D7041E-lab4_SOM

December 11, 2023

[ ]:
```
import numpy as np
import numpy.matlib
from matplotlib import pyplot as plt
import math
import time
from keras.datasets import mnist
```

[ ]:
```
n_samples = 100

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images[:n_samples]
train_labels = train_labels[:n_samples]

test_images = test_images[:n_samples]
test_labels = test_labels[:n_samples]

train_images = train_images / 255.0
test_images = test_images / 255.0

train_images_flattened = train_images.reshape(train_images.shape[0], -1)
test_images_flattened = test_images.reshape(test_images.shape[0], -1)
```

[ ]:
```
def getEuclideanDistance(single_point,array):
    nrows, ncols, nfeatures=array.shape[0],array.shape[1], array.shape[2]
    points=array.reshape((nrows*ncols,nfeatures))

    dist = (points - single_point)**2
    dist = np.sum(dist, axis=1)
    dist = np.sqrt(dist)

    dist=dist.reshape((nrows,ncols))
    return dist
```

[ ]:
```
mu, sigma = 0, 0.1
A = np.random.normal(mu, sigma, 10)
#A.shape, A
```

[ ]:
```
nrows,ncols,nfeatures=3,3,3

#Generate coordinate system
x,y=np.meshgrid(range(ncols),range(nrows))
```

[ ]:
```
sgm0=2
sgmdecay=0.05
t=1
sgm = sgm0 * math.exp(-t*sgmdecay);

width = math.ceil(sgm*3)

dist=np.array([[2,1,3],[3,2,3],[4,4,4]])
bmurow, bmucol =np.unravel_index(np.argmin(dist, axis=None), dist.shape)

g = np.exp(-((np.power(x - bmucol,2)) + (np.power(y - bmurow,2))) /␣
 ↪(2*sgm*sgm));


fromrow = max(0,bmurow - width);
torow   = min(bmurow + width,nrows);
fromcol = max(0,bmucol - width);
tocol   = min(bmucol + width,ncols);
```

[ ]:
```
G = np.dstack([g[fromrow:torow,fromcol:tocol]]*nfeatures);
```

[ ]:
```
def SOM (dispRes, trainingData, ndim=10, nepochs=10, eta0=0.1, etadecay=0.05,␣
 ↪sgm0=20, sgmdecay=0.05, showMode=0):
    nfeatures=trainingData.shape[1]
    ntrainingvectors=trainingData.shape[0]

    nrows = ndim
    ncols = ndim

    mu, sigma = 0, 0.1
    numpy.random.seed(int(time.time()))
    som = np.random.normal(mu, sigma, (nrows,ncols,nfeatures))

    if showMode >= 1:
        print("\nSOM features before training: \n")

        fig, ax=plt.subplots(nrows=nrows, ncols=ncols, figsize=(15,15))

        for k in range(nrows):
            for l in range (ncols):
                A=som[k,l,:].reshape((dispRes[0],dispRes[1]))
                ax[k,l].imshow(A,cmap="plasma")
```

```
                ax[k,l].set_yticks([])
                ax[k,l].set_xticks([])

    #Generate coordinate system
    x,y=np.meshgrid(range(ncols),range(nrows))


    for t in range (1,nepochs+1):
        #Compute the learning rate for the current epoch
        eta = eta0 * math.exp(-t*etadecay);

        #Compute the variance of the Gaussian (Neighbourhood) function for the␣
↪ucrrent epoch
        sgm = sgm0 * math.exp(-t*sgmdecay);

        #Consider the width of the Gaussian function as 3 sigma
        width = math.ceil(sgm*3);

        for ntraining in range(ntrainingvectors):
            trainingVector = trainingData[ntraining,:];

            # Compute the Euclidean distance between the training vector and
            # each neuron in the SOM map
            dist = getEuclideanDistance(trainingVector, som);

            # Find 2D coordinates of the Best Matching Unit (bmu)
            bmurow, bmucol =np.unravel_index(np.argmin(dist, axis=None), dist.
↪shape) ;


            #Generate a Gaussian function centered on the location of the bmu
            g = np.exp(-((np.power(x - bmucol,2)) + (np.power(y - bmurow,2))) /␣
↪(2*sgm*sgm));

            #Determine the boundary of the local neighbourhood
            fromrow = max(0,bmurow - width);
            torow   = min(bmurow + width,nrows);
            fromcol = max(0,bmucol - width);
            tocol   = min(bmucol + width,ncols);


            #Get the neighbouring neurons and determine the size of the␣
↪neighbourhood
            neighbourNeurons = som[fromrow:torow,fromcol:tocol,:];
            sz = neighbourNeurons.shape;

            #Transform the training vector and the Gaussian function into
```

```
            # multi-dimensional to facilitate the computation of the neuron␣
 ↪weights update
            T = np.matlib.repmat(trainingVector,sz[0]*sz[1],1).
 ↪reshape((sz[0],sz[1],nfeatures));
            G = np.dstack([g[fromrow:torow,fromcol:tocol]]*nfeatures);

            # Update the weights of the neurons that are in the neighbourhood␣
 ↪of the bmu
            neighbourNeurons = neighbourNeurons + eta * G * (T -␣
 ↪neighbourNeurons);


            #Put the new weights of the BMU neighbouring neurons back to the
            #entire SOM map
            som[fromrow:torow,fromcol:tocol,:] = neighbourNeurons;

    if showMode >= 1:
        print("\nSOM features AFTER training: \n")

        fig, ax=plt.subplots(nrows=nrows, ncols=ncols, figsize=(15,15))

        for k in range(nrows):
            for l in range (ncols):
                A=som[k,l,:].reshape((dispRes[0],dispRes[1]))
                ax[k,l].imshow(A,cmap="plasma")
                ax[k,l].set_yticks([])
            ax[k,l].set_xticks([])
    return som
```

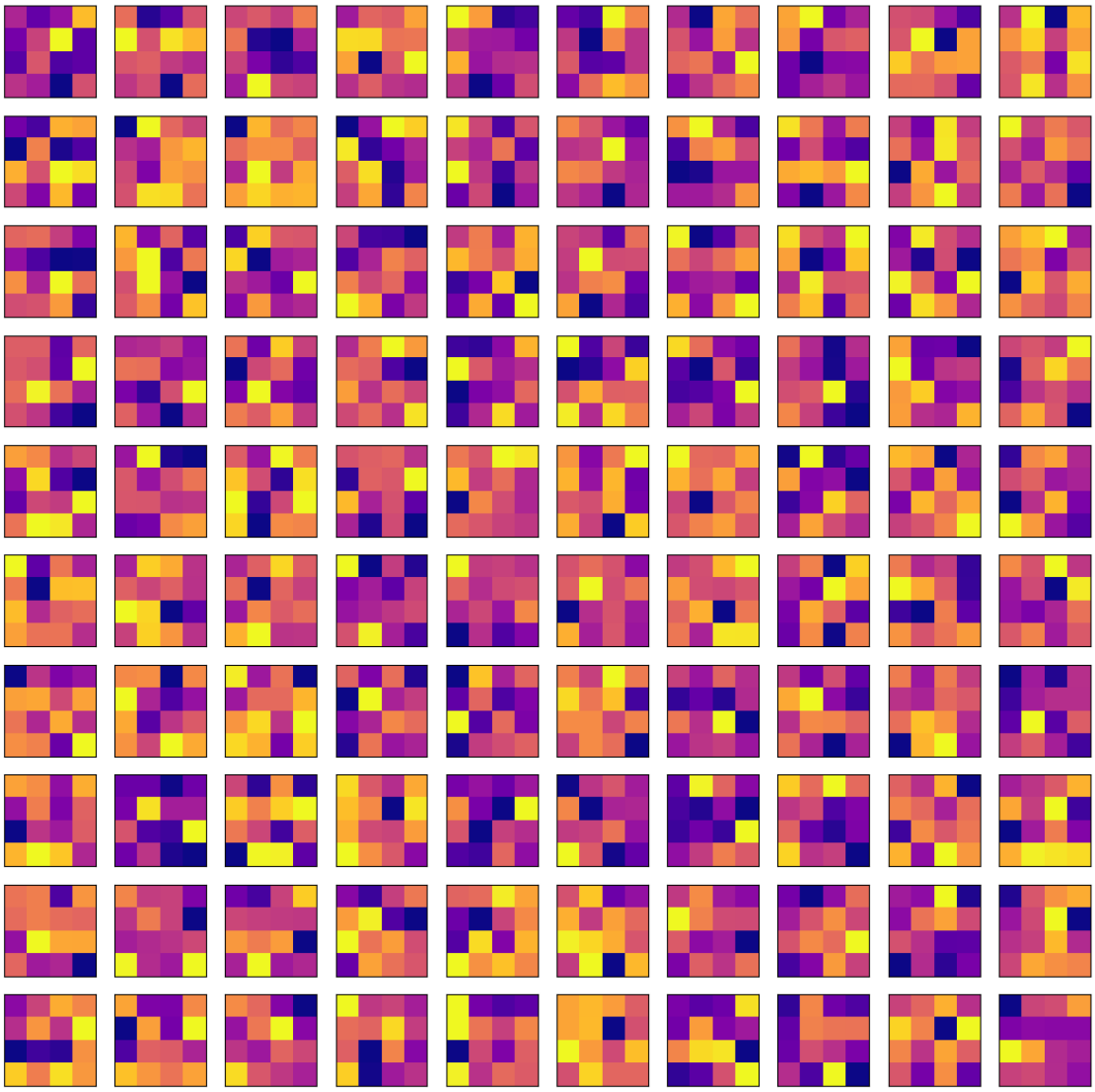
[ ]:
```
import pandas as pd
def parse_input_zoo_data(filename, header='infer'):

    input_data = pd.read_csv(filename, header=header)

    classes = input_data[17].tolist()
    labels = input_data[0].tolist()
    input_database = {
        0: input_data[[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]].
 ↪to_numpy()
    }

    return input_database, labels, classes
```

