assignment_09

December 9, 2017

1 Team Members:

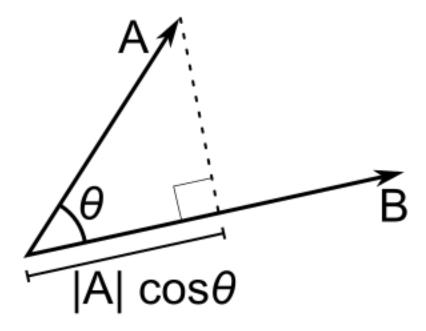
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- 1.0.3 3. Ravikiran Bhat

```
In [5]: import numpy as np
        import matplotlib.pyplot as plt
        import random
        import math
        from IPython.display import Image
        from IPython import display
        %matplotlib inline
        from tsp_solver.greedy import solve_tsp
```

2 Exercise 1

Show that in the SOM algorithm the winner neuron for an input x is that neuron k whose weight vector w maximizes the inner product x which x and y and y are y and y and y are y and y are y are y and y are y are y and y are y and y are y are y and y are y are y and y are y and y are y are y and y are y are y and y are y and y are y are y and y are y are y and y are y and y are y and y are y are y and y are y and y are y are y and y are y and y are y are y and y are y and y are y are y and y are y are y are y and y are y are y and y are y are y and y are y and y are y are y and y are y are y and y are y are y and y are y and y are y and y are y are y and y are y are y and y are y and y are y and y are y and y are y are y and y are y are y and y are y and y are y and y are y are y and y are y and y are y are y and y are y are y and y are y and y are y are y and y are y are y and y are y and y are y and y are y and y are y are y and y are y and y are y and y are y and y are y

```
In [6]: Image(filename ='../ravi/1.png')
Out[6]:
```



Then the inner product or dot product of these 2 vectors is equivalent to:

$$\mathbf{A}.\mathbf{B} = ||\mathbf{A}|| \, ||\mathbf{B}|| \, cos(\theta)$$

. Maximising this inner product implies $cos(\theta) = 1$ or $\theta = 0$. In other words, the euclidean distance between the 2 vectors is minimised. Since we need to minimize the distance between a winning neuron and the input vector, hence the inner product $\langle wk; x \rangle$ needs to be maximised

