will allow the regulators to understand how the algorithm processes one data point and if its output aligns with the expected output.

In our study, we give these three explanations for the regulator to understand how the robo-advisor takes a decision.

- **Feature importance scores**- importance provides a score that indicates how useful or valuable each feature was in the construction of a model. The more an attribute is used to make key decisions with decision trees, the higher its relative importance. In our case, feature importance scores will tell us the relative importance of the questions (ie factors), and their contribution to the risk categorization.
- **Feature relations-** how do features relate to each other and with the output. Correlations provide the first level of relationship between questions (features) and with the output (classes). We can go even deeper to gain further insights into the behaviour of different categories (options) within each feature and see how they vary with each other.
- **Local explanations**- Local explanations in the context of model interpretability try to answer questions regarding specific predictions; why was that particular prediction made? What were the influences of different features while making this specific prediction? As mentioned above, in our case, local explanations will help explain why a particular user was assigned a particular risk category.

Operationalizing these explanations

In order to explain find the feature importance scores, feature relations and local explanations, we reviewed and tested several methods.

Various toolkits have been developed to operationalize concept of fairness, accountability, transparency and explainability in algorithms. In our review of tools, we found FairML, LIME, Aequitas, DeepLift, SHAP and VINE to be particularly relevant. Most focused on explainability, while only a handful talks about fairness. Some aim to be a generalized method or tool that is sector agnostic (FairML, LIME), while others have used these techniques to address the domain-specific issues (Aequitas for policymakers, DeepLift for genome sequencing). Consequently, the end product of the two approaches varies between easily understandable by all to interpretable only to domain experts. We also explored the viability of statistical methods like LASSO (least absolute shrinkage and selection operator), mRMR (minimum Redundancy Maximum Relevance) feature selection and random forest algorithms.

The first step to operationalizing these explanations is to deduce the model or logic of decision making using a sample of the input-output dataset, with no information about the method or logic used to arrive at the decision. We do this using machine learning models. Following that, we explain the methods used to find feature importance scores and feature relations using global explanation methods. Finally, we define the method used to implement local explanations.

Modelling the dataset accurately

Supervised classification is a task in machine learning, where a function is created that maps provided input data to some desired output based on labelled input-output pairs given to the function for learning beforehand. The dataset presented in this paper classifies inputs in five classes (high risk to no risk) making this a multiclass type of classification.

A variety of classifiers are available to model these mapping functions. Each classifier adopts a hypothesis to identify the final function that best fits the relationship between the features and output class. This function could be linear, polynomial, hierarchical etc, based on the kind of data we have (categorical, continuous), the complexity of relationships between variables and number of data samples. The key objective of these learning algorithms is to build a predictive model that accurately predicts the class labels of previously unknown records.

Our approach is to test out different models on the dataset to gather results using a variety of commonly used functions and relationships. Further we wish to understand and explain the decisions of all of these classifiers irrespective of their complexities.

The dataset was modelled using five machine learning algorithms frequently used for predictions; logistic regression (LR), support vector machines (SVM), decision trees (DT), naive bayes (NB) and k-nearest neighbours (KNN). The explanation of these models and how they work can be found in Appendix 3.

The ability of the model to accurately describe the dataset is given by commonly used performance measures such as accuracy, precision, recall, and the f1 score. The definitions are given in Appendix 1

Finding Feature importance scores using SHAP values

SHAP is a unified framework built on top of several model interpretability algorithms such as LIME, and DeepLIFT. The SHAP package can be used for multiple kinds of models like trees or deep neural networks as well as different kinds of data including tabular data and image data.

SHAP emerges from shapley values, used to calculate contributions of each feature. If we have 3 features (A,B,C) contributing to the output of the model then these features are permuted (B,C,A or C,A,B, etc..) to give new target values that are compared to the originals to find an error. Thus shapley values of a feature are its average marginal contributions across permutations.

Determining feature relations using PDP plots

While determining feature importance is a crucial task in any supervised learning problem, ranking features is only part of the story. Once a subset of "important" features is identified we need to assess the relationship between them (or a subset) and the response.This can be done in many ways, but in machine learning it is often accomplished by constructing partial dependence plots(PDPs). These plots portray the marginal effect one or two features have on the target variable and whether it is linear or more complex in nature.

PDP can be used as a **model agnostic global level understanding** method to gather insights into black box models. Model agnostic means that PDP’s make no assumptions regarding the underlying model. The partial dependence function for regression is defined as-

$$\hat{f}_{x_S}(x_S) = E_{x_C}\left[\hat{f}(x_S, x_C)\right] = \int \hat{f}(x_S, x_C) d\mathbb{P}(x_C)$$

Equation 1: Partial Dependence Equation

Xs is the set of features we find interesting, Xc is the complement of that set (set of all features we don’t find interesting but are present in the dataset), f(xs) gives the partial dependence and P(xc) is the marginal probability density of xc. f(hat) is the prediction function.

The whole function f(xs) is estimated as we don’t know the f(hat) (it’s model agnostic) nor do we know the marginal probability distribution.

$$\hat{f}_S = \frac{1}{N}\sum_{i=1}^{N}\hat{f}(\boldsymbol{x}_S, \boldsymbol{x}_{Ci})$$

Equation 2: Marginal Probability Distribution

The approximation here is twofold: we estimate the true model with ˆf, the output of a statistical learning algorithm, and we estimate the integral over xC by averaging over the N xC values observed in the training set

Local explanations using LIME

LIME, or Locally interpretable model agnostic explanations uses local surrogate models to approximate the predictions of the underlying black-box model. Local surrogate models are interpretable models like Linear Regression or a Decision Trees that are used to explain individual predictions of a black-box model. Lime trains a surrogate model by generating a new data-set out of the datapoint of interest. The way it generates the data-set varies dependent on the type of data. Currently Lime supports text, image and tabular data. For text and image data LIME generates the data-set by randomly turning single words or pixels on or off. In the case of tabular data, LIME creates new samples by permuting each feature individually. The model learned by LIME should be a good local approximation of the black box model but that doesn’t mean that it’s a good global approximation.

There are many notable advantages of using LIME, it is model agnostic therefore does not make any assumptions regarding the model itself and can be used for SVM, LR, Neural nets and others. It can also explain tabular text and image data. The disadvantages are the definition of neighbourhood of the data-point of interest is very vague. Lime picks up samples from the neighbourhood of the specified instance, defining this instance is a difficult task. Currently lime takes up a random instance along with the specified one and calculates the proximity. Deciding which instances to pick up is hardcoded in the lime library which means that some influential points further away can be missed easily. Because of this, explanations can be unstable, resulting in a great variation in the explanations of very close data-points. However, in our study, they gave satisfactory results.

Findings

The findings are divided in four parts. The first part gives the results of the models we use to explain the robo advisory decision making. Because these are black box algorithms, we apply the most commonly used ML models to reverse engineer the process. The second and third part details our findings using global explanation methods. The second part reports the feature importance scores and the third part reports the feature relations. The fourth and final part of the findings provides the local explanations to understand the details of one specific prediction.

Part 1- modelling the risk profiling decision

As mentioned above, the aim is to fit an equation or model to the data, that can predict the outputs as accurately as possible. This first step is crucial as it provides an accurate model which the three explanation methods need. The methodology describes the five ML models we use. Part of the input-output data given by the firm is used to train these ML models. They were then used to predict the outputs of other inputs. This is repeated for multiple types of input equations to check for the reliability of the method.

The accuracy of the prediction and the f1-scores of the classes need to be considered together to select the best model for the dataset. The results (for five models and four input equations) have been summarized in the table below (Table 1).

