Problem 1

CODE TEXT

a > Updating rows

```
import pandas as pd
import numpy as np
from scipy import linalg
import scipy.stats as st
```

```
df = pd.read_csv(r"C:\Users\anmol\Downloads\charlie.csv")
```

```
df = df[['x1', 'x2', 'x3', 'x4']]
X = np.array(df)
print(type(df))
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
x_test = X[0:4,:]
print(x_test)
```

```
[[10.  20.7 13.6 15.5]
 [10.5 19.9 18.1 14.8]
 [ 9.7 20.  16.1 16.5]
 [ 9.8 20.2 19.1 17.1]]
```

```
n_rows, n_cols = x_test.shape
print(n_rows,n_cols)
```

```
4 4
```

```
updates = X[4:-1,:]
```

```
def Givens(a, b):
    if b == 0:
        c = 1
        s = 0
    elif np.abs(b) >= np.abs(a):
        t = -a/b
        s = 1/np.sqrt(1 + t**2)
        c = s*t
    else:
        t = -b/a
        c = 1/np.sqrt(1 + t**2)
        s = c*t
    return c, s
```

```
def update_rows(Q, R, u, data):
    next_row = u
    n_rows, n_cols = data.shape
    for j in range(n_cols):
        c, s  = Givens(R[j,j], next_row[j])
        R[j, j] = c*R[j, j] - s*next_row[j]
        #Update jth row of R and u
        t1 = R[j, j+1:n_cols]
```

```
            t2 = next_row[j + 1:n_cols]
            R[j, j+1:n_cols] = c*t1 - s*t2
            next_row[j+1:n_cols] = s*t1 + c*t2
        R_up = np.zeros((len(data)+1, len(data)+1))
        R_up[0:len(data), 0:len(data)] = R
    #     R_up.shape

        m, n = Q.shape
        Q_up = np.zeros((m+1, m+1))
        Q_up[-1][-1] = 1
        Q_up[0:m, 0:m] = Q
        for j in range(n_cols):
            c, s = Givens(R[j, j], next_row[j])
            t1 = Q_up[0:m+1, j]
            t2 = Q_up[0:m+1, m]
            Q_up[0:m+1, j] = c*t1 - s*t2
            Q_up[0:m+1, m] = s*t1 + c*t2
        Q_up.shape

        data = np.vstack([data, np.zeros(n_cols)])
        data[-1] = u

    #     A = np.delete(A, -1, 1)
    #     print(A - data)
        print("Q update :", Q_up)
        print("R update: ", R_up)
    #     print(np.dot(Q_up, R_up) - data)
        return Q_up, R_up


    x_test
```

```
array([[10. , 20.7, 13.6, 15.5],
       [10.5, 19.9, 18.1, 14.8],
       [ 9.7, 20. , 16.1, 16.5],
       [ 9.8, 20.2, 19.1, 17.1]])
```

```
    Q_up, R_up = np.linalg.qr(x_test)
    nc=4


    for i in range(4, len(X)):
        Q_up, R_up = update_rows(Q_up, R_up, X[i], x_test)
        A = np.dot(Q_up, R_up)
        r, c = np.shape(A)
        while c != nc:
            A = np.delete(A, -1, 1)
            c = c-1
        c = nc
        print("A: ",A)
        x_test = np.vstack([x_test, np.zeros(nc)])
        x_test[-1] = df.iloc[i,:]
        print("X_test = ", x_test, "\n")
```

```
Q update : [[-0.13802532  0.15613408  0.07206437 ... -0.04385967 -0.08160296
   0.08907631]
 [-0.14492658 -0.3690783   0.16227286 ... -0.04349659  0.07879631
  -0.18767628]
 [-0.13388456  0.12850264 -0.18449905 ...  0.02404815 -0.0716289
   0.05083207]
 ...
 [-0.15827532  0.02844674  0.2314337  ...  0.87250926 -0.03380239
   0.02464166]
 [-0.11908655  0.20262748  0.04429196 ...  0.          0.86198827
   0.11137467]
 [-0.14173917 -0.51849484 -0.073928   ...  0.          0.
   0.51868778]]
R update:  [[ -81.71260613 -153.76288103 -104.03053437 ...    0.
     0.           0.        ]
 [   0.          36.27032779   18.14377352 ...    0.
     0.           0.        ]
 [   0.           0.         -26.05287269 ...    0.
     0.           0.        ]
 ...
 [   0.           0.           0.         ...    0.
     0.           0.        ]
 [   0.           0.           0.         ...    0.
     0.           0.        ]
 [   0.           0.           0.         ...    0.
     0.           0.        ]]
A:  [[11.27840844 26.88620484 15.31422514 16.16165296]
 [11.84232886  8.8977381   4.15264272  4.76553688]
 [10.94005619 25.2473084  21.0663353  15.83332667]
 [11.05284027 25.44242144 28.15855526 31.21312139]
 [11.39130741  7.40618251  9.2404041   8.01334736]
 [10.83826722 19.92577103 11.35268506 13.80404194]
 [ 8.83271473 18.90194057 16.08040914 16.17705417]
 [ 9.55934812 19.21341754 14.80895297 12.53964233]
 [10.09837108 19.19803251 15.44752469 15.25988164]
 [ 9.55325587 19.53302778 13.45438225 14.5229298 ]
 [10.46472888 19.95735605 16.12988253 15.8495435 ]
 [ 9.26551318 19.05751011 11.65837544 15.77804928]
 [11.19603373 20.99520766 13.60152153 17.52527308]
 [10.00286438 19.63170908 13.68557473 15.50919913]
 [ 8.58013913 19.36201206 16.85136222 15.63665832]
 [ 9.72462252 20.01080622 10.38530367 15.86216033]
 [ 8.3834561  18.62321163 12.53622961 14.28193944]
 [11.77652251 21.1748161  13.63479648 15.42835093]
 [10.2868826  20.2785736  15.14856296 14.68077483]
```