3 Exercise 2

```
In [7]: class SOM:
    def __init__(self,input_,num_of_nodes,eta,initial_wts,threshold):
        self.input_ = input_
        self.num_of_nodes = num_of_nodes
        self.eta = eta
        self.current_wts = initial_wts
        self.t2 = 1000
        self.threshold = threshold

def euclidean_distance_1d(self,x,y):
        return abs(x - y)

def get_winning_neuron(self,x,W):
        winner = min([(self.euclidean_distance_1d(x,w), index) for index,w in enumerate(x)
        return winner)
```

```
distance = [self.euclidean_distance_1d(self.current_wts[winner],\)
                                            self.current_wts[i])\
                for i in range(len(self.current_wts))]
    return distance
def gaussian(self, sigma, distance):
    h = [np.exp(-(d**2)/(2*sigma**2))  for d in distance]
    return h
def compute_width(self,initial_sigma,n,t1):
    return initial_sigma*np.exp(-n/t1)
def weight_adaptation(self,current_wt,eta,h,x):
    new_wts = [(w + (eta*h*(x-w))) for w in current_wt]
    return new_wts
def exponential_decay_update(self,initial_eta,n,t2):
    return initial_eta*np.exp(-n/t2)
def compute_t1(self,t2):
    sigma=2
    return t2/np.log(sigma)
def stopping_criteria(self,w_old,w_new):
    result = 0
    for i,w in enumerate(w_old):
        result += abs(w - w_new[i])
    if (result < self.threshold):</pre>
        print "Stopping criteria check:sum(w_old - w_new) : " \
        +str(result)+"< "+str(self.threshold)+". Iteration end for current input"
        return True
    else:
        print "Stopping criteria check :sum(w_old - w_new) : " \
        +str(result)+"> "+str(self.threshold)
        return False
def train(self):
    sigma = 2
    t1 = self.compute_t1(self.t2)
    n = 1
    for x in self.input_:
        while(True):
            win_idx = self.get_winning_neuron(x,self.current_wts)
            print "\nWinner neuron index : "+str(win_idx)+", weight :"+str(self.curr
            lateral_dist = self.d_ij(win_idx)
            h = self.gaussian(sigma, lateral_dist)
            updates_wts = self.weight_adaptation(self.current_wts,self.eta,h[win_idx
```

```
print "Updated weights :",updates_wts
                        if not self.stopping_criteria(self.current_wts,updates_wts):
                            self.current_wts = np.array(updates_wts)
                            self.eta = self.exponential_decay_update(self.eta,n,self.t2)
                           n += 1
                        else:
                           break
                print "\nFinal adjusted weights :",self.current_wts
In [8]: initial_wts = np.array([[0.15,0.45],
                                [0.3, 0.9]]
        inputs = [0.1, 0.2, 0.4, 0.5]
In [9]: """
        Initial weights: [0.15, 0.45]
        som = SOM(inputs,2,0.1,initial_wts[0],0.01)
        som.train()
Winner neuron index : 0, weight :0.15
Updated weights: [0.14499999999999, 0.415000000000000000]
Stopping criteria check :sum(w_old - w_new) : 0.04> 0.01
Winner neuron index: 0, weight: 0.145
Updated weights: [0.1433445425147285, 0.40341179760309959]
Stopping criteria check :sum(w_old - w_new) : 0.0132436598822> 0.01
Winner neuron index : 0, weight :0.143344542515
Updated weights: [0.14275793792092928, 0.39930556544650508]
Stopping criteria check:sum(w_old - w_new): 0.00469283675039< 0.01. Iteration end for current i
Winner neuron index : 0, weight :0.143344542515
Updated weights: [0.1441112907532954, 0.40065891827887118]
Stopping criteria check:sum(w_old - w_new): 0.0035196275628< 0.01. Iteration end for current in
Winner neuron index : 1, weight :0.403411797603
Updated weights: [0.14681799641802767, 0.40336562394360342]
Stopping criteria check:sum(w_old - w_new): 0.0035196275628< 0.01. Iteration end for current in
Winner neuron index : 1, weight :0.403411797603
Updated weights: [0.1481713492503938, 0.40471897677596957]
Stopping criteria check:sum(w_old - w_new): 0.00613398590854< 0.01. Iteration end for current i
Final adjusted weights : [ 0.14334454  0.4034118 ]
In [10]: """
```

Initial weights : [0.3,0.9]

```
11 11 11
         som = SOM(inputs,2,0.1,initial_wts[1],0.01)
         som.train()
Winner neuron index : 0, weight :0.3
Updated weights: [0.27999999999997, 0.82000000000000006]
Stopping criteria check :sum(w_old - w_new) : 0.1> 0.01
Winner neuron index : 0, weight :0.28
Updated weights: [0.27337817005891402, 0.79351268023565624]
Stopping criteria check :sum(w_old - w_new) : 0.0331091497054> 0.01
Winner neuron index : 0, weight :0.273378170059
Updated weights: [0.27103175168371713, 0.78412700673486879]
Stopping criteria check :sum(w_old - w_new) : 0.011732091876 > 0.01
Winner neuron index : 0, weight :0.271031751684
Updated weights: [0.27018023473230185, 0.78072093892920769]
Stopping criteria check:sum(w_old - w_new): 0.00425758475708< 0.01. Iteration end for current i
Winner neuron index: 0, weight: 0.271031751684
Updated weights: [0.27067810541598047, 0.78121880961288637]
Stopping criteria check:sum(w_old - w_new) : 0.00326184338972< 0.01. Iteration end for current i
Winner neuron index: 0, weight: 0.271031751684
Updated weights: [0.27167384678333778, 0.78221455098024362]
Stopping criteria check:sum(w_old - w_new): 0.00255455085425< 0.01. Iteration end for current i
Winner neuron index: 0, weight: 0.271031751684
Updated weights: [0.27217171746701641, 0.7827124216639223]
Stopping criteria check:sum(w_old - w_new) : 0.00255455085425< 0.01. Iteration end for current i
```

Results show that when starting from initial weights [0.15, 0.45], the network converges (i.e, the stopping criteria is satisfied) in a smaller number of iterations compared to when we start with the initial weights of [0.3, 0.9]. Furthermore, when using initial weights of [0.3, 0.9], the neuron with the initial weight 0.3 is selected as the winning neuron at every iteration.