	Linear Equation		Quadratic Equation		Polynomial Equation		Logarithmic Equation	
Performance Metrics	**Accuracy (%)**	**F1 - Score**	**Accuracy (%)**	**F1 - Score**	**Accuracy (%)**	**F1 - Score**	**Accuracy (%)**	**F1 - Score**
Logistic Regression (LR)	90	- no risk : 0.49 - low risk : 0.91 - moderate : 0.93 - likes risk : 0.86 - high risk : 0.52	78	- no risk : 0.88 - low risk : 0.77 - moderate : 0.73 - likes risk : 0.71 - high risk : 0.91	78	- no risk : 0.96 - low risk : 0.79 - moderate : 0.23 - likes risk : 0.80 - high risk : 0.94	76	- no risk : 0.91 - low risk : 0.77 - moderate : 0.00 - likes risk : 0.78 - high risk : 0.94
Naive Bayes (NB)	75	- no risk : 0.56 - low risk : 0.71 - moderate : 0.81 - likes risk : 0.65 - high risk : 0.26	70	- no risk : 0.79 - low risk : 0.76 - moderate : 0.68 - likes risk : 0.51 - high risk : 0.72	67	- no risk : 0.95 - low risk : 0.82 - moderate : 0.43 - likes risk : 0.00 - high risk : 0.40	68	- no risk : 0.77 - low risk : 0.61 - moderate : 0.58 - likes risk : 0.64 - high risk : 0.80
K- Nearest Neighbours (KNN)	93	- no risk : 0.90 - low risk : 0.94 - moderate : 0.94 - likes risk : 0.92 - high risk : 0.86	96	- no risk : 0.97 - low risk : 0.96 - moderate : 0.96 - likes risk : 0.95 - high risk : 0.96	97	- no risk : 0.99 - low risk : 0.98 - moderate : 0.96 - likes risk : 0.95 - high risk : 0.94	98	- no risk : 0.98 - low risk : 0.97 - moderate : 0.96 - likes risk : 0.98 - high risk : 0.99

Support Vector Machines (SVM)	98	- no risk : 0.63 - low risk : 0.97 - moderate : 0.99 - likes risk : 0.99 - high risk : 0.94	93	- no risk : 0.94 - low risk : 0.92 - moderate : 0.93 - likes risk : 0.93 - high risk : 0.94	96	- no risk : 0.96 - low risk : 0.95 - moderate : 0.95 - likes risk : 0.95 - high risk : 0.95	92	- no risk : 0.92 - low risk : 0.89 - moderate : 0.87 - likes risk : 0.94 - high risk : 0.96
Decision Trees (DT)	89	- no risk : 0.81 - low risk : 0.89 - moderate : 0.90 - likes risk : 0.88 - high risk : 0.81	96	- no risk : 0.97 - low risk : 0.95 - moderate : 0.95 - likes risk : 0.95 - high risk : 0.95	98	- no risk : 0.99 - low risk : 0.98 - moderate : 0.97 - likes risk : 0.95 - high risk : 0.94	99	- no risk : 0.99 - low risk : 0.99 - moderate : 0.99 - likes risk : 0.99 - high risk : 0.99
Best Model	K - Nearest Neighbours		K - Nearest Neighbours		Decision Tree		Decision Tree	
Explanation	K - Nearest Neighbours can generate a highly convoluted decision boundary, points that are very close to each other can be modelled very well using this method.				Decision trees are good at classifying non linearly separable data.			

Table 1- accuracy of the prediction and the f1-scores of the classes for five models (LR, NB, KNN, SVM, DT), and four input equations (linear, quadratic, polynomial and logarithmic)

As our findings show, KNN works best for linear and quadratic equations and Decision Tree modelling works best for polynomial and log equations. DTs perform very well for all input equations except the linear model. It gives very accurate results because the options are categorical, DT can identify them much better. Both DT and KNN's are prone to overfitting i.e. they can be used to draw very convoluted non-linear boundaries to seperate data points by repeatedly dividing data into specific classes or by creating very detailed neighbourhood clusters of data respectively. The overfitting works in our favour in this case as we are looking for a closest representation of the dataset.

The findings also highlight why it is not sufficient to consider only the accuracy. Take the example of SVM on a linear equation. It gives a high accuracy of 98%, higher than the KNN model. However, the f1 score of the no-risk class is only 0.63. This indicates that the SVM model can make very good predictions for other classes, but fails to do it in the no-risk class.

All models would run on the input-output dataset given by the firm, and the model that gives the highest accuracy will be used to power the three explanations. The accuracy and f1-scores will be reported to the regulator.

Part 2- Feature importance scores

Feature importance scores are part of the global explanations and have been found using the SHAP values. They have been represented using SHAP plots. They tell how much each feature (question) contributes to the ADS risk categorization process. Here, we report three importance scores- the feature importance, the class-wise feature importance, and the class and category wise feature importance.

Feature importance-

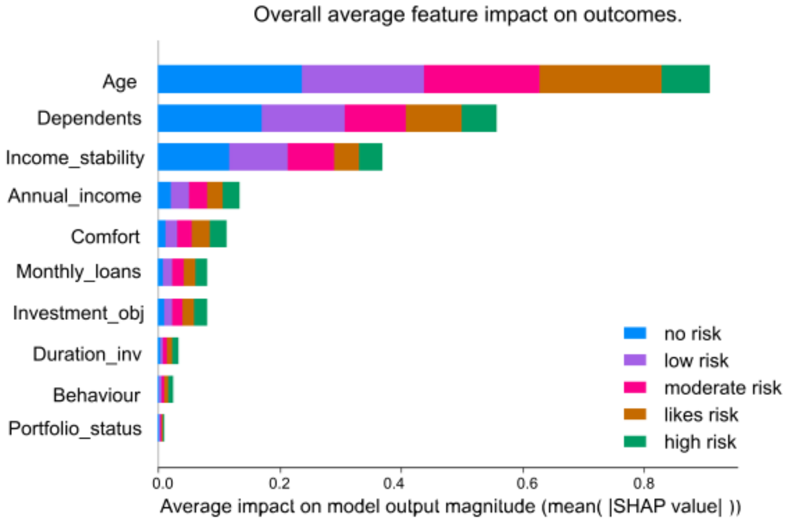


Figure 1- Global explanations

From the plot above we can gather that 'Age' is the most important feature in the model contributing the most to all the categories which is positive as reflects the way we designed our polynomial dataset. This allows the evaluator to understand the inner workings of the risk profiling process and debug the algorithm used. The feature importances are useful but we will benefit by going even deeper into understanding features and their behaviour for each class.

Class and category wise feature importance

The plots below cover the effect of each feature as well as show the importance of the features in each category (risk class). The plots below have features on the y axis ordered based on their importance and shapely values on the x axis. The colour represents the magnitude of each feature. A sample of points are taken as representation and they are scattered to show a general distribution of the data points.