A

```
array([[ 1.13110610e+01,  2.72230480e+01,  1.59335821e+01,
         1.66911543e+01],
       [ 1.18766141e+01,  7.37166481e+00,  1.76633170e+00,
         2.67540881e+00],
       [ 1.09717292e+01,  2.54931194e+01,  2.15747487e+01,
         1.62038248e+01],
       [ 1.10848398e+01,  2.56844301e+01,  2.87014288e+01,
         3.16571089e+01],
       [ 1.14242868e+01,  5.82615347e+00,  6.79791131e+00,
         5.84569976e+00],
       [ 1.08696455e+01,  1.96747132e+01,  1.10210034e+01,
         1.35173207e+01],
       [ 8.85828667e+00,  1.89562973e+01,  1.62580187e+01,
         1.63057033e+01],
       [ 9.58702376e+00,  1.91513371e+01,  1.47954281e+01,
         1.24867756e+01],
       [ 1.01276073e+01,  1.90256161e+01,  1.52633977e+01,
         1.50713859e+01],
       [ 9.58091387e+00,  1.95032537e+01,  1.34841483e+01,
         1.45367151e+01],
       [ 1.04950257e+01,  1.97847946e+01,  1.59494206e+01,
         1.56623593e+01],
       [ 9.29233813e+00,  1.90396020e+01,  1.16966328e+01,
         1.58264037e+01],
       [ 1.12284478e+01,  2.07758924e+01,  1.33328004e+01,
         1.72996038e+01],
       [ 1.00318241e+01,  1.95207446e+01,  1.35884419e+01,
         1.54169082e+01],
       [ 8.60497982e+00,  1.95121026e+01,  1.71845563e+01,
         1.58901584e+01],
       [ 9.75277665e+00,  1.99928849e+01,  1.04162777e+01,
         1.59183571e+01],
       [ 8.40772737e+00,  1.87411818e+01,  1.27940776e+01,
         1.45023151e+01],
       [ 1.18106172e+01,  2.08557516e+01,  1.32087388e+01,
         1.50489945e+01],
       [ 1.03166646e+01,  2.01731556e+01,  1.50685371e+01,
         1.45830214e+01],
       [ 8.97406891e+00,  1.91324586e+01,  9.10606952e+00,
         1.45853160e+01],
       [ 9.93759061e+00,  1.98167034e+01,  1.50241088e+01,
         1.54564536e+01],
       [ 8.77773155e+00,  1.92170230e+01,  1.03645368e+01,
         1.65370879e+01],
       [ 1.14596442e+01,  2.10952621e+01,  1.80888351e+01
```

```
Q_up,R_up
```

```
(array([[-0.11538355,  0.13533728,  0.07005773, ..., -0.01688884,
          0.00375369, -0.03782272],
        [-0.12115273, -0.09140498,  0.09230825, ..., -0.05845602,
         -0.04502551, -0.04928205],
        [-0.11192205,  0.12122418, -0.14914206, ...,  0.01180179,
          0.0512827 , -0.01143141],
        ...,
        [-0.12946956, -0.16272985,  0.1335393 , ...,  0.87046274,
         -0.06377141, -0.07093189],
        [-0.13244988, -0.17487537,  0.18105696, ...,  0.        ,
          0.85723504, -0.03671896],
        [-0.09947347, -0.06710168,  0.18243003, ...,  0.        ,
          0.        ,  0.8534890211]),
```

```
x_test
```

```
array([[10. , 20.7, 13.6, 15.5],
       [10.5, 19.9, 18.1, 14.8],
       [ 9.7, 20. , 16.1, 16.5],
       [ 9.8, 20.2, 19.1, 17.1],
       [11.7, 21.5, 19.8, 18.3],
       [11. , 20.9, 10.3, 13.8],
       [ 8.7, 18.8, 16.9, 16.8],
       [ 9.5, 19.3, 15.3, 12.2],
       [10.1, 19.4, 16.2, 15.8],
       [ 9.5, 19.6, 13.6, 14.5],
       [10.5, 20.3, 17. , 16.5],
       [ 9.2, 19. , 11.5, 16.3],
       [11.3, 21.6, 14. , 18.7],
       [10. , 19.8, 14. , 15.9],
       [ 8.5, 19.2, 17.4, 15.8],
       [ 9.7, 20.1, 10. , 16.6],
       [ 8.3, 18.4, 12.5, 14.2],
       [11.9, 21.8, 14.1, 16.2],
       [10.3, 20.5, 15.6, 15.1],
       [ 8.9, 19. ,  8.5, 14.7],
       [ 9.9, 20. , 15.4, 15.9],
       [ 8.7, 19. ,  9.9, 16.8],
       [11.5, 21.8, 19.3, 12.1],
       [15.9, 24.6, 14.7, 15.3],
       [12.6, 23.9, 17.1, 14.2],
       [14.9, 25. , 16.3, 16.6],
       [ 9.9, 23.7, 11.9, 18.1],
       [12.8, 26.3, 13.5, 13.7],
       [13.1, 26.1, 10.9, 16.8],
       [ 9.8, 25.8, 14.8, 15. ]])
```