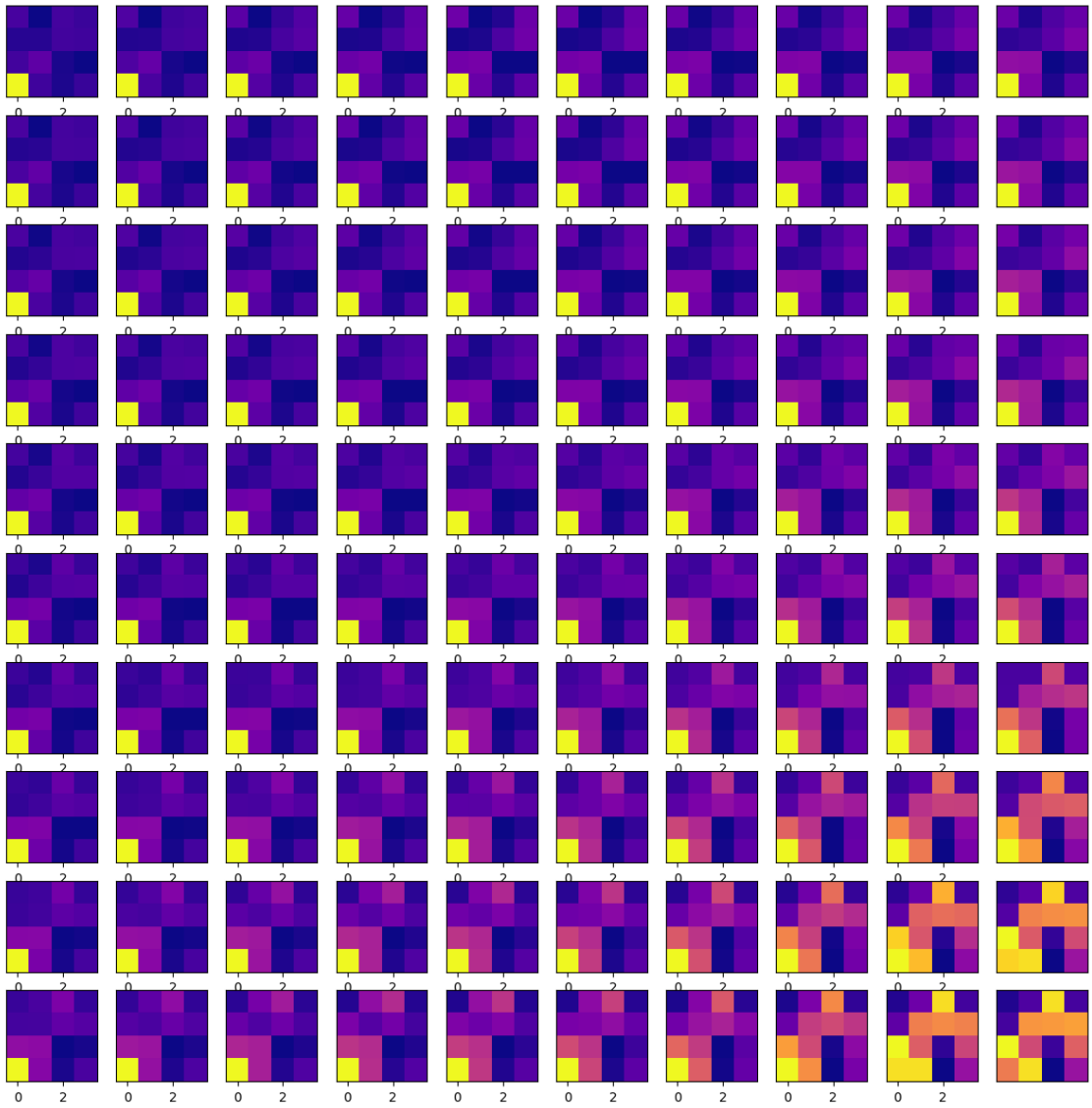
[ ]:
```
input_filename = 'zoo.txt'
input_vector_database, labels, classes =␣
 ↪parse_input_zoo_data(input_filename,None)
```

[ ]:
```
som_trained=SOM ([4,4],input_vector_database[0], ndim=10, nepochs=100, eta0=0.
↪01, etadecay=0.05, sgm0=20, sgmdecay=0.05, showMode=1)
```

SOM features before training:

SOM features AFTER training:



