



# DASHBOARD FOR MACHINE LEARNING MODELS IN HEALTH CARE

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**Abstract:** To trust and use machine learning (ML) models in health settings, decision-makers need to understand the model's performance. Yet, there has been little agreement on what information should be visualized to present models' evaluations. This work presents an approach to construct a dashboard used to visualize supervised ML models for health care applications. The dashboard shows the models' statistical evaluations, feature importance, and sensitivity analysis.

## 1. INTRODUCTION

The use of machine learning (ML) in healthcare domains has grown massively over the last decade. To increase the trust of ML models in healthcare, the decision-makers need to understand if the model works and why. However, most people treat the model as a black box and report the performance without explaining how it works (Fekete, 2013; Liu et al., 2017). In healthcare, understanding the effect of the predictors is crucial to trust the model (Apley & Zhu, 2020). For example, Krause et al. (2016) explain the experience of a stakeholder who struggled whether to employ a model that predicted diabetic risk or not. The model had high accuracy, but the analysts could not explain how the features impacted the prediction. In health care, understanding the effect of the predictors is crucial to trust the model (Apley & Zhu, 2020). Visualization methods are among the most useful tools for understanding a ML model (Alsallakh et al., 2014). Tonekaboni et al. (2019) emphasize that carefully designed visualizations increase the clinicians' understanding.


This paper designed a dashboard that aims to help decision-makers understand the strength and weaknesses of the model and uncover the relationship between features and predictions, which lead to an increase in the decision-makers' trust by visualizing any classification model performance. The dashboard takes the model and the training and testing data and


displays three main sections: statistical measures, feature importance, and sensitivity analysis. The first two sections display some well-known measures, while the third section goes deeper into the relationship between each attribute and the prediction to identify any existing pattern.

This paper is taken from my master's thesis, "Dashboard for Machine Learning Models in Health Care," done in Summer 2021 at George Mason University under the direction of Dr. Janusz Wojtusiak (Bagais, 2021).

## 2. RELATED WORKS

While a considerable amount of literature has been published on explaining the performance of ML models, most studies focus on one measure, a specific ML method, or interactive presentation of ML results. Works on interactive ML are closely related to aspects of this study. In interactive ML, "the model gets updated immediately in response to user input" (Amershi et al., 2014, p. 106). Most model explanation systems that use interactive ML ask the user to input a hypothetical scenario and display the model performance for that scenario. In contrast, this paper focuses on model global explanation and features effect rather than the local explanation (per patient scenario).

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Several related visualization and model explanation systems developed over the past years, including:

**The what-if tool (WIT)** is “an open-source application that allows practitioners to probe, visualize, and analyze ML systems, with minimal coding” (Wexler et al., 2020, p. 56). WIT has four main functions: exploring data using statistics and distributions of all features; investigating user test hypotheses shows model performance based on finding counterfactuals and observing partial dependence plots; evaluating fairness, analyzing and compare model performance based on slices of data; comparing two models, which compares all supported measures and partial dependence plots between the two models (Wexler et al., 2020). As the name suggests, the WIT is an interactive system that shows the model behavior based on user input scenarios. In comparison, this paper focuses on displaying the final model behavior without diving into the local sensitivity analysis.

**Manifold** is “a generic environment for comparing and debugging a broad range of machine learning models” (Zhang et al., 2019, p. 9). Manifold compares ML models using two main visuals: summary statistics at feature level and a comparison of model pairs (Zhang et al., 2019). Both Manifold and this paper display the features' distribution per classification category to explain the relationship between the prediction and the attributes.

**Prospector** provides interactive partial dependence diagnostics to understand the effect of features on prediction. Prospector visualizes patient selection (a list of patients based on prediction and ground truth), Patient inspection (the change of prediction based on the change of feature values for the selected patient), and partial dependence plots (which demonstrate the effect of a feature on the prediction) (Krause et al., 2016). Both Prospector and this work include the visualization of partial dependence plots. However, Prospector focuses more on patient-level analysis while this work focuses on the overall feature effect.