b > updating sequentially column vise

```
"""covariance matrix of the set obtained with the first 2 columns and add sequentially t
```

```
'covariance matrix of the set obtained with the first 2 columns and add sequentia
```

```
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import pylab
from pylab import rcParams
import sklearn


dataset = pd.read_csv(r"C:\Users\anmol\Downloads\charlie.csv")


x1 = np.array(dataset.x1)
x2 = np.array(dataset.x2)
x3 = np.array(dataset.x3)
x4 = np.array(dataset.x4)
dataset = np.array(dataset)


def gs_column_update(col_vector):
    update_array = []
    for v in col_vector:
        w = v - np.sum( np.dot(v,b)*b  for b in update_array )
        if (w > 1e-10).any():
            update_array.append(w/np.linalg.norm(w))
#     return linalg.qr(np.array(update_array))
    return linalg.qr(np.cov(np.array(update_array)))
# You can remove np.cov from above line if you dont want the covariance matrix of the se


gs_column_update([x1,x2])
```

```
C:\Users\anmol\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DeprecationWa
  after removing the cwd from sys.path.
(array([[-0.21603084,  0.97638654],
        [ 0.97638654,  0.21603084]]), array([[-0.00437793,  0.03405998],
        [ 0.        ,  0.00315802]]))
```

```
gs_column_update([x1,x2,x3])
```

```
C:\Users\anmol\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DeprecationWa
  after removing the cwd from sys.path.
(array([[-0.19907418, -0.14160026,  0.96970038],
        [ 0.89974819, -0.4185418 ,  0.12359592],
        [ 0.38835893,  0.89709092,  0.21072545]]),
 array([[-0.00475083,  0.03129522,  0.01350798],
        [ 0.        , -0.01381013,  0.03120279],
        [ 0.        ,  0.        ,  0.00542682]]))
```

```
gs_column_update([x1,x2,x3,x4])
```

```
C:\Users\anmol\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DeprecationWa
  after removing the cwd from sys.path.
(array([[-0.18128004, -0.04561866, -0.04675425,  0.98125966],
        [ 0.81932467, -0.55949018, -0.0059592 ,  0.12506924],
        [ 0.35364567,  0.53807995, -0.76321063,  0.05398372],
        [ 0.41325461,  0.6287763 ,  0.64442848,  0.1362825 ]]),
 array([[-0.00521717,  0.02838435,  0.01225156,  0.01431662],
        [ 0.        , -0.01909227,  0.01864102,  0.02178307],
        [ 0.        ,  0.        , -0.02622891,  0.02232532],
        [ 0.        ,  0.        ,  0.        ,  0.00252412]]))
```

