



COEN 6331: Neural Networks

ASSIGNMENT -2

Submitted by:

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I certify that this submission is my original work and meets the Faculty's Expectations of Originality

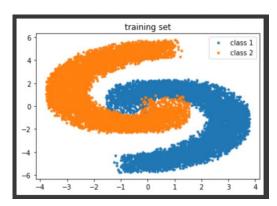
February 24, 2022

ABSTRACT

The objective of this assignment is to study a two-dimensional classification problem that involves nonconvex decision regions via Counter Propagation Network (CPN).

1. Generating two non-convex regions for training:

In order to generate the pattern above in the question a neural network architecture is designed with Keras, that will be used as the data to train the network.



As shown above data obtained from pattern is the dataset that contains two different spirals. Now from this data, choosing the samples in each of the regions, it is possible to train them and study CPN mechanism.

2. Selecting samples for the non-convex regions:

In this case, the number of samples selected are 7000 (random value) that is appended to value 'n_points' in the code.

The pattern generated is appended to a variable 'n' and from this 'n' value, the data sets for classes are derived and named 'd1x' & 'd1y' respectively in the code.

Further, to generate the datasets for training, all the points belonging to the pattern are normalized. But this normalization is done by arranging the data values in 'np.hstack', 'np.vstack' i.e., arranging horizontally and vertically in array stacks (just for simplification of coding process).

```
counter_propagation.py
                       config.py × generator_distributions.py
                                                            distributions.pv
 1 import numpy as np
2 from sources import generator_distributions, distributions
3 # famous data
4 P_trust = 0.95
5 t_critical_student = 2.26
6 number_drills = 20
7 number_stoutnes = 24
 9 # for hi_square
10 decrease_of_freedom = number_stoutnes - 1
11 level main = 0.05
12 hi_critical_23_005 = 35.5 # 23 and 0.05
13 hi_critical_11_005 = 19.7
16 noise=1.5
18 n = np.sqrt(np.random.rand(n_points,1)) * 400 * (1.10*np.pi)/290
19 dlx = -np.cos(n)*n + np.random.rand(n_points,1) * noise -
20 dly = np.sin(n)*n + np.random.rand(n_points,1) * noise -1
22 # X values data
23 drills = np.vstack((np.hstack((dlx,dly)),np.hstack((-dlx,-dly)))) ### combiing 2 rows
24 #print(d1x[0:5])
25 #drills=[item for sublist in drills_ for item in sublist]
26 # generated data from function generate_normal_distribution()
27 #normal_distribution = generator_distributions.generate_normal_distributions(batch = len(dlx), size = len(dlx))
28 #normal_distribution=distributions.generate_normal_distribution(size=len(dlx))
29 normal_distribution= []
30 # result from comparison with data from table and generated normal distribution.
31 \# every number belong to data from table.
32 # 1 - distribution is normal
33 # 0 - distribution isn't normal
34 #print(drills[0:5],dly[0:5])
35 y_train = np.hstack((np.zeros(n_points),np.ones(n_points))) #### normalization is happening here,, combing 2 cols
```

Code for configuring data sets values

```
counter_propagation.py × config.py
                                  generator distributions.py
                                                            distributions.py
 2 Counter propagation neural network.
 5 from sources.generator_distributions import mix_distributions, generate_normal_distributions, generate_expon_distributions, get_y_train
 6 from sources import config
 7 from math import sqrt
 8 import time
10 X_values = config.drills
11 y_values = config.y_train
13 def sum_squares(arr):
14 return sum([x ** 2 for x in arr])
16 # function normalization for vectors X
17 def normalization(arr_x, arr_y):
     sum_y_squares = sum_squares(arr_y)
19
      result = []
20
21
      for row x in arr x:
22
        middle_result = []
23
          sum x squares = sum squares(row x)
24
          for x in row x:
25
          middle_result.append(round(x / sqrt(sum_x_squares + sum_y_squares), 2))
26
          result.append(middle_result)
27
28
      return result
```

Normalization

3. CPN weights, Kohonen & Grossberg Neurons:

a) Feeding the pattern data set as input to the learning of CPN network –

The pattern obtained in initial phase is now translated into values stored in d1x, d1y and are appended in an array to use it as a vector.

b) Selection of Kohonen, Grossberg Neurons-

In this case, number of Kohonen neurons chosen are 2, and Grossberg neurons are 1.

c) Generating random weights-

Initially the weights for these 2 layers are chosen randomly, based on length of the vector (set to 4 in our example). These weights are denoted as 'kohonen_weights' and 'grossberg_weights' respectively.

```
30 class Counter_Propagation:
      def __init__(self, X_values, y_values, kohonen_neurons = 2, grossberg_neurons = 1, len_x_vector = 4):
32
          self.X_values = X_values
33
          self.y_values = y_values
34
          self.kohonen neurons = kohonen neurons
35
          self.grossberg_neurons = grossberg_neurons
36
          self.kohonen_weights = self.generate_weights(kohonen_neurons, len_x_vector)
37
          self.grossberg_weights = self.generate_weights(grossberg_neurons, len_x_vector)
38
39
      # generate weights for each part of network
40
      def generate weights(self, num neurons = 1, length=4):
41
          yy = np.random.rand(num_neurons, length)
42
          result = np.asarray(yy)
43
          print("Generating Random weights----", result)
44
45
          if len(result) == 1:
46
            return result[0]
47
          return result
48
```

Code for b), c) points above

d) Computing Euclidean distance-

Firstly, in order to compute this, the total number of samples in this case was chosen to be 7000 for which each of the samples in vector compute the shortest distance to given 2 neurons in Kohonen layer and 1 neuron in Grossberg layer.

The output of above (Euclidean distance) is stored in an array which generates almost 5000 values, and the winning node is printed corresponding to layer.

Post this the vectors of weights are updated with respect to the layer.

```
49
      # for shorter Evklide's way
50
      def calculate_evklid_way(self, w_vector, x_vector):
51
          zz= sum([ ((w-x) ** 2) for w, x in zip(w_vector, x_vector)])
52
          return zz
53
54
5.5
      # calculate net for Grossberg lay
56
      def sum_activation(self, k_vector, w_vector):
57
        return sum([ k*w for k, w in zip(k_vector, w_vector)])
58
59
      # update vector kohonen weights
60
      def update_kohonen_weights(self, x_vector, w_vector, learning_rate = 0.7):
61
          weights = []
62
63
          for x, w in zip(x_vector, w_vector):
64
              w_new = w + learning_rate * (x - w)
65
              weights.append(w_new)
66
          return np.asarray(weights)
67
      # update weights for grossberg lay
68
69
      def update_grossberg_weights(self, y_value, w_value, learning_rate = 0.1, k = 1):
70
          w_new = w_value + learning_rate * (y_value - w_value) * k
71
          #print(f'grossberg update: {w_value}, {w_new}')
72
          return w_new
73
```