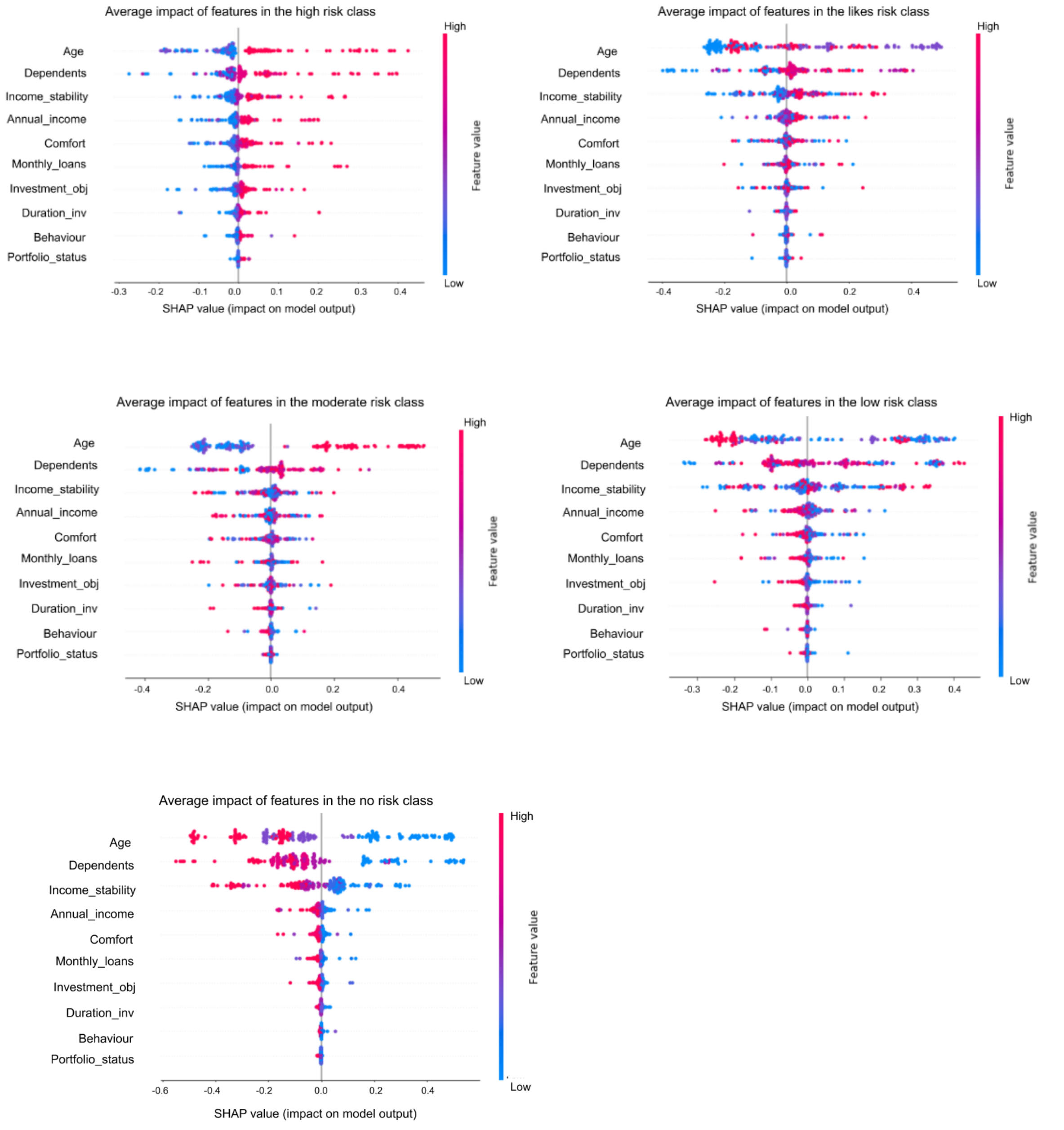


Figure 2- Global explanation for each category.

A strikingly obvious trend can be seen in ‘Age’ where we can see high values of the feature go from contributing highly positively to the high risk class to contributing negatively in the low/no risk class. The second most important feature ‘Dependents’ is very important in the extreme classes but shows no specific trend in the other classes. High values of annual income and stability contribute negatively in low risk taking behaviour of individuals. Basically with these plots we can see the general trends of the data points in the dataset and the model. In this case they can correctly model and communicate the assumptions taken by us while generating the dataset which will be an invaluable insight in cases where the assumptions are not available.

Part 3- Relationships

Relationships between data can be correlations or cause and effect relationships. Correlations give the degree of relationship between two variables. The plots below show partial dependence relationships between one or two features and the outcomes.

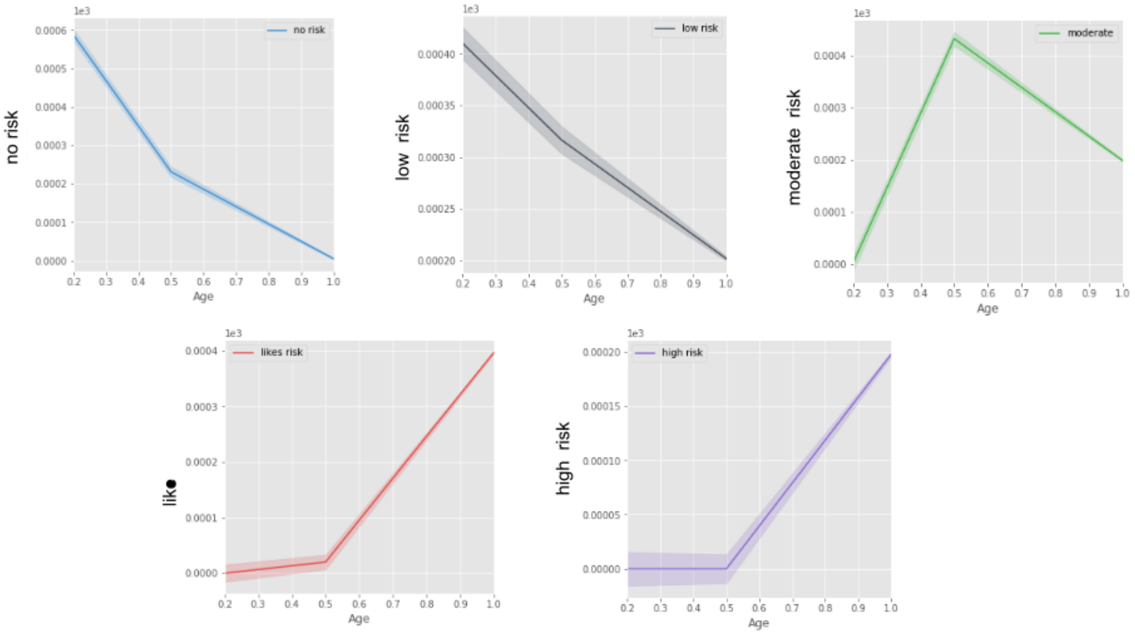


Figure 3- Two dimensional partial dependence plots

Age vs Output categories : Plot shows partial dependence relationship between age and different risk categories. The general observable trend is that as age increases the risk taking behaviour of a person also increases. This helps provide insights into the behaviour of specific features with respect to different outputs.

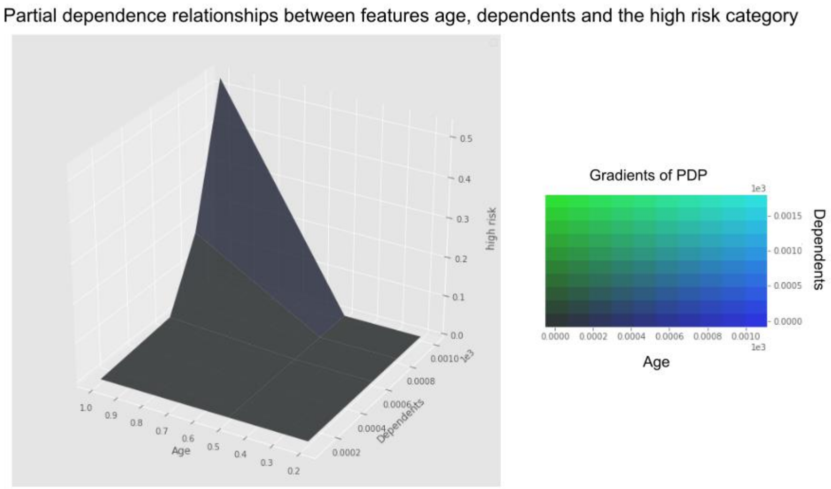


Figure 4(a)- Three dimensional partial dependence plots

While observing a similar plot with high risk, we can see that as age increases; dependents decrease and the high risk taking behaviour also increases.

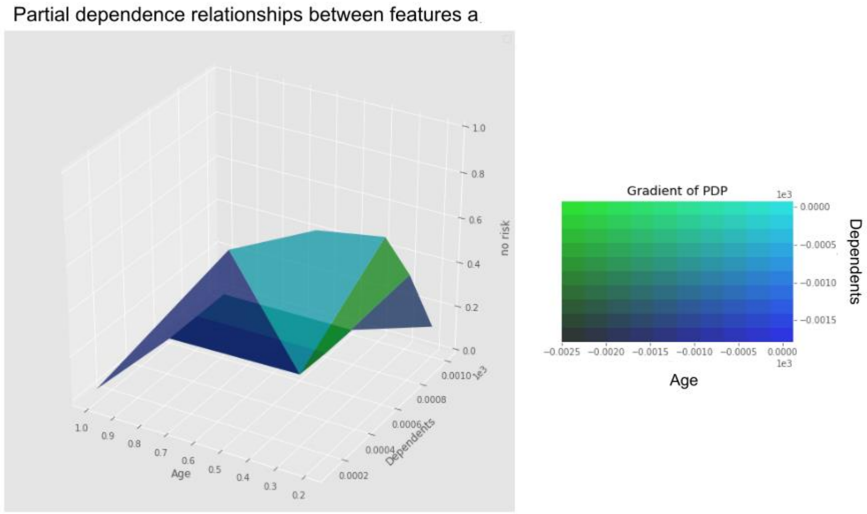
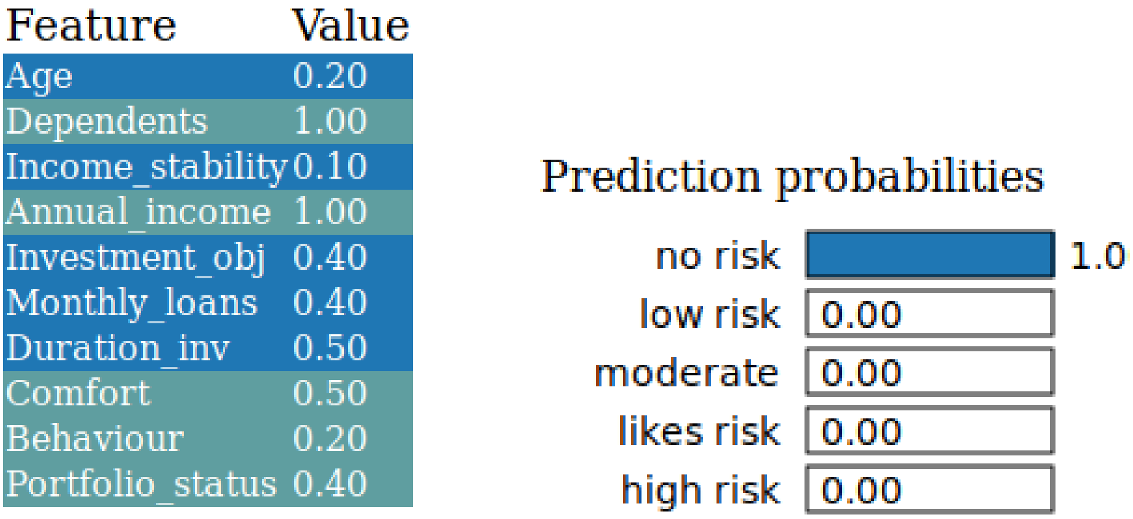


