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In [1]: In [2]:	<pre>from sklearn.model_selection import train_test_split from sklearn import svm, metrics from sklearn.metrics import roc_curve, auc from sklearn.preprocessing import label_binarize from itertools import cycle import pandas as pd</pre>
	<pre>import numpy as np import matplotlib.pyplot as plt import seaborn as sns from sklearn.model_selection import train_test_split from dt import DecisionTreeClassifier</pre>
In [3]:	
In [4]:	<pre>iris= iris.drop(columns="Id"); speciesColumn = {'Iris-setosa':0, 'Iris-versicolor':1, 'Iris-virginica':2} iris=iris.replace({'Species':speciesColumn}) Dataset Summary</pre>
In [5]:	display(iris); SepalLengthCm SepalWidthCm 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 2 2 0 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 0 145 6.7 3.0 5.2 2.3 2
	146 6.3 2.5 5.0 1.9 2 147 6.5 3.0 5.2 2.0 2 148 6.2 3.4 5.4 2.3 2 149 5.9 3.0 5.1 1.8 2
In [6]:	<pre>#discription of columns sepalLength= iris["SepalLengthCm"].describe(); sepalWidth= iris["SepalWidthCm"].describe(); petalLength= iris["PetalLengthCm"].describe();</pre>
	<pre>petalWidth= iris["PetalWidthCm"].describe(); print(sepalLength) print(sepalWidth) print(petalLength) print(petalWidth) count 150.000000</pre>
	mean 5.843333 std 0.828066 min 4.300000 25% 5.100000 50% 5.800000 75% 6.400000 max 7.900000
	Name: SepalLengthCm, dtype: float64 count 150.000000 mean 3.054000 std 0.433594 min 2.000000 25% 2.800000 50% 3.000000
	75% 3.300000 max 4.400000 Name: SepalWidthCm, dtype: float64 count 150.000000 mean 3.758667 std 1.764420 min 1.000000 25% 1.600000
	50% 4.350000 75% 5.100000 max 6.900000 Name: PetalLengthCm, dtype: float64 count 150.000000 mean 1.198667 std 0.763161
	min 0.100000 25% 0.300000 50% 1.300000 75% 1.800000 max 2.500000 Name: PetalWidthCm, dtype: float64
In [7]:	display(iris.duplicated().sum()) SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species
	34 4.9 3.1 1.5 0.1 0 37 4.9 3.1 1.5 0.1 0 142 5.8 2.7 5.1 1.9 2 Checking Balance
In [8]:	<pre>sns.countplot(iris["Species"]); c:\Users\canbo\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinte rpretation.</pre>
	warnings.warn(50 - 40 - 30 - 30 - 30 - 30 - 30 - 30 - 3
	20 -
In [29]:	display(iris.isnull().sum(axis=0)) SepalLengthCm 0 SepalWidthCm 0
In [31]:	PetalLengthCm 0 PetalWidthCm 0 Species 0 dtype: int64 sns.set_style("whitegrid"); sns.pairplot(iris, hue="Species", height=3); plt.show();
	<pre>plt.show();</pre>
	Sepal Fendith Carrier and the separate of the
	4.0 90 3.5 10 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	2.0 Species 0 1
	Detailled 2
	2.5 E 2.0 E 1.5
	Setosa looks more significant than other species. versicolar and virginia looks closer each other than setosa.
In [9]:	Train the classifier clf = DecisionTreeClassifier(max_depth=5) Split dataset to train and test
In [10]:	<pre>X=iris.values.tolist(); y=[]; for row in X: y.append(int(row[4])); del row[4];</pre>
	<pre>X=pd.Series(X); y=pd.Series(y); X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=True);</pre>
	<pre>X_train_list=X_train.values.tolist(); y_train_list=y_train.values.tolist(); X_test_list=X_test.values.tolist(); y_test_list=y_test.values.tolist();</pre> Train The Classifier
In [11]:	<pre>clf.fit(X_train_list,y_train_list); Predict Class of Test values</pre>
In [12]:	<pre>yhat = clf.predict(X_test_list) print("Test Features Expected Classification") print(y_test_list) print("Prediction") print(yhat); xhat = clf.predict(X_train_list) print("Train Features Expected Classification") print(y_train_list)</pre>
	<pre>print(y_train_list) print("Prediction") print(xhat); Test Features Expected Classification [1, 0, 0, 0, 0, 2, 0, 2, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 2, 1, 0, 0, 1, 2, 2, 2, 2] Prediction [1, 0, 0, 1, 0, 2, 0, 2, 0, 1, 1, 1, 1, 1, 1, 1, 2, 1, 0, 0, 0, 2, 1, 1, 0, 1, 2, 2, 2, 2]</pre>