c,d > Hn , aplha_n, R, plotting x_test data generated from classification

```
data = pd.read_csv(r"C:\Users\anmol\Downloads\charlie1.csv")
X = x_test
y = data['Data']
X = np.array(X)
y = np.array(y)
C,sigma = 10,0.001


def Kernel(x, y, sigma):
    return np.exp(-np.linalg.norm(x-y)**2 / ( (sigma ** 2)))


def Gram_Matrix(x):
    K = np.zeros((len(x),len(x)))
    for i in range(0, len(x)):
        for j in range(0, len(x)):
            K[i, j] = Kernel(x[i], x[j], sigma)

    return K


def H(x):
    mat = np.zeros((len(x), len(x)))
    mat[0:len(x), 0:len(x)] = Gram_Matrix(x) + np.eye(len(x))/2*C
    return mat


e = np.ones(len(X))
k = np.zeros((len(X)))

for j in range(0, len(X)):
    k[j] = Kernel(X[j], X[j], sigma)

H_mat = H(X)
al = alpha()


def alpha():
    p1 = np.dot(np.dot(np.linalg.inv(H_mat), e.T),k)
    p2 = np.dot(np.dot(np.linalg.inv(H_mat), e.T), e)
    p3 = (2-p1)/p2
    p3 = k + np.dot(p3, e)
    a = 0.5*np.dot(np.linalg.inv(H_mat),p3)
    return a


H(X)
```

```
array([[1.50000000e+000, 0.00000000e+000, 2.32460533e-218, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       [0.00000000e+000, 1.50000000e+000, 2.67211296e-210, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       [2.32460533e-218, 2.67211296e-210, 1.50000000e+000, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000]
```

```
Gram_Matrix(X)
```

```
array([[1.00000000e+000, 0.00000000e+000, 2.32460533e-218, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       [0.00000000e+000, 1.00000000e+000, 2.67211296e-210, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       [2.32460533e-218, 2.67211296e-210, 1.00000000e+000, ...,
        0.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       ...,
       [0.00000000e+000, 0.00000000e+000, 0.00000000e+000, ...,
        1.00000000e+000, 0.00000000e+000, 0.00000000e+000],
       [0.00000000e+000, 0.00000000e+000, 0.00000000e+000, ...,
        0.00000000e+000, 1.00000000e+000, 0.00000000e+000],
       [0.00000000e+000, 0.00000000e+000, 0.00000000e+000, ...,
        0.00000000e+000, 0.00000000e+000, 1.00000000e+000]])
```

```
alpha()
```

```
array([0.02671756, 0.02671756, 0.02671756, 0.02671756, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038, 0.01145038, 0.01145038, 0.01145038,
       0.01145038, 0.01145038])
```

```
def R_square():
    p1 = 0
    p2 = 0
    total = 0
    for s in range(0, len(X)):
        k = Kernel(X[s], X[s], sigma)
        for j in range(0, len(X)):
            p1 = p1 + al[j]*Kernel(X[s], X[j], sigma)
            for l in range(0, len(X)):
                p2 = p2 + al[j]*al[l]*Kernel(X[j], X[l], sigma)
        total = total + (k - 2 * p1 + p2)
    final = total/len(X)
    return final

final = R_square()
```

```
final
```

```
-0.39947676310859676
```

```
def classification(x):
    t_out = []
    t_in = []
    p = 0
    p1 = 0
    for z in range(0, len(x)):
        k = Kernel(x[z], x[z], sigma)
        for j in range(0, len(X)):
            p = p + al[j]*Kernel(x, X[j], sigma)
            for l in range(0, len(X)):
                p1 = p1 + al[j]*al[l]*Kernel(X[j], X[l], sigma)
        d = k - 2*p + p1
        if d <= final:
            t_in.append(x[z])
        else:
            t_out.append(x[z])

    return t_out, t_in

t_out, t_in = classification(X)


t_out,t_in
```

```
([array([10. , 20.7, 13.6, 15.5]),
  array([10.5, 19.9, 18.1, 14.8]),
  array([ 9.7, 20. , 16.1, 16.5]),
  array([ 9.8, 20.2, 19.1, 17.1]),
  array([11.7, 21.5, 19.8, 18.3]),
  array([11. , 20.9, 10.3, 13.8]),
  array([ 8.7, 18.8, 16.9, 16.8]),
  array([ 9.5, 19.3, 15.3, 12.2]),
  array([10.1, 19.4, 16.2, 15.8]),
  array([ 9.5, 19.6, 13.6, 14.5]),
  array([10.5, 20.3, 17. , 16.5]),
  array([ 9.2, 19. , 11.5, 16.3]),
  array([11.3, 21.6, 14. , 18.7]),
  array([10. , 19.8, 14. , 15.9]),
  array([ 8.5, 19.2, 17.4, 15.8]),
  array([ 9.7, 20.1, 10. , 16.6]),
  array([ 8.3, 18.4, 12.5, 14.2]),
  array([11.9, 21.8, 14.1, 16.2]),
  array([10.3, 20.5, 15.6, 15.1]),
```

```
import matplotlib.pyplot as plt
import matplotlib.font_manager
from sklearn import svm

clf = svm.OneClassSVM(kernel = 'rbf', gamma = 'auto')
clf.fit(t_out,t_in)
```