Figure 4(b)- Three dimensional partial dependence plots.

Age-Dependents-no_risk : The two most important features used by the decision tree model are age and dependents; trends in the behaviour of these two features with the output category are displayed in the plot. The no risk plot shows that as age and dependents decrease; a person is less risk averse i.e. they are more willing to take risk. Further we can also observe that during the middle age as dependents increase, no risk taking increases i.e. a person becomes more risk averse.

Part 4- Local explanations

The plot gives 'local' explanations for a single observation i.e. the reasoning taken by the decision tree model while classifying the observation in a specific category. The observation taken has it's feature values displayed top right along with the final prediction class it belongs to. The contributions of each feature to and against every class are shown. The highest contributions made by the top features are in the no risk class, all other class contributions are negligible thus the final prediction is no risk. Insights provided into which features negatively affect the decisions are also valuable for example; annual income, income stability and portfolio status are actually pushing the decision away from no risk but not strongly enough to change the category of prediction.



Feature	Value
Age	0.20
Dependents	1.00
Income_stability	0.10
Annual_income	1.00
Investment_obj	0.40
Monthly_loans	0.40
Duration_inv	0.50
Comfort	0.50
Behaviour	0.20
Portfolio_status	0.40

Figure 5(a)- Observation for local explanations

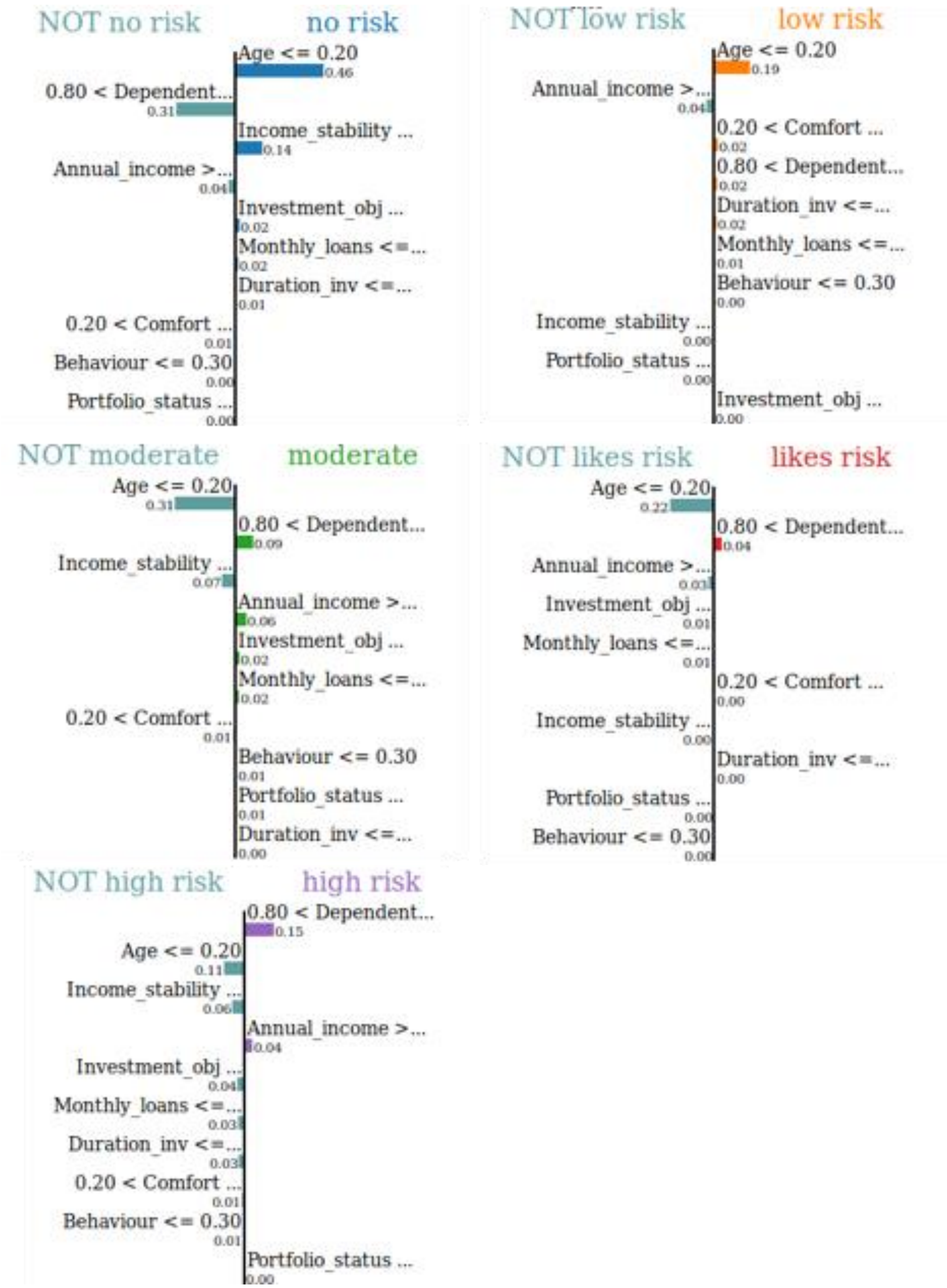


Figure 5(b)- Local explanations for observations

Conclusion

We work ground up, trying to understand the scope and limitations of enforcing regulations on technology by engaging with the technical challenges that it poses. We have survey various methods to select a handful of tools that best explain the ADS. Based on this, we adopted two global and one local explanation method using which, regulators can understand how each question contributes to the output, how they relate to each other and conduct spot checks. The methods used are able to model the dataset with high degree of accuracy. The methods have been tested using various input conditions to ensure its reliability.

Revisiting the SEBI rules for automated tools in investment advisory, our study has proposed an approach to operationalize a few regulations. This includes (1) providing users a meaningful explanation of how the tool works and the outputs it generates; (2) subjecting the tool to a comprehensive system audit and inspection. Indirectly, the explanations provided can be used by the regulator to infer if (3) the tool used acts in the best interest of the client without any unintended machine bias.

Thus, our approach has the potential to enhance the technical capabilities of capital markets regulator without the need for in-house computer science expertise. Considerable work and research would be required to create a comprehensive tool capable of operationalizing all regulations.

Discussion and way forward

With technology permeating various aspects of public life, it needs to comply with the standards set by law. However, designing and implementing regulations without knowledge of how an algorithmic system works and what its externalities are would prove to be ineffective. To formulate regulations that work, they need to be informed by the technical and operational limitations. This is especially true for the case of ADS, where there are glaring problems and yet there is a struggle to enforce concepts like fairness, accountability and transparency. As (Goodman & Flaxman, 2017) point out the GDPR acknowledges that the few if any decisions made by algorithms are purely "technical", that the ethical issues posed by them require rare coordination between 'technical and philosophical resources'. Hence, we need dialogue between technologist and regulators and they need to design safeguards together by pooling their domain knowledge.