Code for d) point

e) Training counter propagation neural network-

The parameters chosen for this process is: - learning rate for kohonen layer, learning rate for Grossberg layer, epochs. Now the training of CPN network is done from below code snippets.

```
80
       # training counter propagation neural network
       def fit(self, lr_kohonen = 0.7, lr_grossberg = 0.1, epochs = 10):
           print("kohonen_neurons used-----", self.kohonen_neurons, " || grossberg_neurons used------",self.grossberg_neurons)
83
           for epoch in range(epochs):
               if epoch % 5 == 0 and lr kohonen > 0.1 and lr grossberg > 0.01:
84
                   lr_kohonen-= 0.05
                 lr_grossberg -= 0.005
 88
               good counter = 0
               for x vector, y value in zip(self.X values, self.y values):
 89
                   kohonen_neurons = []
 92
                   for w iter in range(len(self.kohonen weights)):
                      kohonen_neurons.append(self.calculate_evklid_way(x_vector, self.kohonen_weights[w_iter]))
 93
                   neuron_min = min(kohonen (method) index: (_value: Any, __start: SupportsIndex = ..., __stop: SupportsIndex = ...) -> int
 95
96
                   index = kohonen_neurons.index(neuron_min)
97
                   for i in range(len(kohonen_neurons)):
99
                      if i == index:
100
                          kohonen_neurons[i] = 1
101
                       else:
102
                         kohonen_neurons[i] = 0
103
104
                   self.kohonen_weights[index] = self.update_kohonen_weights(x_vector, self.kohonen_weights[index], learning_rate= lr_kohonen)
105
106
                   # grossberg neurons
107
                   #print("index -", index)
108
                   self.grossberg_weights[index] = self.update_grossberg_weights(y_value, self.grossberg_weights[index], learning_rate=lr_grossberg)
109
                   grossberg_neuron_out = int(round(self.sum_activation(kohonen_neurons, self.grossberg_weights)))
110
                   good_counter += self.good_count(y_value, grossberg_neuron_out)
112
                   #print(f'{y_value} : {grossberg_neuron_out}')
113
               print(f'Success training {epoch+1} epoch: {int(good_counter/len(self.y_values) * 100)}%')
```

```
117
      # work network on test values
118
      def evaluate(self, X_values, y_values):
       self.X_values = X_values
119
120
          self.y_values = y_values
         rr =[]
121
122
         rr1=[]
123
          good_counter= 0
124
         for x_vector, y_value in zip(self.X_values, self.y_values):
125
              kohonen_neurons = []
126
127
             for w_iter in range(len(self.kohonen_weights)):
                kohonen_neurons.append(self.calculate_evklid_way(x_vector, self.kohonen_weights[w_iter]))
129
              neuron_min = min(kohonen_neurons)
130
              index = kohonen_neurons.index(neuron_min)
131
132
              rr.append(neuron_min)
133
              rrl.append(index)
              for i in range(len(kohonen_neurons)):
    if i == index:
134
135
                     kohonen_neurons[i] = 1
137
138
                    kohonen_neurons[i] = 0
139
              grossberg_neuron_out = int(round(self.sum_activation(kohonen_neurons, self.grossberg_weights)))
141
            good_counter += self.good_count(y_value, grossberg_neuron_out)
142
         print(f'Success evaluate: {int(good counter/len(self.y values) * 100)}%')
143
          print("Shortest Euclidean Distance for each Training value-----, rr)
          print("Winning node for each Training value----", rrl)
148 # work neural network
149 if __name__ == '__main__
        #print(X_values[0:5],y_values[0:5],y_values[-5:-1])\
151
152
        net = Counter_Propagation(X_values, y_values, kohonen_neurons=2, grossberg_neurons=1, len_x_vector=len(X_values[0]))
153
154
155
        t_start = time.perf_counter()
156
        lrk=0.7
157
        lrg= 1
        print("Learning rate for Kohonen ----", lrk , " || Learning rate for Grossberg----" , lrg)
158
159
        net.fit(lr_kohonen=0.7, lr_grossberg=1, epochs=5)
        t_stop = time.perf_counter()
161
162
        print(f"Time of fit: {round(t_stop - t_start, 3)}")
163
164
        # testing on synthetic values
165
        normal_distr = generate_normal_distributions(1000, 24)
        expon_distr = generate_expon_distributions(450, 24)
166
167
168
        X_test = mix_distributions(normal_distr, expon_distr)
169
        y_test = get_y_train(X_test)
171
       print("Evaluate")
172
      net.evaluate(X_test, y_test)
173
```

f) Studying effects of learning rate, epochs for training accuracy and winning nodes:

Number of Kohonen neurons	Number of Grossberg neurons	Learning rate for Kohonen layer	Learning rate for Grossberg layer	Epochs	Time taken (min)	Training Accuracy	Winner nodes count for 0th & 1st Neuron
2	1	0.7	1	5	01:316	99%	0- 1000 1- 450
2	1	0.7	0.1	5	01:198	100%	0- 998 1- 452
2	1	1.4	1	10	2:52	99%	1-1450

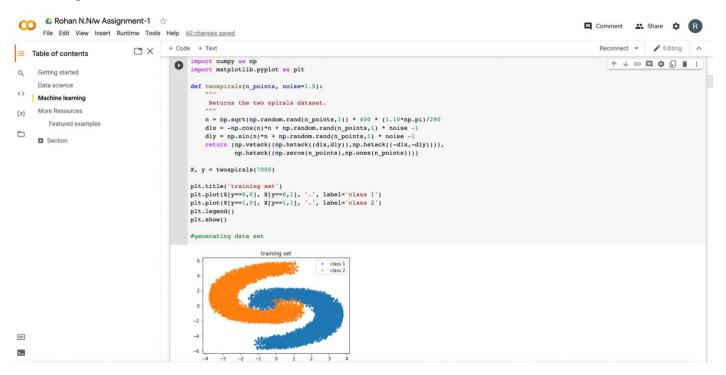
ſ	2	1	0.1	2	10	2.584	99%	0- 1000
								1- 450

So overall, in this case we observe that for a same number of neurons, time taken for 5 and 10 epochs brings no change in training accuracy. Varying the learning rate for both layers only affects the number of winning nodes for the layers by a small amount.

So overall, maintaining the maximum accuracy and by varying learning rates for fixed number of neurons in Kohonen layer and Grossberg layer, the effects and working of a Counter Propagation Network CPN is studied.