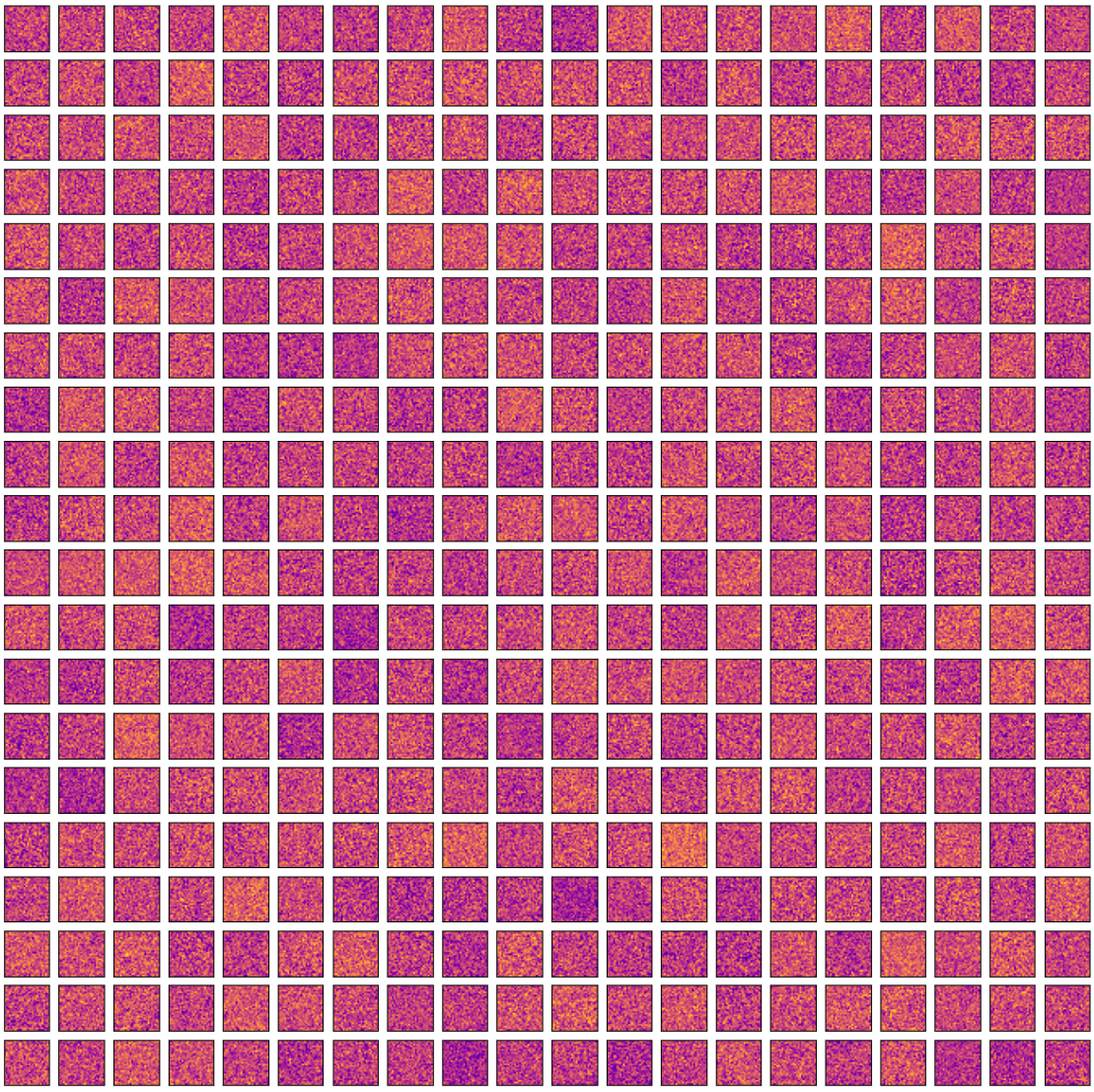


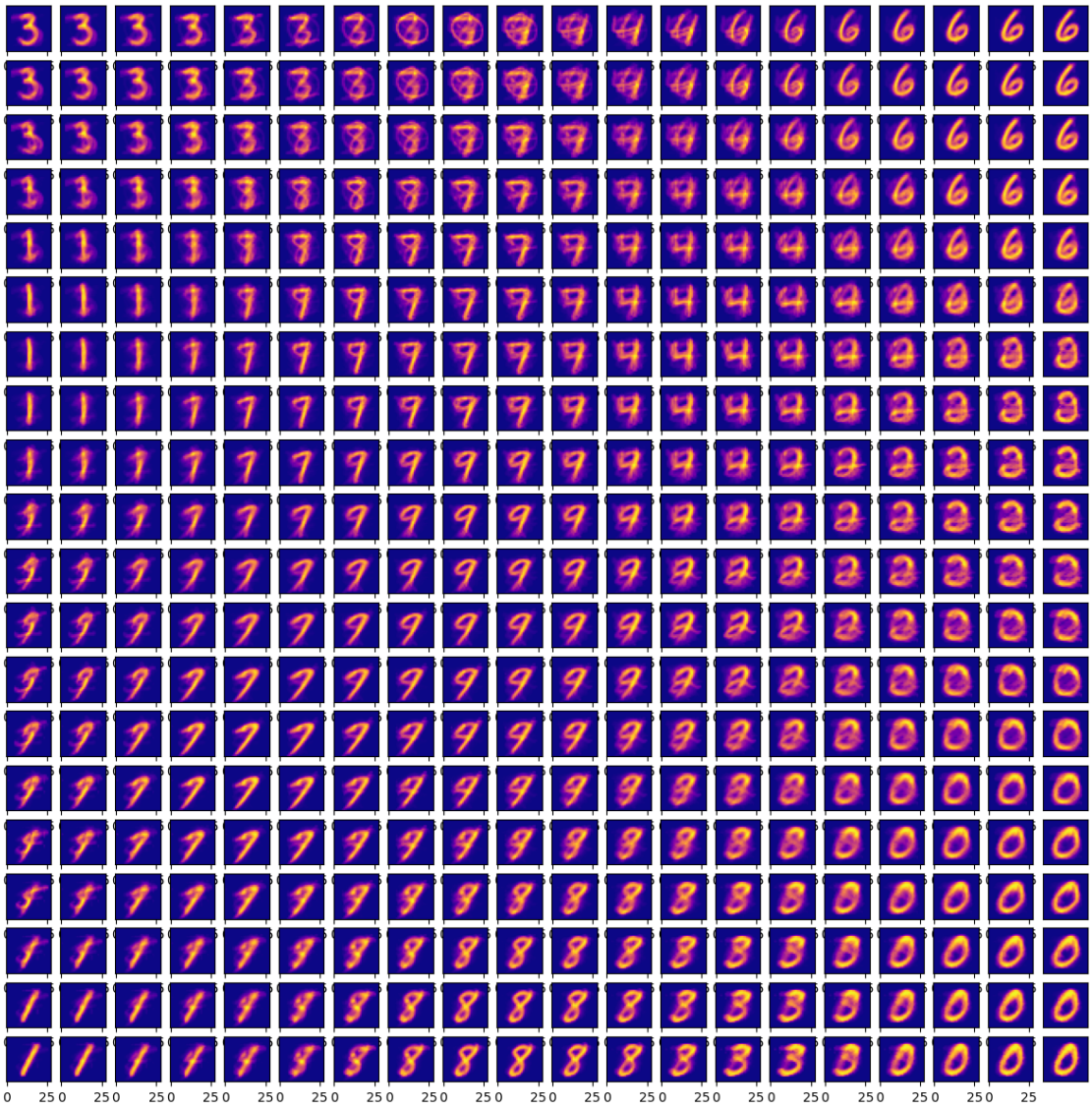
[ ]:
```
ndim20 = 20
ndim40 = 40
ndim80 = 80

som_trained_20x20 = SOM([28, 28], train_images_flattened, ndim=ndim20,␣
↪nepochs=100, showMode=1)

print(som_trained_20x20)

plt.show()
```