Similarly, several systems focus on prediction explanation as part of decision support. The two most notable of the systems are:

**LIME** is “a modular and extensible approach to faithfully explain the predictions of any model in an interpretable manner” (Ribeiro et al., 2016, p. 114). LIME explains the predictors for a specific case, while this paper focuses on the global explanation for the model and its features.

**SHAP** stands for “Shapely Additive explains Explanations.” SHAP explains the output of any ML

model using a game theory approach. SHAP also focuses on local explanations (Lundberg & Lee, 2017).

Some other papers focus on a specific type of data or measures. For example, FeatureInsight, which focuses on defining dictionary features for classification models (Brooks et al., 2015), Samek et al. (2017) paper focus on visualizing deep neural network DNN, Adams & Hand (1999) proposed LC index as an alternative for the ROC curve. Additionally, Raymaekers et al. (2020) advised using a mosaic plot instead of the confusion matrix.

### 3. METHOD

Presentation of ML models and their results plays an essential role in analysts' and decision-makers' understanding and, consequently, trust the models. This work evaluates any classification supervised ML model by visualizing the model's results in one place using a dashboard represented in a website built using Flask. The website's inputs are the model and the attributes for both testing and training sets. The output is the dashboard which contains the following parts: statistical measures to provide an overview of the model performance, features important to show the strength of the attributes, and features sensitivity to Identify the relationship between the attribute and the prediction.

A survey was used to obtain user feedback about the dashboard. The survey was distributed by email to faculty members and graduate students in data analytics, informatics, or health sciences programs at George Mason University, and 15 people responded to the survey. The respondents were provided with three study cases' dashboards to evaluate the dashboard's three sections (the dashboards are available in the examples section in: <https://students.hi.gmu.edu/~wbagais/dashboard>). First, the survey asked about the position and area of work. Then the survey asked the user to evaluate the usefulness of the three sections of the dashboard. The survey was approved by George Mason University IRB number 1766037-1.

To demonstrate the use of the dashboard, a random forest model was built to predict if the patient has Heart Disease using UCI Machine Learning Repository (1988) data set. The output attribute is the status of having heart disease: one if the patient had heart disease and 0 if the patient did not have heart disease (UCI, 1988).

### 3.1 Statistical Measures

This section shows the overall model performance by visualizing the statistical measures and prediction distribution using four visuals: overall model performance, ROC curve, confusion matrix, and prediction distribution.

#### 3.1.1 Overall Model Performance

Accuracy, precision, recall, f-score, and AUC measures are most frequently used to evaluate ML model performance. This section compares them for both training and testing data in a heatmap to show the strength and weaknesses of the model. The heatmap in figure 1 shows that the heart disease predicting model has very good performance in all measures.

The color scales (from white to dark blue) are mapped to performance measurements scaling from 0.5 to 1. (White for value 0.5 and darkest blue for value 1). 0.5 is selected as the lowest score since 0.5 is random.

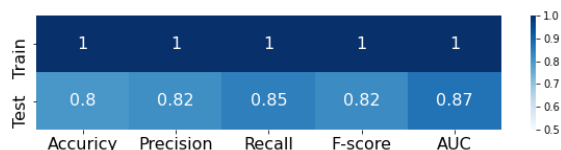


Figure 1 Example of heat map for the statistical measures.

#### 3.1.2 Receiver-Operator Curve (ROC)

The ML model gives a score from 0 to 1 and based on the selected threshold (the default threshold is 0.5), the prediction class is assigned. In other words, if the model prediction score is greater than or equal to 0.5, the model predicts that the patient has heart disease, and when the predicted score is less than 0.5, the model predicts that the patient does not have heart disease. However, a threshold of 0.5 is not always the best. The ROC shows all possible values of true positive rate (recall) and false positive rate as the classification threshold varies. Figure 2 shows the curve for the heart disease model; in the curve, the red points represent the best-selected threshold.

#### 3.1.3 Confusion Matrix

After identifying the best threshold, the confusion matrix is visualized to show classification performance. Usually, the confusion matrix is visualized using a heatmap. Yet, Raymaekers et al.

