

dtaset: https://bit.ly/2TK5Xn5 Name: Manish Singh

from sklearn.tree import DecisionTreeClassifier

1. Importing Required Libraries

In [1]: import pandas as pd import matplotlib.pyplot as plt

species

0.2 Iris-setosa

0.2 Iris-setosa

0.2 Iris-setosa

0.2 Iris-setosa

0.2 Iris-setosa

import seaborn as sns from sklearn.model_selection import train_test_split

from sklearn import metrics print(" All required packages included successfully!")

All required packages included successfully!

2. Importing the Dataset

dataset = pd.read_csv('D:\Data_Set\Iris.csv') dataset.head()

sepal_length sepal_width petal_length petal_width Out[3]: 0 5.1 3.5

1.4

1 4.9 3.0 1.4 2 4.7 1.3 3.2

4.6 3.1 1.5 5.0 1.4 3.6

3. Data Exploration # Shape of Dataset

Dataset Columns dataset.columns Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',

'species'], dtype='object')

Data columns (total 5 columns):

Non-Null Count Dtype

150.000000

3.758667

1.764420

1.000000

1.600000

4.350000

5.100000

6.900000

150 non-null

150.000000

3.054000

0.433594

2.000000

2.800000

3.000000

3.300000

4.400000

float64

float64 float64

float64

object

150.000000

1.198667

0.763161

0.100000

0.300000

1.300000

1.800000

2.500000

dataset.shape

(150, 5)

In [10]: # To display basic data dataset.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 150 entries, 0 to 149

In [5]:

Out[5]:

In [6]:

Out[6]:

sepal_length 150 non-null sepal_width 150 non-null petal_length 150 non-null petal_width 150 non-null

Column

species dtypes: float64(4), object(1) memory usage: 6.0+ KB In [9]: # to display stats about data dataset.describe()

sepal_length sepal_width petal_length petal_width Out[9]: 150.000000 count mean 5.843333 0.828066 std 4.300000 min

5.100000 **25**% 5.800000 **50% 75**% 6.400000 max 7.900000 In [11]: **#Checking Null Values** dataset.isnull().sum()

sepal_length sepal_width 0 petal_length 0 petal_width 0 species dtype: int64 In [21]: #Checking columns count of "Species" dataset['species'].value_counts() 50 Iris-setosa Iris-versicolor 50 Iris-virginica 50

Out[21]: Name: species, dtype: int64 In [23]: #Pie plot to show the overall types of Iris classifications dataset['species'].value_counts().plot(kind = 'pie', autopct = '%1.1f%%', shadow = True, explode = [0.08,0.08,0.08]) <AxesSubplot:ylabel='species'> Iris-setosa lris-versic**ด**ีor

In [24]: #Correlation Heatmap plt.figure(figsize=(9,7)) plt.show()

gini = 0.0samples = 29value = [0, 29, 0]class = Iris-versicolor

y_dataset

In [41]:

8. Prediction on Dataset.

'Iris-setosa', 'Iris-versicolor', 'Iris-virginica', 'Iris-virginica', 'Iris-virginica', 'Iris-virginica'], dtype=object) 9. To check the accuracy of the model.. print("Accuracy:", metrics.accuracy_score(y_test, y_pred)) Accuracy: 0.98

accuracy

macro avg

from sklearn.metrics import classification_report print(classification_report(y_test, y_pred)) precision Iris-setosa 1.00 Iris-versicolor 1.00 Iris-virginica 0.94

dtree.predict([[5, 3.6, 1.4 , 0.2]])

array(['Iris-setosa'], dtype=object)

dtree.predict([[9, 3.1, 5, 1.5]])

array(['Iris-versicolor'], dtype=object)

dtree.predict([[4.1, 3.0, 5.1, 1.8]])

array(['Iris-virginica'], dtype=object)

THANK YOU!

0.98

samples = 3value = [0, 0, 3]class = Iris-virginica y_dataset = dtree.predict(X_test)

recall f1-score

1.00

0.97

0.97

0.98

0.98

0.98

10. Prediction the output class for random values for petal and sepal length and width

Predict the flower type for a flower with sepal length, sepal width, petal length, petal width as 5cm, 3.6cm, 1.4cm and 0.2cm respectively

Predict the flower type for a flower with sepal length, sepal width, petal length, petal width as 9cm, 3.1cm, 5cm and 1.5cm respectively

Predict the flower type for a flower with sepal length, sepal width, petal length, petal width as 4.1cm, 3cm, 5.1cm and 1.8cm respectively