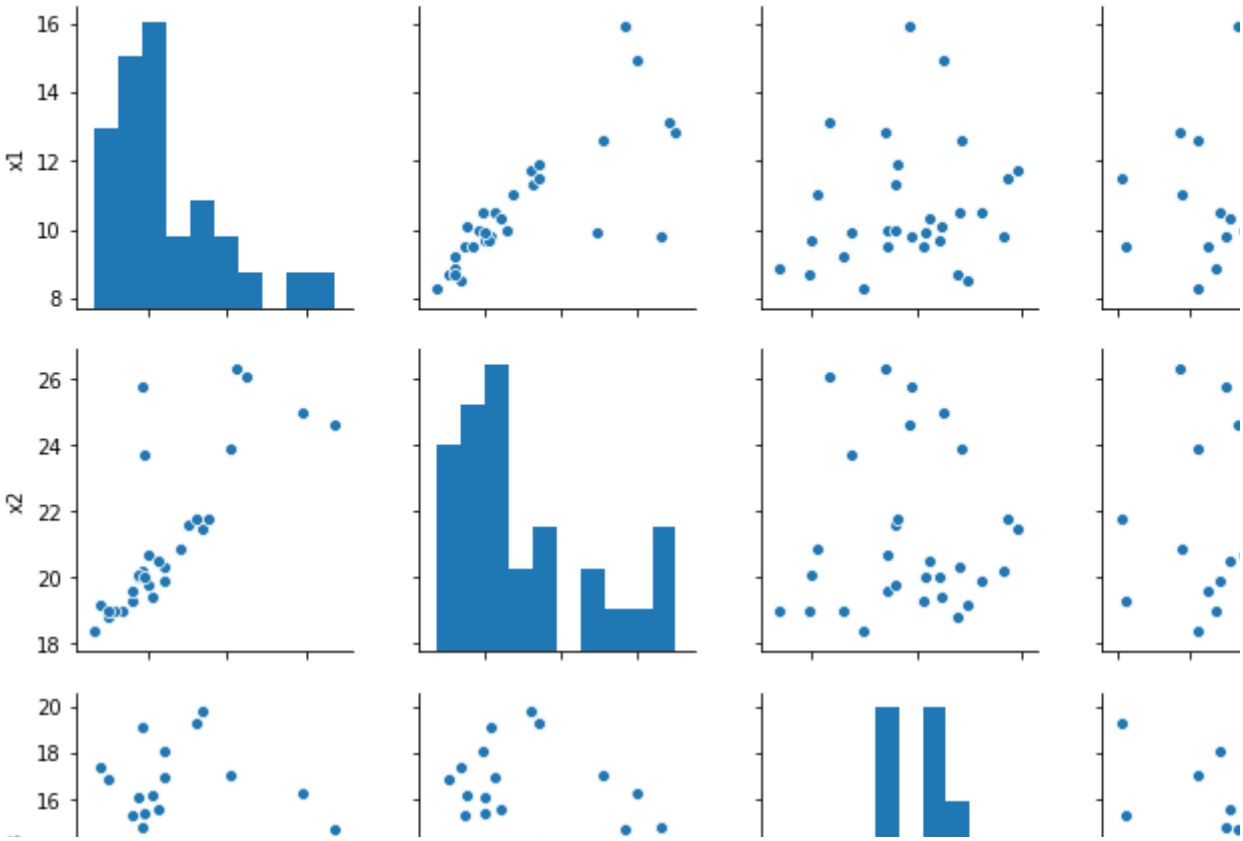
```
OneClassSVM(cache_size=200, coef0=0.0, degree=3, gamma='auto', kernel='rbf',
      max_iter=-1, nu=0.5, random_state=None, shrinking=True, tol=0.001,
      verbose=False)
```

```
n_error_outliers = t_out[t_out == 1].size
print("Number of errors = ",n_error_outliers,"/",y_out.size)
#classification rate
rate = n_error_outliers/y_out.size
print("Classification rate = ",100*(1-rate),"%")
```

```
Number of errors =  4 / 10
Classification rate =  60.0 %
```

```
import seaborn as sns
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x22248e49780>
```