(2020) suggested using a stacked mosaic plot that adds the area perspective to show the proportion of cases in each class. This additional information indicates if the data is skewed or not. The mosaic plot shows the actual classes on the horizontal axis and the predicted classes on the vertical axis. Figure 3 shows an example of a stacked mosaic plot for the confusion matrix with two classes. As seen below, the data set has a higher number of heart disease patients than the number of patients without heart disease. The accuracy is 100% for the training data, which indicates that the model overfitted the training data.

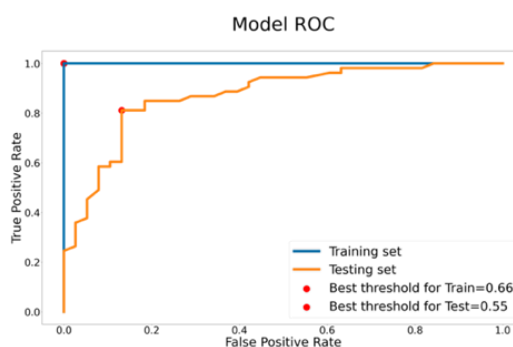


Figure 2 Example of ROC curve.



Figure 3 Example of the stacked mosaic plot.

#### 3.1.4 Prediction Distribution

The model level of confidence is shown using the prediction distribution using a bar chart with color representing the actual classes. A good model will have more cases near 0 and 1 and fewer cases in the middle near the threshold. The larger number of cases near the threshold means that the model is not confident about the decision. Figure 4 shows the prediction distribution for the heart disease prediction model. The training plot shows that the classes are split at 0.5. However, there are some overlaps between 0.4 and 0.6 prediction percentages in the testing set. Additionally, most patients with heart

disease were predicted correctly as cases between 0.8 and 1 are high.

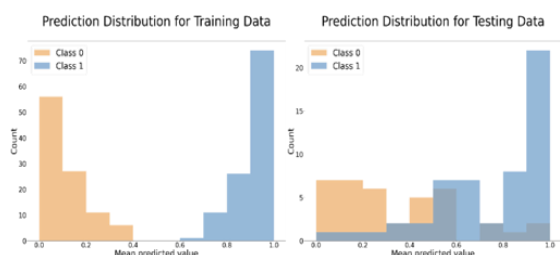


Figure 4 Example of prediction distribution.

### 3.2 Features' Importance

Understanding the relationship between the attributes and the output gives some explanation of the model decision, which can be compared with our knowledge. This section visualizes the features' importance by the following visuals: correlation heatmap, results of LASSO regression, random forest, and permutation bar chart, learning curve based on the number of cases using a line chart, and learning curve based on the number of features using a line chart. When the number of attributes used in a model is large, it is hard to display them all; therefore, the number of displayed attributes is limited to the top 20 to avoid cluttering. The top 20 attributes were selected based on the average of LASSO, random forest, permutation scores after normalizing them between 0 and 1.

#### 3.2.1 Correlation Plot

The first step is to represent the correlation between the features to show how they relate to each. Figure 5 shows an example of the correlation graph using a heatmap. The first column is larger than the others because the relationship between all independent attributes and the output attribute is more important than the relationship between all attributes.

#### 3.2.2 Lasso, Random Forest, and Permutation

Correlation is based on linear relationships and does not consider the model; therefore, features selection techniques are plotted to explain the feature importance. The selected supervised feature selection methods are Lasso, random forest (embedded methods), and permutation (wrapper method). the scores were displayed using a vertical bar chart to

show the difference between each method judgment. For example, figure 6 shows that all methods agree that number of major vessels is the most important feature. However, the random forest gives a high score for age compared to the other methods.

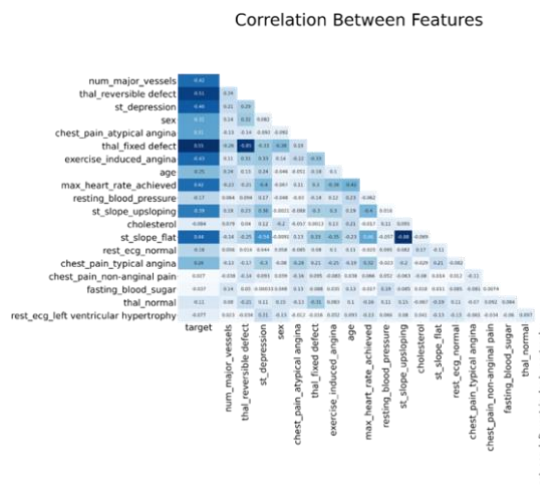


Figure 5 Example of correlation between attributes.

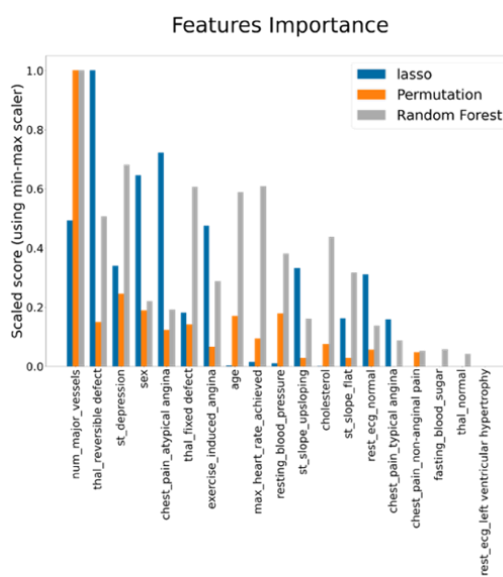


Figure 6 Example of feature importance bar chart.

#### 3.2.3 Learning Curve

The two learning curves used here represent the relationship between the number of cases with the model AUC and the number of attributes with the model AUC. Figure 7 shows the first learning curve for the number of the heart disease model. The testing score line stops increasing after 90. The second learning curve (number of attributes curve) is shown

in figure 8. The AUC did not improve after 13 attributes. In the deep learning community, the term learning curve is also used to visualize convergence of learning as a neural network is learned. However, this meaning of the term is not used here.

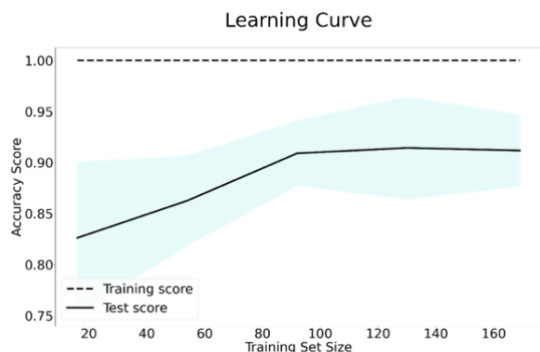


Figure 7 Example of the learning curve for the number of attributes.

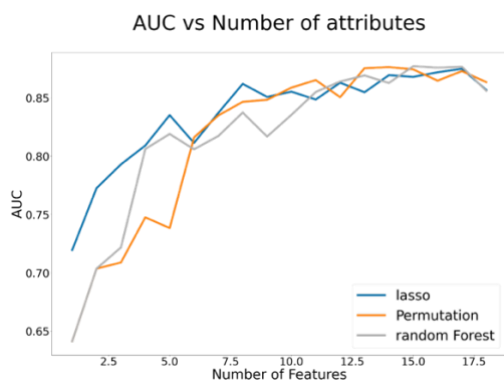


Figure 8 Example of the number of cases learning curve.

### 3.3 Sensitivity Analysis

The purpose of this section is to identify the relationship between an attribute and the model prediction. This analysis is done for the top 20 predictors only. Using a selection button, the dashboard visualizes the impact of a single input attribute into the output attribute using sensitivity measures. The type of plots depends on the data type; therefore, the first step is to identify the categorical and numeric attributes using a default threshold of 10. If the number of unique values for an attribute is less than 10, then the attribute is identified as categorical. Otherwise, the attribute is specified as numeric.

After selecting the attribute, four visuals are displayed: the attribute distribution; the mean prediction based on the chosen attribute; the mean prediction when the attribute value is fixed; and the

difference between the original AUC and the AUC when the selected attribute changes slightly.

A random dataset is needed to check the attribute behavior regardless of the correlation with other attributes for some of the visuals. For numeric attributes, the random data has the same minimum, maximum, mean, and standard deviation as the original data. In addition, the random data have the same probabilities as the original data for the categorical attributes.