1.00

0.95

1.00

0.98

0.98

support

16

19

15

50

50

gini = 0.0samples = 1value = [0, 1, 0]class = Iris-versicolor array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa', ['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor',
'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor',
'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor',
'Iris-versicolor', 'Iris-setosa', 'Iris-virginica' 'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
'Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',

gini = 0.666samples = 100value = [34, 31, 35]class = Iris-virginica

gini = 0.0

samples = 34

value = [34, 0, 0]

class = Iris-setosa

sepal width(cm) ≤ 3.1

gini = 0.375

samples = 4

value = [0, 1, 3]

class = Iris-virginica

petal width(cm) ≤ 1.65

gini = 0.165samples = 33

value = [0, 30, 3]class = Iris-versicolor

gini = 0.0

gini = 0.0samples = 2value = [0, 0, 2]class = Iris-virginica

value = [0, 31, 35]class = Iris-virginica petal length(cm) ≤ 5.05 gini = 0.059samples = 33value = [0, 1, 32]class = Iris-virginica sepal width(cm) ≤ 2.75 gini = 0.0gini = 0.444samples = 30samples = 3value = [0, 0, 30]value = [0, 1, 2]class = Iris-virginica class = Iris-virginica gini = 0.0samples = 1value = [0, 1, 0]class = Iris-versicolor

Iris-virginica sns.heatmap(dataset.corr(), cmap='CMRmap', annot=True, linewidths=2) plt.title("Correlation Graph", size=20) Correlation Graph -1.0 sepal_length -0.11 0.82 1 0.87 - 0.8 - 0.6 sepal_width -0.11 1 -0.42-0.36 0.4 petal_length 0.2 0.87 -0.420.96 0.0 petal_width -0.20.82 -0.36 0.96 sepal_length sepal_width petal_length petal_width 4. Defining dependent and independent variables In [31]: features = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'] X = dataset.loc[:, features].values #defining the feature matrix y = dataset.species 5. Splitting the dataset into training and test sets X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_state=0) 6. Defining the decision tree classifier and fitting the training set In [33]: dtree = DecisionTreeClassifier() dtree.fit(X_train,y_train) DecisionTreeClassifier() 7. Visualizing of Decision tree In [37]: from sklearn import tree feature_name = ['sepal length(cm)', 'sepal width(cm)', 'petal length(cm)', 'petal width(cm)'] class_name= dataset.species.unique() plt.figure(figsize=(20,15)) tree.plot_tree(dtree, filled = True, feature_names = feature_name, class_names= class_name) $[Text(446.4, 733.86, 'petal width(cm) <= 0.75 \\ ngini = 0.666 \\ nsamples = 100 \\ nvalue = [34, 31, 35] \\ nclass = Iris-virginica'),$ $Text(334.7999999999995, 570.78, 'gini = 0.0 \nsamples = 34 \nvalue = [34, 0, 0] \nclass = Iris-setosa'),$ $Text(558.0, 570.78, 'petal length(cm) <= 4.95 \ngini = 0.498 \nsamples = 66 \nvalue = [0, 31, 35] \nclass = Iris-virginica'),$ $Text(223.2, 407.700000000000005, 'petal width(cm) <= 1.65 \nsamples = 33 \nvalue = [0, 30, 3] \nclass = Iris-versicolor'),$ Text(111.6, 244.62, 'gini = $0.0 \times = 29 \times = [0, 29, 0] \times = Iris-versicolor'),$ Text(223.2, 81.54000000000008, 'gini = 0.0\nsamples = 3\nvalue = [0, 0, 3]\nclass = Iris-virginica'), Text(446.4, 81.54000000000008, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]\nclass = Iris-versicolor'), $Text(892.8, 407.700000000000005, 'petal length(cm) <= 5.05 \ngini = 0.059 \nsamples = 33 \nvalue = [0, 1, 32] \nclass = Iris-virginica'),$ $Text(892.8, 81.54000000000008, 'gini = 0.0 \nsamples = 1 \nvalue = [0, 1, 0] \nclass = Iris-versicolor'),$ $Text(1004.4, 244.62, 'gini = 0.0 \setminus samples = 30 \setminus u = [0, 0, 30] \setminus class = Iris-virginica')]$ petal width(cm) ≤ 0.75

petal length(cm) \leq 4.95

gini = 0.498

samples = 66

from sklearn.metrics import confusion_matrix confusion_matrix(y_test, y_pred) array([[16, 0, 0], Out[44]: [0, 18, 1], [0, 0, 15]], dtype=int64)

weighted avg In [44]:

Out[45]:

In [46]:

Out[46]:

In [43]: