report

November 15, 2022

Name: Hüseyin PEKKAN

ID: 201401016

Course: BIL570 /BIL470

[18]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from km import KMeansClusterClassifier
import importlib
import sklearn.metrics as metrics
from sklearn.preprocessing import label_binarize
from dt import DecisionTreeClassifier

%matplotlib inline
```

1 Exploratory Data Analysis (EDA)

[2]:
```
df = pd.read_csv('Iris.csv',index_col='Id')
df['Species']=df.Species.map({'Iris-setosa':0,'Iris-versicolor':
  ↪1,'Iris-virginica':2})
df['Species'] = pd.to_numeric(df['Species'])
df.head(5)
```

[2]:
```
    SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  Species
Id
1             5.1           3.5            1.4           0.2        0
2             4.9           3.0            1.4           0.2        0
3             4.7           3.2            1.3           0.2        0
4             4.6           3.1            1.5           0.2        0
5             5.0           3.6            1.4           0.2        0
```

[7]:
```
print('Shape of DF:',df.shape)
print(df.dtypes,'\n')
df.info()
```

```
Shape of DF: (150, 5)
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species            int64
dtype: object

<class 'pandas.core.frame.DataFrame'>
Int64Index: 150 entries, 1 to 150
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 7.0 KB
```

[8]:
```
df.describe()
```

[8]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667	1.000000
std	0.828066	0.433594	1.764420	0.763161	0.819232
min	4.300000	2.000000	1.000000	0.100000	0.000000
25%	5.100000	2.800000	1.600000	0.300000	0.000000
50%	5.800000	3.000000	4.350000	1.300000	1.000000
75%	6.400000	3.300000	5.100000	1.800000	2.000000
max	7.900000	4.400000	6.900000	2.500000	2.000000

[9]:
```
df[df.duplicated()] # but maybe two iris has same values
```

[9]:

Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
35	4.9	3.1	1.5	0.1	0
38	4.9	3.1	1.5	0.1	0
143	5.8	2.7	5.1	1.9	2

[10]:
```
df.isna().sum()/df.shape[0] #percentage of null values
```

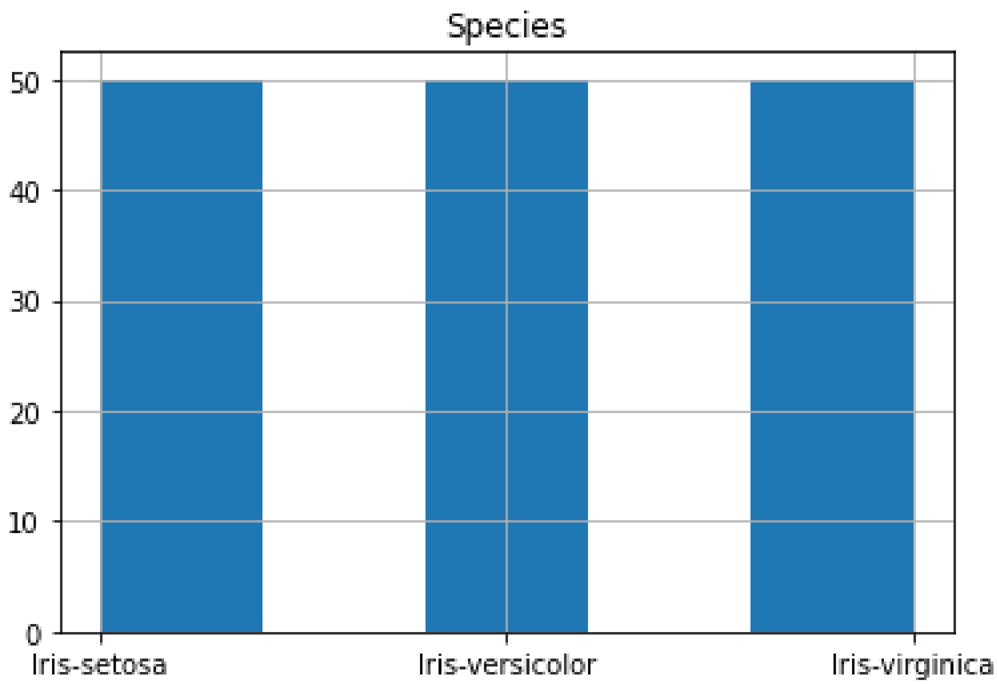
[10]:
```
SepalLengthCm    0.0
SepalWidthCm     0.0
PetalLengthCm    0.0
PetalWidthCm     0.0
```

```
Species          0.0
dtype: float64
```

[11]:
```
df['Species'].value_counts() #Balanced dataset
```

[11]:
```
0    50
1    50
2    50
Name: Species, dtype: int64
```

[12]:
```
labels=['Iris-setosa','Iris-versicolor','Iris-virginica']
hist = df.hist('Species',bins=5)
plt.xticks((0,1,2),labels)
plt.show()
```



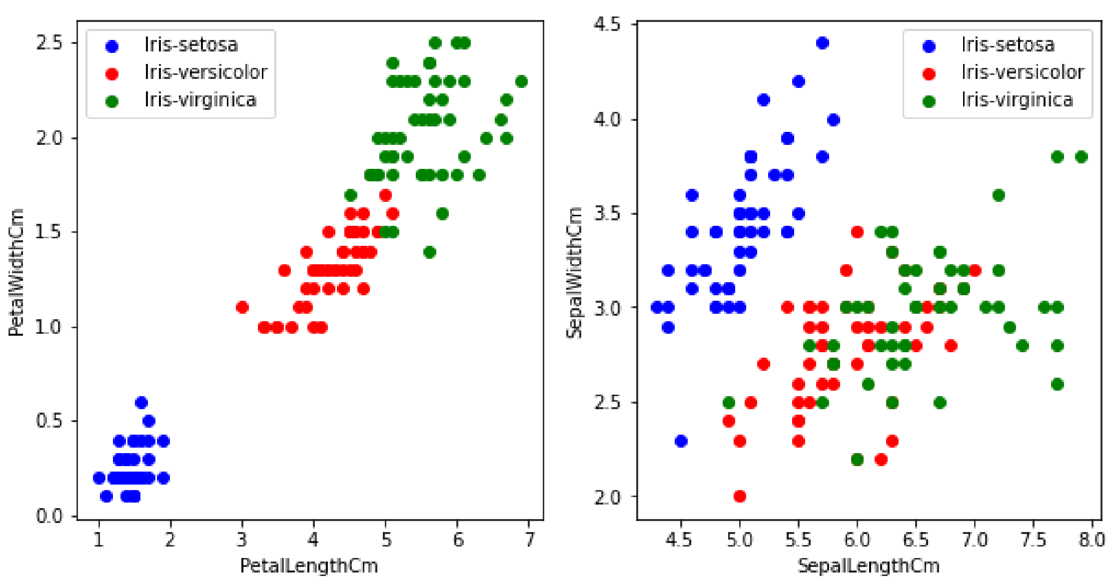
[13]:
```
df.corr()['Species'] # petal width and petal length has a high correlation with␣
↪spicies
```

[13]:
```
SepalLengthCm    0.782561
SepalWidthCm    -0.419446
PetalLengthCm    0.949043
PetalWidthCm     0.956464
Species          1.000000
Name: Species, dtype: float64
```

- setosa petal width and length is smaller but sepal width and length is bigger than others
- versicolor generally groups in the middle
- virginica has large petal width and length, and has large sepal length but smaller sepal width vvvvvvvvvvvvvvvvvvvv description of below vvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvv

[14]:
```
c_dic={0:'b', 1:'r',2:'g'}
f, (ax1, ax2) = plt.subplots(1, 2,figsize=(10,5))
ax1.set_xlabel('PetalLengthCm')
ax1.set_ylabel('PetalWidthCm')
ax2.set_xlabel('SepalLengthCm')
ax2.set_ylabel('SepalWidthCm')

for i in range(0,3):
    X=df[df['Species']==i]['PetalLengthCm']
    Y=df[df['Species']==i]['PetalWidthCm']
    ax1.scatter(x=X,y=Y,c=c_dic[i],label=labels[i])
for i in range(0,3):
    X=df[df['Species']==i]['SepalLengthCm']
    Y=df[df['Species']==i]['SepalWidthCm']
    ax2.scatter(x=X,y=Y,c=c_dic[i],label=labels[i])

