

```
In [123... import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection \
import train_test_split
import seaborn as sns

#import prettytable as pt
```

```
In [123... url = r"https://archive.ics.uci.edu/ml/" \
+ r"machine-learning-databases/iris/iris.data"
data = pd.read_csv(url, names=[ "sepal -length", "sepal -width", "petal -length",
"Class" ])

#data.to_csv("iris_data.csv")
```

Question# 1.1 download IRIS dataset, remove Setosa flowers and assign labels 0 to Versicolor and 1 to Virginica.

```
In [124... a=list(range(0,50))
data.drop(index=a,inplace=True)
label=[]
#print(data.index)
for i in range(len(data)):
    if data["Class"][i+50]=="Iris-versicolor":
        label.append(0)
    elif data["Class"][i+50]=="Iris-virginica":
        label.append(1)
#print(label)
data["label"]=label
Q5_data= pd.read_csv(url, names=[ "sepal -length", "sepal -width", "petal -length",
"Class" ])
Q5_data.drop(index=a,inplace=True)
label=[]
#print(data.index)
for i in range(len(Q5_data)):
    if Q5_data["Class"][i+50]=="Iris-versicolor":
        label.append(0)
    elif Q5_data["Class"][i+50]=="Iris-virginica":
        label.append(1)
#print(label)
Q5_data["label"]=label

# data["Class"]=data["Class"].replace("Iris-versicolor",0)
# data["Class"]=data["Class"].replace("Iris-virginica",1)
#data.to_csv("iris_data1.csv")
```

Question#1.2 for each label and feature compute statistical averages (from training set!) and put them in the following table:

```
In [124... #versicolor_mean=data['petal -length'].loc[data['label'] == 0].mean()
mean_0=[]
mean_0.append(data.loc[(data["label"]==0),:]["petal -length"].mean())
```

```

mean_0.append(data.loc[(data["label"]==0),:]["petal -width"].mean())
mean_0.append(data.loc[(data["label"]==0),:]["sepal -length"].mean())
mean_0.append(data.loc[(data["label"]==0),:]["sepal -width"].mean())
sd_0=[]
sd_0.append(data.loc[(data["label"]==0),:]["petal -length"].std())
sd_0.append(data.loc[(data["label"]==0),:]["petal -width"].std())
sd_0.append(data.loc[(data["label"]==0),:]["sepal -length"].std())
sd_0.append(data.loc[(data["label"]==0),:]["sepal -width"].std())
mean_1=[]
mean_1.append(data.loc[(data["label"]==1),:]["petal -length"].mean())
mean_1.append(data.loc[(data["label"]==1),:]["petal -width"].mean())
mean_1.append(data.loc[(data["label"]==1),:]["sepal -length"].mean())
mean_1.append(data.loc[(data["label"]==1),:]["sepal -width"].mean())
sd_1=[]
sd_1.append(data.loc[(data["label"]==1),:]["petal -length"].std())
sd_1.append(data.loc[(data["label"]==1),:]["petal -width"].std())
sd_1.append(data.loc[(data["label"]==1),:]["sepal -length"].std())
sd_1.append(data.loc[(data["label"]==1),:]["sepal -width"].std())
mean_all=[]
mean_all.append(data["petal -length"].mean())
mean_all.append(data["petal -width"].mean())
mean_all.append(data["sepal -length"].mean())
mean_all.append(data["sepal -width"].mean())
sd_all=[]
sd_all.append(data.loc[(data["label"]==1),:]["petal -length"].std())
sd_all.append(data.loc[(data["label"]==1),:]["petal -width"].std())
sd_all.append(data.loc[(data["label"]==1),:]["sepal -length"].std())
sd_all.append(data.loc[(data["label"]==1),:]["sepal -width"].std())
Q1_d={"Feature":pd.Series(["Petal Lengh","Petal Width","Sepal Lengh","Sepal Wic
    "μ0":pd.Series(mean_0),
    "σ0":pd.Series(sd_0),
    "μ1":pd.Series(mean_1),
    "σ1":pd.Series(sd_1),
    "μall":pd.Series(mean_all),
    "σall":pd.Series(sd_all)}
Q1_df=pd.DataFrame(Q1_d)
print(Q1_df)

```

	Feature	μ_0	σ_0	μ_1	σ_1	μ_{all}	σ_{all}
0	Petal Lengh	4.260	0.469911	5.552	0.551895	4.906	0.551895
1	Petal Width	1.326	0.197753	2.026	0.274650	1.676	0.274650
2	Sepal Lengh	5.936	0.516171	6.588	0.635880	6.262	0.635880
3	Sepal Width	2.770	0.313798	2.974	0.322497	2.872	0.322497