4 Exercise 3

Final adjusted weights: [0.27103175 0.78412701]

```
_eta,
             _no_epochs):
    self.no_of_neurons = _no_of_neurons
    self.no_of_cities = _no_of_cities
    self.lattice_radius = _lattice_radius
    self.lattice_center = _lattice_center
    self.eta = _eta
    self.no_of_epochs = _no_epochs
    self.current_weights = self.points_in_circle()
    print "Initial coordinates of neurons"
    print self.current_weights
    self.cities = self.get_cities()
   print "Initial coordinates of cities"
   print self.cities
    self.sigma = (self.lattice_radius * 2) + 5
    self.t_one = self.no_of_epochs/np.log(self.sigma)
    #city labels
    self.city_labels = ['wismar', 'schwerin', 'rostock',
                       'stralsund', 'greifswald',
                       'neubrandenberg']
111
find euclidean distance between two coordinates
def euclidean_distance_2d(self,x, y):
    return math.sqrt(pow(y[0]-x[0],2) + pow(y[1]-x[1],2))
,,,
find euclidean distance between given input
and all neurons weight, and return winning neuron
with shortest distance
def get_winner(self,x):
    return min([(self.euclidean_distance_2d(x,w),index)
               for index,w in enumerate(self.current_weights)])[1]
return city coordinates
def get_cities(self):
   return np.array([[1.3,5.7],
                     [30.7,98.3],
                     [95.3,69.3],
```

```
[37.3,22.5],
                     [85.5,12.5],
                     [46.6,63.6]])
def compute_distance_for_TspSolve(self):
   a = self.get_cities()
   dist = np.zeros((0,a.shape[0]))
    for i in range(a.shape[0]):
        euclidean = []
        for j in a:
            euclidean.append(tsm.euclidean_distance_2d(a[i],j))
        dist = np.vstack((dist, np.hstack((euclidean))))
    return dist
111
plot cities and neuron locations
def plot_cities(self,epoch):
    #getting x,y coordinates of cities
    cities_x = self.cities[:,0:1]
    cities_y = self.cities[:,1:2]
    #configuration for plot
    fig, ax = plt.subplots()
   plt.xlim([1,120])
   plt.ylim([1,120])
   fig.set_figheight(9)
   fig.set_figwidth(15)
   plt.title("Sigma = " + str(self.sigma)+ \
              ", Learning rate = " + str(self.eta) + \
              ", Current epoch = " + str(epoch))
    plt.xlabel("x-coordinates of cities and neuron weights")
    plt.ylabel("y-coordinates of cities and neuron weights")
    #plot cities
    ax.plot(cities_x, cities_y, 'ro')
    #plot neurons
    if epoch is 0:
        ax.add_patch(plt.Circle(self.lattice_center,
                                radius=self.lattice_radius,
                                color='g',
                                fill=False))
    #plot connections between neurons
```

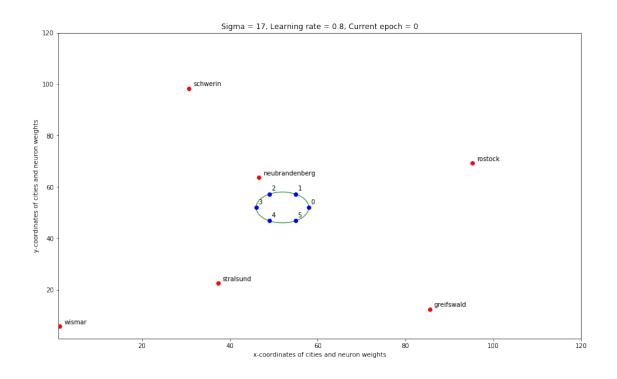
```
if epoch is not 0:
            ax.plot(self.current_weights[:,0:1],
                    self.current_weights[:,1:2],
                    marker='o', linestyle='--',
                    color='b')
        else:
            ax.plot(self.current_weights[:,0:1],
                    self.current_weights[:,1:2],'bo')
        #showing name of the cities in the plot
        for i, label in enumerate(self.city_labels):
            ax.annotate(label, (cities_x[i]+1,cities_y[i]+1))
        #showing name of the neurons in the plot
#
          print current_weights
        for index, weight in enumerate(self.current_weights):
            ax.annotate(index, (weight[0]+0.5, weight[1]+1.5))
    111
   generate points in circle lattice structure
    111
   def points_in_circle(self):
       points = np.empty((0,2))
       circle_center = self.lattice_center
       radius = self.lattice_radius
       n = self.no_of_neurons
       for x in xrange(0,n):
            point = [circle_center[0]+np.cos(2*np.pi/n*x)*radius,
                     circle_center[1]+np.sin(2*np.pi/n*x)*radius]
            points = np.vstack([points,point])
        return points
   update weight function
    I I I
   def weight_adaptation(self,neuron,winner_neuron,x):
        current_weight = self.current_weights[neuron]
       h_ij = self.calculate_H_i_j(neuron, winner_neuron)
       new_weight = (current_weight + (self.eta*(h_ij)*(x-current_weight)))
        self.current_weights[neuron] = new_weight
       return True
   update learning rate funtion
   def eta_update(self,n):
        self.eta = self.eta*np.exp(-n/1000000000.0)
```