ax1.legend()
ax2.legend()
```

[14]: <matplotlib.legend.Legend at 0x1b72986ddf0>

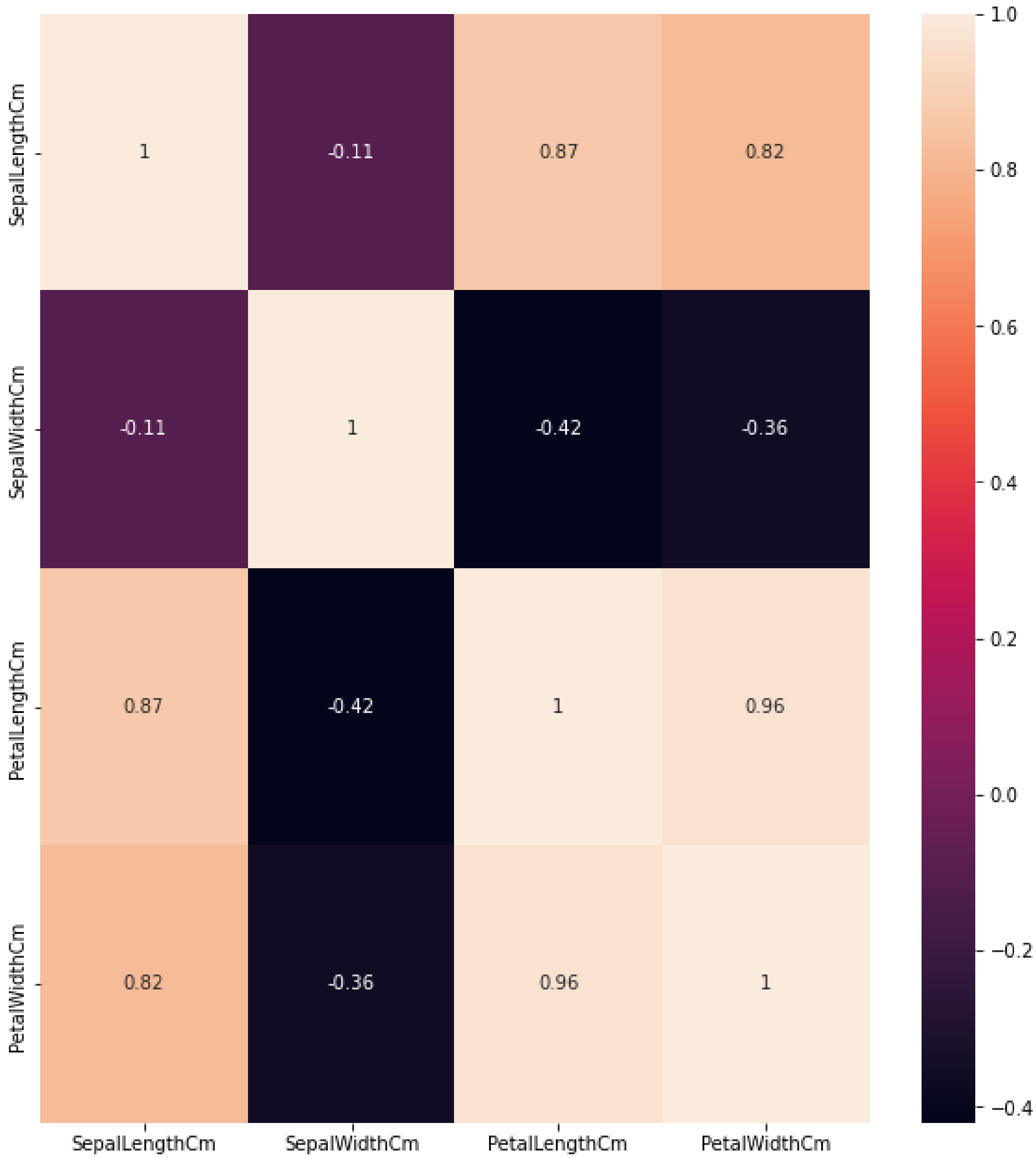


- high correlation between petal length and petal width
- sepal length and sepal width has weak correlation vvvvvvvvvvvvvvvvvvvv description of

below vvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvv

[15]:
```
plt.figure(figsize=(10,11))
sns.heatmap(df.drop('Species',axis=1).corr(),annot=True)
plt.plot()
```

[15]: []



[16]:
```
df.groupby('Species').agg(['mean', 'median']).rename(index={0:'Iris-setosa',1:
↪'Iris-versicolor',2:'Iris-virginica'})
```

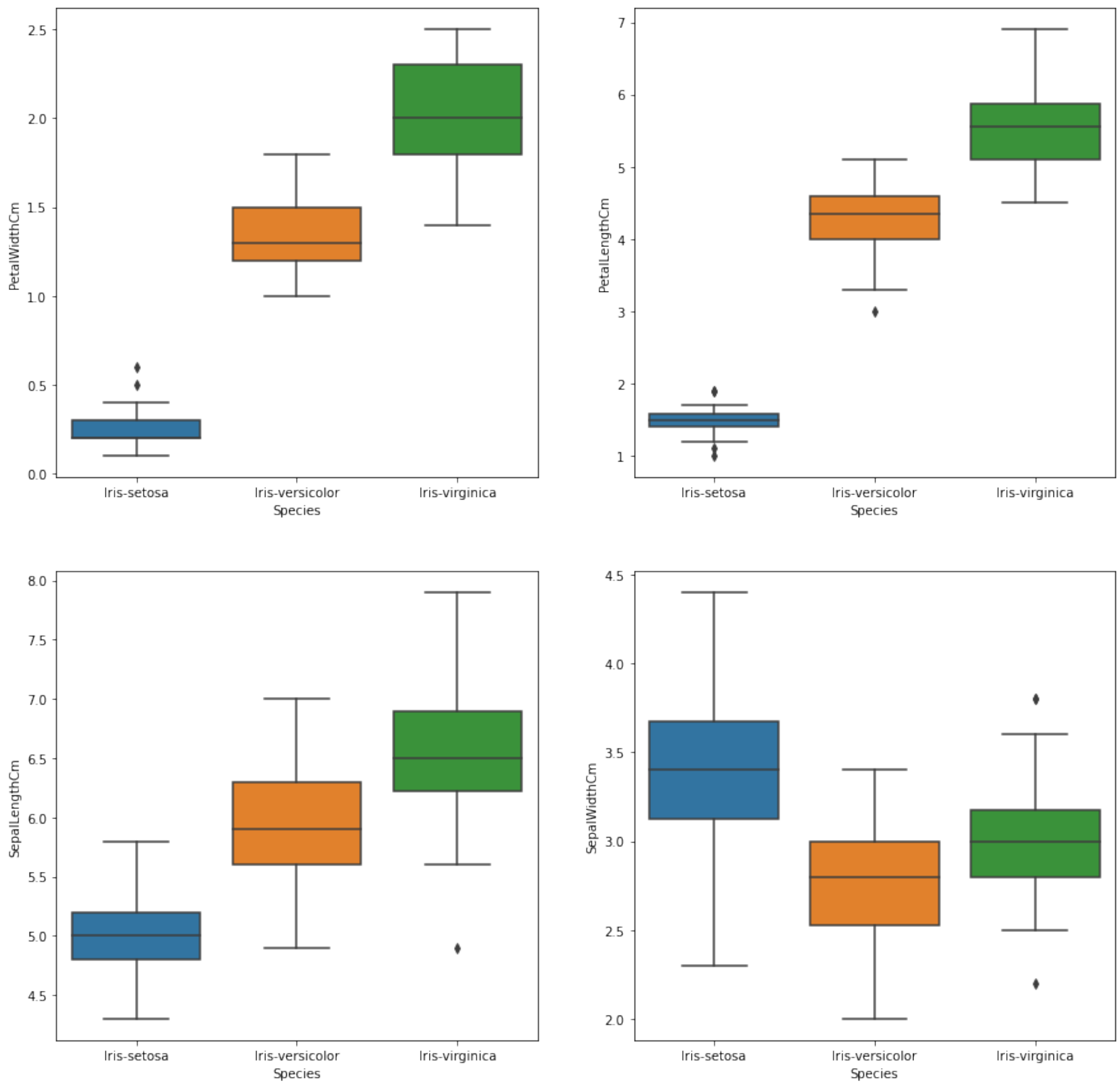
[16]:

```
                   SepalLengthCm        SepalWidthCm        PetalLengthCm        \
                            mean median          mean median          mean median
Species
Iris-setosa                5.006    5.0         3.418    3.4         1.464   1.50
Iris-versicolor            5.936    5.9         2.770    2.8         4.260   4.35
Iris-virginica             6.588    6.5         2.974    3.0         5.552   5.55

                   PetalWidthCm
                           mean median
Species
Iris-setosa               0.244    0.2
Iris-versicolor           1.326    1.3
Iris-virginica            2.026    2.0
```

- Iris-Setosa is not disturbed widely
- Iris-Versicolor is disturbed widely
- Iris-Virginica is highly disturbed vvvvvvvvvvvvvvvvvvvv description of below vvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvv

[17]:

```
f, axes = plt.subplots(2, 2,figsize=(15,15))
sns.boxplot( y="PetalWidthCm", x= "Species", data=df, orient="v" , ax=axes[0,␣
↪0]).set_xticklabels(labels)
sns.boxplot( y="PetalLengthCm", x= "Species", data=df, orient="v" , ax=axes[0,␣
↪1]).set_xticklabels(labels)
sns.boxplot( y="SepalLengthCm", x= "Species", data=df, orient="v" , ax=axes[1,␣
↪0]).set_xticklabels(labels)
sns.boxplot( y="SepalWidthCm", x= "Species", data=df, orient="v" , ax=axes[1,␣
↪1]).set_xticklabels(labels)
plt.show()

ax1.legend()
ax2.legend()
```

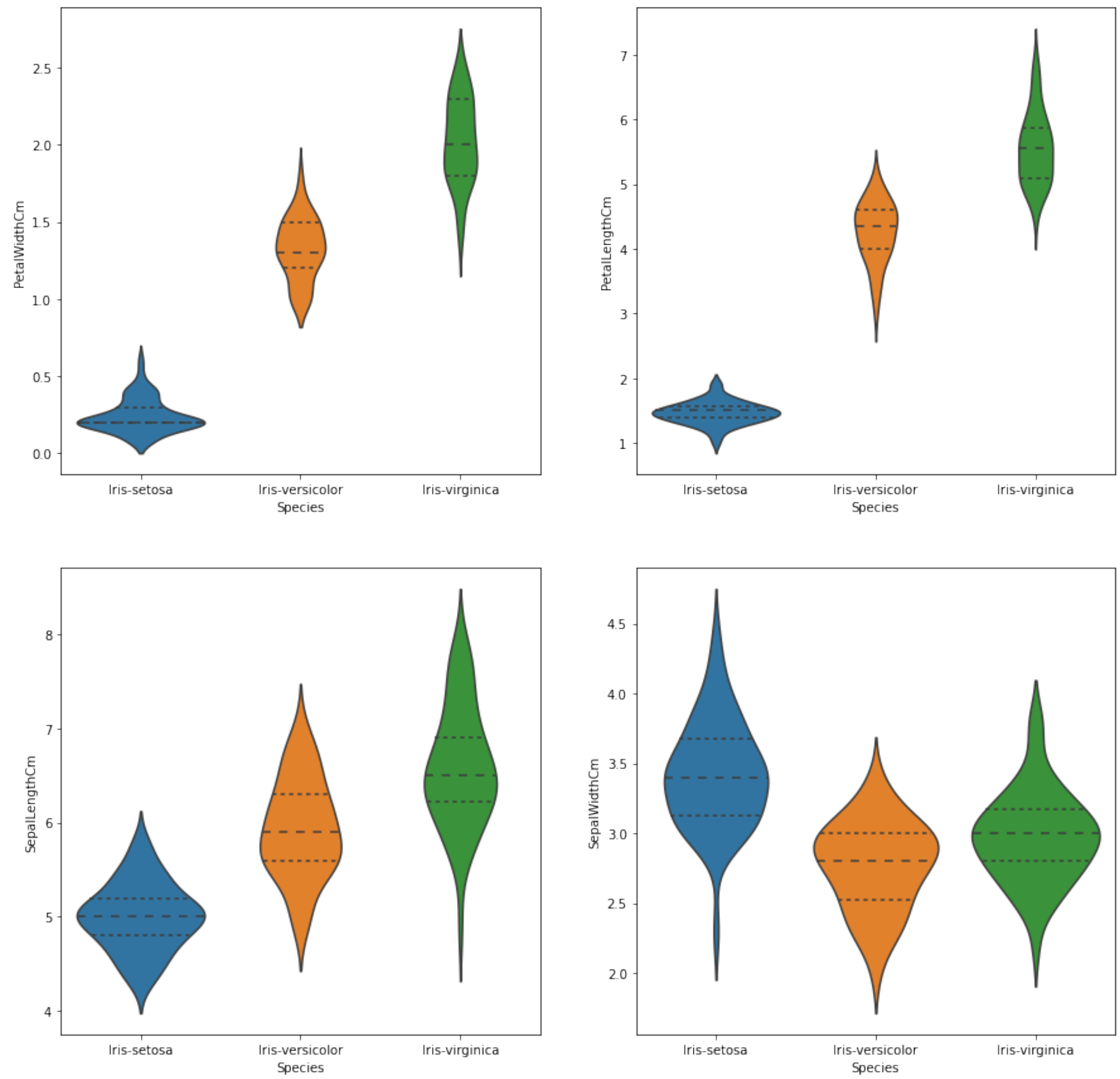


[17]: <matplotlib.legend.Legend at 0x1b72ac2c040>

- Iris-Setosa is not disturbed widely in case of petal width and length
- Iris-Setosa is good disturbed in case of sepal width
- Iris-Versicolor is disturbed widely on every manner
- Iris-Virginica is highly disturbed vvvvvvvvvvvvvvvvvvvv description of below vvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvvv

[686]:
```
fig, axes = plt.subplots(2, 2, figsize=(15,15))
sns.violinplot( y="PetalWidthCm", x= "Species", data=df, orient="v" ,␣
 ↪ax=axes[0, 0],inner="quartile").set_xticklabels(labels)
sns.violinplot( y="PetalLengthCm", x= "Species", data=df, orient="v" ,␣
 ↪ax=axes[0, 1],inner="quartile").set_xticklabels(labels)
```

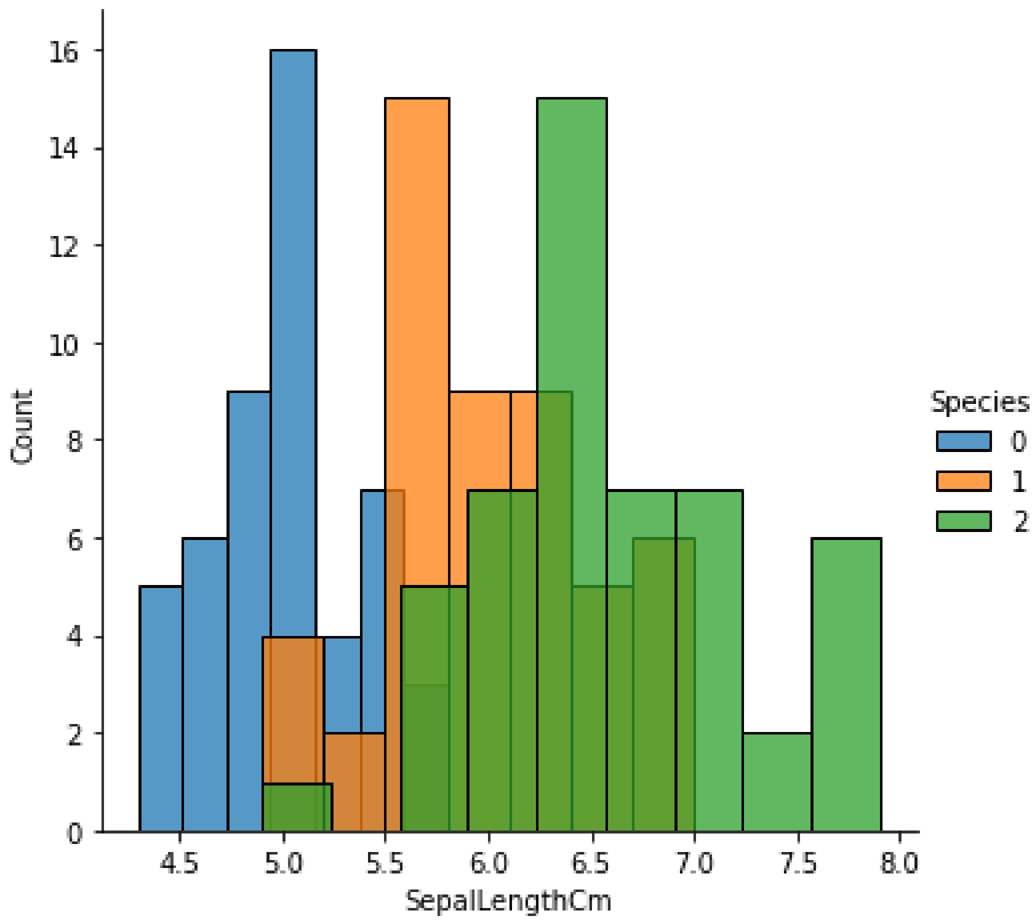
```
sns.violinplot( y="SepalLengthCm", x= "Species", data=df, orient="v" ,␣
↪ax=axes[1, 0],inner="quartile").set_xticklabels(labels)
sns.violinplot( y="SepalWidthCm", x= "Species", data=df, orient="v" ,␣
↪ax=axes[1, 1],inner="quartile").set_xticklabels(labels)
plt.show()
```

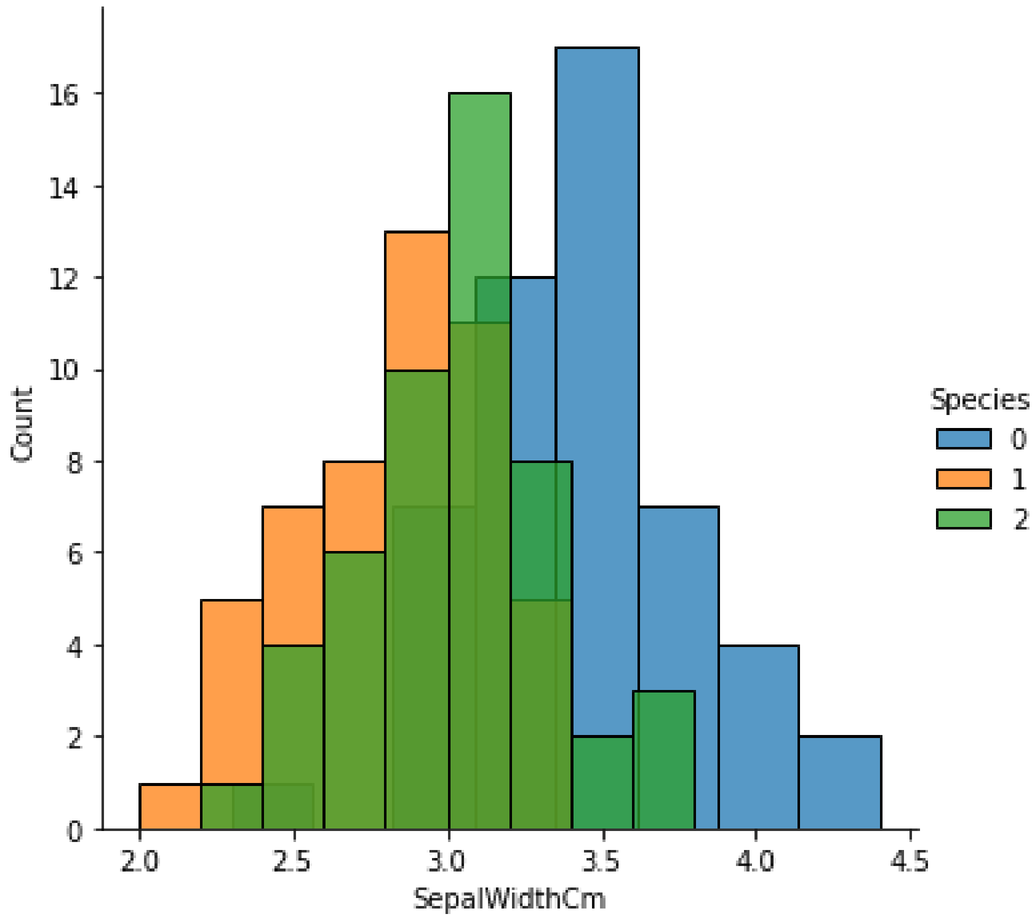


Same Things with others

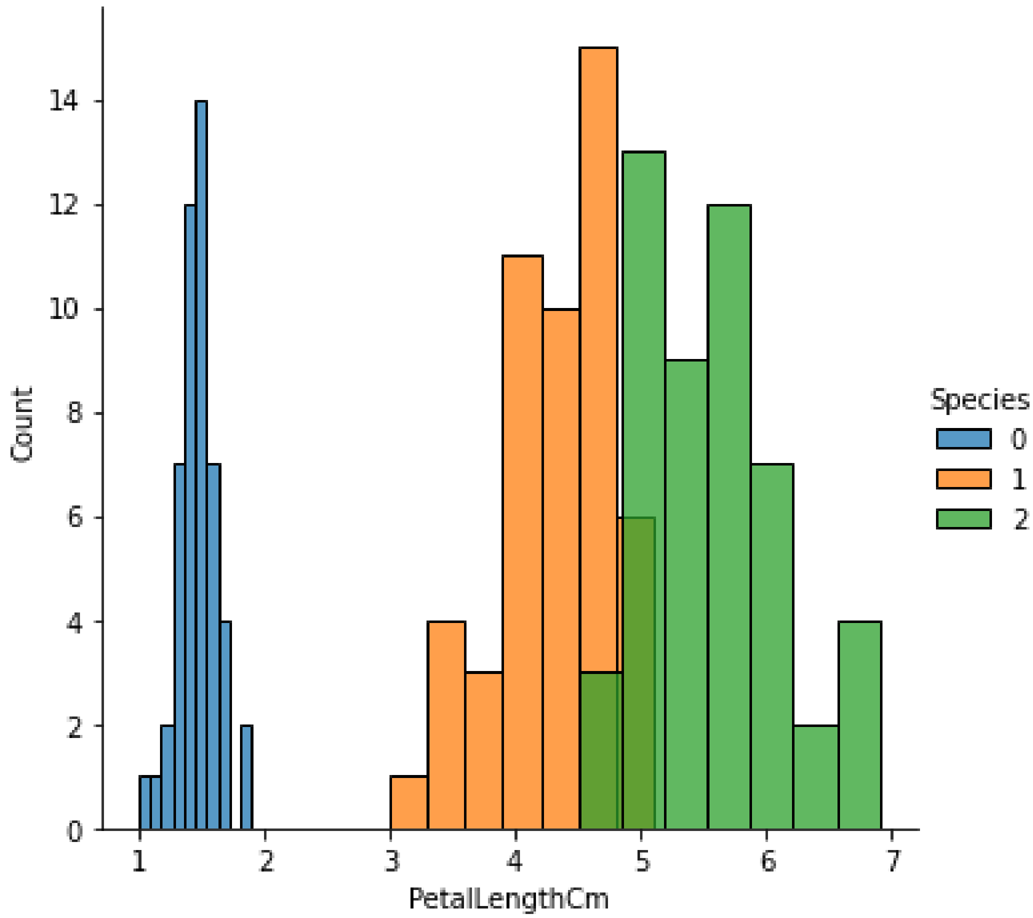
[687]:
```
sns.FacetGrid(df, hue="Species", height=5) \
.map(sns.histplot, "SepalLengthCm") \
.add_legend()