Question# 1.3 for each class, compute the correlation matrix for your 4 features. Which features have the highest and lowest cor- relations?

```

In [124... corrM=Q1_df.corr()
print(corrM)

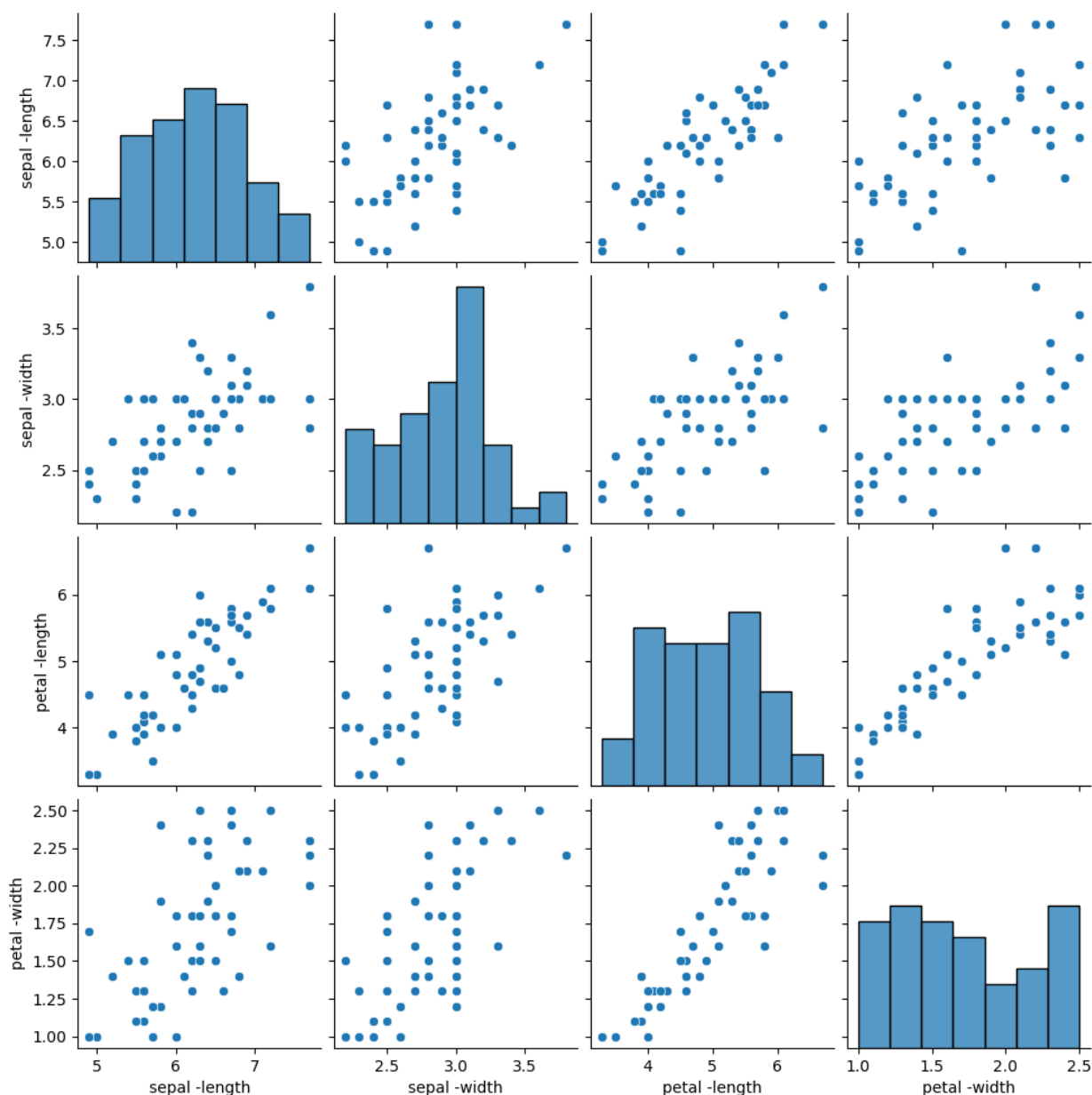
```

	μ_0	σ_0	μ_1	σ_1	μ_{all}	σ_{all}
μ_0	1.000000	0.975090	0.979489	0.967863	0.994450	0.967863
σ_0	0.975090	1.000000	0.987055	0.974510	0.986369	0.974510
μ_1	0.979489	0.987055	1.000000	0.997539	0.995253	0.997539
σ_1	0.967863	0.974510	0.997539	1.000000	0.988352	1.000000
μ_{all}	0.994450	0.986369	0.995253	0.988352	1.000000	0.988352
σ_{all}	0.967863	0.974510	0.997539	1.000000	0.988352	1.000000

Question#4. discuss your findings

Question#2.1 generate histograms of pairwise relationships for a training set (include these histograms in submitted homework). X rain. You can use "pairplot" method of the seaborn package:

```
In [124... X = data[["sepal -length", "sepal -width", "petal -length", "petal -width"]]
y = data["label"]
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.5)
features = ["sepal -length", "sepal -width", "petal -length", "petal -width"]
pair_plot = sns.pairplot(X_train[features])
plt.show()
```



Question#2.2 examine the histograms and for each feature design a simple classifier ("weak learner") for labels. Your classifier can only consist of simple comparison using that single feature. For example,

```
In [124... from socket import TCP_NOTSENT_LOWAT

X_test["sepal_length_label"]=X_test["sepal -length"].apply(lambda x: 1 if x>data
X_test["sepal_width_label"]=X_test["sepal -width"].apply(lambda x: 1 if x>data
X_test["petal -length_label"]=X_test["petal -length"].apply(lambda x: 1 if x>da
X_test["petal -width_label"]=X_test["petal -width"].apply(lambda x: 1 if x>data
X_test.loc[:, "Ture_lable"]=y_test

#Ture Positive
TP_pl=X_test.loc[(X_test["petal -length_label"]==1)&(X_test["Ture_lable"]==1),:]
TP_pw=X_test.loc[(X_test["petal -width_label"]==1)&(X_test["Ture_lable"]==1),:]
TP_sl=X_test.loc[(X_test["sepal_length_label"]==1)&(X_test["Ture_lable"]==1),:]
TP_sw=X_test.loc[(X_test["sepal_width_label"]==1)&(X_test["Ture_lable"]==1),:]

#False positive
FP_pl=X_test.loc[(X_test["petal -length_label"]==1)&(X_test["Ture_lable"]==0),:]
FP_pw=X_test.loc[(X_test["petal -width_label"]==1)&(X_test["Ture_lable"]==0),:]
FP_sl=X_test.loc[(X_test["sepal_length_label"]==1)&(X_test["Ture_lable"]==0),:]
FP_sw=X_test.loc[(X_test["sepal_width_label"]==1)&(X_test["Ture_lable"]==0),:]

#Ture Negative
TN_pl=X_test.loc[(X_test["petal -length_label"]==0)&(X_test["Ture_lable"]==0),:]
TN_pw=X_test.loc[(X_test["petal -width_label"]==0)&(X_test["Ture_lable"]==0),:]
TN_sl=X_test.loc[(X_test["sepal_length_label"]==0)&(X_test["Ture_lable"]==0),:]
TN_sw=X_test.loc[(X_test["sepal_width_label"]==0)&(X_test["Ture_lable"]==0),:]

#False Negative
FN_pl=X_test.loc[(X_test["petal -length_label"]==0)&(X_test["Ture_lable"]==1),:]
FN_pw=X_test.loc[(X_test["petal -width_label"]==0)&(X_test["Ture_lable"]==1),:]
FN_sl=X_test.loc[(X_test["sepal_length_label"]==0)&(X_test["Ture_lable"]==1),:]
FN_sw=X_test.loc[(X_test["sepal_width_label"]==0)&(X_test["Ture_lable"]==1),:]

#Accuracy
ACC_pl=(TN_pl+TP_pl)/50
ACC_pw=(TN_pw+TP_pw)/50
ACC_sl=(TN_sl+TP_sl)/50
ACC_sw=(TN_sw+TP_sw)/50
#X_test['TP_pl'] = np.where((X_test['petal -length_label'] == 1) & (X_test['Ture_lable'] == 1), 1, 0)
#X_test.to_csv("x_test.csv")
Q2_d={"Classifier":pd.Series(["Petal Lengh","Petal Width","Sepal Lengh","Sepal
    "TP":pd.Series([TP_pl,TP_pw,TP_sl,TP_sw]),
    "TN":pd.Series([TN_pl,TN_pw,TN_sl,TN_sw]),
    "FP":pd.Series([FP_pl,FP_pw,FP_sl,FP_sw]),
    "FN":pd.Series([FN_pl,FN_pw,FN_sl,FN_sw]),
    "ACC":pd.Series([ACC_pl,ACC_pw,ACC_sl,ACC_sw])}
Q2_df=pd.DataFrame(Q2_d)

print(Q2_df)
```

	Classifier	TP	TN	FP	FN	ACC
0	Petal Length	22	25	0	3	0.94
1	Petal Width	22	24	1	3	0.92
2	Sepal Length	14	18	7	11	0.64
3	Sepal Width	13	16	9	12	0.58

Question#2.3 discuss your findings and rank your "weak" learners by ac- curacy (from most accurate to least accurate)

In []:

