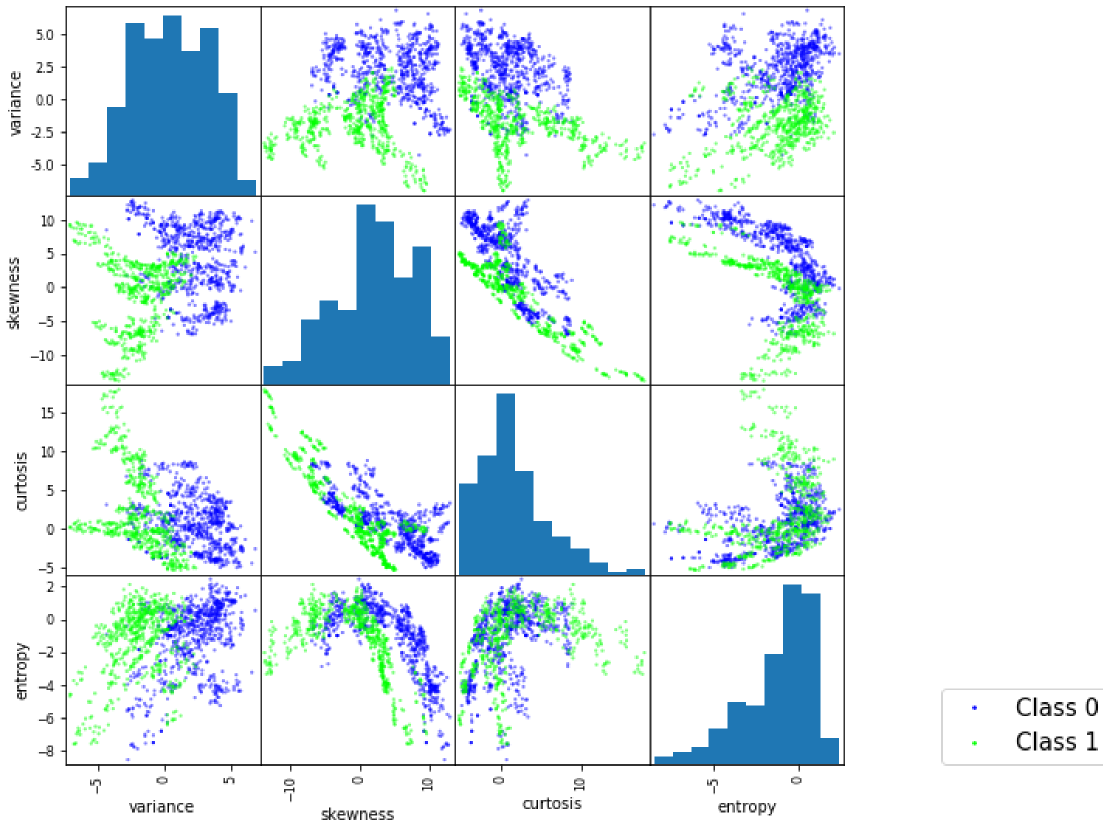
Assignment_1

June 4, 2018

Problem 1: b) i) Make scatterplots of the independent variables in the dataset. Use color to show Classes 0 and 1.

In [268]:
```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
from pandas.plotting import scatter_matrix
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
cols=['variance','skewness', 'curtosis','entropy','class']
note_df=pd.read_csv('data_banknote_authentication.txt',header=None, names=cols)
# print (note_df)
df=note_df[note_df.columns[0:4]]
target=note_df['class']
g=scatter_matrix(df, c=target,figsize=(9,9), marker='.',s=20,cmap='brg');
#,hist_kwds={'bins':20},  alpha=.8
handles = [plt.plot([],[],color=plt.cm.brg(i/1.), ls="", marker=".", \
                    markersize=np.sqrt(10))[0] for i in range(2)]
lbl=["Class 0", "Class 1"]
plt.suptitle("Scatter plots for independent variables")
plt.rc('legend',fontsize=15)
plt.legend(handles,lbl,loc=(1.5,0))
plt.figure(figsize=(20, 20))
plt.show()
```