sns.FacetGrid(df, hue="Species", height=5) \
.map(sns.histplot, "SepalWidthCm") \
```

```
.add_legend()

sns.FacetGrid(df, hue="Species", height=5) \
.map(sns.histplot, "PetalLengthCm") \
.add_legend()

sns.FacetGrid(df, hue="Species", height=5) \
.map(sns.histplot, "PetalLengthCm") \
.add_legend()
plt.show()
```

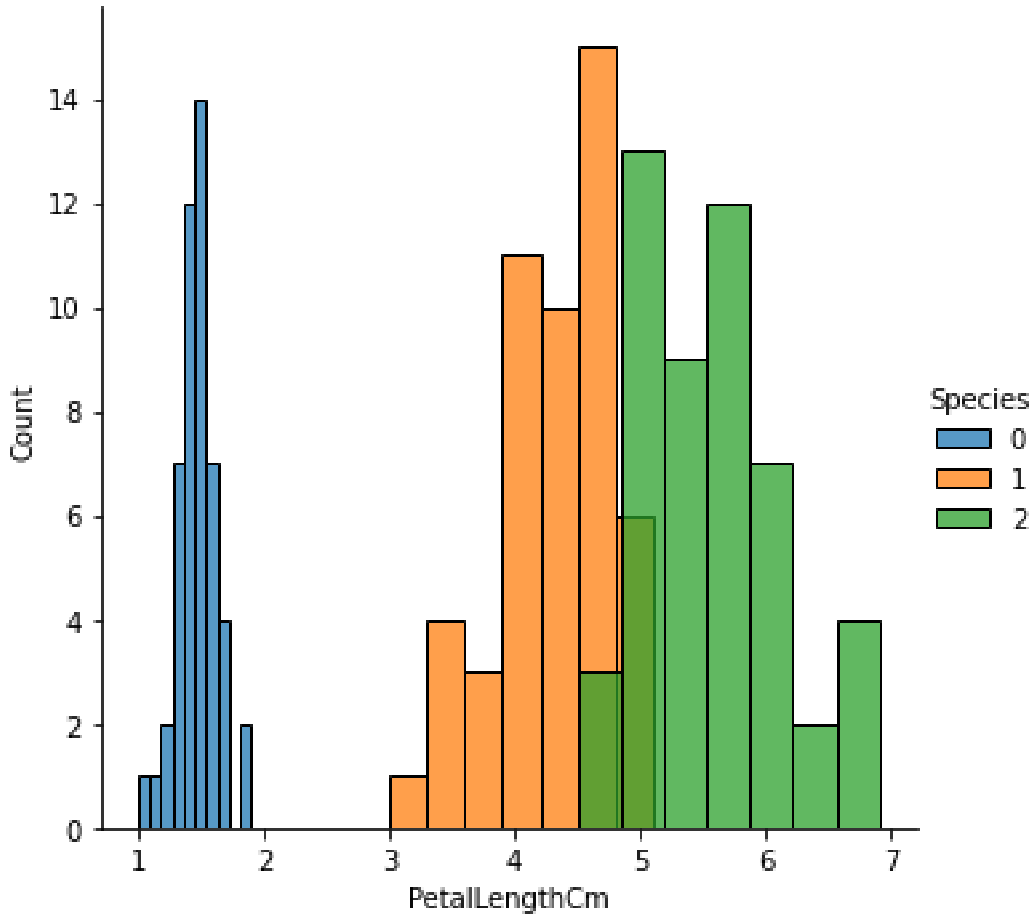




Count
16
14
12
10
8
6
4
2
0
2.0
2.5
3.0
3.5
4.0
4.5
SepalWidthCm
Species
0
1
2

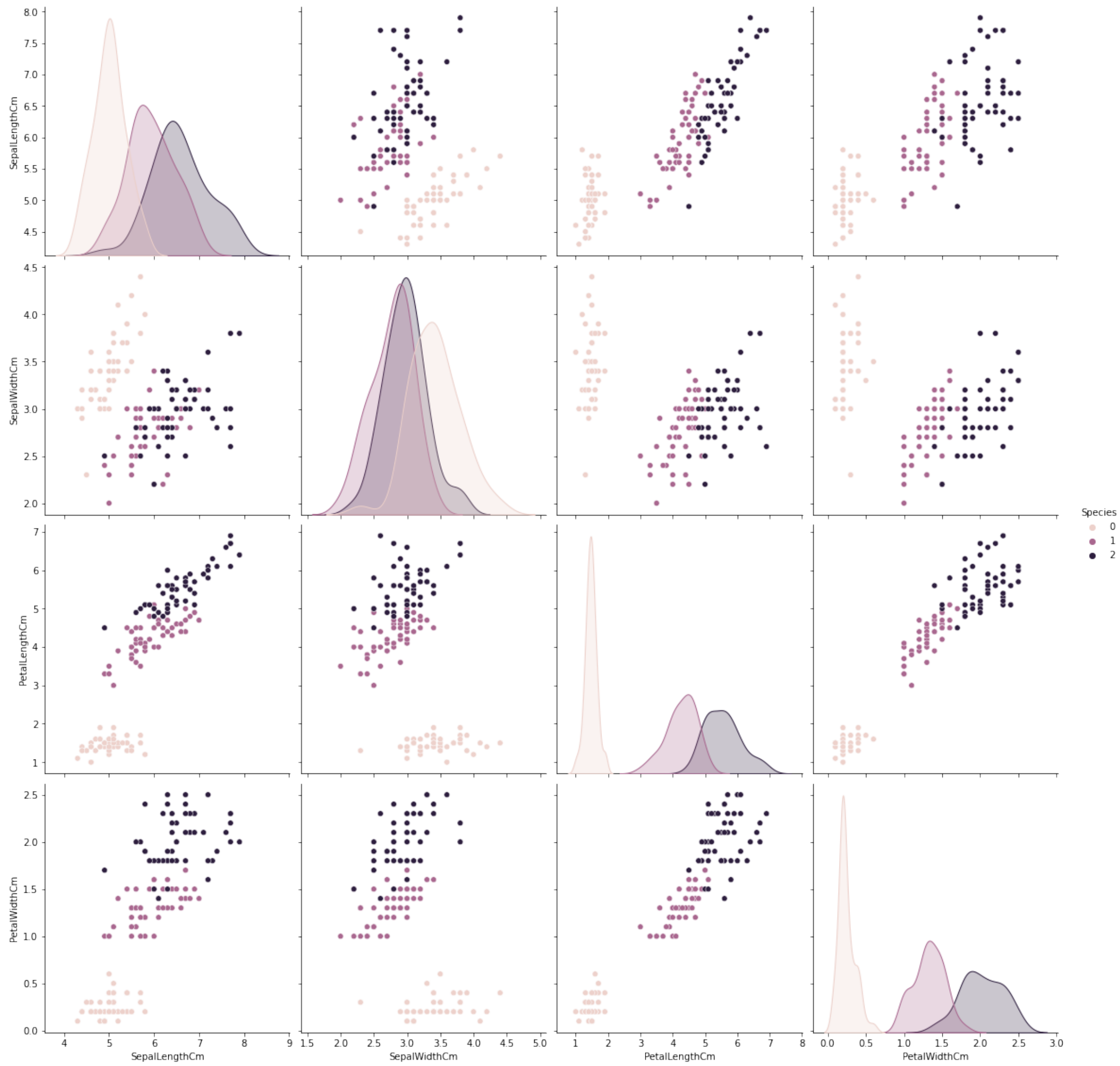


Count
0
2
4
6
8
10
12
14
1
2
3
4
5
6
7
PetalLengthCm
Species
0
1
2



[688]:
```
sns.pairplot(df,hue="Species",height=4)
```

[688]: <seaborn.axisgrid.PairGrid at 0x284a5c3e6a0>



2 Train the classifier

Split dataset to train and test

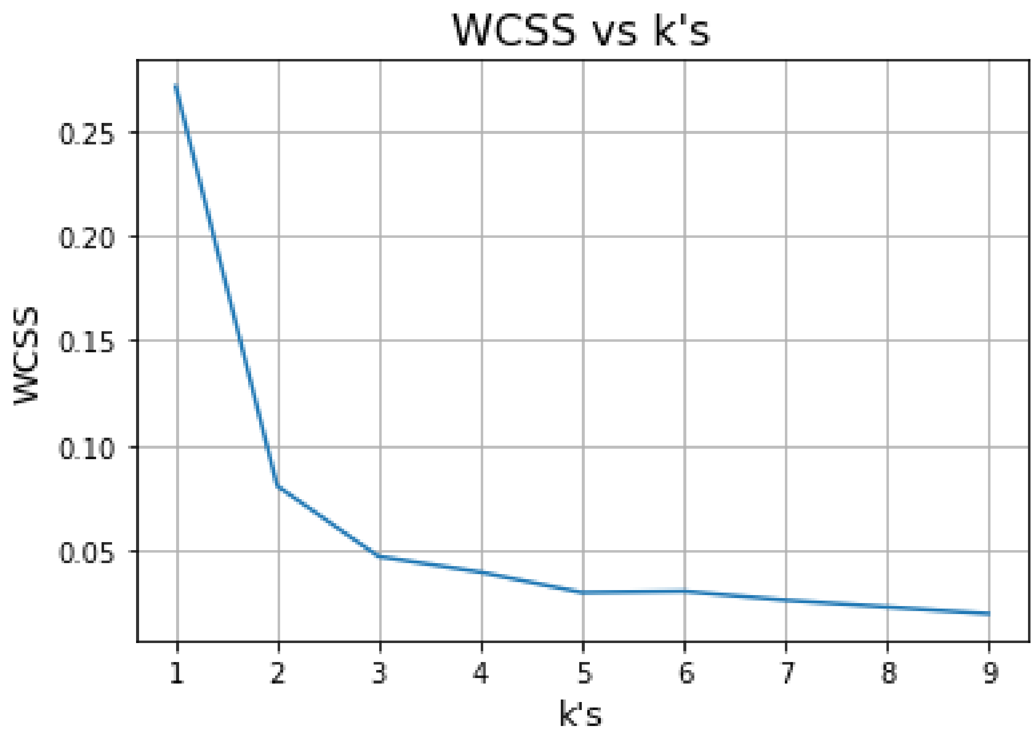
[3]:
```
import pandas as pd
from sklearn import preprocessing
x = df.iloc[:,:4].values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
normalized_X = pd.DataFrame(x_scaled)
```

[4]:

```
def distance_btwn(point1,point2):
    return␣
 ↪((point1[0]-point2[0])**2+(point1[1]-point2[1])**2+(point1[2]-point2[2])**2+(point1[3]-poin
 ↪5
```

[49]:
```
X=df.values.tolist();
y=[];
for row in X:
    y.append(int(row[4]));
    del row[4];
X=pd.Series(normalized_X.values.tolist());
y=pd.Series(y);
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2);

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();
ks = []
distances = []
for i in range(1,10):
    clf = KMeansClusterClassifier(n_cluster=i,m_iter=10000)
    clf.fit(X_train_list,y_train_list);
    centroids=clf.centroids
    temp=0
    for r in X_train_list:
        closesest_dist = 9223372036854775806
        for center in centroids:
            distance = distance_btwn(r,center)
            if distance < closesest_dist:
                closesest_dist = distance
        temp+=((closesest_dist)**(2))
    ks.append(i)
    distances.append(temp/len(X_train_list))
```

[8]:
```
fig = plt.figure(1)
plt.title("WCSS vs k's", fontsize='16')
plt.plot(ks, distances)
plt.xlabel("k's",fontsize='13')
plt.ylabel("WCSS",fontsize='13')
plt.grid()
plt.show()
```



[73]:
```
clf = KMeansClusterClassifier(n_cluster=3,m_iter=10000) #n=3 from elbow method
clf.fit(X_train_list,y_train_list);
```

2.0.1 Train The Classifier

[74]:
```
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)
print("Prediction")
print(xhat);
```

```
Test Features Expected Classification
[0, 1, 0, 2, 0, 1, 2, 2, 0, 0, 2, 0, 0, 2, 1, 1, 0, 2, 1, 2, 1, 0, 2, 1, 0, 0,
1, 2, 2, 2]
Prediction
[0, 1, 0, 2, 0, 1, 2, 2, 0, 0, 2, 0, 0, 2, 1, 1, 0, 2, 1, 1, 1, 0, 2, 1, 0, 0,
2, 1, 2, 2]
Train Features Expected Classification
```