SOM features before training:

```
SOM features AFTER training:

[[[ 5.44653750e-33 -9.29035390e-33 -8.68659588e-34 … -7.50361508e-33
   -1.01681843e-32  5.90381360e-33]
  [ 2.44651626e-33  1.94963348e-33  1.26934512e-33 … -2.70488114e-34
   -1.39692610e-33 -1.01906463e-34]
  [-7.16252223e-34 -1.65814292e-33 -4.15858055e-34 … -5.89024683e-34
    6.41111117e-34  4.38707878e-35]
  …
  [-6.23825362e-30 -3.05013801e-30  6.57893206e-30 …  4.98806717e-30
    3.53624177e-30 -2.94202961e-30]
  [-1.40734633e-29  2.28384771e-29 -1.21145373e-30 …  9.31561222e-31
    4.04209607e-29 -3.17876585e-29]
  [ 2.71397356e-28  1.31901072e-28 -3.60300083e-29 … -1.58972157e-28
    1.85675525e-28 -1.11768922e-28]]

 [[ 9.28727356e-34 -3.79606288e-34 -1.11903531e-33 … -1.42951770e-33
   -9.23891821e-34  1.42648440e-33]
  [ 1.46947831e-34  5.86122850e-35 -7.75684024e-35 … -5.29807484e-35
    2.11909313e-34  1.83640460e-34]
  [-2.38763650e-36 -2.90717064e-35  9.39439758e-35 … -1.83736081e-35
   -8.19084888e-36 -9.88301291e-35]
  …
  [ 7.63682240e-31  1.94527057e-30 -5.03070175e-32 …  6.06777259e-31
   -2.34230135e-31 -1.14960160e-30]
  [-2.68509825e-30  1.14581770e-29  2.61770613e-30 … -2.89616361e-30
    6.30194309e-30 -5.23819041e-30]
  [ 5.05344243e-29 -1.01554604e-29  1.02568922e-28 … -4.47139499e-29
   -3.04388219e-29 -3.93802455e-29]]

 [[-7.37870134e-35 -3.67812602e-35  1.00739262e-34 … -6.32925370e-35
   -7.70437523e-35  1.48901031e-34]
  [-4.23468865e-36 -1.96344313e-36 -1.93526162e-35 … -3.04175154e-35
   -1.07927757e-35 -2.61363600e-35]
  [-5.34975372e-36  1.17520207e-35 -9.58396360e-36 … -5.27188727e-37
   -6.48387949e-36  1.72859848e-35]
  …
  [-1.82454308e-31  3.75494343e-32  2.15025171e-31 … -1.89112263e-31
   -1.18968469e-32  2.80472766e-31]
  [ 2.11379700e-30  2.24177581e-30 -4.73782026e-31 …  3.35539480e-31
    3.95052092e-30 -1.21432870e-30]
  [ 2.07659109e-29 -1.39717089e-29 -2.68012328e-29 … -1.08501428e-30
    8.56225392e-30  1.64303586e-30]]

 …
```

```
[[-3.98746546e-37 -6.68428491e-37  2.54379492e-37 …  2.27871959e-36
  -8.31668087e-37  1.29926988e-36]
 [ 1.10099816e-37  3.14111026e-38 -2.54778416e-37 …  5.37213435e-38
  -4.00492574e-37  1.23287617e-37]
 [ 5.31184874e-38 -9.66590368e-38 -8.50964807e-41 … -8.53079093e-38
   7.19546653e-38 -3.67543143e-38]
 …
 [-6.63423601e-33  2.72700350e-33 -1.75133426e-33 … -8.88364380e-33
   8.24435109e-34  5.69673579e-33]
 [ 1.26429943e-32  2.77029549e-32 -5.71695777e-32 …  3.75514336e-32
   1.06071708e-32 -5.61181715e-33]
 [ 1.09678989e-30  8.31060159e-31 -7.93599625e-32 …  5.26252902e-31
   2.54798939e-31 -4.92365719e-31]]

[[-9.45934846e-37  2.22440850e-36  2.93302955e-36 …  6.64292153e-36
  -6.93388642e-36  6.31283052e-36]
 [-1.08014302e-36 -6.43851721e-37 -2.40147003e-37 … -3.14322976e-37
   3.12407415e-38  5.92682194e-37]
 [ 3.71550526e-38 -1.15186316e-39  2.53742154e-37 …  1.03098342e-37
   2.00114577e-38  2.78895609e-37]
 …
 [ 7.08061605e-34 -1.30595762e-32  4.80610565e-33 …  1.39524423e-32
   1.12304614e-32 -6.32581885e-33]
 [ 6.96881230e-33 -4.92472481e-33 -4.28421805e-32 …  8.04786451e-32
   1.00175290e-31 -9.58497787e-32]
 [-2.28813934e-31  5.92444677e-31 -2.12070503e-31 … -2.92616259e-31
   2.60221491e-30 -4.61122114e-33]]

[[-1.99459159e-35 -1.11074855e-35  3.94087912e-35 … -3.44550964e-35
   1.09220674e-35 -1.06888567e-36]
 [ 2.97053993e-36  5.81737612e-37 -6.93598525e-36 … -6.89021115e-36
  -7.47804753e-36 -2.15039780e-36]
 [ 5.86083639e-36  2.33301820e-36 -6.19191728e-37 …  1.56049451e-38
   3.41866175e-36 -3.71060122e-37]
 …
 [-2.17321886e-32 -3.59953257e-32  7.76726376e-32 …  2.98414620e-33
   9.60027900e-32  1.89277633e-32]
 [ 4.34876475e-31  1.13189153e-31  9.33283242e-31 … -9.44893310e-31
   4.64694651e-32 -1.20835015e-31]
 [-2.46771559e-30  1.90702834e-30 -1.33244165e-30 …  2.77194266e-30
   5.63718003e-30 -4.38380602e-30]]]
```





[ ]:
```
#verification of correctness on the training set:


def SOM_Test (trainingData, som_, classes, grid_, confusion_matrix, ndim=60):
    nfeatures=trainingData.shape[1]
    ntrainingvectors=trainingData.shape[0]

    nrows = ndim
    ncols = ndim

    nclasses=np.max(classes)
```

```
    som_cl=np.zeros((ndim,ndim,nclasses+1))


    for ntraining in range(ntrainingvectors):
        trainingVector = trainingData[ntraining,:];
        class_of_sample= classes[ntraining]
        # Compute the Euclidean distance between the training vector and
        # each neuron in the SOM map
        dist = getEuclideanDistance(trainingVector, som_);

        # Find 2D coordinates of the Best Matching Unit (bmu)
        bmurow, bmucol =np.unravel_index(np.argmin(dist, axis=None), dist.
↪shape) ;


        som_cl[bmurow, bmucol,class_of_sample]=som_cl[bmurow,␣
↪bmucol,class_of_sample]+1



    for i in range (nrows):
        for j in range (ncols):
            grid_[i,j]=np.argmax(som_cl[i,j,:])


    for ntraining in range(ntrainingvectors):
        trainingVector = trainingData[ntraining,:];
        class_of_sample= classes[ntraining]
        # Compute the Euclidean distance between the training vector and
        # each neuron in the SOM map
        dist = getEuclideanDistance(trainingVector, som_);

        # Find 2D coordinates of the Best Matching Unit (bmu)
        bmurow, bmucol =np.unravel_index(np.argmin(dist, axis=None), dist.
↪shape) ;

        predicted=np.argmax(som_cl[bmurow, bmucol,:])
        confusion_matrix[class_of_sample-1,␣
↪predicted-1]=confusion_matrix[class_of_sample-1, predicted-1]+1

    return grid_, confusion_matrix
```

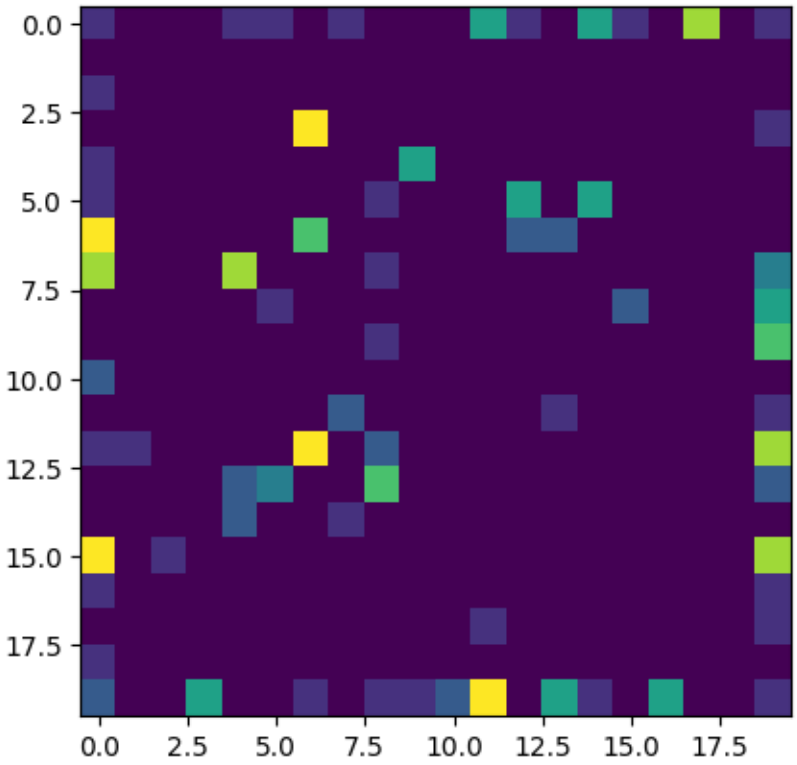
[ ]:
```
def get_confusion_matrix(train_images, SOM, ndim=20):
    nrows=ndim
    ncols=ndim
    grid_color=np.zeros((nrows,ncols))
```

```
    nclasses=np.max(classes)

    confusion_matrix=np.zeros((nclasses,nclasses))
    grid_color,confusion_matrix=SOM_Test (train_images, SOM, classes,␣
 ↪grid_color, confusion_matrix, ndim)

    plt.close()
    plt.imshow(grid_color)
    plt.show()

    return confusion_matrix, train_images_flattened.shape, np.
 ↪sum(confusion_matrix)
```