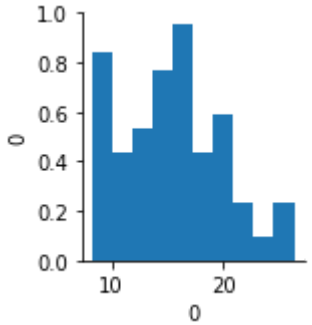

```
type(t_out)
```

```
list
```

```
plot_data = pd.DataFrame(np.array(t_out).reshape(328,))
```

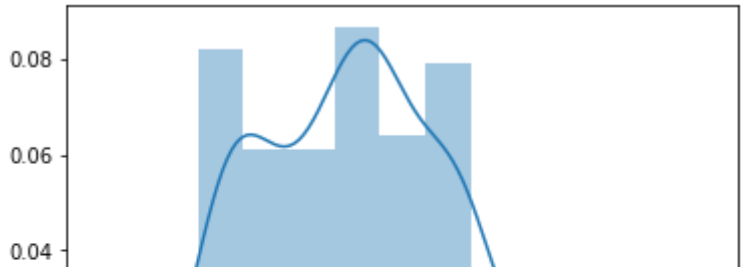
```
import seaborn as sns
sns.pairplot(plot_data)
```

```
<seaborn.axisgrid.PairGrid at 0x2224ca298d0>
```