```
[1, 0, 1, 2, 1, 2, 0, 1, 0, 1, 1, 0, 2, 0, 2, 2, 1, 2, 1, 2, 0, 1, 0, 0, 2, 2,
2, 2, 1, 1, 1, 0, 0, 2, 2, 0, 2, 1, 2, 1, 2, 2, 1, 1, 1, 1, 0, 1, 1, 1, 2, 0, 1,
1, 0, 0, 0, 1, 1, 2, 1, 0, 0, 2, 1, 0, 0, 2, 0, 1, 1, 0, 1, 1, 2, 0, 2, 1, 1, 2,
0, 0, 0, 0, 1, 2, 0, 1, 0, 2, 1, 2, 2, 2, 2, 2, 2, 0, 2, 0, 1, 0, 2, 2, 1, 1, 2,
1, 1, 2, 0, 0, 0, 0, 0, 2, 0, 1, 2, 0]
Prediction
[1, 0, 1, 2, 1, 2, 0, 1, 0, 2, 1, 0, 2, 0, 2, 2, 1, 1, 1, 2, 0, 1, 0, 0, 1, 2,
1, 2, 1, 1, 1, 0, 0, 1, 2, 0, 2, 1, 2, 1, 2, 2, 2, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1,
1, 0, 0, 0, 1, 1, 2, 1, 0, 0, 2, 1, 0, 0, 2, 0, 1, 1, 0, 1, 1, 2, 0, 2, 1, 1, 2,
0, 0, 0, 0, 1, 2, 0, 1, 0, 1, 1, 2, 2, 1, 1, 1, 2, 0, 2, 0, 1, 0, 2, 2, 1, 1, 1,
1, 1, 1, 0, 0, 1, 0, 0, 2, 0, 1, 1, 0]
```

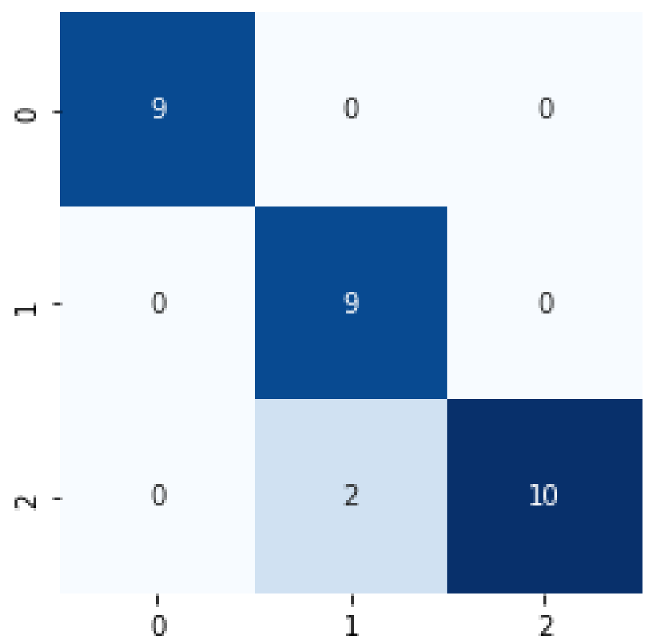
2.0.2 Predict Class of Test values

3 Results

3.0.1 Confusion Matrix of Test

[11]:
```python
conf_mat = metrics.confusion_matrix(y_test_list, yhat)
sns.heatmap(conf_mat, square=True, annot=True, cmap='Blues', fmt='d',
    cbar=False)
```

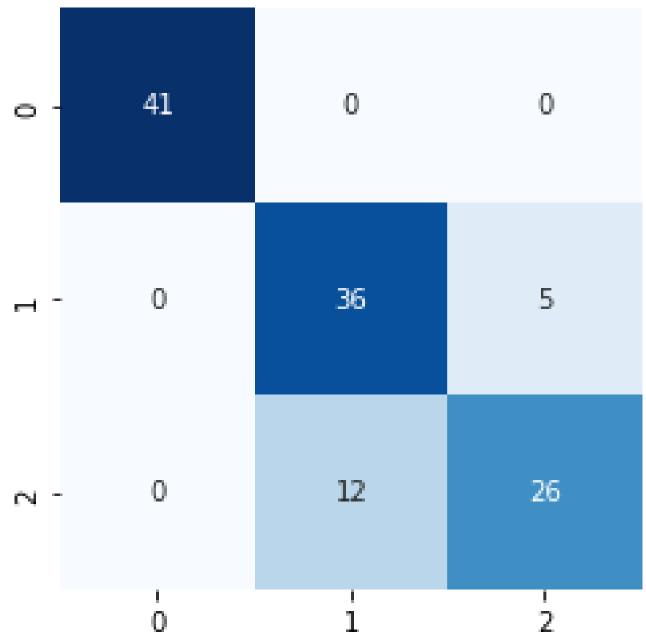
[11]: <AxesSubplot:>



3.0.2 Confusion Matrix of Train

[12]:
```
conf_mat = metrics.confusion_matrix(y_train_list, xhat)
sns.heatmap(conf_mat, square=True, annot=True, cmap='Blues', fmt='d',␣
↪cbar=False)
```

[12]: <AxesSubplot:>



NEEDED FUNCTIONS FOR SCORES

[13]:
```
def perf_measure(yactual, yhat):
    TP = 0
    FP = 0
    TN = 0
    FN = 0

    for i in range(len(yhat)):
        if yactual[i]==yhat[i]==2:
           TN += 1
        if yhat[i]==2 and yactual[i]!=yhat[i]:
           FN += 1
        if yactual[i]==yhat[i]==1:
           TP += 1
        if yhat[i]==1 and yactual[i]!=yhat[i]:
           FP += 1
        if yactual[i]==yhat[i]==0:
           TN += 1
```

```
        if yhat[i]==0 and yactual[i]!=yhat[i]:
           FN += 1



    return(TP, FP, TN, FN)
TP,FP,TN,FN = perf_measure(y_test_list, yhat)
```

3.0.3 F1-Score

[14]:
```
precision = TP/(FP+TP)
recall = TP/(FN+TP)
Accuracy = (TP + TN)/ (TP + FN + TN + FP)
F1 = 2 * (precision * recall ) / (precision+recall)
F1
```

[14]: 0.9

3.0.4 Accuracy

[15]:
```
Accuracy
```

[15]: 0.9333333333333333

3.0.5 Precision

[16]:
```
precision
```

[16]: 0.8181818181818182

3.0.6 Recal

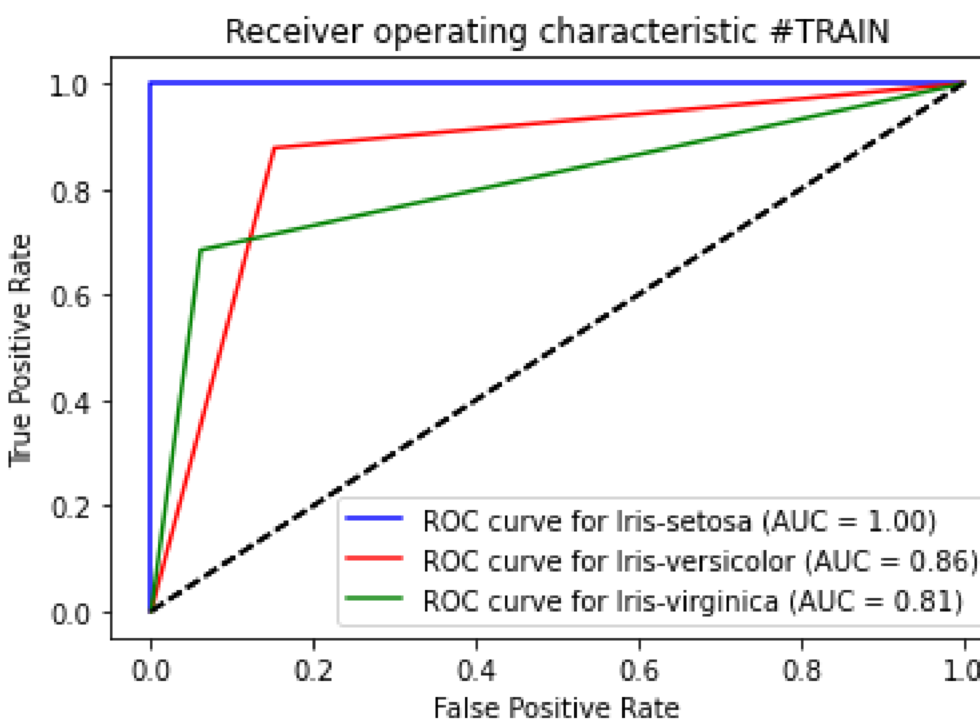
[17]:
```
recall
```

[17]: 1.0

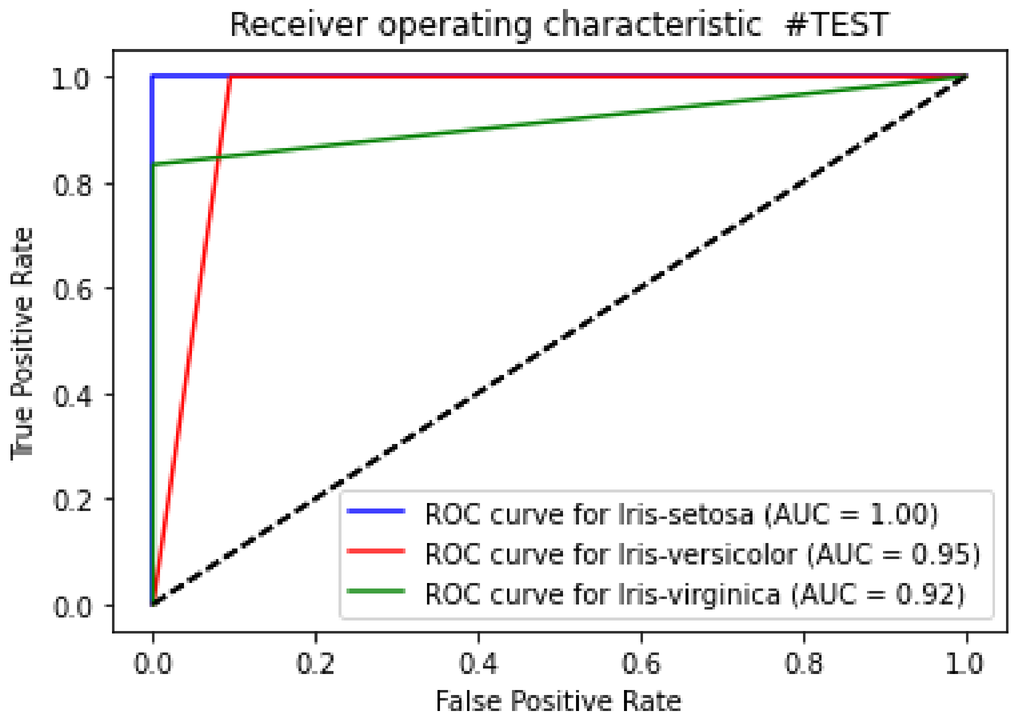
3.0.7 Plot of ROC Curve (Test/Train) and Value of AUC (Test/Train)

[19]:
```
#train
y_train_list = np.array(y_train_list)
y_train_list = label_binarize(y_train_list, classes=[0, 1, 2])
n_classes = y_train_list.shape[1]