Question#3.1 For each such ensemble classifier, split data into training and test. Apply your classifiers on testing data, compute confusion matrix and summarize the results in a table below (note that no training is done, we are just combining the "weak" learners).

```
In [124... data["sepal_length_label"]=data["sepal -length"].apply(lambda x: 1 if x>data["sepal_length"] else 0)
data["sepal_width_label"]=data["sepal -width"].apply(lambda x: 1 if x>data["sepal_width"] else 0)
data["petal -length_label"]=data["petal -length"].apply(lambda x: 1 if x>data["petal_length"] else 0)
data["petal -width_label"]=data["petal -width"].apply(lambda x: 1 if x>data["petal_width"] else 0)

Q3_1_2_3=[]
for i in range(len(data)):
    if (data["sepal_length_label"][i+50]+data["sepal_width_label"][i+50]+data["petal_length_label"][i+50]+data["petal_width_label"][i+50])>3:
        Q3_1_2_3.append(1)
    else:
        Q3_1_2_3.append(0)
data["Q3_1_2_3"]=Q3_1_2_3

Q3_1_2_4=[]
for i in range(len(data)):
    if (data["sepal_length_label"][i+50]+data["sepal_width_label"][i+50]+data["petal_length_label"][i+50]+data["petal_width_label"][i+50])>3:
        Q3_1_2_4.append(1)
    else:
        Q3_1_2_4.append(0)
data["Q3_1_2_4"]=Q3_1_2_4

Q3_1_3_4=[]
for i in range(len(data)):
    if (data["sepal_length_label"][i+50]+data["petal -length_label"][i+50]+data["petal -width_label"][i+50]+data["sepal_width_label"][i+50])>3:
        Q3_1_3_4.append(1)
    else:
        Q3_1_3_4.append(0)
data["Q3_1_3_4"]=Q3_1_3_4

Q3_2_3_4=[]
for i in range(len(data)):
    if (data["sepal_width_label"][i+50]+data["petal -length_label"][i+50]+data["petal -width_label"][i+50]+data["sepal_length_label"][i+50])>3:
        Q3_2_3_4.append(1)
    else:
        Q3_2_3_4.append(0)
data["Q3_2_3_4"]=Q3_2_3_4
#data.to_csv("Q3.csv")
```

```
#print(data)
```

```
In [124... X3_1 = data[["sepal -length","sepal -width","petal -length","petal -width","Q3_1_2_3"]]
y3_1 = data["label"]
X3_1_train,X3_1_test,y3_1_train,y3_1_test=train_test_split(X3_1, y3_1, train_size=0.2, random_state=42)
X3_1_test.loc[:, "Ture_lable"] = y3_1_test
X3_1_test.to_csv("Q3.csv")
TP_Q3_1_2_3=X3_1_test.loc[(X3_1_test["Q3_1_2_3"]==1)&(X3_1_test["Ture_lable"]==1)]
FP_Q3_1_2_3=X3_1_test.loc[(X3_1_test["Q3_1_2_3"]==1)&(X3_1_test["Ture_lable"]==0)]
TN_Q3_1_2_3=X3_1_test.loc[(X3_1_test["Q3_1_2_3"]==0)&(X3_1_test["Ture_lable"]==1)]
FN_Q3_1_2_3=X3_1_test.loc[(X3_1_test["Q3_1_2_3"]==0)&(X3_1_test["Ture_lable"]==0)]
ACC_Q3_1_2_3=(TN_Q3_1_2_3+TP_Q3_1_2_3)/50
# (TP_Q3_1_2_3,FP_Q3_1_2_3,TN_Q3_1_2_3,FN_Q3_1_2_3)
TP_Q3_1_2_4=X3_1_test.loc[(X3_1_test["Q3_1_2_4"]==1)&(X3_1_test["Ture_lable"]==1)]
FP_Q3_1_2_4=X3_1_test.loc[(X3_1_test["Q3_1_2_4"]==1)&(X3_1_test["Ture_lable"]==0)]
TN_Q3_1_2_4=X3_1_test.loc[(X3_1_test["Q3_1_2_4"]==0)&(X3_1_test["Ture_lable"]==1)]
FN_Q3_1_2_4=X3_1_test.loc[(X3_1_test["Q3_1_2_4"]==0)&(X3_1_test["Ture_lable"]==0)]
ACC_Q3_1_2_4=(TN_Q3_1_2_4+TP_Q3_1_2_4)/50
#print(TP_Q3_1_2_3,X3_1_test["Ture_lable"].sum())
TP_Q3_1_3_4=X3_1_test.loc[(X3_1_test["Q3_1_3_4"]==1)&(X3_1_test["Ture_lable"]==1)]
FP_Q3_1_3_4=X3_1_test.loc[(X3_1_test["Q3_1_3_4"]==1)&(X3_1_test["Ture_lable"]==0)]
TN_Q3_1_3_4=X3_1_test.loc[(X3_1_test["Q3_1_3_4"]==0)&(X3_1_test["Ture_lable"]==1)]
FN_Q3_1_3_4=X3_1_test.loc[(X3_1_test["Q3_1_3_4"]==0)&(X3_1_test["Ture_lable"]==0)]
ACC_Q3_1_3_4=(TN_Q3_1_3_4+TP_Q3_1_3_4)/50
TP_Q3_2_3_4=X3_1_test.loc[(X3_1_test["Q3_2_3_4"]==1)&(X3_1_test["Ture_lable"]==1)]
FP_Q3_2_3_4=X3_1_test.loc[(X3_1_test["Q3_2_3_4"]==1)&(X3_1_test["Ture_lable"]==0)]
TN_Q3_2_3_4=X3_1_test.loc[(X3_1_test["Q3_2_3_4"]==0)&(X3_1_test["Ture_lable"]==1)]
FN_Q3_2_3_4=X3_1_test.loc[(X3_1_test["Q3_2_3_4"]==0)&(X3_1_test["Ture_lable"]==0)]
ACC_Q3_2_3_4=(TN_Q3_2_3_4+TP_Q3_2_3_4)/50
Q3_d={"Classifier":pd.Series(["(1),(2),(3)","(1),(2),(4)","(1),(3),(4)","(2),(3),(4)"],
                             "TP":pd.Series([TP_Q3_1_2_3,TP_Q3_1_2_4,TP_Q3_1_3_4,TP_Q3_2_3_4]),
                             "TN":pd.Series([TN_Q3_1_2_3,TN_Q3_1_2_4,TN_Q3_1_3_4,TN_Q3_2_3_4]),
                             "FP":pd.Series([FP_Q3_1_2_3,FP_Q3_1_2_4,FP_Q3_1_3_4,FP_Q3_2_3_4]),
                             "FN":pd.Series([FN_Q3_1_2_3,FN_Q3_1_2_4,FN_Q3_1_3_4,FN_Q3_2_3_4]),
                             "ACC":pd.Series([ACC_Q3_1_2_3,ACC_Q3_1_2_4,ACC_Q3_1_3_4,ACC_Q3_2_3_4])}
Q3_df=pd.DataFrame(Q3_d)
print(Q3_df)
```

	Classifier	TP	TN	FP	FN	ACC
0	(1),(2),(3)	21	18	3	8	0.78
1	(1),(2),(4)	22	18	3	7	0.80
2	(1),(3),(4)	24	21	0	5	0.90
3	(2),(3),(4)	25	0	4	4	0.92

Question# 3.2 discuss your findings and rank your ensemble learners by accuracy (from most accurate to least accurate)

Question# 3.3 compare "weak learners" and ensemble results.