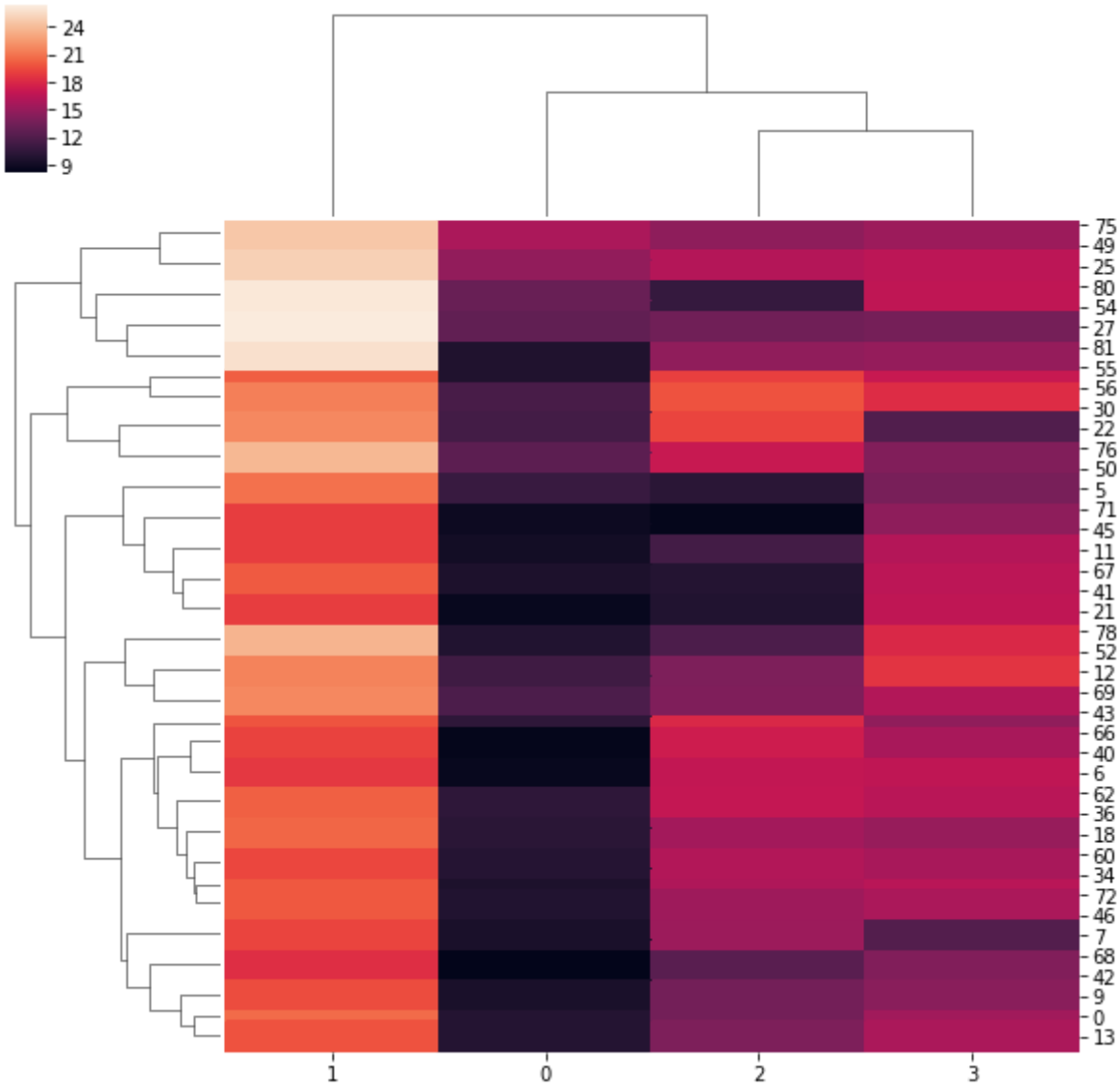

```
sns.distplot(plot_data)
```

```
C:\Users\anmol\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarni
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
<matplotlib.axes._subplots.AxesSubplot at 0x2224cc86828>
```



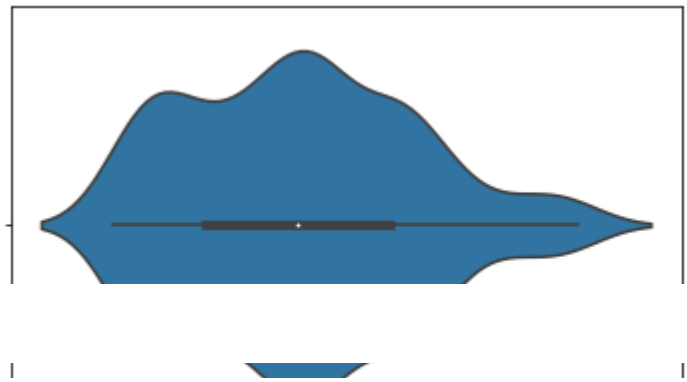

```
sns.clustermap(X)
# extra work not required.
```

```
<seaborn.matrix.ClusterGrid at 0x2224cc50860>
```




```
sns.violinplot([X])
# extra work not required.
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2224a6a99b0>
```