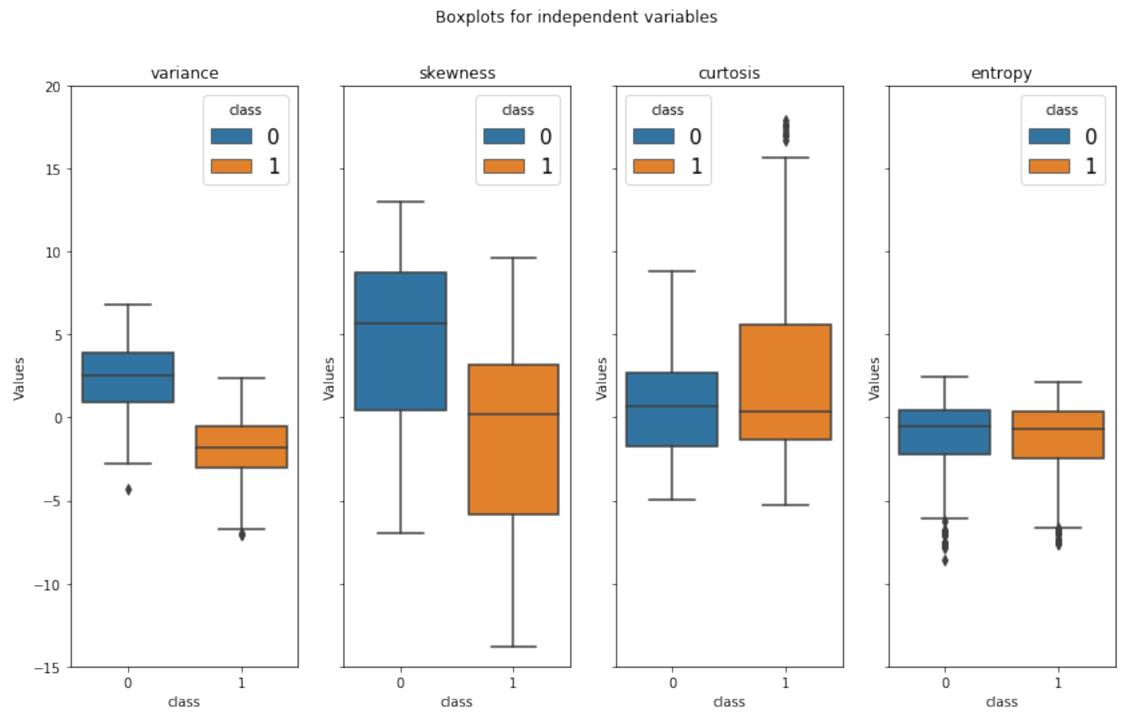
Scatter plots for independent variables




```
<matplotlib.figure.Figure at 0x7fc959499dd8>
```

b) ii) Make boxplots for each of the independent variables.

```
In [203]: # Plotting the data
          fig, ax = plt.subplots(1, len(cols)-1, figsize=(14,8), sharex=True, sharey=True)
          plt.suptitle("Boxplots for independent variables")
          for i, r in enumerate(cols[:-1]):
              sns.boxplot(data=note_df, x='class', y=r, dodge=False, hue='class', ax=ax[i])
              ax[i].set_ylim([-15, 20])
              ax[i].set_title(r)
              ax[i].set(ylabel='Values', xlabel='class')
```



b) iii) Select the first 200 rows of Class 0 and the first 200 rows of Class 1 as the test set and the rest of the data as the training set.

```
In [204]: df0,df1,test_df, train_df=pd.DataFrame(columns=cols),pd.DataFrame(columns=cols),pd.Da
          df0, df1=note_df[note_df['class'] == 0],note_df[note_df['class'] == 1]
          test_df=pd.concat([df0[:200], df1[:200]], ignore_index=True)
          train_df=pd.concat([df0[200:], df1[200:]],ignore_index=True)
          train_df.to_csv('train_df.csv', encoding='utf-8', index=True)
          test_df.to_csv('test_df.csv', encoding='utf-8', index=True)
```

c) i) Write code for k-nearest neighbors with Euclidean metric (or use a software package).

```
In [277]: def KNN(train,test,k, param,dis,test_error,train_error,wt):
              X_train,X_test=train.iloc[:,0:4],test.iloc[:,0:4]
              y_train,y_test=train[['class']].values.ravel(),test[['class']].values.ravel()
              #attributes in X_train and class values in y_train
              e,err=0,0
              #Scaling
              knn_classifier = KNeighborsClassifier(p=param,metric=dis,n_neighbors=k,weights=wt
              knn_classifier.fit(train, y_train)
              y_pred_train=knn_classifier.predict(train)
              y_pred_test = knn_classifier.predict(test)
              cm=confusion_matrix(y_test, y_pred_test)
              n=len(y_pred_test)
              m=len(y_pred_train)
              for c in range(m):
                  if (y_pred_train[c]!=y_train[c]):
```

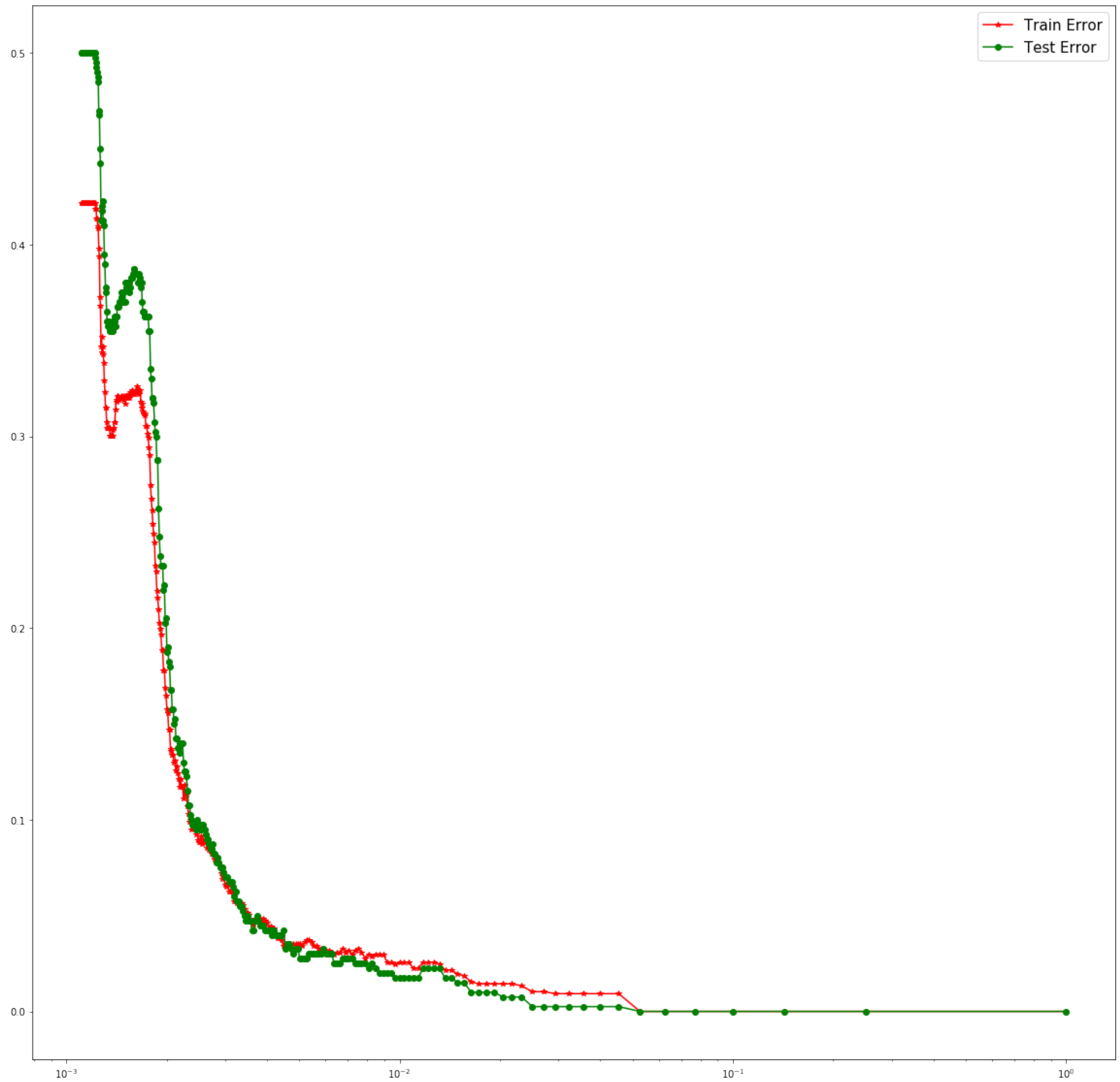
```
            err=err+1
    train_error.append(err/m)
    for d in range(n):
        if (y_pred_test[d]!=y_test[d]):
            e=e+1
    test_error.append(e/n)
    return cm
```