Question#4.1 you design 4 such density-based classifiers, one for

each of the 4 features. For each classifier, compute the confusion matrix (from a testing set! as before) and summarize them in a table below

```
In [124... from scipy.stats import norm
Q4_X = data[["sepal -length", "sepal -width", "petal -length", "petal -width", "label"]]
Q4_y = data["label"]
Q4_X_train, Q4_X_test, Q4_y_train, Q4_y_test = train_test_split(Q4_X, Q4_y, train_size=0.8, random_state=42)
#print(Q4_X_train)
Q4_1_mu_sl = Q4_X_train["sepal -length"].loc[Q4_X_train['label'] == 1].mean()
Q4_0_mu_sl = Q4_X_train["sepal -length"].loc[Q4_X_train['label'] == 0].mean()
Q4_1_mu_sw = Q4_X_train["sepal -width"].loc[Q4_X_train['label'] == 1].mean()
Q4_0_mu_sw = Q4_X_train["sepal -width"].loc[Q4_X_train['label'] == 0].mean()
Q4_1_mu_pl = Q4_X_train["petal -length"].loc[Q4_X_train['label'] == 1].mean()
Q4_0_mu_pl = Q4_X_train["petal -length"].loc[Q4_X_train['label'] == 0].mean()
Q4_1_mu_pw = Q4_X_train["petal -width"].loc[Q4_X_train['label'] == 1].mean()
Q4_0_mu_pw = Q4_X_train["petal -width"].loc[Q4_X_train['label'] == 0].mean()
Q4_1_std_sl = Q4_X_train["sepal -length"].loc[Q4_X_train['label'] == 1].std()
Q4_0_std_sl = Q4_X_train["sepal -length"].loc[Q4_X_train['label'] == 0].std()
Q4_1_std_sw = Q4_X_train["sepal -width"].loc[Q4_X_train['label'] == 1].std()
Q4_0_std_sw = Q4_X_train["sepal -width"].loc[Q4_X_train['label'] == 0].std()
Q4_1_std_pl = Q4_X_train["petal -length"].loc[Q4_X_train['label'] == 1].std()
Q4_0_std_pl = Q4_X_train["petal -length"].loc[Q4_X_train['label'] == 0].std()
Q4_1_std_pw = Q4_X_train["petal -width"].loc[Q4_X_train['label'] == 1].std()
Q4_0_std_pw = Q4_X_train["petal -width"].loc[Q4_X_train['label'] == 0].std()

#print(Q4_X_test, "\n", Q4_X_test.iloc[[0], [1]])
Q4_petal_length = []
for i in range(len(Q4_X_test)):
    P_0 = norm.pdf((Q4_X_test.iloc[[i], [2]] - Q4_0_mu_pl) / Q4_0_std_pl)
    P_1 = norm.pdf((Q4_X_test.iloc[[i], [2]] - Q4_1_mu_pl) / Q4_1_std_pl)
    if P_0 > P_1:
        Q4_petal_length.append(0)
    else:
        Q4_petal_length.append(1)
Q4_X_test["pl_label"] = Q4_petal_length

Q4_petal_width = []
for i in range(len(Q4_X_test)):
    P_0 = norm.pdf((Q4_X_test.iloc[[i], [3]] - Q4_0_mu_pw) / Q4_0_std_pw)
    P_1 = norm.pdf((Q4_X_test.iloc[[i], [3]] - Q4_1_mu_pw) / Q4_1_std_pw)
    if P_0 > P_1:
        Q4_petal_width.append(0)
    else:
        Q4_petal_width.append(1)
Q4_X_test["pw_label"] = Q4_petal_width

Q4_sepal_length = []
for i in range(len(Q4_X_test)):
    P_0 = norm.pdf((Q4_X_test.iloc[[i], [0]] - Q4_0_mu_sl) / Q4_0_std_sl)