Problem 2

```
# Load the digit data
digits = datasets.load_digits()
# View the features of the first observation
digits.data[0:1]
# View the target of the first observation
digits.target[0:1]
# Create dataset 1
data1_features = digits.data[:1000]
data1_target = digits.target[:1000]

# Create dataset 2
data2_features = digits.data[1000:]
data2_target = digits.target[1000:]
```

```
parameter_candidates = [
  {'C': [1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001,0.1,1,0.00001], 'kernel': ['rbf','li
]
```

```
# Create a classifier object with the classifier and parameter candidates
clf = GridSearchCV(estimator=svm.SVC(), param_grid=parameter_candidates, n_jobs=-1)

# Train the classifier on data1's feature and target data
clf.fit(data1_features, data1_target)
```

```
C:\Users\anmol\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:1943
  warnings.warn(CV_WARNING, FutureWarning)
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'C': [1, 10, 100, 1000], 'kernel': ['linear']}, {'C': [1, 10,
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

```
# View the accuracy score
print('Best score for data1:', clf.best_score_)
```

```
Best score for data1: 0.942
```

```
# View the best parameters for the model found using grid search
print('Best C:',clf.best_estimator_.C)
print('Best Kernel:',clf.best_estimator_.kernel)
print('Best Gamma:',clf.best_estimator_.gamma)
```

```
Best C: 10
Best Kernel: rbf
Best Gamma: 0.001
```

We can verify my code above by implementing the code for best parameter selection which is provided on scikit learn

```
# http://scikit-learn.org/stable/auto_examples/model_selection/plot_grid_search_digits.h


from __future__ import print_function

from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.svm import SVC

print(__doc__)

# Loading the Digits dataset
digits = datasets.load_digits()

# To apply an classifier on this data, we need to flatten the image, to
# turn the data in a (samples, feature) matrix:
n_samples = len(digits.images)
X = digits.images.reshape((n_samples, -1))
y = digits.target

# Split the dataset in two equal parts
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.5, random_state=0)

# Set the parameters by cross-validation
tuned_parameters = [{'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],
                     'C': [1, 10, 100, 1000]},
                    {'kernel': ['linear'], 'C': [1, 10, 100, 1000]}]

scores = ['precision', 'recall']

for score in scores:
    print("# Tuning hyper-parameters for %s" % score)
    print()

    clf = GridSearchCV(SVC(), tuned_parameters, cv=5,
                       scoring='%s_macro' % score)
    clf.fit(X_train, y_train)

    print("Best parameters set found on development set:")
    print()
    print(clf.best_params_)
    print()
    print("Grid scores on development set:")
    print()
    means = clf.cv_results_['mean_test_score']
    stds = clf.cv_results_['std_test_score']
    for mean, std, params in zip(means, stds, clf.cv_results_['params']):
        print("%0.3f (+/-%0.03f) for %r"
              % (mean, std * 2, params))
    print()

    print("Detailed classification report:")
    print()
```

```
        print("The model is trained on the full development set.")
        print("The scores are computed on the full evaluation set.")
        print()
        y_true, y_pred = y_test, clf.predict(X_test)
        print(classification_report(y_true, y_pred))
        print()

    # Note the problem is too easy: the hyperparameter plateau is too flat and the
    # output model is the same for precision and recall with ties in quality.
```

```
Automatically created module for IPython interactive environment
# Tuning hyper-parameters for precision

Best parameters set found on development set:



Grid scores on development set:

0.986 (+/-0.016) for {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
0.959 (+/-0.029) for {'C': 1, 'gamma': 0.0001, 'kernel': 'rbf'}
0.988 (+/-0.017) for {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
0.982 (+/-0.026) for {'C': 10, 'gamma': 0.0001, 'kernel': 'rbf'}
0.988 (+/-0.017) for {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
0.982 (+/-0.025) for {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}
0.988 (+/-0.017) for {'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
0.982 (+/-0.025) for {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'}
0.975 (+/-0.014) for {'C': 1, 'kernel': 'linear'}
0.975 (+/-0.014) for {'C': 10, 'kernel': 'linear'}
0.975 (+/-0.014) for {'C': 100, 'kernel': 'linear'}
0.975 (+/-0.014) for {'C': 1000, 'kernel': 'linear'}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        89
           1       0.97      1.00      0.98        90
```