xhat= np.array(xhat)
xhat = label_binarize(xhat, classes=[0, 1, 2])
fpr = dict()
```

```
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i],_ = metrics.roc_curve(y_train_list[:, i], xhat[:, i])
    roc_auc[i] = metrics.auc(fpr[i], tpr[i])
plt.figure()
for i in range(n_classes):
    color = "blue" if i==0 else "red" if i ==1 else "green"
    specie = "Iris-setosa" if i==0 else "Iris-versicolor" if i ==1 else␣
 ↪"Iris-virginica"
    plt.plot(fpr[i], tpr[i], label='ROC curve for %s (AUC = %0.2f)' %␣
 ↪(specie,roc_auc[i]),color=color)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic #TRAIN')
plt.legend(loc="lower right")
plt.show()
```



[20]:
```
#test
y_test_list = np.array(y_test_list)
y_test_list = label_binarize(y_test_list, classes=[0, 1, 2])
n_classes = y_test_list.shape[1]

yhat= np.array(yhat)
yhat = label_binarize(yhat, classes=[0, 1, 2])
fpr = dict()
tpr = dict()
roc_auc = dict()
thresholds=np.linspace(0,1,100)
for i in range(n_classes):
    fpr[i], tpr[i],_ = metrics.roc_curve(y_test_list[:, i], yhat[:, i])
    roc_auc[i] = metrics.auc(fpr[i], tpr[i])
plt.figure()
for i in range(n_classes):
    color = "blue" if i==0 else "red" if i ==1 else "green"
    specie = "Iris-setosa" if i==0 else "Iris-versicolor" if i ==1 else␣
↪"Iris-virginica"
    plt.plot(fpr[i], tpr[i], label='ROC curve for %s (AUC = %0.2f)' %␣
↪(specie,roc_auc[i]),color=color)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic  #TEST')
plt.legend(loc="lower right")
plt.show()
```



[21]:
```
clf = DecisionTreeClassifier(max_depth=5)
X=df.values.tolist();
y=[];
for row in X:
    y.append(int(row[4]));
    del row[4];
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);

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();
clf.fit(X_train_list,y_train_list);
```

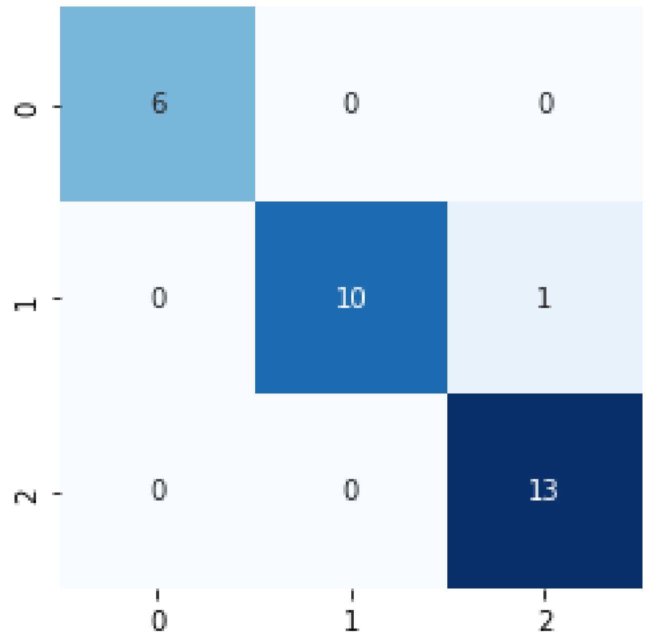
[22]:
```
yhat = clf.predict(X_test_list)
print("Test Features Expected Classification")
print(y_test_list)
print("Prediction")
print(yhat);
xhat = clf.predict(X_train_list)
```

```python
print("Train Features Expected Classification")
print(y_train_list)
print("Prediction")
print(xhat);
```