    P_1 = norm.pdf((Q4_X_test.iloc[[i], [0]] - Q4_1_mu_sl) / Q4_1_std_sl)
    if P_0 > P_1:
        Q4_sepal_length.append(0)
    else:
        Q4_sepal_length.append(1)
Q4_X_test["sl_label"] = Q4_sepal_length
```



```

Q4_sepal_width=[]
for i in range(len(Q4_X_test)):
    P_0=norm.pdf((Q4_X_test.iloc[[i],[1]] - Q4_0_mu_sw)/Q4_0_std_sw)
    P_1=norm.pdf((Q4_X_test.iloc[[i],[1]] - Q4_1_mu_sw)/Q4_1_std_sw)
    if P_0>P_1:
        Q4_sepal_width.append(0)
    else:
        Q4_sepal_width.append(1)
Q4_X_test["sw_label"]=Q4_sepal_width
Q4_X_test.to_csv("Q4.csv")
#print(Q4_X_test)
#Ture Positive
Q4_TP_pl=Q4_X_test.loc[(Q4_X_test["pl_label"]==1)&(Q4_X_test["label"]==1),:]["1"]
Q4_TP_pw=Q4_X_test.loc[(Q4_X_test["pw_label"]==1)&(Q4_X_test["label"]==1),:]["1"]
Q4_TP_sl=Q4_X_test.loc[(Q4_X_test["sl_label"]==1)&(Q4_X_test["label"]==1),:]["1"]
Q4_TP_sw=Q4_X_test.loc[(Q4_X_test["sw_label"]==1)&(Q4_X_test["label"]==1),:]["1"]

#False Positive
Q4_FP_pl=Q4_X_test.loc[(Q4_X_test["pl_label"]==1)&(Q4_X_test["label"]==0),:]["1"]
Q4_FP_pw=Q4_X_test.loc[(Q4_X_test["pw_label"]==1)&(Q4_X_test["label"]==0),:]["1"]
Q4_FP_sl=Q4_X_test.loc[(Q4_X_test["sl_label"]==1)&(Q4_X_test["label"]==0),:]["1"]
Q4_FP_sw=Q4_X_test.loc[(Q4_X_test["sw_label"]==1)&(Q4_X_test["label"]==0),:]["1"]

#True Negative
Q4_TN_pl=Q4_X_test.loc[(Q4_X_test["pl_label"]==0)&(Q4_X_test["label"]==0),:]["1"]
Q4_TN_pw=Q4_X_test.loc[(Q4_X_test["pw_label"]==0)&(Q4_X_test["label"]==0),:]["1"]
Q4_TN_sl=Q4_X_test.loc[(Q4_X_test["sl_label"]==0)&(Q4_X_test["label"]==0),:]["1"]
Q4_TN_sw=Q4_X_test.loc[(Q4_X_test["sw_label"]==0)&(Q4_X_test["label"]==0),:]["1"]

#False Negative
Q4_FN_pl=Q4_X_test.loc[(Q4_X_test["pl_label"]==0)&(Q4_X_test["label"]==1),:]["1"]
Q4_FN_pw=Q4_X_test.loc[(Q4_X_test["pw_label"]==0)&(Q4_X_test["label"]==1),:]["1"]
Q4_FN_sl=Q4_X_test.loc[(Q4_X_test["sl_label"]==0)&(Q4_X_test["label"]==1),:]["1"]
Q4_FN_sw=Q4_X_test.loc[(Q4_X_test["sw_label"]==0)&(Q4_X_test["label"]==1),:]["1"]
#Accuracy
Q4_ACC_pl=(Q4_TN_pl+Q4_TP_pl)/50
Q4_ACC_pw=(Q4_TN_pw+Q4_TP_pw)/50
Q4_ACC_sl=(Q4_TN_sl+Q4_TP_sl)/50
Q4_ACC_sw=(Q4_TN_sw+Q4_TP_sw)/50

Q4_d={"Classifier":pd.Series(["(1) Petal Lengh","(2) Petal Width","(3) Sepal Le
    "TP":pd.Series([Q4_TP_pl,Q4_TP_pw,Q4_FP_sl,Q4_FP_sw]),
    "TN":pd.Series([Q4_TN_pl,Q4_TN_pw,Q4_TN_sl,Q4_TN_sw]),
    "FP":pd.Series([Q4_FP_pl,Q4_FP_pw,Q4_FP_sl,Q4_FP_sw]),
    "FN":pd.Series([Q4_FN_pl,Q4_FN_pw,Q4_FN_sl,Q4_FN_sw]),
    "ACC":pd.Series([Q4_ACC_pl,Q4_ACC_pw,Q4_ACC_sl,Q4_ACC_sw])}
Q4_df=pd.DataFrame(Q4_d)
print(Q4_df)