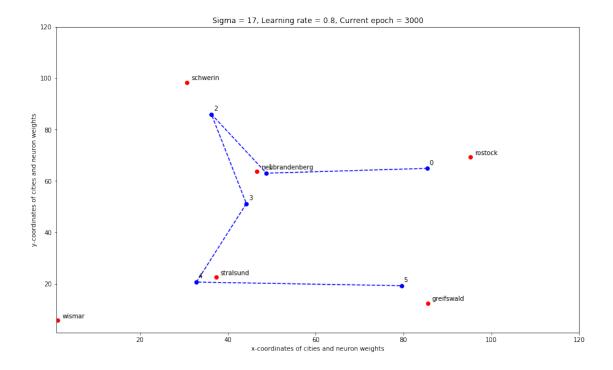
```
111
calcuate H_ij function
def calculate_H_i_j(self,current_neuron,winner_neuron):
    distance = self.euclidean_distance_2d(self.current_weights[winner_neuron],
                                          self.current_weights[current_neuron])
    return np.exp(-(distance**2)/(2*(self.sigma**2)))
111
sigma updation function
def sigma_update(self,n):
    self.sigma = self.sigma * np.exp(-(n/1000000000.0))
111
get neighbors of winning neuron
111
def get_neighors(self, winner):
   neuron_positions = range(self.current_weights.shape[0])
    if winner is len(neuron_positions)-1:
        return [neuron_positions[winner],
                neuron_positions[winner-1],
                neuron_positions[0]]
    else:
        return [neuron_positions[winner],
                neuron_positions[winner-1],
                neuron_positions[winner+1]]
111
sort the visit order
def find_visit_order(self):
   order = []
    for city in self.cities:
        order.append(self.get_winner(city))
    self.sorted_order = []
    for i in range(len(order)):
        self.sorted_order.append(order.index(i))
    self.city_order = []
    for index in self.sorted_order:
        self.city_order.append(self.city_labels[index])
```

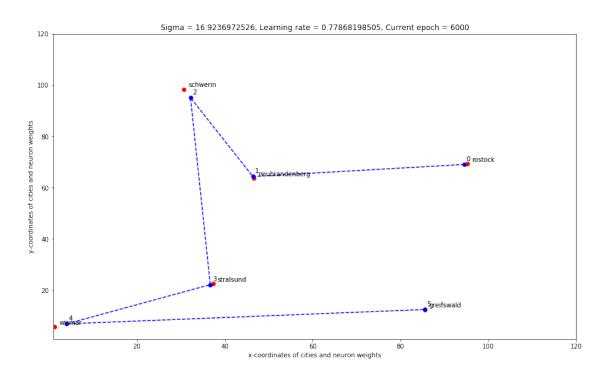
```
return self.sorted_order
             calculate the distance to visit
             def calculate_total_path(self,order):
                 distance = 0
                 for index in range(len(order)-1):
                     distance += self.euclidean_distance_2d(self.cities[order[index]],
                                                        self.cities[order[index+1]])
                 distance += self.euclidean_distance_2d(self.cities[order[0]],
                                                        self.cities[order[-1]])
                 self.total_distance = distance
                 return self.total_distance
             training function
             def train(self):
                 for epoch in range(self.no_of_epochs):
                     for city in self.cities:
                         winner_neuron = self.get_winner(city)
                         winner_with_neighbors = self.get_neighors(winner_neuron)
                         for neuron in winner_with_neighbors:
                              self.weight_adaptation(neuron, winner_neuron, city)
                         self.eta_update(epoch)
                     if epoch % 3000 is 0:
                         self.plot_cities(epoch+3000)
                     self.sigma_update(epoch)
                 print self.calculate_total_path(self.find_visit_order())
In [14]: '''
         Initialization
         111
         no\_of\_neurons = 6
         no\_of\_cities = 6
         lattice_radius = 6
         lattice_center = (52, 52)
         eta = 0.8
         no\_of\_epochs = 30000
         tsm = TravellingSalesMan(no_of_neurons,
                                  no_of_cities,
                                  lattice_radius,
                                  lattice_center, eta,
                                  no_of_epochs)
```