```
Test Features Expected Classification
[2, 0, 2, 2, 1, 1, 1, 2, 0, 1, 0, 0, 1, 1, 0, 1, 0, 2, 2, 1, 2, 1, 1, 2, 2, 2,
2, 2, 2, 1]
Prediction
[2, 0, 2, 2, 2, 1, 1, 2, 0, 1, 0, 0, 1, 1, 0, 1, 0, 2, 2, 1, 2, 1, 1, 2, 2, 2,
2, 2, 2, 1]
Train Features Expected Classification
[2, 2, 1, 0, 2, 2, 2, 2, 1, 1, 1, 2, 1, 0, 0, 2, 0, 2, 1, 0, 2, 1, 0, 0, 0, 2,
0, 2, 0, 0, 2, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 2, 1, 2, 2, 2, 2, 1, 0, 0, 2, 2, 0,
0, 0, 0, 0, 2, 0, 1, 2, 0, 1, 1, 1, 0, 1, 0, 1, 2, 2, 1, 1, 0, 2, 2, 0, 0, 1, 1,
2, 1, 0, 1, 1, 2, 2, 0, 1, 2, 0, 1, 1, 2, 2, 2, 0, 0, 1, 1, 1, 1, 0, 0, 1, 2, 0,
2, 0, 1, 0, 0, 2, 0, 2, 1, 0, 0, 1, 0]
Prediction
[2, 2, 1, 0, 2, 2, 2, 2, 1, 1, 1, 2, 1, 0, 0, 2, 0, 2, 1, 0, 2, 1, 0, 0, 0, 2,
0, 2, 0, 0, 2, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 2, 1, 2, 2, 2, 2, 1, 0, 0, 2, 2, 0,
0, 0, 0, 0, 2, 0, 1, 2, 0, 1, 1, 1, 0, 1, 0, 1, 2, 2, 1, 1, 0, 2, 2, 0, 0, 1, 1,
2, 1, 0, 1, 1, 2, 2, 0, 1, 2, 0, 1, 1, 2, 2, 2, 0, 0, 1, 1, 1, 1, 0, 0, 1, 2, 0,
2, 0, 1, 0, 0, 2, 0, 2, 1, 0, 0, 1, 0]
```

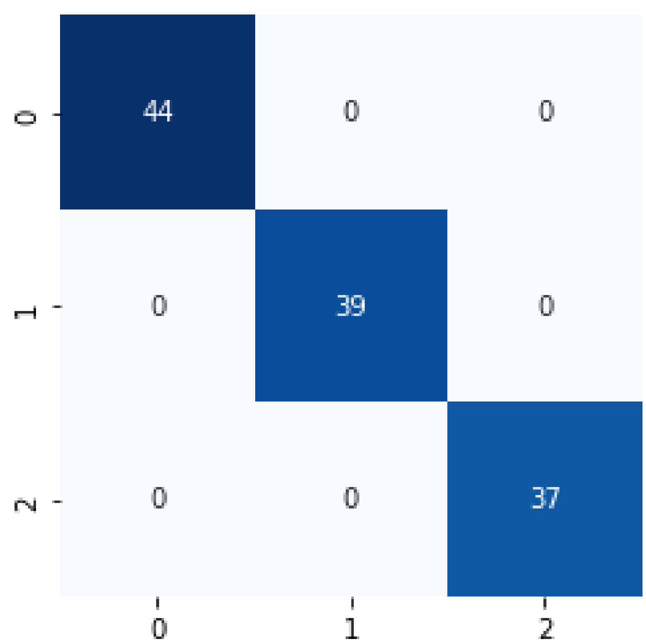
[23]:
```python
conf_mat = metrics.confusion_matrix(y_test_list, yhat)
sns.heatmap(conf_mat, square=True, annot=True, cmap='Blues', fmt='d',
 cbar=False)
```

[23]:
```
<AxesSubplot:>
```



[24]:
```
conf_mat = metrics.confusion_matrix(y_train_list, xhat)
sns.heatmap(conf_mat, square=True, annot=True, cmap='Blues', fmt='d',␣
↪cbar=False)
```

[24]: <AxesSubplot:>



[25]:
```python
TP,FP,TN,FN = perf_measure(y_test_list, yhat)
```

[26]:
```python
precision = TP/(FP+TP)
recall = TP/(FN+TP)
Accuracy = (TP + TN)/ (TP + FN + TN + FP)
F1 = 2 * (precision * recall ) / (precision+recall)
F1
```

[26]: 0.9523809523809523

[27]:
```python
Accuracy
```

[27]: 0.9666666666666667

[28]:
```python
precision
```

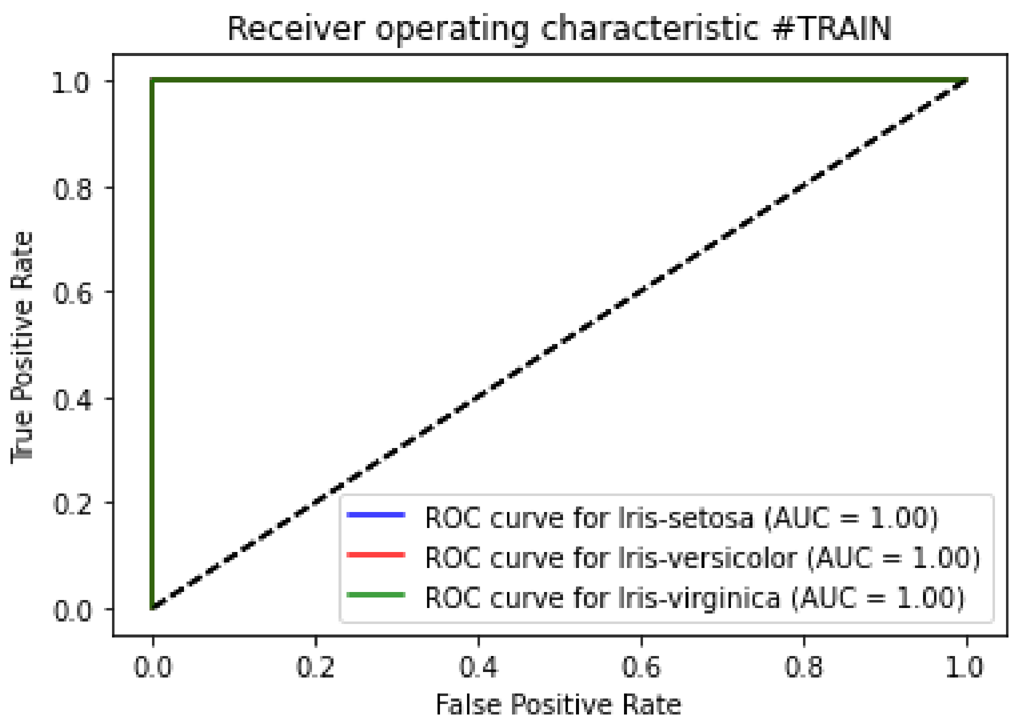
[28]: 1.0

[29]:
```python
recall
```

[29]: 0.9090909090909091

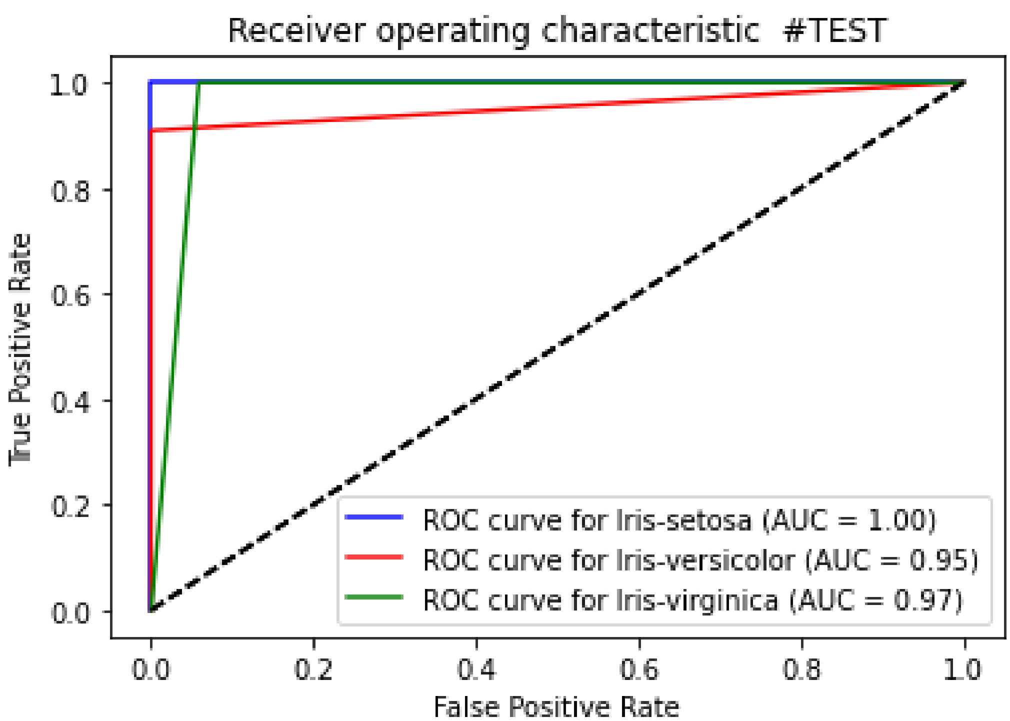
[30]:
```python
#train
y_train_list = np.array(y_train_list)
y_train_list = label_binarize(y_train_list, classes=[0, 1, 2])
n_classes = y_train_list.shape[1]

xhat= np.array(xhat)
xhat = label_binarize(xhat, classes=[0, 1, 2])
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i],_ = metrics.roc_curve(y_train_list[:, i], xhat[:, i])
    roc_auc[i] = metrics.auc(fpr[i], tpr[i])
plt.figure()
for i in range(n_classes):
    color = "blue" if i==0 else "red" if i ==1 else "green"
    specie = "Iris-setosa" if i==0 else "Iris-versicolor" if i ==1 else␣
 ↪"Iris-virginica"
    plt.plot(fpr[i], tpr[i], label='ROC curve for %s (AUC = %0.2f)' %␣
 ↪(specie,roc_auc[i]),color=color)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic #TRAIN')
plt.legend(loc="lower right")
plt.show()
```

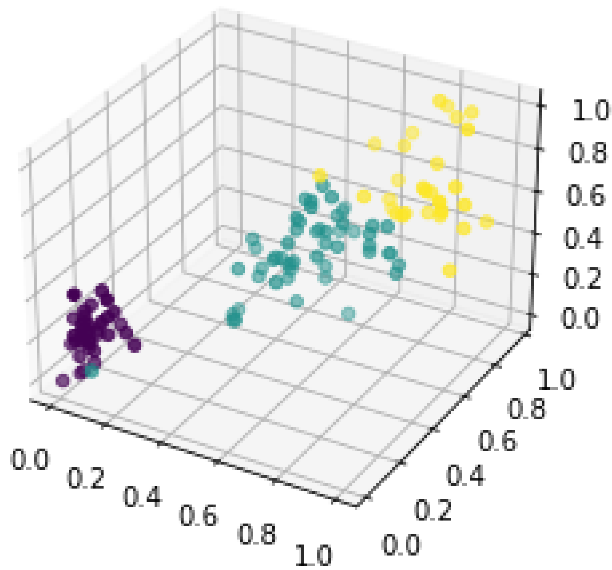


[31]:
```
#test
y_test_list = np.array(y_test_list)
y_test_list = label_binarize(y_test_list, classes=[0, 1, 2])
n_classes = y_test_list.shape[1]

yhat= np.array(yhat)
yhat = label_binarize(yhat, classes=[0, 1, 2])
fpr = dict()
tpr = dict()
roc_auc = dict()
thresholds=np.linspace(0,1,100)
for i in range(n_classes):
    fpr[i], tpr[i],_ = metrics.roc_curve(y_test_list[:, i], yhat[:, i])
    roc_auc[i] = metrics.auc(fpr[i], tpr[i])
plt.figure()
for i in range(n_classes):
    color = "blue" if i==0 else "red" if i ==1 else "green"
```

```
    specie = "Iris-setosa" if i==0 else "Iris-versicolor" if i ==1 else␣
↪"Iris-virginica"
    plt.plot(fpr[i], tpr[i], label='ROC curve for %s (AUC = %0.2f)' %␣
↪(specie,roc_auc[i]),color=color)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic  #TEST')
plt.legend(loc="lower right")
plt.show()
```



[76]:
```
fig = plt.figure()
ax = plt.axes(projection='3d')
tmp = pd.DataFrame(X_train_list)
ax.scatter3D(tmp.iloc[:,3], tmp.iloc[:,2], tmp.iloc[:,0], c=xhat,␣
↪cmap='viridis');
```



Sonuç olarak decision tree'nin knn'den daha iyi bir sınıflandırma yaptığını gözlemledik ve bu gayet normal çünkü decision tree uzayı birden fazla parçalara ayırabiliyor. Fakar knn sadece belli noktalar etrafında toplama işlemi yapabiliyor.