| | Importing Modules |
|------------------------------|--|
| In [1]: | <pre>import pandas as pd import numpy as np</pre> |
| | <pre>import matplotlib.pyplot as plt import seaborn as sns from sklearn.linear_model import LogisticRegression import warnings</pre> |
| | <pre>from sklearn.preprocessing import LabelEncoder warnings.simplefilter("ignore") from sklearn.preprocessing import StandardScaler from sklearn.model_selection import train_test_split</pre> |
| | <pre>from sklearn.metrics import accuracy_score</pre> |
| In [2]: | Load the Dataset |
| In [3]: | <pre>df = pd.read_csv('Iris.csv') df.head()</pre> |
| Out[3]: | Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species |
| | 0 1 5.1 3.5 1.4 0.2 Iris-setosa 1 2 4.9 3.0 1.4 0.2 Iris-setosa 2 3 4.7 3.2 1.3 0.2 Iris-setosa |
| | 3 4 4.6 3.1 1.5 0.2 Iris-setosa 4 5 5.0 3.6 1.4 0.2 Iris-setosa |
| In [4]: | <pre>df.info()</pre> |
| | <pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 150 entries, 0 to 149 Data columns (total 6 columns): # Column Non-Null Count Dtype</class></pre> |
| | 0 Id 150 non-null int64 1 SepalLengthCm 150 non-null float64 |
| | 2 SepalWidthCm 150 non-null float64 3 PetalLengthCm 150 non-null float64 4 PetalWidthCm 150 non-null float64 5 Species 150 non-null object |
| | dtypes: float64(4), int64(1), object(1) memory usage: 7.2+ KB |
| In [5]: | Checking for Null Values df.isnull().sum() |
| Out[5]: | #isnull() finds if there any NULL value is present or not and it gives the output in the form of TRUE or FALSE i.e., we used sum() function so that we can get Id 0 SepalLengthCm 0 |
| | SepalWidthCm 0 PetalLengthCm 0 PetalWidthCm 0 Species 0 |
| | Some Basic Information about the Dataset |
| In [6]: | df.columns |
| Out[6]: | <pre>Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',</pre> |
| In [7]: | df.shape |
| Out[7]: In [8]: | (150, 6) df.describe() |
| Out[8]: | Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm count 150.000000 150.000000 150.000000 150.000000 |
| | mean 75.500000 5.843333 3.054000 3.758667 1.198667 std 43.445368 0.828066 0.433594 1.764420 0.763161 |
| | min 1.000000 4.300000 2.000000 1.000000 25% 38.250000 5.100000 2.800000 1.600000 0.300000 50% 75.500000 5.800000 4.350000 1.300000 |
| | 50% 75.500000 5.800000 3.000000 4.350000 1.300000 75% 112.750000 6.400000 3.300000 5.100000 1.800000 max 150.000000 7.900000 4.400000 6.900000 2.500000 |
| | Drop the Unwanted Columns |
| In [9]: | <pre>df = df.drop(columns='Id') #Drop will delete the particular column given inside the paranthesis here the column is 'Id'</pre> |
| In [10]: | df.head() |
| Out[10]: | SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species 1 |
| | 1 4.9 3.0 1.4 0.2 Iris-setosa 2 4.7 3.2 1.3 0.2 Iris-setosa 3 4.6 3.1 1.5 0.2 Iris-setosa |
| - | 4 5.0 3.6 1.4 0.2 Iris-setosa |
| In [11]: | <pre>df.shape #after dropping one column ['Id'] now we have only 5 columns left (150, 5)</pre> |
| Out[11]: | Label Encoding |
| In [12]: | <pre>df["Species"] = LabelEncoder().fit_transform(df["Species"])</pre> |
| In [13]: | #This LabelEncoder() will change the categorical values of the 'Species' column into a numerical values df.head() |
| Out[13]: | SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species 0 5.1 3.5 1.4 0.2 0 |
| | 1 4.9 3.0 1.4 0.2 0 2 4.7 3.2 1.3 0.2 0 |
| | 3 4.6 3.1 1.5 0.2 0 4 5.0 3.6 1.4 0.2 0 |
| | Data Visualization |
| In [14]: | <pre>df["Species"].value_counts() #This will provide the count value of each type of species</pre> |
| Out[14]: | 0 50 1 50 2 50 Name: Species, dtype: int64 |
| In [15]: | <pre>sns.countplot(x='Species', data=df)</pre> |
| Out[15]: | <axessubplot:xlabel='species', ylabel="count"> 50</axessubplot:xlabel='species',> |
| | 40 - |
| | 30 - 8 20 - |
| | 10 - |
| Tn [46]. | 0 1 2 Species |
| In [16]: Out[16]: | <pre>sns.pairplot(df, hue='Species', height=3.0) <seaborn.axisgrid.pairgrid 0x2a4be7b39a0="" at=""></seaborn.axisgrid.pairgrid></pre> |
| | 8.0 7.5 7.0 |
| | WO 6.5 |
| | 5.0 4.5 |
| | 4.5 |
| | Wind 3.5 - 10 - 10 - 10 - 10 - 10 - 10 - 10 - 1 |
| | 25 |
| | 2.0 - Species 0 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 |
| | Betallendthought of the second |
| | |
| | 2.5 |
| | <u>Eq. 15 </u> |
| | E 15 - C C C C C C C C C C C C C C C C C C |
| | 0.0 |
| | Splitting the Data |
| In [17]: | <pre>x = df.iloc[:,:4] y = df.iloc[:,4] #x will store all the data from column 1 to 4 (0 to 3 in programming) i.e., SepalLengthCm, SepalWidthCm, PetalLengthCm and PetalWidthCm</pre> |
| Tn F407 | #y will store the data of only column 5 (4 in programming) i.e., Species |
| In [18]: Out[18]: | SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm |
| | 0 5.1 3.5 1.4 0.2 1 4.9 3.0 1.4 0.2 2 4.7 3.2 1.3 0.2 |
| | 3 4.6 3.1 1.5 0.2 4 5.0 3.6 1.4 0.2 |
| In [19]: | y.head() |
| Out[19]: | 0 0 1 0 2 0 3 0 |
| | 4 0 Name: Species, dtype: int32 |
| In [20]: | Training and Testing the Data x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2,random_state=0) |
| In [21]: | #It will split the data into training data and testing data (testing data will be 20% of the whole data and remaining 80% will be the training data) |
| In [21]: Out[21]: | x_train.shape (120, 4) |
| In [22]: | /00 |
| Out[22]: In [23]: | (30, 4) y_train.shape |
| Out[23]: | |
| <pre>In [24]: Out[24]:</pre> | y_test.shape (30,) |
| | Create the Model (classification) |
| In [25]: | <pre>model = LogisticRegression().fit(x_train,y_train) model</pre> |
| Out[25]: | ▼ LogisticRegression |
| In [26]: | <pre>LogisticRegression() y_pred = model.predict(x_test)</pre> |
| In [27]: | <pre>y_pred = model.predict(x_test)</pre> <pre>y_pred</pre> |
| Out[27]: | array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1, 0, 0, 2, 0, 0, 1, 1, 0]) |
| In [28]: | <pre>score = accuracy_score(y_pred,y_test) score</pre> |
| Out[28]: | Testing the Model |
| In [29]: | Testing the Model model.predict([[5,3.2,1.1,0.3]]) |
| | |