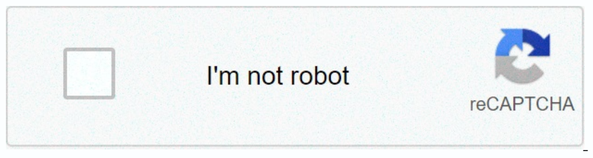

Continue

Classification report scikit learn

The Yellowbrick Classification Report visualizer displays the accuracy, recall, F1, and support scores for the model. To support easier interpretation and problem detection, the report integrates numeric scores with a color-coded heat map. All heat maps in the range (0.0, 1.0) make it easy to compare classification models between different classification reports. sklearn.model_selection import time From Sklearn.naive_bayes, import GaussianNB from yellowbrick.classifier import ClassificationReport from yellowbrick.datasets import load_occupancy # Load classification dataset X, y = load_occupancy() # Specify the target classes = [unsatt occupied] # Create tscv = TimeSeriesSplit() training and test data train_index, test_index tscv.split(X) test_index: X_train, X_test = X.iloc[train_index], X.iloc[test_index], y_train, y_test = y.iloc[train_index], y.iloc[test_index] # Instance the classification model and visualizer model = GaussianNB() visualizer = ClassificationReport(model, classes=classes, support=True) visual y_train X_train izer #Fit the visualizer and the model visualizer.score(X_test, y_test) # Evaluate the model on the test data visualizer.show() # Finalize and display the figure (Source code, png , pdf) The classification report displays a representation of the main classification metrics by class. This gives a deeper intuition to classifier behavior over global accuracy, which masks functional weaknesses in a class with a multi-class problem. Visual classification reports are used to compare classification models to select reddish models, such as stronger rating metrics or more balanced. Metrics are true and false positive, and true and false are negative. Positive and negative in this case are the generic names of the classes of binary classification problem. In the example above, true and false are considered busy, true, and false blanks. Therefore, the real positive is when the actual class is positive, like the estimated class. A false positive is when the actual class is negative, but the estimated class is positive. Using this terminology, metrics are defined as precisionPrecision as a measure of the classifier's accuracy. For each class, this is the ratio of true positive to true and false positive. He said another way, in any case, qualified positive, what percentage was correct? recallRecall is a measure of the classifier's completeness; the ability of the classifier to correctly find all positive cases. For each class, this is the ratio of the sum of the true positives to the true positives and the false negatives. He said another way, in any case, to actually be positive, what percentage was properly classified? f1 scoreThe F1 score is a weighted harmonic mean accuracy and that the best score is 1.0 and the worst is 0.0. 0.0. f1 scores are lower than precision meters because it embeds accuracy and recall in the calculation. As a general rule, the weighted average of F1 should be used to compare classifier models, not global accuracy. SupportSupport is the number of actual occurrences of the class in the specified dataset. Unbalanced support for training data may indicate structural deficiencies in the classifier's reported scores and indicate the need for stratified sampling or balance recovery. Support does not change between models, but diagnoses the evaluation process. Note: This example divides data into training and test sets using TimeSeriesSplit. For more information about the cross-validation method, see the scikit-learn documentation. The same function above is available in the related quick method classification_report. This method creates the ClassificationReport object with the related arguments, matches it, and then (optionally) displays it immediately. sklearn.model_selection import sklearn.naive_bayes load_occupancy yellowbrick.classifier import classification_report # Load the classification data set X, y = load_occupancy() # Specify target classes = [unoccupied, busy] # Create training and test data tscv = TimeSeriesSplit() train_index, test_index in tscv.split(X): X_train, X_test = X.iloc[train_index], X.iloc[test_index] y_train, y_test = y.iloc[train_index], y.iloc[test_index] # Rendering viewer = classification_report(GaussianNB(), X_train, y_train, X_test, y_test, classes=classes, support=True) (Source code, png, pdf) Visual classification report for classifier scoring. Class yellowbrick.classifier.classification_report. Classification force_model is_fitted ScoreVisualizer Classification report that shows the precision, recall, F1, and support scores for the model. Integrates numeric scores as well as a color-coded heat map. Parameters modelestimatorA scikit-learn estimator, which should be a classifier. If the model is not a classifier, an exception arises. If the internal model is not equipped, the display is also suitable when installed, unless is_fitted otherwise. axmatplotlib axes, default: NoneA axes to represent the shape. If not specified, the current axes will be used (or, if necessary, created). class labels touse for the legend ordered by the index of the sorted classes discovered in the fit() method. By specifying classes in this way, you can change class names to a more accurate format or classes are tagged. Some visuals can also use this field to filter the visualization for specific classes. For more advanced use, specify the instead of class labels. cmapstring, default: 'YlOrRd'Enter a color map to determine the heat map of the predicted class in the classification report relative to the actual class. support: {True, False, None, percentage, 'count'}, default: NoneSpecify if support is displayed. It can be further determined whether the aid should be reported as a raw number or as a percentage. encoderdict or LabelEncoder, default: NoneA classes are mapped to human readable tags. There is often a discrepancy between the class labels you want and the labels in the target variable that are transferred to fit() or score(). The encoder does not match this discrepancy, ensuring that classes are properly tagged in the visual. is_fittedbool or str, default='auto'Specify whether the veiled valuer is already mounted. If it is false, the appaler will be appropriate even if the viewer fits, otherwise the appareager will not be modified. If auto (default), the assistive method verifies that the installer is installed before it is re-installed. force_modelbool default: The false setting does not check whether it is based is anestiling classifier. This prevents an exception if the visualization is initialized, but can result in unexpected or unwanted behavior. show: bool, default: TrueIf True, True, show(), which in turn asks for plt.show() however, can not be called egt.savefig from this signature, nor clear_figure. If false, simply request finalize() kwargsdictKeyword arguments passed to the visualizer base classes. Returns the vizClassificationReportRes return © Copyright 2016-2019, for scikit-yb developers. 4c8882fe review. Made with sphinx, using the theme provided by Read the Docs. Docs.