# **EE7207 NN Assignment Report**

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## Question 1

Assuming that the RBF neural network has 20 neurons in the hidden layer, find center vectors for the 20 neurons using SOM neural network.

**My thinking:** These 20 center vectors are exactly the weights in SOM neural network. So I initialize weights by normal distribution with 33 (-1,+1) small numbers. Followed by three essential process: Competition, Cooperation, Weights adaptation. In these successive process, we should focus on continuously changing parameters:

$$\sigma(n) = \sigma_0 \exp(-\frac{n}{\tau_1})$$
 ;  $\eta(n) = \eta_0 \exp(-\frac{n}{\tau_2})$  ;  $h_{ji}(n) = \exp(-\frac{d_{ji}^2}{2\sigma_{(n)}^2})$ 

Width parameter  $\sigma(n)$  and learning-rate parameter  $\eta(n)$  are affected by iteration times n, in this way, neighborhood function is also changing. So the adaptive process:  $w_j(n+1) = w_j(n) + \eta(n)h_{ji}(n)[X-w_j(n)]$  is affected by the above continuously changing parameters.

# Getting center vectors' python code is as below:

```
import math
import numpy as np
Learn YITA = 0.1; max iteration = 500
train sample = np.loadtxt('./data train.csv', dtype=float, delimiter=',')
class Neuron: #single neuron
   def __init__(self, row, col):
       self.weight = np.random.normal(0.0, 1.0, 33) # get 33 random weight
       self.row = row
       self.col = col
   def GETdistance(self, sample):
       return np.sqrt(np.sum(np.square(sample- self.weight)))
   def NEWeight(self, sample, Learn YITA, h):
       self.weight = self.weight + Learn_YITA*h*(sample - self.weight)
class NeuronNET: #neuron sets
   def __init__(self):
       self.NNET = []
       for row in range(0, 4):
           for col in range(0, 5):
              self.NNET.append(Neuron(row, col)) #VIP
   def mindistance(self,sample):
       minD = 0
       min posi = -1
       for Neu_posi in range(0, 20):
           D = self.NNET[Neu_posi].GETdistance(sample)
           if min posi == -1:
              minD = D
```

```
min_posi = Neu_posi
           elif D < minD:</pre>
               minD = D
               min_posi = Neu_posi
       return min_posi
# Create A somNN
NN = NeuronNET()
# iterate to get trainned weights
for iteration in range(0, max_iteration):
   for i in range(0, 330):
       sample = train_sample[i, :]
       min_posi = NN.mindistance(sample)
       WINNER = NN.NNET[min_posi]
  # for every neuron get their distance to winner then mew weight could form
       for ID in range(0, 20):
           PosWIN = np.array([WINNER.row, WINNER.col])
           PosEVERY = np.array([NN.NNET[ID].row, NN.NNET[ID].col])
           d = np.sqrt(np.sum(np.square(PosEVERY - PosWIN)))
           delta = 2 * np.exp(-iteration/max_iteration)
           h = np.exp(-d**2/(2*delta**2))
           NN.NNET[ID].NEWeight(sample, Learn_YITA, h)
CV = np.ndarray([20,33])
for i in range(0,20):
   CV[i,:] = NN.NNET[i].weight
np.savetxt('CenterVec.csv', CV, '%.6f', delimiter=' ')
```

Center vectors are saved as a (.csv) document for check and future usage. We could also add some code to see the cluster result during the iteration process for better understanding:

499iteration-> 20, 13, 24, 21, 43, 13, 31, 19, 16, 19, 11, 3, 6, 3, 16, 11, 15, 11, 16, 19, It's shown that after 500 times iteration the cluster is distributed quite fine. The final center vector is partly shown below:

```
-0.477472 \quad -0.601359 \quad -0.029485 \quad -0.679823 \quad -0.348837 \quad -0.688440 \quad -0.542532 \quad -0.231930 \quad -0.197813 \quad -0.170868 \quad -0.456670 \quad -0.476472 \quad -0.476472 \quad -0.601359 \quad -0.029485 \quad -0.679823 \quad -0.348837 \quad -0.688440 \quad -0.542532 \quad -0.231930 \quad -0.197813 \quad -0.170868 \quad -0.456670 \quad -0.476472 \quad -0.4
                                                0.309499 -0.010444 -0.126530 0.080613 -0.312401 0.252495 -0.366548 0.265432 -0.461684 0.248304 -0.422040 0.41524
                                                0.335875 \quad 0.378206 \quad -0.087589 \quad 0.469862 \quad -0.291267 \quad 0.636261 \quad -0.242671 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.643664 \quad -0.423611 \quad 0.608222 \quad -0.303406 \quad 0.724779 \quad 0.608222 \quad -0.308222 \quad
                                              0.339379 0.538144 -0.071730 0.606988 -0.306420 0.766245 -0.249837 0.790982 -0.381346 0.770056
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               -0.255876 0.827265
                                              -0.653437 \quad -1.002814 \quad -0.070964 \quad -1.186550 \quad 0.026060 \quad -1.288165 \quad 0.334641 \quad -0.941408 \quad 0.303672 \quad -0.789827 \quad -0.067405 \quad -0.90814 \quad -
                                                0.053825 \quad -0.633965 \quad -0.194359 \quad -0.882550 \quad -0.183929 \quad -0.671023 \quad 0.006210 \quad -0.480572 \quad -0.011617 \quad -0.412511 \quad -0.199150 \quad -0.4812511 \quad -0.4812511 \quad -0.199150 \quad -0.4812511 \quad -0.4812511
                                                0.331173 \quad -0.242183 \quad -0.156706 \quad -0.081006 \quad -0.215259 \quad 0.070986 \quad -0.150193 \quad 0.017111 \quad -0.355142 \quad 0.078163 \quad -0.333055 \quad 0.2580 \quad -0.081096 \quad
                                          0.326285 0.163044 -0.128583 0.371995 -0.202504 0.438507 -0.194482 0.431124 -0.359755 0.427847 -0.316548 0.573197
    10 0.260357 0.421687 -0.113040 0.568763 -0.186431 0.649121 -0.193723 0.681683 -0.327451 0.670343 -0.280641 0.743995
    11 0.206174 -0.291301 0.446905 -0.653022 0.645148 -0.840567 0.972473 -1.392493 0.950923 -1.360602 0.492493 -1.32412
                                                0.307239 \quad -0.114933 \quad 0.336015 \quad -0.378619 \quad 0.536950 \quad -0.577894 \quad 0.815133 \quad -0.913386 \quad 0.812786 \quad -1.001616 \quad 0.620653 \quad -1.09339 \quad -1.0939 \quad -1.09339 \quad -1.0939 \quad -1.09339 \quad -1.09339 \quad -1.09339 \quad -1.09339 \quad -1.09339 \quad -1.093
                                                0.316856 -0.069809 0.207641 -0.046421 0.252045 -0.127109 0.429810 -0.343852 0.339307 -0.357841 0.433764 -0.40343
                                      0.227159 0.142584 -0.003025 0.322706 0.070421 0.264162 0.166707 0.143754 0.036289 0.168448 0.140704 0.231381 0.
15 0.008900 0.302827 -0.230592 0.526461 0.128006 0.433333 0.229330 0.475592 -0.036377 0.457454 0.005299 0.519097 -
16 0.324680 0.298961 0.831877 -0.129591 0.992284 -0.590214 1.344371 -1.288511 1.372091 -1.560116 1.012020 -1.667816
                                          0.342594 0.364090 0.730214 0.067025 0.979720 -0.393161 1.263715 -0.937592 1.330205 -1.267178 1.228040 -1.450685
                                            0.329842 \quad 0.339388 \quad 0.654713 \quad 0.263480 \quad 0.785299 \quad -0.059689 \quad 1.028914 \quad -0.467873 \quad 1.082801 \quad -0.714021 \quad 1.267205 \quad -0.903938 \quad -0.714021 \quad 
    19 0.255205 0.434223 0.307652 0.456233 0.434414 0.329888 0.645986 0.095909 0.698129 0.001786 0.935695 -0.115683 1
                                              0.159015 0.482316 -0.120441 0.569808 0.322588 0.445182 0.454459 0.477733 0.222954 0.441097 0.505624 0.369269 0.
```

## **Question 2**

Assuming the RBF neural network has only 1 neuron in the output layer, determine the weights from the hidden layer to output layer using the linear least square estimation algorithm.