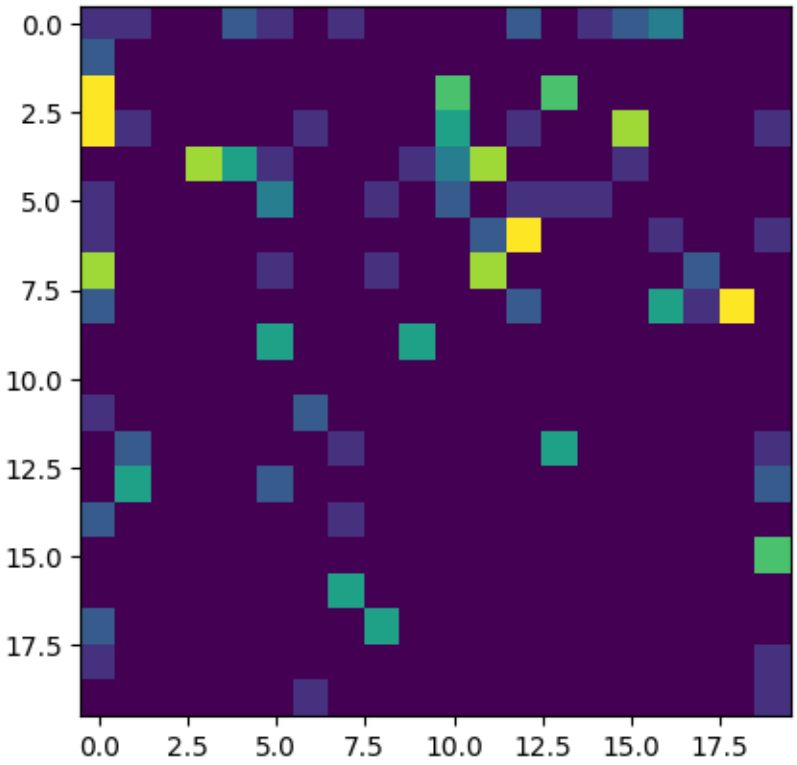
[ ]:
```
def calulate_accuracy(confusion_matrix):
    true_positives = np.trace(confusion_matrix)
    total_samples = np.sum(confusion_matrix)
    accuracy = true_positives / total_samples

    print("Accuracy:", accuracy)
```

[ ]:
```
print("Training Set")
confusion_matrix, shape, sum_matrix =␣
 ↪get_confusion_matrix(train_images_flattened, som_trained_20x20, ndim20)
print(confusion_matrix)
calulate_accuracy(confusion_matrix)

print("Test Set")
confusion_matrix, shape, sum_matrix =␣
 ↪get_confusion_matrix(test_images_flattened, som_trained_20x20, ndim20)
print(confusion_matrix)
```

```
Training Set
```




```
[[40.  1.  0.  0.  0.  0.  0.]
 [ 5. 14.  0.  0.  0.  0.  0.]
 [ 3.  0.  2.  0.  0.  0.  0.]
 [ 3.  0.  0.  9.  0.  0.  1.]
 [ 0.  0.  0.  1.  3.  0.  0.]
 [ 2.  1.  0.  0.  0.  5.  0.]
 [ 2.  2.  0.  0.  0.  0.  6.]]
Accuracy: 0.79
Test Set
```




```
[[40.  0.  0.  0.  0.  0.  1.]
 [ 4. 15.  0.  0.  0.  0.  0.]
 [ 2.  0.  3.  0.  0.  0.  0.]
 [ 2.  1.  0.  9.  0.  0.  1.]
 [ 1.  0.  0.  0.  3.  0.  0.]
 [ 2.  0.  0.  0.  0.  5.  1.]
 [ 1.  1.  2.  0.  0.  0.  6.]]
```

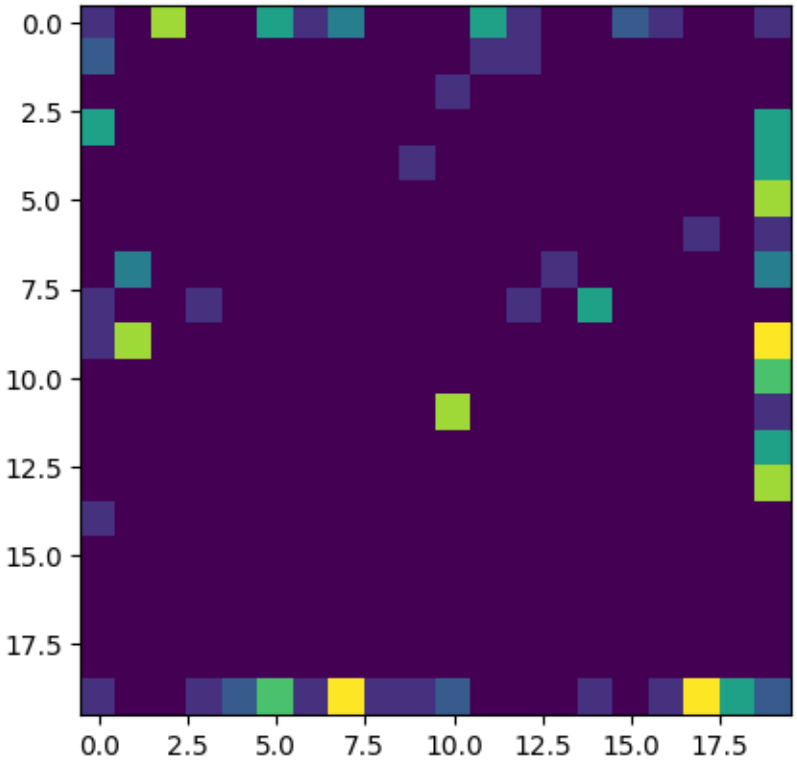
0.0.1 Question 6: What is the resulting effect of changing learning rate with a fixed number of itterations

It increases up to the learning rate of 0.75 and then seems to decrease.

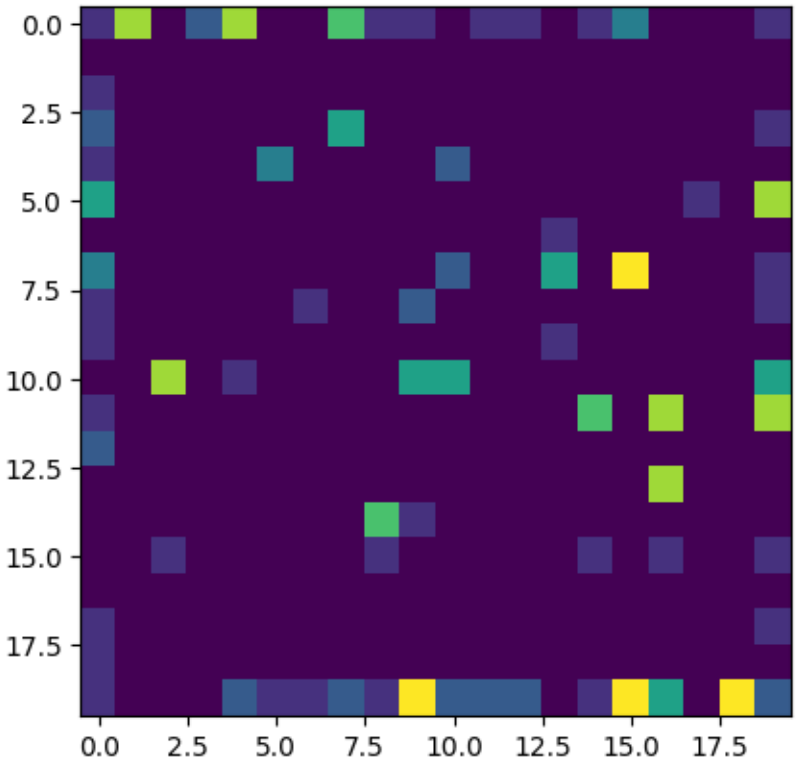
[ ]:
```
learning_rates = [0.01, 0.1, 0.25, 0.5, 0.75, 0.85, 0.95]

for learning_rate in learning_rates:
    print(f"\n--- Training with learning rate: {learning_rate} ---")
    som = SOM([28, 28], train_images_flattened, ndim=ndim20, nepochs=100,␣
 ↪eta0=learning_rate, etadecay=0.05, sgm0=20, sgmdecay=0.05, showMode=0)
    confusion_matrix, shape, sum_matrix =␣
 ↪get_confusion_matrix(train_images_flattened, som, ndim20)
    print(confusion_matrix)
```

```
    calulate_accuracy(confusion_matrix)
```