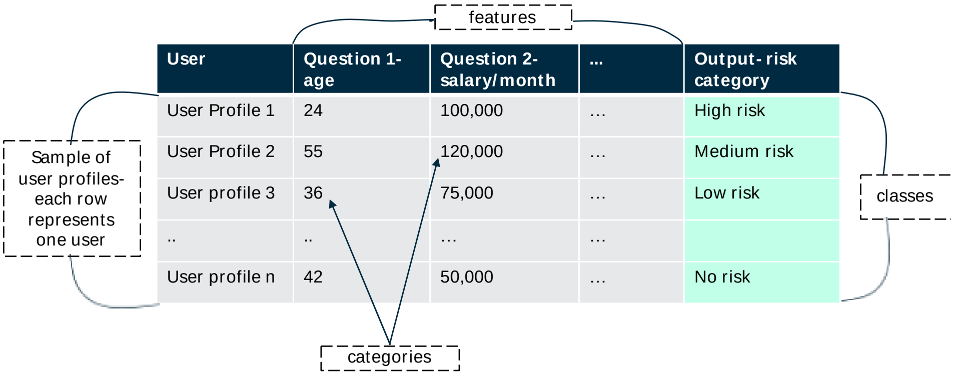
One way to achieve this is by creating regulatory sandboxes. Sandboxes act as test beds where experiments can happen in a controlled environment. They are initiated by regulators for live testing innovations of private firms in an environment that is under the regulators supervision (Jenik & Lauer, 2017). It can provide a space for dialogue and developing regulatory frameworks for the speed at which technological innovation happens, in a way that “doesn’t smother the fintech sector with rules, but also doesn’t diminish consumer protection” (BBVA, 2017). This method would help build collaborative regulations and also open up the dialogue of building in explainability by design in ADS early on in the process.

Future work needs to be on the regulatory and technical front. On the regulatory front, we need to work with the regulators to understand the grasp-ability of various explanation methods. Appropriate explanations also need to be extended to the user.

On the technical front, our work can be expanded to include increasingly more complex situations. A standardized and robust documentation process for algorithms also needs to be initiated to maintain accountability and makes it easier to audit the system.

Appendix

Appendix 1- Definitions and key terms



User	Question 1- age	Question 2- salary/month	...	Output- risk category
User Profile 1	24	100,000	…	High risk
User Profile 2	55	120,000	…	Medium risk
User profile 3	36	75,000	…	Low risk
..	..	…	…	
User profile n	42	50,000	…	No risk

1. Feature- A feature is a measurable property of the object you’re trying to analyze. In datasets, features appear as columns[1].

[1] https://www.datarobot.com/wiki/feature/

2. Accuracy- Accuracy gives the percentage of correctly predicted samples out of all the available samples. Accuracy is not always the right metric to consider in imbalanced class problems; in the risk dataset class 2 has the most samples, greatly outnumbering samples in class 1 and 5. This could mean that even if most samples are incorrectly labelled as belonging to class 2 then the accuracy would still be relatively high giving us an incorrect understanding of the models working. Just considering the accuracy, the most accurate classifier is the decision tree, closely followed by knn and svm who supersede the logistic regression and naive bayes classifiers.

3. Recall- the ability of a model to find all the relevant samples. This gives the number of true positive samples by the sum of true positive and false negative samples. True positive samples are the samples correctly predicted as true by the model and false negatives are data points the model identifies as negative that actually are positive (for example points that belong to class 2 that are predicted as not belonging to class 2).

   For example, in the performance metrics for logistic regression we find that the performance is thrown off by class moderate/medium -risk takers, this is most probably because the class has too many samples in the training data causing it to overfit(logistic regression is prone to overfitting). Comparatively, except naive bayes all other classifiers show consistently high recall values.

4. Precision- it is defined as the number of true positives divided by the number of true positives plus the number of false positives. False positives are cases the model incorrectly labels as positive that are actually negative, or in our example, individuals the model classifies as class 2 that are not. While recall expresses the ability to find all relevant instances in a dataset, precision expresses the proportion of the data points our model says was relevant actually were relevant.

5. F1 score- Sometimes trying to increase precision can decrease recall and vice versa, an optimal way to combine precision and recall into one metric is by using their harmonic mean also called the F1-Score.
   F1 = 2* (precision*recall)/(precision + recall)

Appendix 2- Details of sample dataset generation that has been used for this study

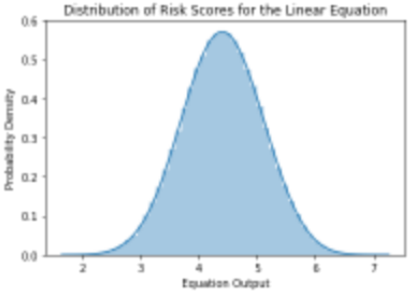
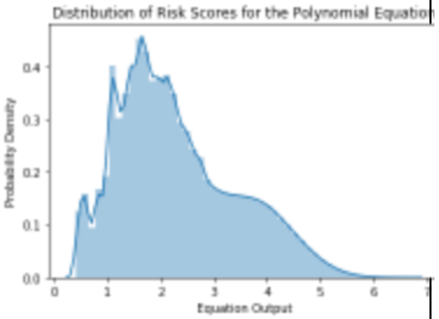
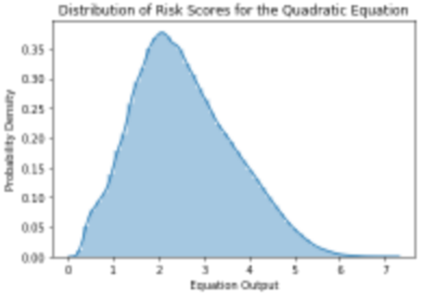
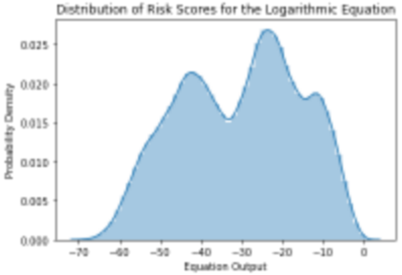
We generated a dataset by permuting all possible sequences of the answers for each question asked by prominent robo advisory apps in India. In this case, we used the questions from PayTM money. The table shows the frequently asked questions in robo-advisory apps with corresponding options. The weights to the questions (features) and scores given to the options (categories) were set at our discretion in order to generate the dataset. The values are for representation and the method we propose would work for any values.

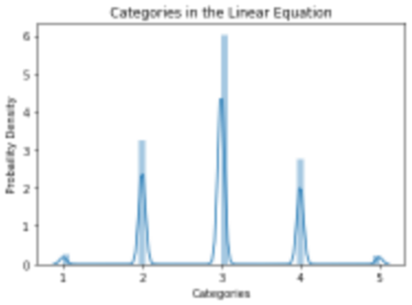
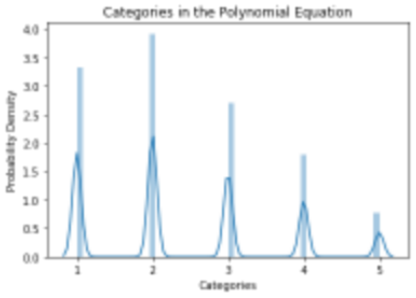
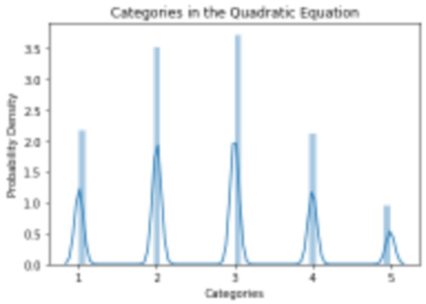
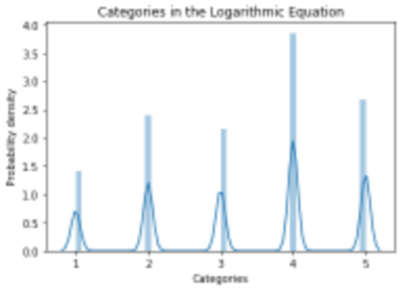
Variable names	Questions	Weight	Option1	Score (option 1)	Option2	Score (option 2)	Option3	Score (option 3)	Option4	Score (option 4)	Option5	Score (option 5)
x(1,1)	What's your age (in years)	1	18-35	1	36-55	0.5	55+	0.2				
x(2,1)	How many people depend on you financially?	0.83	No one	1	Spouse only	0.8	spouse and children	0.6	Parents only	0.6	Spouse, children and parents	0.1
x(2,2)	What's your annual income range?	0.83	Below INR 1 lac	0.2	Between INR 1 Lac - INR 5 Lac	0.4	Between INR 5 lac - 10 Lac	0.6	Between INR 10 Lac - INR 25 Lac	0.8	Above 25 Lac	1