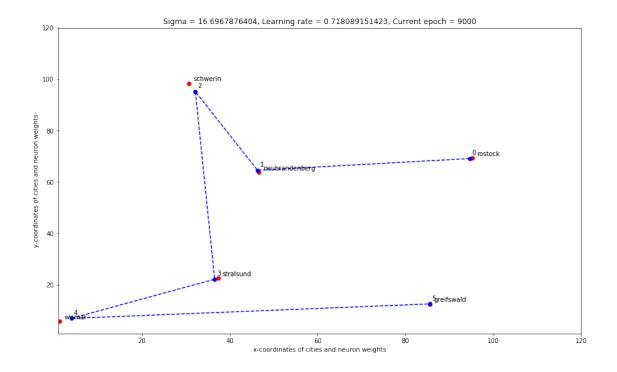
```
tsm.plot_cities(0)
tsm.train()
```

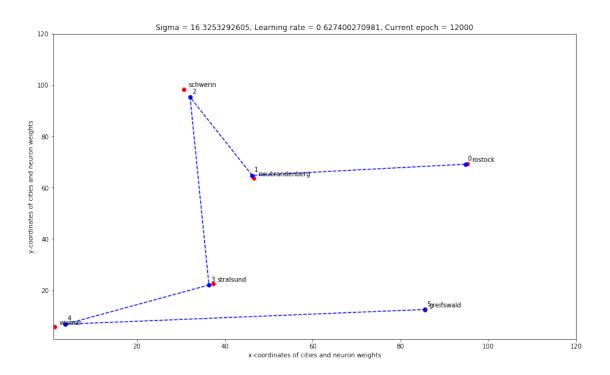
```
Initial coordinates of neurons
[[ 58.
                52.
 [ 55.
                57.19615242]
 [ 49.
                57.19615242]
 [ 46.
                52.
 [ 49.
                46.80384758]
 [ 55.
                46.80384758]]
Initial coordinates of cities
[[ 1.3
         5.7]
 [ 30.7 98.3]
 [ 95.3 69.3]
 [ 37.3 22.5]
 [ 85.5 12.5]
 [ 46.6 63.6]]
345.129019896
```