APPENDIX: OUTPUTs // CODE

Generating data set -



Code output -1:

```
!python3 /content/Neural_Networks/counter_propagation.py
  Generating Random weights---- [[0.10451289 0.27258738]
      [0.42827559 0.00331772]]
     Generating Random weights---- [[0.78307658 0.07353826]]
     Learning rate for Kohonen ---- 0.7 || Learning rate for Grossberg---- 1
     kohonen_neurons used----- 2 || grossberg_neurons used----- 1
     Success training 1 epoch: 100%
     Success training 2 epoch: 100%
     Success training 3 epoch: 100%
     Success training 4 epoch: 100%
     Success training 5 epoch: 100%
     Time of fit: 1.316
     Evaluate
     Success evaluate: 100%
     Shortest Euclidean Distance for each Training value----- [7.0725088636247015, 452.2080374625433, 511.48328711717915, 538.5469875750558, 7.072
     [22] import numpy as np
     a = np.array([1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1
     unique, counts = np.unique(a, return_counts=True)
     dict(zip(unique, counts))
     {0: 1000, 1: 450}
```

Code output -2:

```
!python3 /content/Neural_Networks/counter_propagation.py
                Generating Random weights---- [[0.43753171 0.24688073]
                                          [0.79827069 0.54397452]]
                                  Generating Random weights---- [[0.14482283 0.12450256]]
                                   kohonen_neurons used----- 2 || grossberg_neurons used----- 1 Success training 1 epoch: 99%
                                   Success training 2 epoch: 99%
Success training 3 epoch: 99%
                                  Success training 4 epoch: 99%
Success training 5 epoch: 99%
                                   Time of fit: 1.198
                                   Evaluate
                                    Success evaluate: 100%
                                  Shortest Euclidean Distance for each Training value----- [482.43719246539933, 521.4448656117901, 528.0170317224772, 381.7258889739552, 488.38 Winning node for each Training value----- [0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0
import numpy as np
                                   a = np.array({0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0
                                   dict(zip(unique, counts))
                                  {0: 998, 1: 452}
```

Code output -3:

```
[8] !python3 /content/Neural_Networks/counter_propagation.py
    Generating Random weights---- [[0.92550424 0.03577393]
     [0.56863496 0.29513009]]
    Generating Random weights----- [[0.23586267 0.89567496]]
    Learning rate for Kohonen ---- 1.4 || Learning rate for Grossberg---- 1
    kohonen_neurons used---- 2 || grossberg_neurons used----
    Success training 1 epoch: 99%
    Success training 2 epoch: 99%
Success training 3 epoch: 99%
    Success training 4 epoch: 99%
    Success training 5 epoch: 99%
    Success training 6 epoch: 99%
    Success training 7 epoch: 99%
Success training 8 epoch: 99%
    Success training 9 epoch: 99%
    Success training 10 epoch: 99%
    Time of fit: 2.52
    Evaluate
    Shortest Euclidean Distance for each Training value----- [463.46378153047146, 19.769211374042282, 458.3508770353984, 479.70528450649624, 19.7
    ↑ ↓ © □ ‡ 🖟 🗎 :
 import numpy as np
    dict(zip(unique, counts))
 [→ {1: 1450}
```

Code output -4:

```
!python3 /content/Neural_Networks/counter_propagation.py
   Generating Random weights----- [[0.02824559 0.65261106]
[0.19534586 0.00488573]]
      Generating Random weights---- [[0.30654624 0.14717478]]
      Learning rate for Kohonen ---- 0.1 || Learning rate for Grossberg---- 2 kohonen_neurons used----- 2 || grossberg_neurons used----- 1 Success training 1 epoch: 99%
      Success training 2 epoch: 99%
      Success training 3 epoch: 99%
      Success training 4 epoch: 99%
Success training 5 epoch: 99%
Success training 6 epoch: 99%
      Success training 7 epoch: 99%
Success training 8 epoch: 99%
Success training 9 epoch: 99%
Success training 9 epoch: 99%
      Success training 10 epoch: 99%
Time of fit: 2.584
      Evaluate
      Success evaluate: 100%
      Shortest Euclidean Distance for each Training value----- [17.3115775475725, 319.1260375394163, 17.3115775475725, 260.8723078472197, 329.61607
      [19] import numpy as np
      dict(zip(unique, counts))
      {0: 1000, 1: 450}
```