c) ii) Test all the data in the test database with k nearest neighbors. Take decisions by majority polling. Plot train and test errors in terms of 1/k for k 1, 4, 7, . . . , 901. You are welcome to use smaller increments of k.

```
In [278]: from sklearn.neighbors import KNeighborsClassifier
          from sklearn.preprocessing import StandardScaler
          from sklearn.metrics import classification_report, confusion_matrix
```

```
In [279]: i=np.linspace(1,901,301)
          test_error,train_error=[],[]
          for k in i.tolist():
              _=KNN(train_df,test_df,int(k),_,'euclidean',test_error,train_error,'uniform')
```

```
In [281]: plt.figure(figsize=(20, 20))
          plt.xscale('log',basex=10)
          plt.plot((1/i),train_error,'r*-', label= 'Train Error')
          plt.plot((1/i),test_error,'go-', label= 'Test Error')
          plt.legend()
          plt.show()
```



Which k is the most suitable k among those values? Calculate the confusion matrix,true positive rate, true negative rate, precision, and F-score when k = k.

```
In [287]: def statics(m):
              tp,fp,fn,tn= m[0][0],m[0][1],m[1][0],m[1][1]
              true_pos_r=tp/(tp+fn)
              true_neg_r=tn/(tn+fp)
              prec=tp/(tp+fp)
              Fscore=2*prec*true_pos_r/(prec+true_pos_r)
              print('True positive rate=',true_pos_r)
              print('True negative rate=',true_neg_r)
              print('Precision=',prec)
              print('Fscore=',Fscore)

          best_k = 3*test_error.index(min(o for o in test_error if o > 0))+1
          print('Best k:',best_k)
```

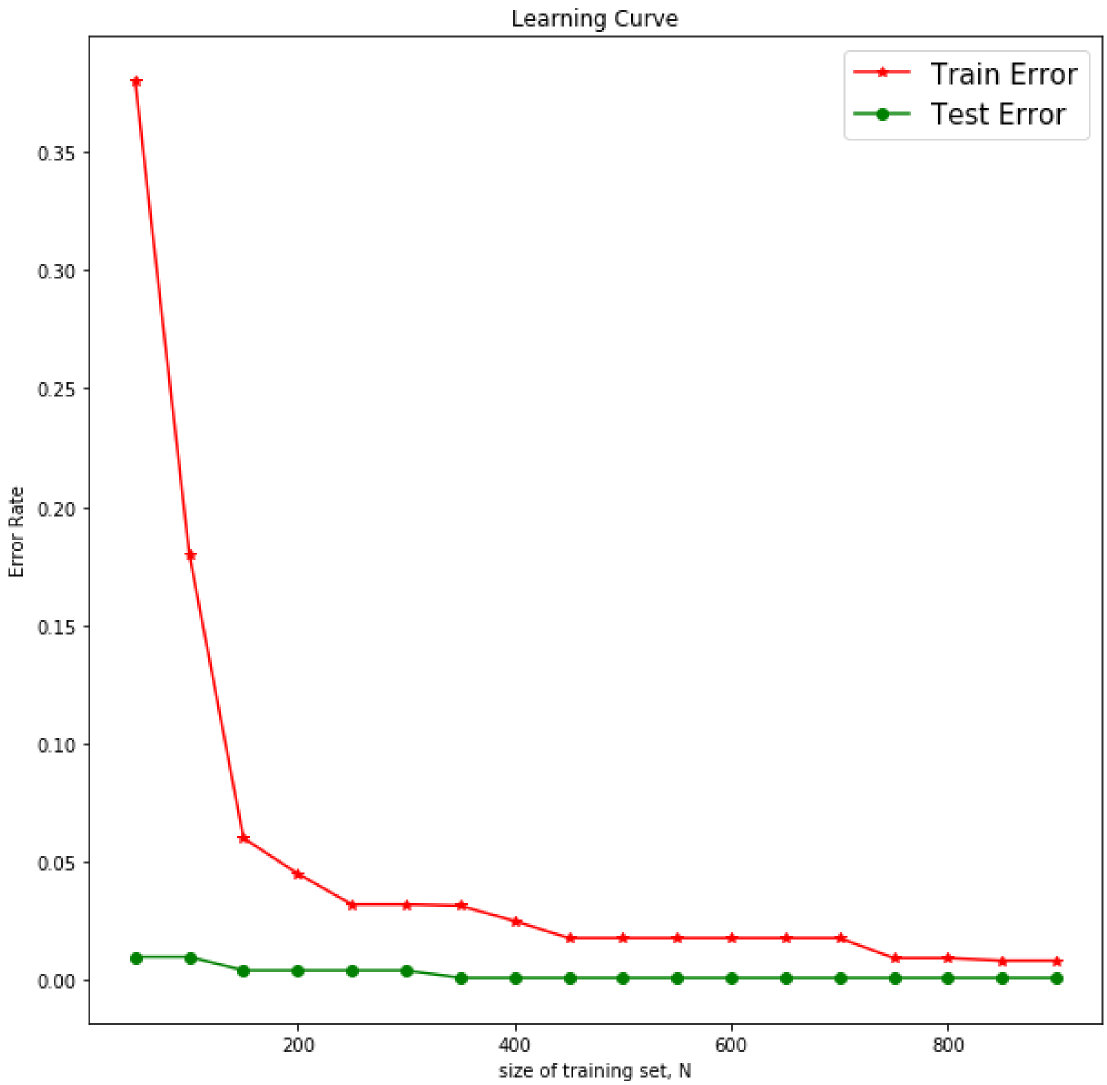
```
conf_mat=KNN(train_df,test_df,best_k,_,'euclidean',test_error,train_error,'uniform')
print('Confusion Matrix=\n',conf_mat)
statics(conf_mat)
```

```
Best k: 22
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395
```