	Train Features Expected Classification [0, 0, 0, 0, 2, 0, 2, 0, 1, 2, 1, 2, 1, 2, 0, 1, 0, 2, 0, 1, 2, 2, 0, 2, 2, 1, 2, 0, 1, 0, 1, 0, 0, 0, 1, 0, 2, 0, 1, 0, 2, 2, 0, 0, 1, 0, 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 2, 1, 0, 2, 1, 2, 2, 0, 2, 2, 2, 1, 1, 2, 0, 1, 0, 0, 2, 0, 1, 1, 0, 2, 1, 1, 1, 0, 2, 0, 1, 2, 2, 1, 1, 2, 2, 1, 1, 2, 2, 0, 2, 2, 0, 2, 2, 0, 1, 1, 2, 0, 1] Prediction [0, 0, 0, 2, 0, 2, 0, 1, 2, 1, 2, 1, 2, 0, 1, 0, 2, 0, 1, 2, 2, 0, 2, 2, 1, 1, 0, 1, 0, 0, 0, 1, 0, 2, 0, 1, 0, 2, 2, 0, 1, 2, 2, 1, 1, 2, 2, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 2, 1, 0, 2, 1, 1, 2, 2, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 2, 1, 1, 2, 2, 1, 1, 2, 0, 1, 0, 2, 1, 1, 2, 2, 1, 2, 1, 2, 2, 1, 2, 2, 1, 1, 2, 2, 1, 1, 2, 2, 2, 1, 1, 1, 1, 1, 0, 2, 1, 1, 2, 2, 1, 2, 2, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
	1, 0, 1, 2, 2, 1, 1, 2, 2, 0, 2, 2, 0, 0, 2, 1, 1, 2, 0, 1] Results
In [14]:	<pre>Confusion Matrix of Test y_pred2= pd.Series(yhat); y_test2= pd.Series(y_test_list); mt= metrics.confusion_matrix(y_test2, y_pred2) df_cm= pd.DataFrame(mt, range(3), range(3))</pre>
	<pre>sns.set(font_scale=1.4) sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}) plt.show()</pre> -10
	- 0 11 0 -8 -4
	0 1 2 Confusion Matrix of Train
In [16]:	<pre>x_pred2= pd.Series(xhat); x_test2= pd.Series(y_train_list); mt= metrics.confusion_matrix(x_test2, x_pred2) df_cm= pd.DataFrame(mt, range(3), range(3)) sns.set(font_scale=1.4) sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})</pre>
	plt.show() -40 -30
	- 0 39 0 -20 - 0 0 42 -10
	0 1 2 F1-Score
In [17]:	<pre>f1=metrics.f1_score(y_test2, y_pred2, average='weighted'); print("F1-Score Test:") print(f1); f2=metrics.f1_score(x_test2, x_pred2, average='weighted'); print("F1-Score Train:") print(f2);</pre> F1-Score Test:
	0.932777777778 F1-Score Train: 1.0 Accuracy
In [18]:	<pre>print("Accuracy Test") print(accuracy) accuracy2 = metrics.accuracy_score(x_test2, x_pred2); print("Accuracy Train") print(accuracy2)</pre>
	Accuracy Test 0.933333333333 Accuracy Train 1.0 Precision
In [19]:	<pre>precision=metrics.precision_score(y_test2,y_pred2,average='weighted') print("Precision Test") print(precision) precision2=metrics.precision_score(x_test2,x_pred2,average='weighted') print("Precision Train") print(precision2)</pre> Precision Test
	0.9435897435897436 Precision Train 1.0 Recal
In [20]:	<pre>recall=metrics.recall_score(y_test2, y_pred2, average='weighted') print("Recall Test") print(recall) recall2=metrics.recall_score(x_test2, x_pred2, average='weighted') print("Recall Train") print(recall2)</pre> Recall Test
	0.9333333333333333333333333333333333333
In [27]:	<pre>#Test Datas1 y_testb= label_binarize(y_test2, classes=[0,1,2]); y_predprod= label_binarize(y_pred2, classes=[0,1,2]); fpr,tpr,threshold= metrics.roc_curve(y_testb[:,2],y_predprod[:,2]) roc_auc = metrics.auc(fpr, tpr) plt.plot(fpr,tpr,label="class 0, auc="+str(roc_auc))</pre>
	<pre>plt.ylabel('True Positive Rate') plt.xlabel('False Positive Rate') plt.legend(loc=4) plt.show() fpr,tpr,threshold= metrics.roc_curve(y_testb[:,1],y_predprod[:,1]) roc_auc = metrics.auc(fpr, tpr) plt.plot(fpr,tpr,label="class 1, auc="+str(roc_auc))</pre>
	<pre>plt.ylabel('True Positive Rate') plt.xlabel('False Positive Rate') plt.legend(loc=4) plt.show() fpr,tpr,threshold= metrics.roc_curve(y_testb[:,0],y_predprod[:,0]) roc_auc = metrics.auc(fpr, tpr) plt.plot(fpr,tpr,label="class 2, auc="+str(roc_auc)) plt.ylabel('True Positive Rate')</pre>
	plt.xlabel('False Positive Rate') plt.legend(loc=4) plt.show() 1.0
	0.8 Use Late Age and the Age a
	0.0 0.2 0.4 0.6 0.8 1.0 False Positive Rate
	1.0 positive one of the second of the secon
	0.0 0.2 0.4 0.6 0.8 1.0
	False Positive Rate 1.0 98 0.8
	₹ 0.6
In [28]:	9 0.8 9 0.6 0.4 0.2
	0.0 0.2 0.4 0.6 0.8 1.0 False Positive Rate #Train datas1 x_testb= label_binarize(x_test2, classes=[0,1,2]);
	#Train datas1 x_testb= label_binarize(x_test2, classes=[0,1,2]); x_predprod= label_binarize(x_pred2, classes=[0,1,2]); fpr, tpr, threshold= metrics.roc_curve(x_testb[:,2],x_predprod[:,2]) roc_auc = metrics.auc(fpr, tpr) plt.ylabel('True Positive Rate') plt.ylabel('True Positive Rate') plt.legend(loc=4) plt.slow() fpr, tpr, threshold= metrics.roc_curve(x_testb[:,1],x_predprod[:,1]) roc_auc = metrics.auc(fpr, tpr) plt.plt.plt.plt.plt.plt.plt.plt.plt.plt.
	Class 2, auc=1.0