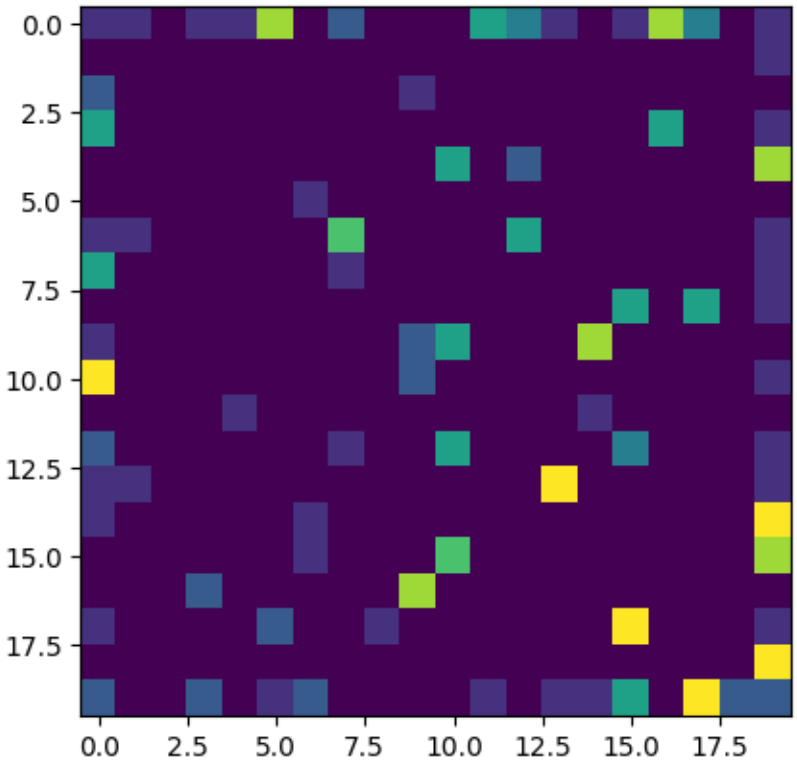
```
--- Training with learning rate: 0.01 ---
```



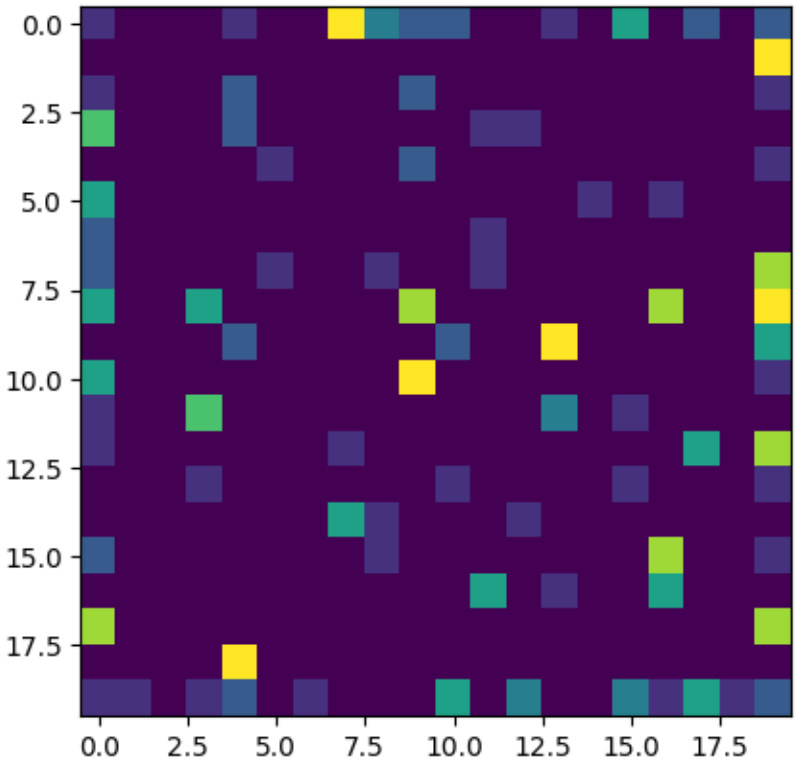

```
[[38.  3.  0.  0.  0.  0.  0.]
 [11.  8.  0.  0.  0.  0.  0.]
 [ 2.  0.  3.  0.  0.  0.  0.]
 [ 5.  0.  0.  8.  0.  0.  0.]
 [ 1.  0.  0.  1.  2.  0.  0.]
 [ 2.  0.  0.  1.  0.  5.  0.]
 [ 3.  2.  0.  1.  0.  1.  3.]]
Accuracy: 0.67

--- Training with learning rate: 0.1 ---
```



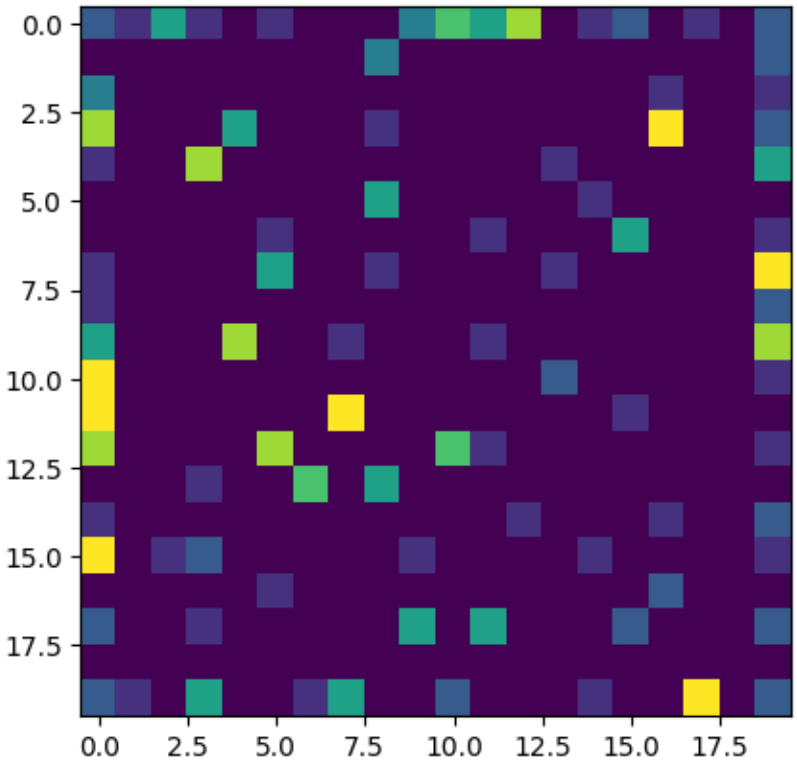

```
[[40.  1.  0.  0.  0.  0.  0.]
 [ 4. 15.  0.  0.  0.  0.  0.]
 [ 1.  1.  3.  0.  0.  0.  0.]
 [ 5.  1.  0.  7.  0.  0.  0.]
 [ 1.  0.  0.  0.  3.  0.  0.]
 [ 1.  0.  0.  0.  0.  7.  0.]
 [ 1.  3.  0.  1.  0.  1.  4.]]
Accuracy: 0.79

--- Training with learning rate: 0.25 ---
```