For the third visuals (the mean prediction when the attribute value is fixed), an edited version of the partial dependency plots (PDP) is used. Partial Dependence Plots (PDP) show the marginal effect of the selected attribute on the prediction. (Jerome H. Friedman, 2001). The Prospector system uses this concept to examine the impact of an attribute by fixing the value of the selected attribute while keeping all other attributes as they were (Krause et al., 2016). However, this approach ignores the effect of the interaction between other attributes. Wojtusiak et al. paper added the results using randomly generated data to show the interaction between the selected attribute and predictions (2018).

The second visual (the mean prediction based on the selected attribute) shows a similar plot that visualizes the mean prediction for each selected attribute value.

For the second plot, for each unique value,  $i$  in the selected attribute  $X$ : the first plot selects the cases with the selected value (where  $X=i$ ). In the dashboard, this plot is referred to as "Mean Prediction for  $X$ ." In the third plot, all values in the selected attribute (column)  $X$  are set to  $i$ . In the dashboard, this plot is referred to as "Mean prediction based on fixed values for  $X$ ." Figure 9 shows an example when  $X$  is age, and  $i$  is 63. Figure 9.a shows the original data, figure 9.b shows the selected cases for Mean prediction for age, and figure 9.c shows the cases for Mean prediction based on fixed values for age.



Figure 9 An illustration of how partial dependence is computed for age 63.

### 3.3.1 Distribution Plot

The distribution plot provides a general idea about the attribute trend for testing, training, and random data. For numerical attributes, the distribution is shown using a line plot and colored by the data type. Figure 10 shows the distribution of age attribute for the heart disease data set. Since the data set is small, the testing data did not follow the training data trend. The peak number of patients in the training and random data is in the late 50s.

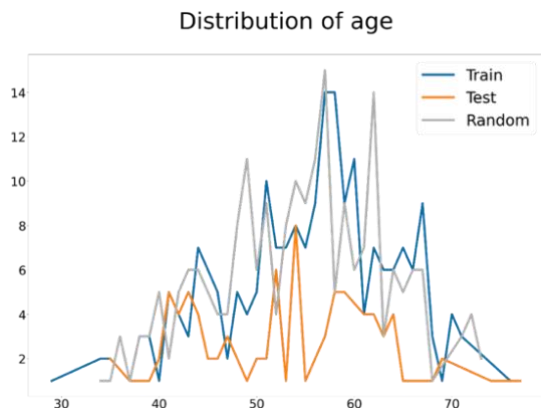


Figure 2 Example of distribution plot for age.

For categorical attributes, the distribution is shown using a bar chart. Figure 11 shows the destruction of the number of major vessels. Most patients had a value of 0, and a very small number of patients had a value of 4.

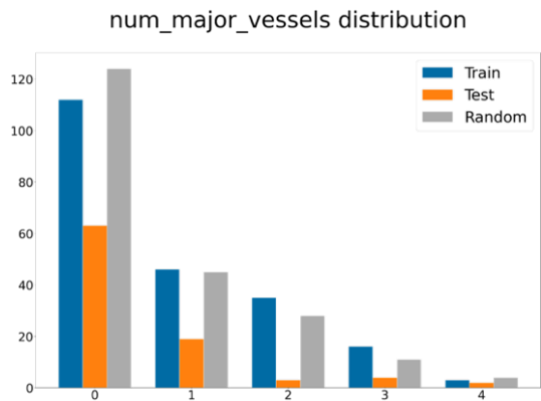


Figure 3 Example of the destruction of the number of major vessels.

### 3.3.2 Mean prediction based on the selected attribute values

For numerical attributes, the plot shows the predictions' means per each value of the selected attribute using training and testing data. The horizontal axis represents the attribute values, and the vertical axis represents the predictions' means. The training and testing trends show the model behavior for each value in the selected attribute. Figure 12 shows the predictions' means based on age, showing no clear trend between age and heart disease. The training and testing data trends show a drop in the AUC percentage around age 60.