x(3,1)	What % of your monthly income do you pay in outstanding loans, EMI etc?	0.65	None	1	Up to 20% of income	0.8	20-30% income	0.6	30-40% of income	0.4	50% or above of income	0.2
x(3,2)	Please select the stability of your income	0.65	Very low stability	0.1	Low stability	0.3	Moderate Stability	0.6	High Stability	1	Very high stability	1
x(4,1)	Where is most of your current portfolio parked?	0.5	Savings and fixed deposits	0.4	Bonds/debt	0.6	Mutual Funds	0.5	Real Estate or Gold	0.4	Stock Market	0.8
x(5,1)	What's your primary investment objective?	0.8	retirement planning	0.65	Monthly Income	0.6	Tax Saving	0.4	Capital Preservation	0.5	Wealth Creation	1
x(5,2)	How long do you plan to stay invested?	0.8	Less than 1 year	0.5	1 to 3 years	0.8	3 to 5 years	0.65	5 to 10 years	0.6	more than 10 years	0.7
x(6,1)	To achieve high returns, you are comfortable with high risk investments	0.7	Strongly agree	1	Agree	0.9	Neutral	0.5	Disagree	0.2	Strongly disagree	0.1
x(6,2)	If you lose 20% of your invested value one month after investment, you will	0.65	Sell and preserve cash	0.2	Sell and move cash to fixed deposits or liquid fund	0.3	Wait till market recovers and then sell	0.5	Keep investments as they are	0.8	Invest more	1

Table- Frequently asked questions in robo-advisory apps with corresponding options. The weights to the questions (features) and scores given to the options (categories) were set a our discretion in order to generate the dataset. The values are for representation and the method would work for any set values.

Types of Equations	Linear Equation	Polynomial Equation	Quadratic Equation	Logarithmic Equation
Equations	w_11*Age + w_21*Dependents + w_22*Annual_Income + w_31*Monthly_loans + w_32*Income_stability + w_41*Portfolio_status + w_51*Investment_obj + w_52*Duration_inv + w_61*Comfort + w_62*Behaviour = output	w_11*Age + w_21*Dependents + w_22* Annual_Income [k]*Age + w_31* Monthly_loans[l] *Age*Dependents + w_32* Income_stability [m] + w_41* x_41[n]* Age* Dependents *Duration_inv[o] + w_51* Investment_obj [o]* Age* Dependents * Duration_inv [p] + w_52* Duration_inv [p]* Investment_obj [o]* Age* Dependents + w_61* Comfort [q]*Age*Dependents + w_62* Behaviour [r]*Age*Dependents*	w_11*(Age**3) + w_21*Age* (Dependents **2) + w_22*Age* Annual_Income [k] + w_31*(Monthly_loans [l]**2) + w_32*(Income_stability [m]**3) + w_41*Dependents*Portfolio_status[n] + w_51*(Investment_obj [o]**2)* Monthly_loans [l] + w_52* Duration_inv[p]*Dependents + w_61* Monthly_loans [l]* Comfort [q] + w_62* Behaviour [r]* Dependents	w_11*3*math.log(Age,3) + w_21*2*math.log(Age[i]* Dependents[j], 2) + w_22*3* math.log(Age[i]* Annual_Income [k],2) + w_31*3* math.log(Age[i]* Monthly_loans[l], 2) + w_32*3* math.log(Age[i]*Income_stability[m], 2) + w_41*Portfolio_status[n] + w_51*3* math.log(Age[i]* Income_stability[m]* Investment_obj[o], 2) + w_52* Duration_inv[p]* Behaviour [r] + w_61*2* math.log(Comfort [q]*Age[i]

		Income_stability [m]* Duration_inv [p]		,2) + w_62*Behaviour[r]*Age[i] = output
Range of outputs [min, max]	[1.764, 7.15]	[0.394, 6.74]	[0.18, 7.15]	[-69.70, 1.69]
Distribution of risk scores				
Boundaries	▪ No risk: less than 3 ▪ Low risk: 3 to 4 ▪ Moderate risk: 4.1 to 4.9 ▪ Likes risk: 5 to 5.8 ▪ High risk: more than 5.8	▪ No risk: less than 1.5 ▪ Low risk: 1.6 to 2.3 ▪ Moderate risk: 2.4 to 3.3 ▪ Likes risk: 3.4 to 4.3 ▪ High risk: more than 4.3	▪ No risk: less than 1.5 ▪ Low risk: 1.6 to 2.3 ▪ Moderate risk: 2.4 to 3.3 ▪ Likes risk: 3.4 to 4.3 ▪ High risk: more than 4.3	▪ No risk: less than -50 ▪ Low risk: -49 to -40 ▪ Moderate risk: -39 to -30 ▪ Likes risk: -30 to -17 ▪ High risk: more than - 17

After boundary class category distribution				
Total number of observations in each category	▪ No risk : 1 : 60,923 ▪ Low risk : 2: 8,17,511 ▪ Moderate risk : 3 : 15,15,986 ▪ Likes risk: 4 : 6,90,604 ▪ High risk: 5 : 60,701	▪ No risk : 1 : 9,96,032 ▪ Low risk : 2: 11,76,069 ▪ Moderate risk : 3 : 8,08,223 ▪ Likes risk: 4 : 5,36,121 ▪ High risk: 5 : 2,33,555	▪ No risk : 1 : 6,53,408 ▪ Low risk : 2: 10,55,754 ▪ Moderate risk : 3 : 11,18,259 ▪ Likes risk: 4 : 6,37,694 ▪ High risk: 5 : 2,84,885	▪ No risk : 1 : 4,22,859 ▪ Low risk : 2: 7,17,505 ▪ Moderate risk : 3 : 4,22,859 ▪ Likes risk: 4 : 11,56,591 ▪ High risk: 5 : 8,04,616
Final data sample chosen for models (stratified/ solving the imbalanced class problem)	**9,43,718 rows of data.** ▪ No risk : 1 : 18,277 ▪ Low risk : 2 : 2,45,254 ▪ Moderate risk : 3 : 4,54,796 ▪ Likes risk : 4 : 2,07,181 ▪ High risk : 5 : 18,210	**11,25,000 rows of data.** ▪ No risk : 1 : 2,98,810 ▪ Low risk : 2 : 3,52,821 ▪ Moderate risk : 2,42,467 ▪ Likes risk : 4 : 1,60,836 ▪ High risk : 5 : 70,066	**11,25,000 rows of data.** ▪ No risk : 1 : 196022 ▪ Low risk : 2 : 316726 ▪ Moderate risk : 335478 ▪ Likes risk : 4 : 191308 ▪ High risk : 5 : 85466	**11,25,000 rows of data.** ▪ No risk : 1 : 1,26,858 ▪ Low risk : 2 : 2,15,251 ▪ Moderate risk : 3 : 1,94,529 ▪ Likes risk : 4 : 3,46,977 ▪ High risk : 5 : 2,41,385

Correlations of variables with final category column	▪ Age 0.453045 ▪ Dependents 0.374792 ▪ Annual_income 0.404084 ▪ Monthly_loans 0.232607 ▪ Income_stability 0.302768 ▪ Portfolio_status 0.103018 ▪ Investment_obj 0.222040 ▪ Duration_inv 0.109305 ▪ Comfort 0.345110 ▪ Behaviour 0.283973 ▪ output 0.931334 ▪ categories 1.000000	▪ Age 0.742770 ▪ Dependents 0.516709 ▪ Annual_income 0.109562 ▪ Monthly_loans 0.053320 ▪ Income_stability 0.214954 ▪ Portfolio_status 0.014864 ▪ Investment_obj 0.063204 ▪ Duration_inv 0.036067 ▪ Comfort 0.074225 ▪ Behaviour 0.018715 ▪ output 0.966746 ▪ categories 1.000000	▪ Age 0.640698 ▪ Dependents 0.485437 ▪ Annual_income 0.109455 ▪ Monthly_loans 0.371431 ▪ Income_stability 0.213423 ▪ Portfolio_status 0.040315 ▪ Investment_obj 0.118964 ▪ Duration_inv 0.043781 ▪ Comfort 0.131617 ▪ Behaviour 0.114555 ▪ output 0.963646 ▪ categories 1.000000	▪ Age 0.849599 ▪ Dependents 0.119673 ▪ Annual_income 0.110896 ▪ Monthly_loans 0.088254 ▪ Income_stability 0.318025 ▪ Portfolio_status 0.003605 ▪ Investment_obj 0.057762 ▪ Duration_inv 0.004719 ▪ Comfort 0.094796 ▪ Behaviour 0.015175 ▪ output 0.971413 ▪ categories 1.000000

