Iterative Orthogonal Feature Projection for Diagnosing Bias in Black-Box Models

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Abstract

Predictive models are increasingly deployed for the purpose of determining access to services such as credit, insurance, and employment. Despite potential gains in productivity and efficiency, several potential problems have yet to be addressed, particularly the potential for unintentional discrimination. We present an iterative procedure, based on orthogonal projection of input attributes, for enabling interpretability of black-box predictive models. Through our iterative procedure, one can quantify the relative dependence of a black-box model on its input attributes. The relative significance of the inputs to a predictive model can then be used to assess the fairness (or discriminatory extent) of such a model.

1. Introduction

Access to large-scale data has led to an increase in the use of predictive modeling to drive decision making, particularly in industries like banking, insurance, and employment services (Bryant et al., 2008) and (Mayer-Schönberger & Cukier, 2013). The increased use of predictive models has led to greater efficiency and productivity. However, improper deployment of these models can lead to several unwanted consequences. One key concern is unintentional discrimination (Crawford & Schultz, 2014; Barocas & Selbst, 2014). It is important that decisions made in determining who has access to services are, in some sense, fair. A predictive model can be susceptible to discrimination if it was trained on inputs that exhibit discriminatory patterns. In such a case, the predictive model can learn patterns of discrimination from data leading to high dependence on protected attributes like race, gender, religion, and sexual orientation. A predictive model that significantly weights these protected attributes would tend to exhibit disparate outcomes for these groups of individuals. Hence, the focus of this paper is on auditing predictive models to determine the relative significance of a model’s inputs in determining outcomes. Given the relative significance of a model to its inputs, judgement can be more easily made about the model’s fairness.

The potential increased efficiency and societal gains from leveraging predictive modeling seem limitless, and have rightly necessitated the widespread adoption of these models. In particular, use of predictive modeling for decision making in determining access to services is starting to become the de facto standard in industries such as banking, insurance, housing, and employment. As the need for more accurate forecasts or predictions has heightened, there has been an increase in the use of complicated, often uninterpretable predictive models in making forecasts from data. Increasingly, these predictive models tend to have millions of parameters and are typically considered black-boxes by practitioners. This is because the models often generate highly accurate results, but an in-depth understanding of the underlying reasons behind these accurate results is generally lacking. Hence, practitioners resort to feeding in input to these black-box models, then generate results without truly understanding why their models are performing well. In fields such as computer vision or speech recognition where the task is often to identify or recognize a signal structure, a true understanding of the internal workings of the underlying model generating the predictions can be excused. However, in industries such as banking, insurance, and employment where access to these services is essential for livelihood, it is of paramount importance that the practitioner applying a predictive model in this setting truly understands the internal workings of her model.

2. Related Work

As automated decision-making systems began to gain widespread use in rendering decisions, researchers have be-
gun to look at the issue of fairness and discrimination in data mining. Increasingly, the emerging subfield around the topic is known as discrimination aware data mining, or fairness aware data mining (Pedreshi et al., 2008). The literature on fairness is broad including works from social choice theory, game theory, economics, and law (Romei & Ruggieri, 2014). In the computer science literature, work on identifying and studying bias in predictive models has only begun to emerge in the past few years.

More recently, studies have started to emerge that seek to identify and correct potential bias in predictive modeling. In general, these works can be broadly classified into 3 broad categories: data transformation, algorithm manipulation, and outcome manipulation methodologies (Zemel et al., 2013; Adler et al., 2016). For data transformation techniques, the input data to a data mining system is perturbed as a means of quantifying bias in the data. In (Calders & Verweer, 2010) Kamiran & Calders present a method to transform data labels in order to remove discrimination. With their proposed method, a Naive-Bayes classifier is trained on positive labels, then a set of highly ranked negatively labeled items from the protected set are changed to achieve statistical parity of outcomes. The modified data generated is then used to learn a fairer classifier. In (Friedler et al., 2014) Friedler et al. also present a data repair methodology for transforming biased data into one that predictive models can hopefully learn fair models on. In general, data transformation methodologies are typically seeking to learn fair representations of a dataset upon which less biased predictive models can be developed.

As another class of methodologies, algorithm manipulation methods seek to augment the underlying algorithm in order to reduce discrimination. Algorithm augmentation is usually done via a penalty that adds a cost of discrimination to a models cost function. These algorithms typically add regularizers that quantify the degree of bias. A seminal work in this area is the study by Kamishima et al. in (Kamishima et al., 2011) where they quantify prejudice by adding a mutual information based regularizer to the cost function of a logistic regression model. Since the Kamishima et al. work, more approaches that seek to change underlying cost functions with regularizers for statistical parity have emerged for other kinds of algorithms like decision trees and support vector machines. Techniques presented in this area typically only work for one particular method like logistic regression or Naive Bayes, so the overall impact can be limited. Algorithm manipulation methods also assume that underlying predictive models are known, completely specified with well-behaved cost functions. Usually, this is not the case, as a variety of models are typically combined in a number of ways where it becomes difficult to untangle the cost function for the combined model.

In the third approach, other studies have presented work that manipulates the outcomes of predictive models towards achieving statistical parity across groups. In these cases, algorithms presented typically change the labels of data mining algorithms seeking to balance the outcomes across multiple groups. In (Pedreshi et al., 2008), Pedreschi et al. alter the confidence of classification rules inferred.