**My thinking:** Choose commonly used Gaussian basis function, initial its width  $\sigma$ =1.5. Then just calculate estimated weights  $W = (\Phi^T \Phi)^{-1} \Phi^T d$  step by step. Add a bias term to the weights. No iteration need, so it's much straight forward than Question1.

Getting estimated weights' python code part is as below:

```
import math
import numpy as np
input_dim = 33; bias = 1
CenterVec = np.loadtxt('./CenterVec.csv', delimiter=' ', dtype=float)
data_train = np.loadtxt('./data_train.csv',delimiter=',', dtype=float)
label_train = np.loadtxt('./data_train.csv',delimiter=',', dtype=float)
data_test = np.loadtxt('./data_test_csv', delimiter=',', dtype=float)
# claculate PHI--->distance between CenterVec and sample
PHI = np.ndarray([330,21])
for i in range(0, 330):
    PHI row = []
    for j in range(0,20):
        CV_row = CenterVec[j,:]; deta = 1.5
        distance =
sum(np.exp(-np.square(CV row-data train[i,:]/(2*deta**2))))
        PHI row.append(distance)
    PHI row.append(bias)
    PHI[i,:] = np.array(PHI row,dtype=float)
# using LSE method to calculate WEIGHTS
WEIGHTS = np.linalg.inv(np.transpose(PHI) @ PHI) @ np.transpose(PHI) @
label_train
The result of weights are:
[0.42823569, -1.25723447, 1.33417983, -0.48274879,\n
 -2.90833306, 0.86768626, 0.49103258, -3.17424631,\n
  2.41291994, 2.71123575, 0.52821417, -1.67386369,\n
  0.7195139 , 1.92755066, -1.5037657 , -0.18649565.\n
  0.80467508, 0.11648976, -0.7530848, 0.11718663,\n -13.86378143])
```

#### **Question 3**

Calculate the classification accuracy of the training data.

The following accuracy calculation codes are appended to codes in Question2:

```
# using data_train to test accuracy
TestVAL = PHI @ WEIGHTS
right = 0; wrong = 0; TestLABLE = 0
for i in range(0,330):
   if TestVAL[i] > 0:
        TestLABLE = 1
```

```
else:
    TestLABLE = -1
if TestLABLE == label_train[i]:
    right+=1
else:
    wrong+=1
accuracy = right/(right+wrong)

print('accuracy = %.5f'%(accuracy))
print('rightNUM = %d wrongNUM = %d'%(right,wrong))

The accuracy result is shown below:
accuracy = 0.94848
rightNUM = 313 wrongNUM = 17

Question 4

Predict the labels for testing data.
The following labels prediction codes are appended to codes in Question3:
```

```
# predict labels of test data
PHIT = np.ndarray([21,21],dtype=float)
for i in range(0, 21):
   PHIT_row = []
   for j in range(0,20):
       row = CenterVec[j,:]; delta = 1.5
       distance =
np.sum(np.exp(-np.square(row-data test[i,:]/(2*delta**2))))
       PHIT row.append(distance)
   PHIT row.append(bias)
   PHIT[i,:] = np.array(PHIT_row,dtype=float)
RBFVAL = PHIT @ WEIGHTS
# get predict labels
predictLAB = np.zeros([21], dtype=float)
for i in range(0,21):
   if RBFVAL[i] > 0:
       predictVAL = 1
   else:
       predictVAL = -1
   predictLAB[i] = predictVAL
print('PredictLabel: '); print(predictLAB)
```

#### The predict labels result is shown below:

PredictLabel:

```
[ 1. 1. 1. -1. 1. -1. 1. -1. 1. -1. 1. -1. 1. 1. 1. -1. 1. -1. 1. -1. 1. -1. 1.
```