Table 2- Table used for dataset generation

Appendix 3- Explaining the machine learning models

Logistic Regression

Logistic Regression is a commonly used statistical method for analysing and predicting data with one or more independent variables and one binary dependent variable; for example spam or not spam email classifiers, benign or malignant tumour detection. A logistic regression classifier tries to fit data according to a linear hypothesis function such as Y= W(i)x(i) + B (Similar to a line equation) where Y is the dependent variable, X represents independent variables from 1 to n, B gives an error bias (negligible) and W is the weight assigned to each variable. W is an important value as it tells us the individual contributions of variables in determining Y, our target.

The independent variable is always binary, in our case there will be five logistic regression classifiers with their independent variables as 1 (Low Risk) or Not 1 (Not Low Risk), 2 or Not 2 and so forth till case 5 (High Risk). This format of multiclass classification is called one vs rest, the input sample is passed through all the classifiers and probability of the sample belonging to classes 1 to 5 is calculated and the highest probability class wins.

The interpretation of weights in logistic regression is dependent on the probability of class classification, the weighted sum is transformed by the logistic function to a probability. Therefore the interpretation equation is:

$$log\left(\frac{P(y=1)}{1-P(y=1)}\right)=log\left(\frac{P(y=1)}{P(y=0)}\right)=\beta_0+\beta_1x_1+\ldots+\beta_px_p$$

Equation 3(a)- Log odds of logistic regression

The log function calculates the odds of an event occurring.

$$\frac{P(y=1)}{1-P(y=1)}=odds=exp\left(\beta_0+\beta_1x_1+\ldots+\beta_px_p\right)$$

Equation 3(b)- Log odds of logistic regression

Logistic regression is used over linear regression as completely linear model does not output probabilities, but it treats the classes as numbers (0 and 1) and fits the best hyperplane (for a single feature, it is a line) that minimizes the distances between the points and the hyperplane. So it simply interpolates between the points, and you cannot interpret it as probabilities. A linear model also extrapolates and gives you values below zero and above one. Logistic regression is also widely used, interpretable and fits our use case relatively well.

Support Vector Machine (SVM) Classifier

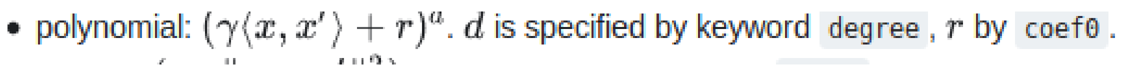
A support vector machine finds an equation of a hyper-plane that separates two or more classes in a multidimensional space; for example if we consider a two dimensional space this “hyperplane” will become a line dividing the plane on which the data lies into two separate classes. If the data is not linearly separable i.e. there is no clear line separating the classes (This happens in many cases imagine two classes in the data forming concentric circles) then data can be transformed onto a different plane (say we view the concentric circles from z axis) it becomes a linearly separable problem again (Imagine the points in the circle having different depth), after separating we can transform it back to the original plane : this is done using a kernel function in SVM.

Support vector machines have become wildly popular due to their robust efficiency and high accuracy despite requiring very few samples to train. They have disadvantages especially when it comes to time and space complexity but the SVM algorithm along with it’s variations are being used commercially in face detection, protein fold predictions find some example

SVM for multiclass classification trains n*(n-1)/2 classifiers, where n is the number of classes in the problem. Therefore for our problem there will be 10 different classifiers each will choose permutations of classes as the binary dependent variable(Y) i.e. 1 or 2, 2 or 3, 1 or 4 and all others. During this each classifier predicts one class instead of probabilities for each

Interpreting the above is quite difficult, the benefit of a linear model was that the weights / parameters of the model could be interpreted as the importance of the features. Well we can’t do that now, once we engineer a high or infinite dimensional feature set, the weights of the model implicitly correspond to the high dimensional space which isn’t useful in aiding our understanding of SVM’s. What we can do is fit a logistic regression model which estimates the

probability of label y being 1, given the original features, where **f(x) is the SVM decision function**:



- polynomial: $(\gamma\langle x, x'\rangle + r)^d$. d is specified by keyword `degree`, r by `coef0`.

Gamma support vectors rho and degree

$$P(y = 1|x) = \frac{1}{1 + \exp(Af(x) + B)},$$

Equation 4- Output equation of support vector machine.

We use maximum likelihood estimation to fit the parameters of this logistic regression model, the technique is called Platt Scaling.

For our use case we use a polynomial kernel for learning hyperplane boundaries as our original equation used to generate data is correlated in a polynomial fashion but this adds some more complexity to the algorithm. The polynomial kernel can be written as K(x,xi) = 1+((xxi))d(this is the previously mentioned f(x)) , x is the input vector and xi represents support vectors (hyperplane equations).

Decision Tree classifier

Decision trees belong to the family of tree based learning algorithms, they are widely used for supervised classification as they create precise, well defined and hierarchical decision boundaries for categorical and continuous data. This differs from classifiers that use a single separation boundary (or line) such as logistic regression by iteratively splitting the data into subparts by identifying multiple divisive boundaries.

The conditions that make these divisions try to ensure an absence of impurities in the populations contained by them; for example a condition that decision tree will make to describes a 'banana' could be in the sequence type="fruit", colour = "yellow", shape = "crescent", spots = "true" this leaves no place for uncertainty or impurity. The algorithm stops when all classes are pure or there are no features left to divide upon.

Unfortunately such sharp dividing conditions are not always possible or may exceed certain time and space limitations in real life. Therefore when a clear separation of classes is not possible then we can have a stopping condition that tolerates some impurity (For example gini impurity measures quality of such splits by calculating the probability of an incorrect classification of a randomly picked datapoint).

The impurity itself can be calculated using a measure of randomness, **entropy:** H= -p(x)log(p(x))or -plog(p) -qlog(q) where p =probability of success and q = prob of failure

Ideally H should be as small as possible.

For a dataset like ours with multiple features, deciding the splitting feature i.e. most important dividing condition at each step is a complex task, this feature should reduce the impurity through the split or one with gives the most information gain. **Information gain** at each node is calculated by the lowest entropy generated nodes by the split.

Starting from the root node, you go to the next nodes and the edges tell you which subsets you are looking at. Once you reach a leaf node, the node tells you the predicted outcome. All the edges are connected by 'AND'. For example: If feature x is [smaller/bigger] than threshold c AND etc… then the predicted outcome is the mean value of y of the instances in that node.

Individual decisions made by the tree can also be explained by going down a particular path based on the input given.

Decision trees can be used to explain the dataset by themselves.

Naïve Bayes

Naive Bayes classifiers are a family of classifiers that work on predicting future outcomes using conditional probability, given a history of behaviour; for example given say a year long history of weather forecasts with features such as humidity, rainfall, temperature a classifier from the naive Bayes family can be trained and used to predict future weather conditions.

The Bayes algorithm works under a "naive" assumption that all the features are independent in nature, in our case that means the naive Bayes classifier is going to assume that our variables such as age, income are uncorrelated so finding probabilities can be thought of as a simple counting calculation. This implies that the classifier won't be a right fit for our case as we know that the data was generated using many correlations (such as age will affect an individual's income, behaviour etc..). Due to its simplicity it has found a place in many real world systems such as credit scoring systems, weather prediction and many others so for the sake of representing and explaining all classifiers we will try this one out as well.