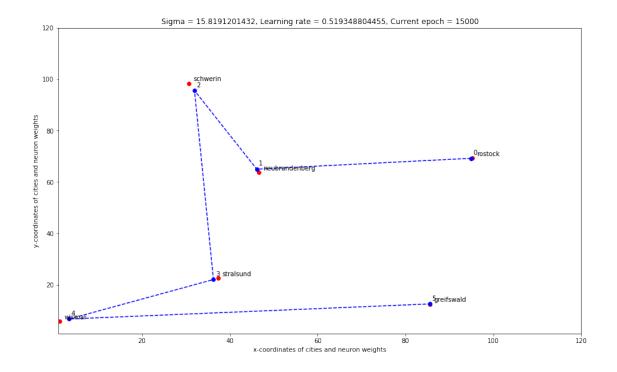


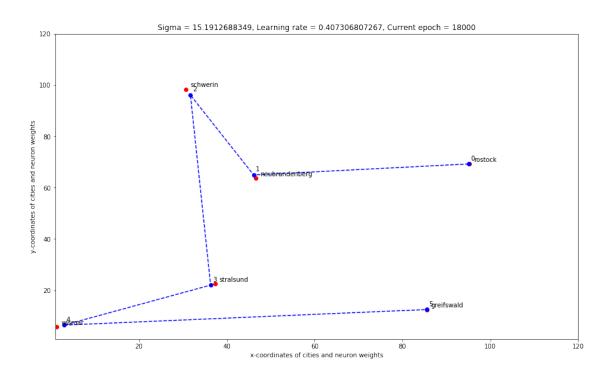


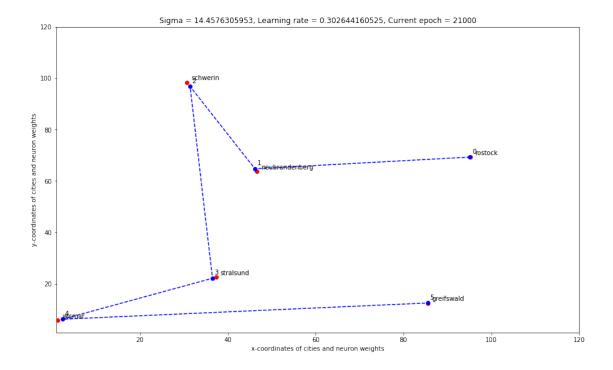


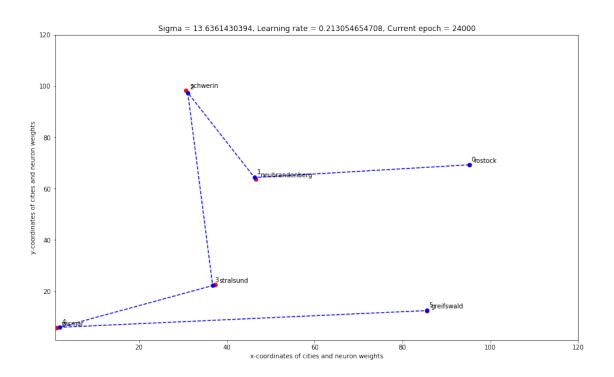


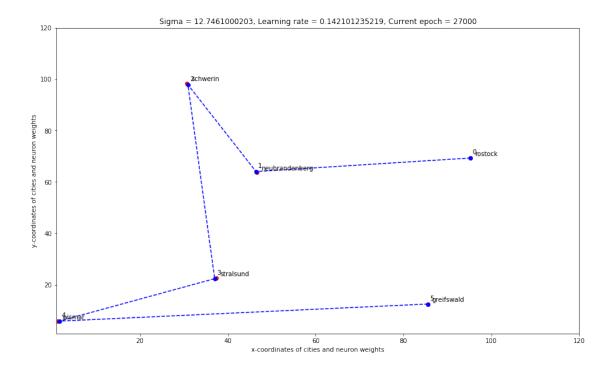


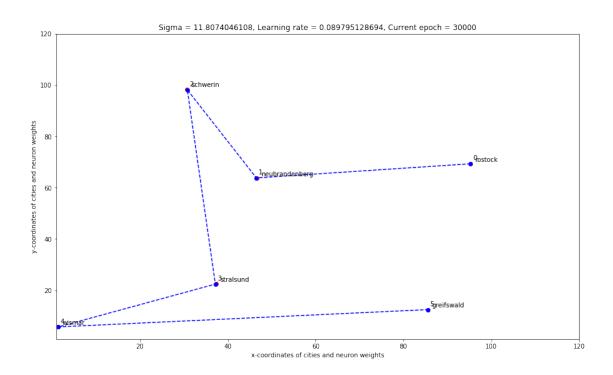












5 Initial order of cities before training

```
0.'wismar'
1.'schwerin'
2.'rostock'
3.'stralsund'
4.'greifswald'
5.'neubrandenberg'
```

6 After training

7 Path using TSP library

8 Observations:

If two cities are in straight line and closer together, neurons stuck in the middle and cannot move towards the cities.

If we update only the winning neuron, sometimes observed one or two neurons stays in its initial position.

So we are updating the neighborhood neurons of winning neurons using H_ij function, then all neurons started to move towards cities.

Paths that we obtained using TSP library are different, as compare to algorithm that we implement. However, total distance is approximately closer.