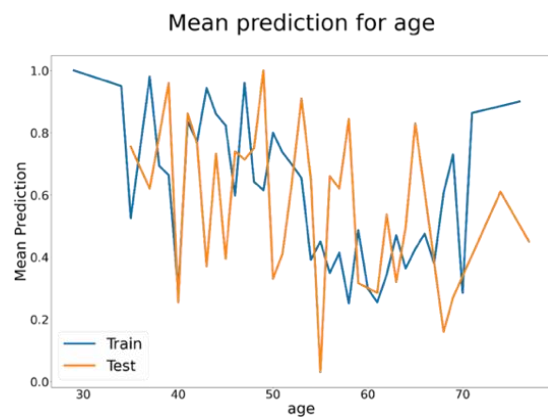


Figure 4 Example of mean prediction based on age.

For categorical variables, the prediction distribution is visualized for each selected attribute value. Figure 13 shows the prediction distribution for the number of major vessels. From the training data, the number of vessels is positively correlated with having heart disease when its value is 0 and negatively correlated with heart disease when its value is 1, 2, or 3.

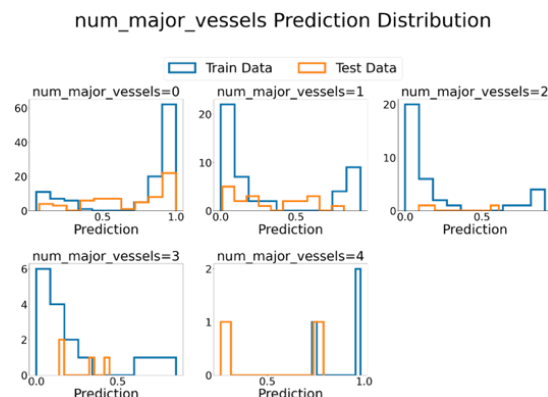


Figure 5 Example of prediction distribution for the number of major vessels.

### 3.3.3 Mean Prediction Based on Fixed Values

To check the effect of an attribute ignoring the interaction with other attributes, this work uses the method introduced by Wojtusiak et al. (2018) when examining models for predicting 30-day post-hospitalization mortality. For numeric attributes, the selected attribute values are set to a fixed value, then the mean AUC is calculated. This calculation is done for all unique values of the selected attribute as a fixed value. The result of the random dataset shows the effect of that attribute regardless of all other attributes changes (Wojtusiak et al., 2018). Figure 14 shows the mean prediction when age is fixed for all cases. Training, testing, and random data have the same trend. The plot shows a correlation between age and having heart disease. Patients at age 60 have the lowest AUC probability of having heart disease. While this drop needs more investigation, explaining the trend is beyond the dashboard scope.

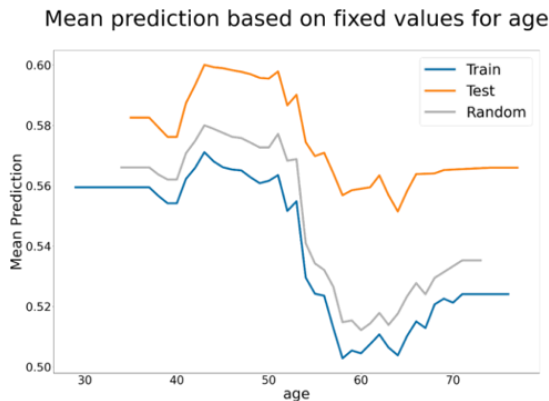


Figure 14 Mean prediction when age is fixed for all cases.

For categorical attributes, for each value for the selected attribute, all data is set to that value, and the prediction distribution is visualized using a histogram plot. Figure 15 shows the prediction distribution for the number of major vessels. When the number of major vessels is set to 0 for all patients, the data is skewed to the left. For the other types, the training data were skewed, but the random data were symmetric. Therefore, the trend might be caused by the correlation between the number of major vessels and other attributes.

num\_major\_vessels Prediction Distribution based on fixed values

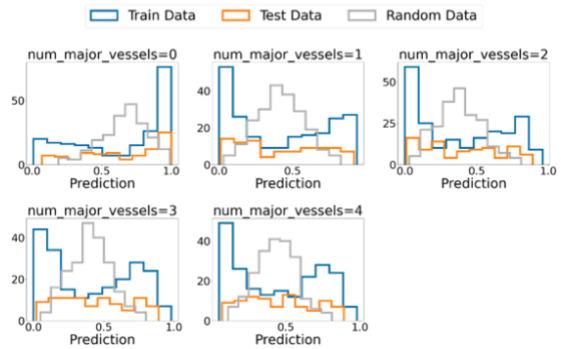


Figure 6 Number of major vessels prediction distribution based on fixed values.

