In [1]: import sklearn from sklearn import datasets from sklearn import model_selection from sklearn import tree from sklearn import metrics import matplotlib.pyplot as plt from sklearn import ensemble from sklearn.model_selection import KFold import numpy as np Zadanie 1 In [2]: dane = datasets.load_iris() x = dane["data"] y = dane["target"] In [3]: X_train,X_test, Y_train,Y_test = model_selection.train_test_split(x,y,train_size=0.8) model = tree.DecisionTreeClassifier() In [5]: model.fit(X_train,Y_train) Out[5]: DecisionTreeClassifier DecisionTreeClassifier() In [6]: y_pred = model.predict(X_test) metrics.accuracy_score(Y_test,y_pred) Out[7]: **0.86666666666666** matrix = metrics.confusion_matrix(Y_test,y_pred) In [9]: display = metrics.ConfusionMatrixDisplay(confusion_matrix=matrix,display_labels=model.classes_) In [10]: display.plot() plt.show() - 12 14 True label - 8 0 - 6 2 -2 1 0 Predicted label In [11]: metrics.classification_report(Y_test,y_pred) Out[11]: ' 1.00 1.00 1.00 precision recall f1-score support\n\n 14\n 0.71 0.71 0.71 7\n 2 0.78 0.78 0.78 9\n\n 1 accuracy 0.87 30∖n macro avg 0.83 0.83 0.83 30\nweighted avg 0.87 0.87 0.87 30\n' In [12]: tree.plot_tree(model) Out[12]: [Text(0.4, 0.9, 'x[2] <= 2.45\ngini = 0.665\nsamples = 120\nvalue = [36, 43, 41]'), Text(0.2, 0.7, 'gini = 0.0\nsamples = 36\nvalue = [36, 0, 0]'), Text(0.3000000000000004, 0.8, 'True '), Text(0.6, 0.7, $'x[3] <= 1.75 \setminus = 0.5 \setminus = 84 \setminus = [0, 43, 41]'$), Text(0.5, 0.8, ' False'), Text(0.4, 0.5, $'x[2] \le 4.95 \cdot = 0.085 \cdot = 45 \cdot = [0, 43, 2]'$), Text(0.2, 0.3, 'gini = 0.0\nsamples = 42\nvalue = [0, 42, 0]'), Text(0.6, 0.3, $'x[0] \leftarrow 6.4 \cdot = 0.444 \cdot = 3 \cdot = 3 \cdot = [0, 1, 2]'$), Text(0.4, 0.1, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'), Text(0.8, 0.1, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'), Text(0.8, 0.5, 'gini = 0.0\nsamples = 39\nvalue = [0, 0, 39]')] $x[2] \le 2.45$ gini = 0.665 samples = 120 Tr value = [36, 43, 41] $x[3] \le 1.75$ gini = 0.0gini = 0.5samples = 36 samples = 84value = [36, 0, 0] value = [0, 43, 41] x[2] <= 4.95 gini = 0.0 gini = 0.085samples = 39samples = 45 value = [0, 0, 39] value = [0, 43, 2] x[0] <= 6.4gini = 0.0 gini = 0.444 samples = 3 samples = 42 value = [0, 42, 0] value = [0, 1, 2] gini = 0.0gini = 0.0 samples = 2samples = 1value = [0, 0, 2] value = [0, 1, 0] Zadanie 2 In [13]: dane_wina = datasets.load_wine() x2 = dane_wina['data'] y2 = dane_wina['target'] In [14]: X_train,X_test, Y_train,Y_test = model_selection.train_test_split(x2,y2,train_size=0.7) In [15]: model_linear = sklearn.svm.SVC(kernel='linear') model_rbf = sklearn.svm.SVC(kernel="rbf") model_poly = sklearn.svm.SVC(kernel='poly') In [16]: model_linear.fit(X_train,Y_train) model_rbf.fit(X_train,Y_train) model_poly.fit(X_train,Y_train) Out[16]: 🔻 SVC SVC(kernel='poly') In [17]: y_pred_lin = model_linear.predict(X_test) y_pred_rbf = model_rbf.predict(X_test) y_pred_poly = model_poly.predict(X_test) metrics.accuracy_score(Y_test,y_pred_lin) Out[18]: 