Plot the best error rate, which is obtained by some value of k, against the size of training set, when the size of training set is N 50,100, 150, . . . , 900.

```
In [290]: n=np.linspace(50,900,18)
          # print(n)
          test_error_n,train_error_n=[],[]
          test_error,train_error=[],[]
          # print(i)
          for N in n.tolist():
          #     print('N:=',N)
              train_df_n=pd.concat([df0[:int(N/2)], df1[:int(N/2)]], ignore_index=True)
              test_df_n=pd.concat([df0[int(N/2):], df1[int(N/2):]],ignore_index=True)
              for k in range(1,int(N),40):
                  _= KNN(train_df_n,test_df_n,k,_,'euclidean',test_error,train_error,'uniform'
              test_error_n.append(min(o for o in test_error if o > 0))
              train_error_n.append(min(o for o in train_error if o > 0))

          plt.figure(figsize=(10, 10))
          plt.ylabel('Error Rate')
          plt.xlabel('size of training set, N')
          plt.plot(n,train_error_n,'r*-', label= 'Train Error')
          plt.plot(n,test_error_n,'go-', label= 'Test Error')
          plt.title('Learning Curve')
          plt.legend()
          plt.show()
```



Replace the Euclidean metric with the following metrics and test them. Summarize the test errors (i.e., when k = k) in a table. Use all of your training data and select the best k when k 1, 11, 21, . . . , 901. d)i)A)Minkowski Distance which becomes Manhattan Distance with p = 1.

In [301]:
```
i=np.linspace(1,900,91)
test_error,train_error=[],[]
for k in i.tolist():
    _= KNN(train_df,test_df,int(k),_,'manhattan',test_error,train_error,'uniform')
best_k = 1+test_error.index(min(o for o in test_error if o > 0))*10
print(min(o for o in test_error if o > 0))
print('Best k:',best_k)
conf_mat_m=KNN(train_df,test_df,best_k,_,'manhattan',test_error,train_error,'uniform
print('Confusion Matrix=\n',conf_mat_m)
statics(conf_mat_m)
```

```
0.0025
Best k: 31
```

```
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395
```

with log10(p) 0.1, 0.2, 0.3, . . . , 1. In this case, use the k you found for the Manhattan distance in 1(d)iA. What is the best log10(p)?

```
In [296]: p=np.linspace(0.1,1,10)
          test_error,train_error=[],[]
          for lg_p in p.tolist():
              print('parameter=',lg_p)
              conf_mat_manh=KNN(train_df,test_df,best_k,10**(lg_p),'minkowski',test_error,trai
              print('Confusion Matrix=\n',conf_mat_manh)
              statics(conf_mat_manh)
              print('\n')
```

```
parameter= 0.1
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395


parameter= 0.2
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395


parameter= 0.30000000000000004
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395
```

```
parameter= 0.4
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395


parameter= 0.5
Confusion Matrix=
 [[199   1]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9950248756218906
Precision= 0.995
Fscore= 0.9974937343358395


parameter= 0.6
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
Precision= 0.98
Fscore= 0.98989898989899


parameter= 0.7000000000000001
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
Precision= 0.98
Fscore= 0.98989898989899


parameter= 0.8
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
```

```
Precision= 0.98
Fscore= 0.98989898989899


parameter= 0.9
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
Precision= 0.98
Fscore= 0.98989898989899


parameter= 1.0
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
Precision= 0.98
Fscore= 0.98989898989899
```