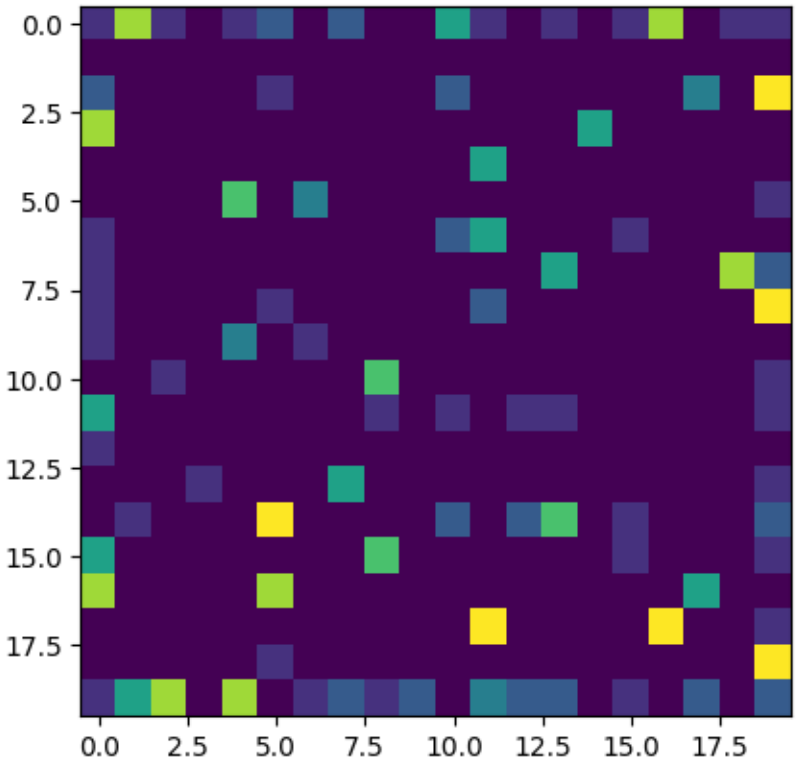

```
[[40.  1.  0.  0.  0.  0.  0.]
 [ 4. 15.  0.  0.  0.  0.  0.]
 [ 1.  1.  3.  0.  0.  0.  0.]
 [ 2.  0.  0. 11.  0.  0.  0.]
 [ 2.  0.  0.  0.  2.  0.  0.]
 [ 0.  2.  0.  0.  0.  6.  0.]
 [ 2.  1.  0.  0.  0.  1.  6.]]
Accuracy: 0.83

--- Training with learning rate: 0.5 ---
```



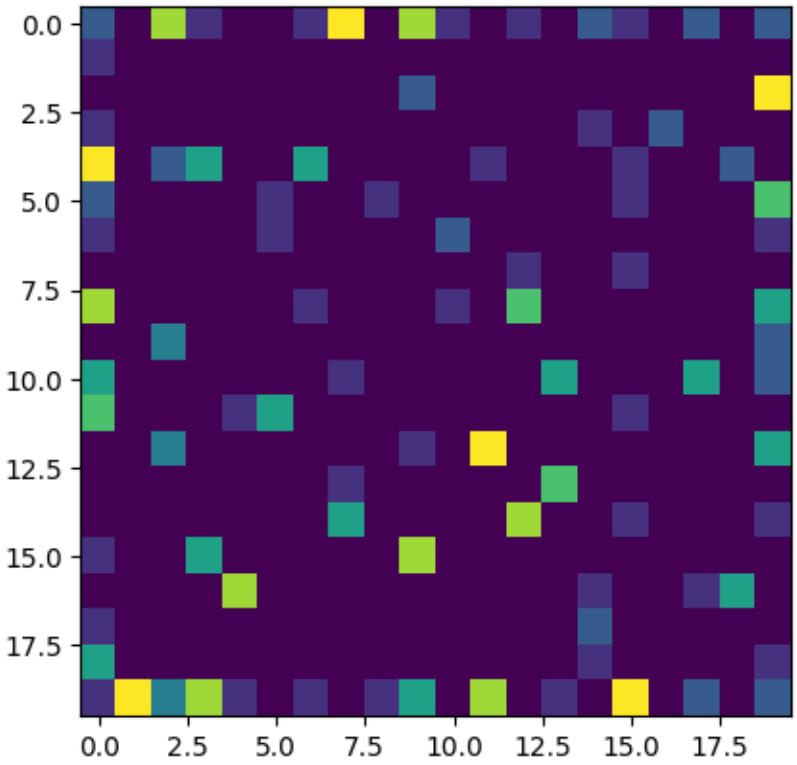

```
[[40.  1.  0.  0.  0.  0.  0.]
 [ 2. 17.  0.  0.  0.  0.  0.]
 [ 0.  1.  4.  0.  0.  0.  0.]
 [ 1.  0.  0. 12.  0.  0.  0.]
 [ 1.  0.  0.  1.  2.  0.  0.]
 [ 0.  1.  0.  0.  0.  7.  0.]
 [ 0.  2.  0.  1.  0.  1.  6.]]
Accuracy: 0.88

--- Training with learning rate: 0.75 ---
```




```
[[41.  0.  0.  0.  0.  0.  0.]
 [ 1. 18.  0.  0.  0.  0.  0.]
 [ 1.  1.  3.  0.  0.  0.  0.]
 [ 0.  0.  0. 13.  0.  0.  0.]
 [ 1.  0.  0.  0.  3.  0.  0.]
 [ 0.  1.  0.  0.  0.  7.  0.]
 [ 0.  3.  0.  0.  0.  0.  7.]]
Accuracy: 0.92

--- Training with learning rate: 0.85 ---
```




```
[[40.  1.  0.  0.  0.  0.  0.]
 [ 2. 17.  0.  0.  0.  0.  0.]
 [ 1.  0.  4.  0.  0.  0.  0.]
 [ 2.  1.  0. 10.  0.  0.  0.]
 [ 0.  0.  0.  0.  4.  0.  0.]
 [ 0.  0.  0.  0.  0.  8.  0.]
 [ 0.  2.  0.  1.  0.  1.  6.]]
Accuracy: 0.89

--- Training with learning rate: 0.95 ---
```



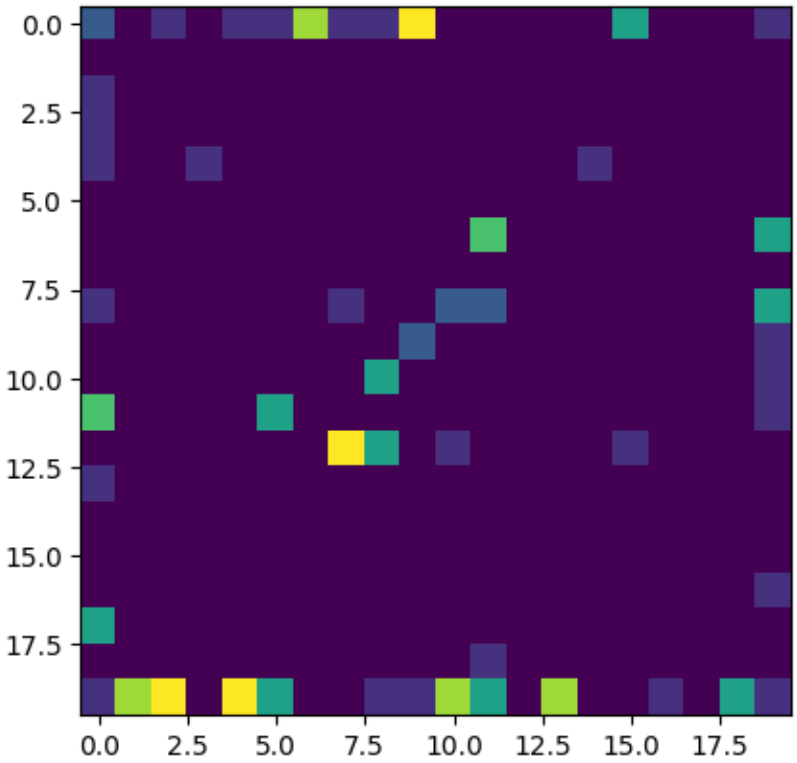

```
[[41.  0.  0.  0.  0.  0.  0.]
 [ 3. 16.  0.  0.  0.  0.  0.]
 [ 1.  1.  3.  0.  0.  0.  0.]
 [ 0.  0.  0. 13.  0.  0.  0.]
 [ 0.  0.  0.  0.  4.  0.  0.]
 [ 0.  0.  0.  0.  0.  8.  0.]
 [ 0.  2.  0.  1.  0.  1.  6.]]
Accuracy: 0.91
```

0.0.2 Question 7/8: For a fixed number of iterations what is the effect of increasing exponental decay of the neighbourhood parameter