If the naive Bayes classifier wants to calculate the probability of observing features *f1* to *fn*, given a class *c (*In our case c here, represents the risk class and f values represent all our question-answer scores)*, then*

$$p(f_1, \dots, f_n|c) = \prod_{i=1}^{n} p(f_i|c)$$

Equation 5(a)- Naïve bayes output probability

This means that when Naive Bayes is used to classify a new example, the posterior probability is much simpler to work with:

$$p(c|f_1, \dots, f_n) \propto p(c)p(f_1|c) \dots p(f_n|c)$$

Equation 5(b)- Group conditional probability

But we have left p(fn | c) undefined i.e. the occurrence of a certain feature given a class which means we haven’t taken the distribution of the features into account yet. Therefore for our case we have used a **gaussian naive Bayes** classifier that simply assumes p (fn | c) is a gaussian normal distribution, this works well for our data which is a normal distribution.

Then the formula for our low risk class used by the classifier will be something like:

P (low-risk / Age, Income, Dependents ..) = P(low-risk / Age-category) * P(low-risk / Income-category) etc/ P(Age) * P(income) etc

This will be calculated for all risk categories and the class with the highest probability is given as the final prediction.

Naive Bayes is an interpretable model because of the independence assumption. It can be interpreted on the modular level. The contribution made by each feature towards a specific class prediction is clear, since we can interpret the conditional probability.

K-Nearest Neighbours (KNN)

Neighbours-based classification is a type of *instance-based learning* or *non-generalizing learning*: it does not try to construct a general internal model, but simply stores instances of the training data. K nearest neighbours is perhaps the simplest algorithm, a data point is classified by a majority vote of its neighbours. The input is assigned the class most common among its 'k' nearest neighbours, where 'k' is a small positive integer, the value of 'k' is chosen depending on the data. KNN is very useful in applications that require searching for similar items; such as recommender systems, bio-surveillance software, document retrieval systems such as concept search which is used in many e-Discovery software packages.

These neighbours are decided using brute force techniques that calculate distance from the data point of interest to all the other data points in the dataset, by using formulae like Euclidean distance. This means that the time and space complexity of this operation is very high; for n samples in d dimensions the time complexity will be O(d*n*n) which makes this algorithm too slow to run on large datasets such as ours but we will still cover it as it would be useful to see people and question-answers that could be grouped into one risk category.

Since KNN is an instance based algorithm there is no learned model, there are no parameters to learn, so there is no interpretability on a modular level. There is a lack of global model interpretability because the model is inherently local and there are no global weights or structures explicitly learned.

To explain a prediction at a local level, we can always retrieve the k neighbours that were used for the prediction. This is useful for our dataset as there will be thousands of neighbouring data points but presenting those 'k' nearest points could be a very useful explanation for each category.

Bibliography

Narayanan, A. (2016, June 27). *Investor Business Daily*. Retrieved October 2019, from https://www.investors.com/etfs-and-funds/etfs/fund-industry-wakens-from-slumber-to-take-on-digital-advice-upstarts/

Carey, T. (2019, September 24). *Investopedia*. Retrieved October 2019, from https://www.investopedia.com/robo-advisors-2019-where-have-all-the-assets-gone-4767826

Goodman, B., & Flaxman, S. (2017). *European Union regulations on algorithmic decision-making and a ''right to explanation''.* Retrieved October 2019, from https://ora.ox.ac.uk/catalog/uuid:593169ee-0457-4051-9337-e007064cf67c/download_file?file_format=pdf&safe_filename=euregs.pdf&type_of_work=Journal+article

EU GDPR. (2016). *EU GDPR Chapter 3*. Retrieved October 2019, from https://gdpr.eu/article-22-automated-individual-decision-making/

Wachter, S., Mittelstadt, B., & Floridi, L. (2016, December 28). Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation. *International Data Privacy Law 2017*.

Shneiderman, B. (2017, May 30). *Algorithmic Accountability*. The Alan Turing Institute.

Citron, D. K., & Pasquale, F. A. (2014). The Scored Society: Due Process for Automated Predictions. *Washington Law Review, 89*, 1-34.

Kapur, D., & Khosla, M. (2019). *Regulation in India: Design, Capacity, Performance.* Hart Studies in Comparitive Public Law.

Padmanabhan, A., & Rastogi, A. (2019). Big Data. In D. Kapur, & M. Khosla, *Regulation in India: Design, Capacity, Performance* (pp. 251-278). Hart Studies in Comparitive Public Law.

Ciocca, P., & Biancotti, C. (2018, October 23). Data superpowers in the age of AI: A research agenda. *VOX CEPR Portal*.

Thelisson, E., Padh, K., & Celis, E. L. (2017, July 15). Regulatory Mechanisms and Algorithms towards Trust in AI/ML.

Cowls, J., King, T., Taddeo, M., & Floridi, L. (2019, May 15). Designing AI for Social Good: Seven Essential Factors. *SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3388669*.

Rudin, C. (2019, May 13). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 206-215.

IOSCO. (2014, July). *Report on the IOSCO Social Media and Automation of Advice Tools Surveys* . Retrieved September 2019, from https://www.iosco.org/library/pubdocs/pdf/IOSCOPD445.pdf

Kaya, O. (2017, August 10). *Robo-advice – a true innovation in asset management.* Retrieved September 2019, from https://www.dbresearch.com/PROD/RPS_EN-PROD/PROD0000000000449125/Robo-advice_%E2%80%93_a_true_innovation_in_asset_managemen.pdf

Abraham, F., Schmukler, S. L., & Tessada, J. (2019, Febuary). *Robo-Advisors: Investing through Machines.* Retrieved October 2019, from http://documents.worldbank.org/curated/en/275041551196836758/text/Robo-Advisors-Investing-through-Machines.txt

FINRA. (2016, March). *Report on Digital Investment Advice.* Retrieved September 2019, from FINANCIAL INDUSTRY REGULATORY AUTHORITY: https://www.finra.org/sites/default/files/digital-investment-advice-report.pdf

Dastin, J. (2018, October 10). *Amazon scraps secret AI recruiting tool that showed bias against women*. (Reuters) Retrieved September 2019, from https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G

ProPublica. (2016, May 23). *Machine Bias There's software used across the country to predict future criminals. And it's biased against blacks.* Retrieved September 2019, from https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Datta, A., Tschantz, M. C., & Datta, A. (2015, February 18). Automated Experiments on Ad Privacy Settings. *Proceedings on Privacy Enhancing Technologies* , 92-112.

Costello, M., Hawdon, J., Ratliff, T., & Grantham, T. (2016, May). Who views online extremism? individual attributes leading to exposure. *Computers in Human Behavior*.

Baer, D. (2019, November). *The 'Filter Bubble' Explains Why Trump Won and You Didn't See It Coming*. Retrieved October 2019, from The Cut: https://www.thecut.com/2016/11/how-facebook-and-the-filter-bubble-pushed-trump-to-victory.html

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019, October 25). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*.

Kari, P. (2019, October 25). *Healthcare algorithm used across America has dramatic racial biases*. Retrieved October 2019, from Guardian: https://www.theguardian.com/society/2019/oct/25/healthcare-algorithm-racial-biases-optum

Castelluccia , C., & Le Métayer, D. (March 2019). *Understanding algorithmic decision-making: Opportunities and challenges.* Study, European Parliamentary Research Services, Panel for the Future of Science and Technology.

Maurell, v. d. (2019). *Embracing Robo Advisory looks promising or the longitivity of Financial Advisors.* Global Financial Markets Institute, New York.

Wired.com. (2019, November 19). *The apple card didn't see gender and that's the problem.* Retrieved December 2019, from https://www.wired.com/story/the-apple-card-didnt-see-genderand-thats-the-problem/

FAT ML. (n.d.). *Principles for Accountable Algorithms and a Social Impact Statement for Algorithms.* Retrieved December 2019, from https://www.fatml.org/resources/principles-for-accountable-algorithms

Philippe Bracke, A. D. (2019). *Machine learning explainability in finance: an application to default risk analysis.* https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2019/machine-learning-explainability-in-finance-an-application-to-default-risk-analysis.pdf, Bank of England.

Hall, P., & Gill, N. (2018). *An Introduction to Machine Learning Interpretability*. (N. Tache, Ed.) O'Reilly.

BBVA. (2017, November 18). *What is a regulatory sandbox?* Retrieved December 2019, from https://www.bbva.com/en/what-is-regulatory-sandbox/

Jenik, I., & Lauer, K. (2017). *Regulatory Sandboxes and Financial Inclusion.* CAGP. https://www.cgap.org/sites/default/files/Working-Paper-Regulatory-Sandboxes-Oct-2017.pdf.