0.9259259259259259 In [19]: metrics.accuracy_score(Y_test,y_pred_rbf) Out[19]: 0.72222222222222 In [20]: metrics.accuracy_score(Y_test,y_pred_poly) Out[20]: 0.7407407407407407 In [21]: matrix_lin = metrics.confusion_matrix(Y_test,y_pred_lin) matrix_rbf = metrics.confusion_matrix(Y_test,y_pred_rbf) matrix_poly = metrics.confusion_matrix(Y_test,y_pred_poly) In [22]: display1 = metrics.ConfusionMatrixDisplay(confusion_matrix=matrix_lin,display_labels=model.classes_) display2 = metrics.ConfusionMatrixDisplay(confusion_matrix=matrix_rbf,display_labels=model.classes_) display3 = metrics.ConfusionMatrixDisplay(confusion_matrix=matrix_poly,display_labels=model.classes_) In [23]: display1.plot() display2.plot() display3.plot() plt.show() T 20.0 - 17.5 20 0 0 -- 15.0 - 12.5 True label 19 1 - 10.0 - 7.5 5.0 2 -11 - 2.5 2 0 Predicted label 20.0 - 17.5 19 0 0 -- 15.0 - 12.5 True label 20 0 - 10.0 7.5 2 -11 - 2.5 2 0 Predicted label T 20.0 - 17.5 19 - 15.0 - 12.5 True label - 10.0 20 0 - 7.5 - 5.0 2 -10 - 2.5 Predicted label In [24]: metrics.classification_report(Y_test,y_pred_lin) precision recall f1-score support\n\n 13\n\n accuracy Out[24]: ' 0.98 0.90 0.90 0.90 21\n 0.92 0.85 0.88 0.95 1.00 20\n 1 0.92 0.93 0.93 0.93 54\n' 0.93 54\n macro avg 0.92 54\nweighted avg In [25]: metrics.classification_report(Y_test,y_pred_rbf,zero_division=True) precision recall f1-score support\n\n Out[25]: ' 0.86 0.95 0.90 0.65 0.95 0.77 21\n 0.00 0.00 0.00 13\n\n accuracy 20\n 1 0.50 0.72 54\n' 54\nweighted avg 0.63 0.72 54\n macro avg 0.63 0.56 0.57 In [26]: metrics.classification_report(Y_test,y_pred_poly) Out[26]: ' precision recall f1-score support\n\n 20\n 0.67 0.95 0.78 21\n 2 0.50 0.08 0.13 13\n\n accuracy 0.86 0.95 0.90 1 0.68 0.74 54\n' 54\nweighted avg 0.74 54\n macro avg 0.66 0.61 0.70 0.67 Zadanie 3 In [27]: dane_domy = datasets.fetch_california_housing() x3 = dane_domy['data'] y3 = dane_domy['target'] In [28]: X_train,X_test, Y_train,Y_test = model_selection.train_test_split(x3,y3,train_size=0.75) In [29]: model_boost = ensemble.GradientBoostingRegressor() In [30]: kf = KFold(n_splits=10, shuffle=True, random_state=50) In [34]: print(model_selection.cross_val_score(model_boost,x3,y3,cv=kf)) [0.77881172 0.7867148 0.78881941 0.78398672 0.78651334 0.78666609 0.8068168 0.78909195 0.79188371 0.7869703] In [35]: model_boost.fit(X_train,Y_train) Out[35]: GradientBoostingRegressor GradientBoostingRegressor() In [37]: y_pred = model_boost.predict(X_test) In [38]: print(metrics.r2_score(Y_test,y_pred)) print(metrics.mean_absolute_error(Y_test,y_pred)) 0.7929867314675171 0.36510129848669515 In [42]: x5 = model_boost.feature_importances_ feature_names = dane_domy['feature_names'] In [43]: plt.bar(feature_names, x5) plt.xticks(rotation=45) plt.ylabel('Feature Importance') plt.xlabel('Feature Name') plt.title('Feature Importances') Out[43]: Text(0.5, 1.0, 'Feature Importances') Feature Importances 0.6 -0.5 0.4 Feature Importar 0.1 Feature Name In [44]: plt.show()