```

	Classifier	TP	TN	FP	FN	ACC
0	(1) Petal Lengh	21	26	2	26	0.94
1	(2) Petal Width	21	27	1	27	0.96
2	(3) Sepal Lengh	5	23	5	23	0.86
3	(4) Sepal Width	11	17	11	17	0.68

Question#4.2 discuss your findings and rank your density-based "weak" learners by accuracy (from most accurate to least accurate)

In []:

Question#5.1 For each such ensemble classifier, compute confusion matrix (on testing data!) and summarize the results in a table below

```
In [124... Q5_1_mu_sl=data["sepal -length"].loc[data['label'] == 1].mean()
Q5_0_mu_sl=data["sepal -length"].loc[data['label'] == 0].mean()
Q5_1_mu_sw=data["sepal -width"].loc[data['label'] == 1].mean()
Q5_0_mu_sw=data["sepal -width"].loc[data['label'] == 0].mean()
Q5_1_mu_pl=data["petal -length"].loc[data['label'] == 1].mean()
Q5_0_mu_pl=data["petal -length"].loc[data['label'] == 0].mean()
Q5_1_mu_pw=data["petal -width"].loc[data['label'] == 1].mean()
Q5_0_mu_pw=data["petal -width"].loc[data['label'] == 0].mean()
Q5_1_std_sl=data["sepal -length"].loc[data['label'] == 1].std()
Q5_0_std_sl=data["sepal -length"].loc[data['label'] == 0].std()
Q5_1_std_sw=data["sepal -width"].loc[data['label'] == 1].std()
Q5_0_std_sw=data["sepal -width"].loc[data['label'] == 0].std()
Q5_1_std_pl=data["petal -length"].loc[data['label'] == 1].std()
Q5_0_std_pl=data["petal -length"].loc[data['label'] == 0].std()
Q5_1_std_pw=data["petal -width"].loc[data['label'] == 1].std()
Q5_0_std_pw=data["petal -width"].loc[data['label'] == 0].std()

Q5_petal_length=[]
for i in range(len(Q5_data)):
    P_0=norm.pdf((Q5_data.iloc[[i],[2]] - Q5_0_mu_pl)/Q5_0_std_pl)
    P_1=norm.pdf((Q5_data.iloc[[i],[2]] - Q5_1_mu_pl)/Q5_1_std_pl)
    if P_0>P_1:
        Q5_petal_length.append(0)
    else:
        Q5_petal_length.append(1)
Q5_data["pl_label"]=Q5_petal_length

Q5_petal_width=[]
for i in range(len(Q5_data)):
    P_0=norm.pdf((Q5_data.iloc[[i],[3]] - Q5_0_mu_pw)/Q5_0_std_pw)
    P_1=norm.pdf((Q5_data.iloc[[i],[3]] - Q5_1_mu_pw)/Q5_1_std_pw)
    if P_0>P_1:
        Q5_petal_width.append(0)
    else:
        Q5_petal_width.append(1)
Q5_data["pw_label"]=Q5_petal_width

Q5_sepal_length=[]
for i in range(len(Q5_data)):
    P_0=norm.pdf((Q5_data.iloc[[i],[0]] - Q5_0_mu_sl)/Q5_0_std_sl)
    P_1=norm.pdf((Q5_data.iloc[[i],[0]] - Q5_1_mu_sl)/Q5_1_std_sl)
    if P_0>P_1:
        Q5_sepal_length.append(0)
    else:
        Q5_sepal_length.append(1)
Q5_data["sl_label"]=Q5_sepal_length

Q5_sepal_width=[]
for i in range(len(Q5_data)):
    P_0=norm.pdf((Q5_data.iloc[[i],[1]] - Q5_0_mu_sw)/Q5_0_std_sw)
    P_1=norm.pdf((Q5_data.iloc[[i],[1]] - Q5_1_mu_sw)/Q5_1_std_sw)
```

```

    if P_0>P_1:
        Q5_sepal_width.append(0)
    else:
        Q5_sepal_width.append(1)
Q5_data["sw_label"]=Q5_sepal_width

#####
Q5_data["sepal_length_label"]=Q5_data["sepal -length"].apply(lambda x: 1 if x>data["sepal -length"].median() else 0)
Q5_data["sepal_width_label"]=Q5_data["sepal -width"].apply(lambda x: 1 if x>data["sepal -width"].median() else 0)
Q5_data["petal -length_label"]=Q5_data["petal -length"].apply(lambda x: 1 if x>data["petal -length"].median() else 0)
Q5_data["petal -width_label"]=Q5_data["petal -width"].apply(lambda x: 1 if x>data["petal -width"].median() else 0)

Q5_1_2_3=[]
for i in range(len(Q5_data)):
    if (Q5_data["sepal_length_label"][i+50]+Q5_data["sepal_width_label"][i+50]+Q5_data["petal -length_label"][i+50]+Q5_data["petal -width_label"][i+50])>3:
        Q5_1_2_3.append(1)
    else:
        Q5_1_2_3.append(0)
Q5_data["Q3_1_2_3"]=Q5_1_2_3

Q5_1_2_4=[]
for i in range(len(Q5_data)):
    if (Q5_data["sepal_length_label"][i+50]+Q5_data["sepal_width_label"][i+50]+Q5_data["petal -length_label"][i+50]+Q5_data["petal -width_label"][i+50])>2:
        Q5_1_2_4.append(1)
    else:
        Q5_1_2_4.append(0)
Q5_data["Q3_1_2_4"]=Q5_1_2_4

Q5_1_3_4=[]
for i in range(len(Q5_data)):
    if (Q5_data["sepal_length_label"][i+50]+Q5_data["petal -length_label"][i+50]+Q5_data["petal -width_label"][i+50])>2:
        Q5_1_3_4.append(1)
    else:
        Q5_1_3_4.append(0)
Q5_data["Q3_1_3_4"]=Q5_1_3_4

Q5_2_3_4=[]
for i in range(len(Q5_data)):
    if (Q5_data["sepal_width_label"][i+50]+Q5_data["petal -length_label"][i+50]+Q5_data["petal -width_label"][i+50])>2:
        Q5_2_3_4.append(1)
    else:
        Q5_2_3_4.append(0)
Q5_data["Q3_2_3_4"]=Q5_2_3_4

#####

X5_1 = Q5_data[["sepal -length","sepal -width","petal -length","petal -width","label"]]
y5_1 = Q5_data["label"]
X5_1_train,X5_1_test,y5_1_train,y5_1_test=train_test_split(X5_1, y5_1, train_size=0.8, random_state=42)
X5_1_test.loc[:,"Ture_label"]=y5_1_test
X5_1_test.to_csv("Q3.csv")
TP_Q5_1_2_3=X5_1_test.loc[(X5_1_test["Q3_1_2_3"]==1)&(X5_1_test["Ture_label"]==1)]
FP_Q5_1_2_3=X5_1_test.loc[(X5_1_test["Q3_1_2_3"]==1)&(X5_1_test["Ture_label"]==0)]
TN_Q5_1_2_3=X5_1_test.loc[(X5_1_test["Q3_1_2_3"]==0)&(X5_1_test["Ture_label"]==1)]
FN_Q5_1_2_3=X5_1_test.loc[(X5_1_test["Q3_1_2_3"]==0)&(X5_1_test["Ture_label"]==0)]
ACC_Q5_1_2_3=(TN_Q5_1_2_3+TP_Q5_1_2_3)/50
# (TP_Q3_1_2_3,FP_Q3_1_2_3,TN_Q3_1_2_3,FN_Q3_1_2_3)
TP_Q5_1_2_4=X5_1_test.loc[(X5_1_test["Q3_1_2_4"]==1)&(X5_1_test["Ture_label"]==1)]
FP_Q5_1_2_4=X5_1_test.loc[(X5_1_test["Q3_1_2_4"]==1)&(X5_1_test["Ture_label"]==0)]