### 3.3.4 Original AUC vs. AUC when the selected attribute change slightly

The prediction should not change dramatically when the attribute value changes slightly. For example, in the prediction of the heart disease model, if the patient's age increases or decreases by two years, the change percentage of getting heart disease should not change significantly. To ensure that the model is stable, the prediction comparison is visualized for numeric attributes only.

For numeric attributes, the data changed by adding or subtracting the standard deviation. The closer the data to the diagonal line, the less sensitive the model is to the small change. Figure 16 shows the age AUC vs. Age minus/plus standard deviation using test data. Most data are around the diagonal line; therefore, the model is not sensitive to small changes to age.

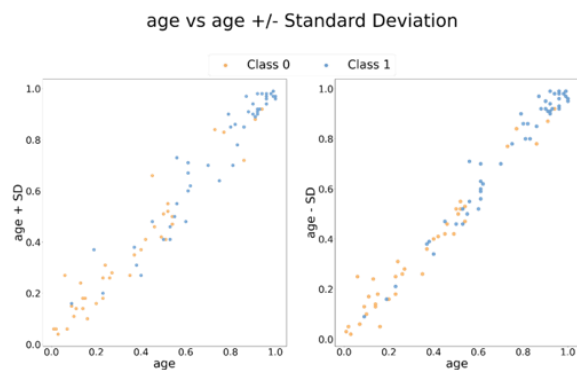


Figure 7 Age AUC vs. Age plus/ minus standard deviation AUC.

## 4. RESULTS

### 4.1 Survey Results

Fifteen people evaluated the dashboards. Most people agreed that the dashboard visuals give a better understanding of the model behavior than other methods they have experienced.

The comments were divided into positive, natural, and negative comments. In general, the positive comments were related to the comprehensive understanding of the model and clarity of the graphs. The negative comments suggested reducing the number of visuals, and two comments considered that the dashboard is not useful.

**Statistical measures section.** Most of the comments agreed that this section is important to understand how the model performs. This section was the most interesting section for one of the reviewers in terms of understanding. However, for “Prediction Distribution and Classification Reports,” one of the comments suggests that they are unnecessary.

**Features’ importance section.** Several reviews mentioned that this section is important to give an idea about the data. The correlation plot got the most attention; however, the size of the plots was too small to read.

**Sensitivity analysis section.** Most of the comments agreed that selecting a variable is very helpful to understand the performance. However, one of the comments found it hard to understand the categorical attributes plots.

Finally, most of the comments were positive. Comments related to the size of plots, typos, and rewording were reflected on the dashboard. The other suggestions would be considered as future work due to time limitations.

## 5. CONCLUSION AND DISCUSSION

The present work was designed to demonstrate an approach to visualizing classification model performance in a dashboard with three sections: statistical measures, which provide an overview of the model performance; feature importance which gives an overview of the data; and sensitivity analysis which identifies the relationship between the attribute and the prediction. The dashboard adds to a growing body of literature on understanding and evaluating classification learning. The advantages of the

dashboard are that it visualizes any classification model, uses visuals that are simple and easy to understand, and summarizes all the results in one place. Yet, unlike interactive dashboards, this dashboard does not react to user changes.

### 5.1 Limitation and Future Work

The survey results cannot be generalized due to sample size limitations. However, the purpose of the survey was to understand how people interact with the dashboard, and the most interesting part was the reviewers’ comments. Second, some design-related changes like the colors and sizes of the plots are recommended. For example, when the names of the columns are long, the size of the figures in the feature importance section becomes small, which requires zooming in to read. Third, visualizing the regression model results and comparing models is considered a future work.

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