For log(p) 0.1, 0.2, 0.3,0.4,0.5, precision and Fscore is highest (0.995 and 0.997). Among them the best would be 0.1.C. which becomes Chebyshev Distance with p

```
In [300]: test_error,train_error=[],[]
          for k in i.tolist():
              _= KNN(train_df,test_df,int(k),_,'chebyshev',test_error,train_error,'uniform')
          best_k = 1+10*test_error.index(min(o for o in test_error if o > 0))
          print(min(o for o in test_error if o > 0))
          print('Best k=',best_k)
          conf_mat_cheby=KNN(train_df,test_df,best_k,_,'chebyshev',test_error,train_error,'uni
          print('Confusion Matrix=\n',conf_mat)
          statics(conf_mat_cheby)
```

```
0.01
Best k= 31
Confusion Matrix=
 [[196   4]
 [  0 200]]
True positive rate= 1.0
True negative rate= 0.9803921568627451
Precision= 0.98
Fscore= 0.98989898989899
```

ii)Mahalanobis Distance

```
In [302]: def KNN_Mahalanobis(V,x):
              err,e=0,0
              knn_classifier = KNeighborsClassifier(algorithm='brute',metric='mahalanobis',met
              knn_classifier.fit(train_df,y_train)
              y_pred_train=knn_classifier.predict(train_df)
              y_pred_test = knn_classifier.predict(test_df)
              cm=confusion_matrix(y_test, y_pred_test)
              n=len(y_pred_test)
              m=len(y_pred_train)
              for c in range(m):
                  if (y_pred_train[c]!=y_train[c]):
                      err=err+1
              train_error.append(err/m)
              for d in range(n):
                  if (y_pred_test[d]!=y_test[d]):
                      e=e+1
              test_error.append(e/n)
              return cm
```

```
In [307]: from sklearn.neighbors import DistanceMetric
          X_train=train_df.iloc[:,0:4]
          V=np.linalg.pinv(np.cov(X_train))
          test_error,train_error=[],[]
          # dis=DistanceMetric.get_metric('mahalanobis',VI=V)
          for k in i.tolist():
          #     print((i.tolist()))
              _=KNN_Mahalanobis(V,int(k))
          best_k = 1+10*test_error.index(min(o for o in test_error if o > 0))
          print(min(o for o in test_error if o > 0))
          print(best_k)
          conf_mat=KNN_Mahalanobis(V,best_k)
          print('Confusion Matrix=\n',conf_mat)
          statics(conf_mat)
```

```
0.02
11
Confusion Matrix=
 [[200   0]
 [200   0]]
True positive rate= 0.5
True negative rate= nan
Precision= 1.0
Fscore= 0.6666666666666666
```

The majority polling decision can be replaced by weighted decision, in which the weight of each point in voting is proportional to its distance from the query/test data point. In this case, closer neighbors of a query point will have a greate inuence than neighbors which are further away. Use weighted voting with Euclidean, Manhattan, and Chebyshev distances and report the best test errors when k 1, 11, 21, . . . , 901.

```
In [317]: for met in ['euclidean','manhattan','chebyshev']:
              print(met)
              best_k=0
              for k in i.tolist():
                  _=KNN(train_df,test_df,int(k),_,met,test_error,train_error,'distance')
              best_k = test_error.index(min(o for o in test_error if o > 0))
              print(min(o for o in train_error if o > 0))
              print('K=',best_k)
              conf_mat=KNN(train_df,test_df,best_k,_,met,test_error,train_error,'distance')
              print('Confusion Matrix=\n',conf_mat)
              print(min(o for o in test_error if o > 0))
```

```
euclidean
0.015432098765432098
K= 99
Confusion Matrix=
 [[199   1]
 [  0 200]]
0.0025
manhattan
0.015432098765432098
K= 99
Confusion Matrix=
 [[200   0]
 [  0 200]]
0.0025
chebyshev
0.015432098765432098
K= 99
Confusion Matrix=
 [[198   2]
 [  0 200]]
0.0025
```

```
In [ ]: All have the same error statistics.
```