```

```

TN_Q5_1_2_4=X5_1_test.loc[(X5_1_test["Q3_1_2_4"]==0)&(X5_1_test["Ture_lable"]==0)]
FN_Q5_1_2_4=X5_1_test.loc[(X5_1_test["Q3_1_2_4"]==0)&(X5_1_test["Ture_lable"]==1)]
ACC_Q5_1_2_4=(TN_Q5_1_2_4+TP_Q5_1_2_4)/50
#print(TP_Q3_1_2_3,X3_1_test["Ture_lable"].sum())
TP_Q5_1_3_4=X5_1_test.loc[(X5_1_test["Q3_1_3_4"]==1)&(X5_1_test["Ture_lable"]==0)]
FP_Q5_1_3_4=X5_1_test.loc[(X5_1_test["Q3_1_3_4"]==1)&(X5_1_test["Ture_lable"]==1)]
TN_Q5_1_3_4=X5_1_test.loc[(X5_1_test["Q3_1_3_4"]==0)&(X5_1_test["Ture_lable"]==0)]
FN_Q5_1_3_4=X5_1_test.loc[(X5_1_test["Q3_1_3_4"]==0)&(X5_1_test["Ture_lable"]==1)]
ACC_Q5_1_3_4=(TN_Q5_1_3_4+TP_Q5_1_3_4)/50

TP_Q5_2_3_4=X5_1_test.loc[(X5_1_test["Q3_2_3_4"]==1)&(X5_1_test["Ture_lable"]==0)]
FP_Q5_2_3_4=X5_1_test.loc[(X5_1_test["Q3_2_3_4"]==1)&(X5_1_test["Ture_lable"]==1)]
TN_Q5_2_3_4=X5_1_test.loc[(X5_1_test["Q3_2_3_4"]==0)&(X5_1_test["Ture_lable"]==0)]
FN_Q5_2_3_4=X5_1_test.loc[(X5_1_test["Q3_2_3_4"]==0)&(X5_1_test["Ture_lable"]==1)]
ACC_Q5_2_3_4=(TN_Q5_2_3_4+TP_Q5_2_3_4)/50

Q5_d={"Classifier":pd.Series(["(1),(2),(3)","(1),(2),(4)","(1),(3),(4)","(2),(3),(4)"],
                             "TP":pd.Series([TP_Q5_1_2_3,TP_Q5_1_2_4,TP_Q5_1_3_4,TP_Q5_2_3_4]),
                             "TN":pd.Series([TN_Q5_1_2_3,TN_Q5_1_2_4,TN_Q5_1_3_4,TN_Q5_2_3_4]),
                             "FP":pd.Series([FP_Q5_1_2_3,FP_Q5_1_2_4,FP_Q5_1_3_4,FP_Q5_2_3_4]),
                             "FN":pd.Series([FN_Q5_1_2_3,FN_Q5_1_2_4,FN_Q5_1_3_4,FN_Q5_2_3_4]),
                             "ACC":pd.Series([ACC_Q5_1_2_3,ACC_Q5_1_2_4,ACC_Q5_1_3_4,ACC_Q5_2_3_4])}
Q5_df=pd.DataFrame(Q5_d)
print(Q5_df)

```

	Classifier	TP	TN	FP	FN	ACC
0	(1),(2),(3)	15	22	5	8	0.74
1	(1),(2),(4)	17	21	6	6	0.76
2	(1),(3),(4)	18	26	1	5	0.88
3	(2),(3),(4)	20	2	3	3	0.90

5.2 discuss your findings and rank your ensembles learners by accuracy (from most accurate to least accurate)

Question#5.3 compare "weak learners" and ensemble results.

Question#1. give a quick summary on comparing classifiers in Method I and Method II