3. Feature Ranking Methodology

3.1. Problem Overview

For this paper, the main goal of our work is to present a methodology for determining a black-box algorithm’s dependence on its inputs. More specifically, given the input and output to a black-box model, we seek to produce an input ranking that corresponds to the black-box’s predictive dependence on each input. We take predictive dependence as the change in performance of the black-box algorithm (defined as Mean Squared Error (regression) or Classification accuracy (Classification)).

3.2. Orthogonal Feature Projection

Traditionally, to make causal claims about the dependence between an input variable and a target, an experiment is needed to remove the effect of confounding variables. For example, let’s assume Harvard University were running a classifier to determine its admissions decisions. If Harvard University is then accused of discriminating on the basis of gender in its admissions decisions, how would one show definitive proof of this accusation? Hypothetically, we would find two groups of applicants that are similar in all characteristics except gender, send in those applications to the university’s classifier and then look at the difference in outcomes for these two groups. If the difference in outcomes between the two groups is significant, then one might conclude that the university is discriminating on the basis of gender in its admissions decisions.

The intuition underlying the experimental process motivates our use of the orthogonal transformation for auditing a black-box model. In the above example, the experimental process is able to show the dependence of the university’s classifier on race. Furthering this approach, we propose using orthogonal transformation as a tool of creating multiple copies of input data that can then be used to query a black-box model in order to determine the model’s dependence on its input. Now we proceed to our overview of the iterative orthogonal transformation process.

3.2.1. ORTHOGONAL FEATURE PROJECTION

Orthogonal projection is a particular type of a larger class of linear transformations. Intuitively, given two vectors whose inner product is zero, one can conclude that no linear
transformation of one vector can produce the other.

Algorithm 1 Linear Feature Transformation Algorithm
INPUT: An \( n \times k \) data matrix \( X_{\text{pre}} \) where \( x_1, x_2, \ldots, x_k \) represent attribute vectors for \( n \) samples.
Current feature is \( x_1 \)
OUTPUT: An \( n \times k - 1 \) transformed matrix \( X_{\text{new}} \) that can be decomposed into \( x_2^*, x_3^*, \ldots, x_k^* \) where each vector \( x_i^* \in X_{\text{new}} \) is orthogonal to current feature \( x_1 \).

Remove current attribute vector \( x_1 \) from \( X_{\text{pre}} \) returning \( X_{\text{del}} \)
Initialize an \( n \times k - 1 \) vector \( X_{\text{new}} \)
for each feature \( x_i^* \) in \( X_{\text{del}} \) do
   obtain \( x_i^* \), the component of \( x_i \) that is orthogonal to current attribute vector \( x_1 \)
   where \( x_i^* = x_i - \left( \frac{x_i \cdot x_1}{x_1 \cdot x_1} \right) x_1 \)
   join \( x_i^* \) column wise to \( X_{\text{new}} \)
end for
Return \( X_{\text{new}} \)

Algorithm 2 General Ranking Framework
INPUT: An \( n \times k \) data matrix \( X \) that can be decomposed into \( x_1, x_2, \ldots, x_k \) attribute vectors
Output of the black-box algorithm is \( y \)
Initial baseline predictive performance \( b \) of the black-box algorithm.
OUTPUT: Vector \( R \in \mathbb{R}^k \) of predictive dependence of the black-box on each input feature
for each attribute \( x_i^* \) in \( X \) do
   Combine non-linear transformations (log, polynomial, exponential etc) of each attribute \( x_i \) with vector \( X \) as \( X_{\text{poly}} \)
   obtain \( X_{\text{new}} \) from the Feature Transformation Algorithm given \( X_{\text{poly}} \)
   obtain black-box’s predictive performance (MSE or classification accuracy) given \( X_{\text{new}} \) as \( b_{\text{new}} \)
   predictive dependence on \( x_i^* = | b - b_{\text{new}} | \) in \( R \)
end for
Return \( R \)

4. Variable Case Studies
In this section, we demonstrate our ranking methodologies on real world data set in order to demonstrate how we expect our proposed approach to be used. We are leverage information from a major bank in Europe that developed an internal algorithm for calculating customer credit limit. The credit limit model is critical to the bank’s revenue and also determine how the bank treats its customers. Suppose regulators in the Bank’s region get complaints that the bank is discriminating on the basis of gender, we show our one might leverage the algorithms proposed to audit the bank’s algorithm.

Our dataset set in this case is demographic information for 400 thousand customers for the bank, as well as output values indicating each individual’s credit limit as calculated by the bank’s model. Leveraging our algorithms, we are able to rank the inputs to the bank’s model in order to quantify the dependence of the bank’s credit limit model on its various inputs.

As we see in each of the rankings produced, the predictive dependence of the bank’s credit limit algorithm on gender is consistently low across the board for all the three different ranking algorithms indicating that the bank’s algorithm is not overly dependent on gender in making credit limit determinations. With simple bar plots like those shown in figure 4, we hope analysts can easily interpret the results from FairML in order to make determinations about how to investigate a particular system and what to focus on. We also ran these ranking analysis on the bank’s algorithm for calculating probability of default. Due to space concerns,
we have included this plot in the appendix of this document.

5. Conclusion and Future Work

In this paper, we have presented an overview, and a case study demonstrating an approach for ranking the inputs to black-box algorithms. This work is being developed as part of a larger project, FairML, which is a toolbox to automatically enable interpretability of black-box models. In this paper, we have presented our orthogonal transformation methodology for determining a black-box algorithms dependence on its inputs. Ultimately, we hope to contribute to the large body of work regarding how to develop methods to audit black-box machine learning systems.

6. Citations and References

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