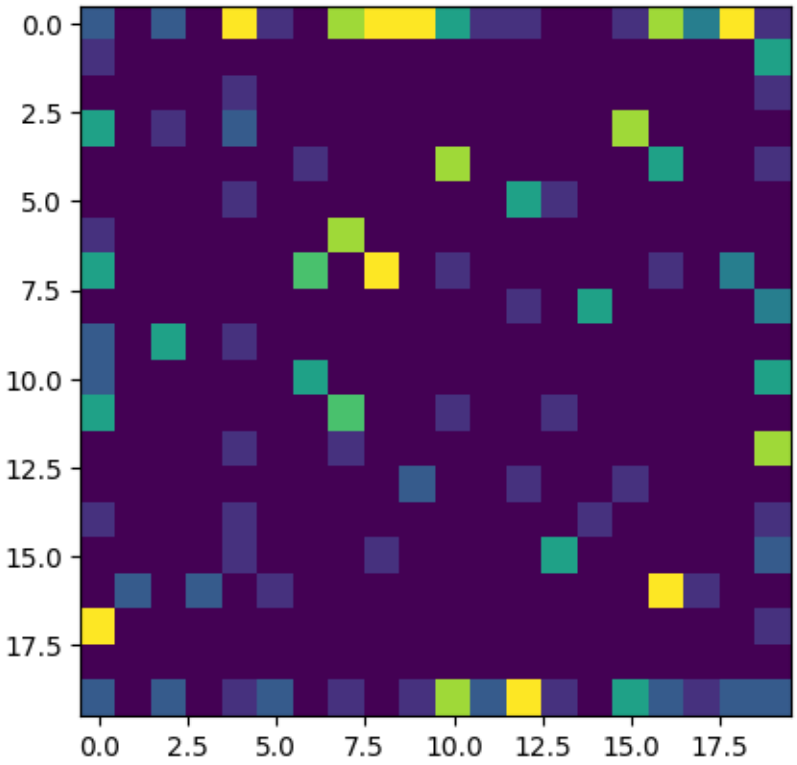
It seems to increase the accuracy (atleast until 0.5).

[ ]:
```
decay_values = [0.01, 0.05, 0.1, 0.5]
for decay_value in decay_values:
    som = SOM([28, 28], train_images_flattened, ndim=20, nepochs=100, eta0=0.
 ↪75, etadecay=0.05, sgm0=20, sgmdecay=decay_value, showMode=0)

    confusion_matrix, shape, sum_matrix =␣
 ↪get_confusion_matrix(train_images_flattened, som, ndim20)
    print(confusion_matrix)
```

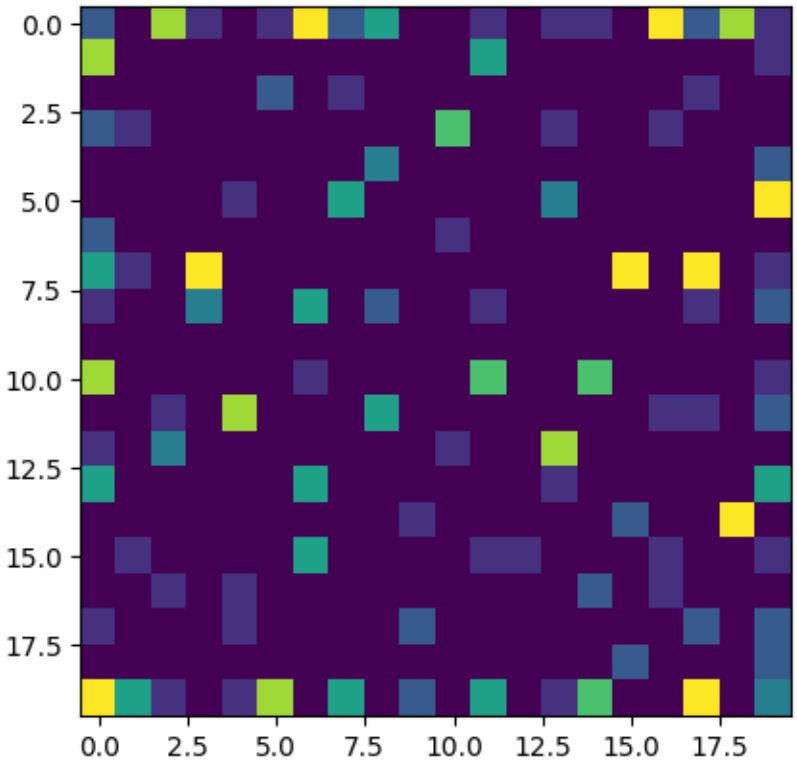
```
    calulate_accuracy(confusion_matrix)
```



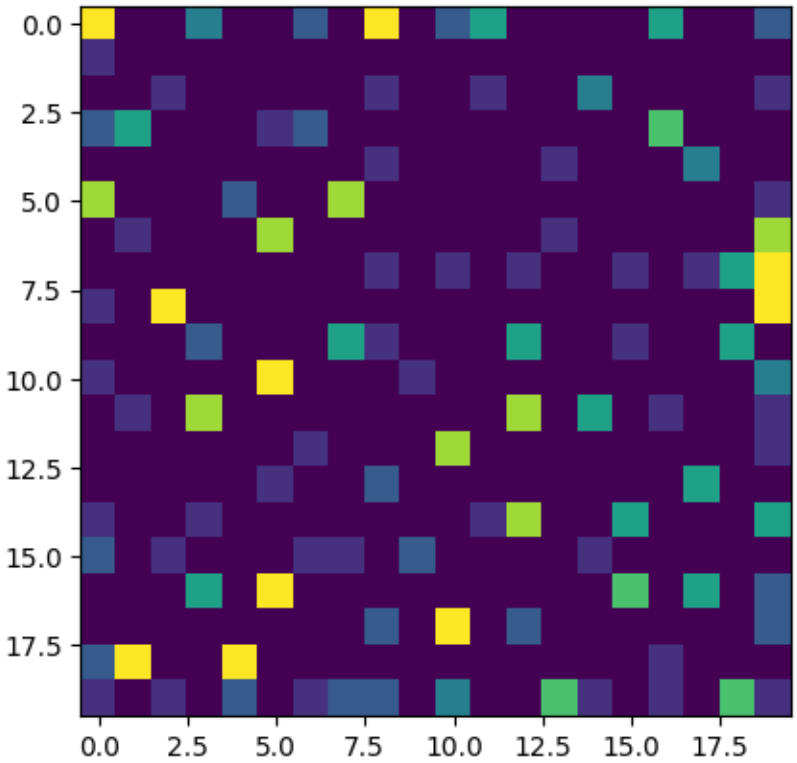

```
[[38.  3.  0.  0.  0.  0.  0.]
 [10.  9.  0.  0.  0.  0.  0.]
 [ 4.  1.  0.  0.  0.  0.  0.]
 [ 2.  0.  0. 11.  0.  0.  0.]
 [ 1.  1.  0.  0.  2.  0.  0.]
 [ 3.  0.  0.  0.  1.  4.  0.]
 [ 5.  1.  0.  0.  0.  0.  4.]]
Accuracy: 0.68
```




```
[[41.  0.  0.  0.  0.  0.  0.]
 [ 2. 17.  0.  0.  0.  0.  0.]
 [ 1.  1.  3.  0.  0.  0.  0.]
 [ 0.  0.  0. 13.  0.  0.  0.]
 [ 1.  0.  0.  1.  2.  0.  0.]
 [ 0.  1.  0.  0.  0.  7.  0.]
 [ 0.  2.  0.  0.  0.  0.  8.]]
Accuracy: 0.91
```




```
[[41.  0.  0.  0.  0.  0.  0.]
 [ 1. 18.  0.  0.  0.  0.  0.]
 [ 0.  0.  5.  0.  0.  0.  0.]
 [ 0.  0.  0. 13.  0.  0.  0.]
 [ 0.  0.  0.  0.  4.  0.  0.]
 [ 0.  0.  0.  0.  0.  7.  1.]
 [ 0.  0.  0.  0.  0.  0. 10.]]
Accuracy: 0.98
```




```
[[41.  0.  0.  0.  0.  0.  0.]
 [ 1. 18.  0.  0.  0.  0.  0.]
 [ 0.  0.  5.  0.  0.  0.  0.]
 [ 0.  0.  0. 13.  0.  0.  0.]
 [ 0.  0.  0.  0.  4.  0.  0.]
 [ 0.  0.  0.  0.  0.  8.  0.]
 [ 0.  0.  0.  0.  0.  0. 10.]]
Accuracy: 0.99
```

0.0.3 Question 9: What is a biological neuron? How does it relate to the concept of neurons in SOM?

Biological neurons send binary “fire or not fire” signals while artificial neurons send continious values