CogSci131 Assignment2

July, 2019

In [12]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.spatial import distance
names = ["football","baseball","basketball","tennis","softball","canoeing","handball"
```

In [13]:
```
# load the csv provided on bcourses
similarities = np.loadtxt(open("similarities.csv", "rb"), delimiter=",", skiprows=1)
similarities
#array.shape will give the dimension for np array which is 21*21
```

Out[13]:
```
array([[1.        , 0.18518519, 0.48148148, 0.14814815, 0.74074074,
        0.07407407, 0.77777778, 0.77777778, 0.88888889, 0.11111111,
        0.14814815, 0.40740741, 0.85185185, 0.92592593, 0.7037037 ,
        0.03703704, 0.        , 0.74074074, 0.07407407, 0.48148148,
        0.03703704],
       [0.18518519, 1.        , 0.33333333, 0.18518519, 0.96296296,
        0.        , 1.        , 0.92592593, 0.59259259, 0.62962963,
        0.        , 0.40740741, 0.22222222, 0.37037037, 0.81481481,
        0.        , 0.7037037 , 0.77777778, 0.11111111, 0.07407407,
        0.        ],
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        0.11111111],
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        0.81481481, 0.37037037, 0.18518519, 0.03703704, 0.11111111,
```

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 0.18518519],
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```

```
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 0.25925926, 0.18518519, 0.07407407, 0.33333333, 0.62962963,
 1.        ]])
```

In [14]:
```
#1.The dataset provides similarities, not distances. Write down three ways you could c
#similarity to a distance dij and choose one to use in the code. Explain why you chos
#we could use Euclidean, Manhanttan or 1-similarities as distances.  I choose 1-simil
distances=[]
distances=1-similarities
distances
```

Out[14]:
```
array([[0.        , 0.81481481, 0.51851852, 0.85185185, 0.25925926,
        0.92592593, 0.22222222, 0.22222222, 0.11111111, 0.88888889,
        0.85185185, 0.59259259, 0.14814815, 0.07407407, 0.2962963 ,
        0.96296296, 1.        , 0.25925926, 0.92592593, 0.51851852,
        0.96296296],
       [0.81481481, 0.        , 0.66666667, 0.81481481, 0.03703704,
        1.        , 0.        , 0.07407407, 0.40740741, 0.37037037,
        1.        , 0.59259259, 0.77777778, 0.62962963, 0.18518519,
        1.        , 0.2962963 , 0.22222222, 0.88888889, 0.92592593,
        1.        ],
       [0.51851852, 0.66666667, 0.        , 0.40740741, 0.11111111,
```

```
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 0.55555556, 1.        , 0.33333333, 0.96296296, 0.7037037 ,
 0.96296296],
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 0.51851852, 0.        , 0.92592593, 0.7037037 , 0.48148148,
 0.59259259, 0.74074074, 0.85185185, 0.44444444, 0.88888889,
```

```
 0.37037037],
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 0.74074074, 0.81481481, 0.92592593, 0.66666667, 0.37037037,
 0.        ]])
```

In [15]:
```
#2.Write the code that follows a gradient in order to find positions that minimize th
```

```
D = 2
N = distances.shape[0]
assert(distances.shape[1] == N and N==len(names))
# Pick a position for each point. Note this is an NxD matrix
# so that pos[11,1] is the y coordinate for the 11th item, coordinate start from 0
# and pos[11] is a (row) vector for the position of the 11th item
pos = np.random.normal(0.0,1.0,size=(N,D))
pos
```

```
Out[15]: array([[ 0.38808236, -0.5117374 ],
               [ 0.4079298 , -0.74066719],
               [-0.35472144,  0.19781971],
               [-0.28252064, -0.36168756],
               [-0.34245253,  0.75021195],
               [ 0.21055759,  0.07102482],
               [-0.19958935,  0.15247627],
               [ 0.72564412, -0.47970665],
               [ 2.42713002, -0.23332432],
               [ 1.95553183,  1.03073615],
               [ 0.20406865,  0.24580944],
               [-1.33661673,  0.36783334],
               [ 0.61386319,  1.10541977],
               [ 0.84254918, -1.35074653],
               [ 2.24115926, -0.47220576],
               [ 1.48042411, -0.69015011],
               [-0.54337685, -1.07991108],
               [ 0.65788642,  0.53321827],
               [-1.40730659,  0.70196234],
               [ 0.55242083,  2.29517766],
               [ 0.14030958,  0.2154872 ]])
```

```
In [16]: def dist(a,b):
             # Compute the Euclidean distance between two locations (numpy arrays) a and b
             # Thus, dist(pos[1], pos[2]) gives the distance between the locations for items 1
             mdps = distance.euclidean(a, b)
             return mdps
```

```
In [17]: def stress(p):
         # Take a matrix of positions (called here "p") and return the stress
             psy_dis=[]
             mdps=[]
             for i in range(0,20):
                 for j in range(i+1, 21):# in total 21 items
                     mdps.append(dist(p[i],p[j]))
                     psy_dis.append(distances[i,j])
             tmp=np.array(psy_dis)-np.array(mdps)
             stress=np.sum(tmp**2)
             print(stress)
```

```
        return stress
```

```
In [18]: def add_delta(p, i, d, delta):
             # This is a helper function that will make a new vector which is the same as p (a
             # p[i,d] has been increased by delta (which may be positive or negative)
             v = np.array(p)
             v[i, d] += delta
             return v


         def subtract_delta(p, i, d, delta):
             # This is a helper function that will make a new vector which is the same as p (a
             # p[i,d] has been increased by delta (which may be positive or negative)
             v = np.array(p)
             v[i, d] -= delta
             return v

         def compute_gradient(p, i,d, delta = 0.001):
             # compute the gradient of the stress function with repect to the [i,d] entry of a
             # (e.g. the derivative of stress with respect to the i'th coordinate of the x'th
             # Here, to compute numerically, you can use the fact that
             # f'(x) = (f(x+delta)-f(x-delta))/(2 delta) as delta -> 0
             gradient=(stress(add_delta(p,i,d,delta=0.001))-stress(subtract_delta(p,i,d,delta=0
             return gradient
```

```
In [ ]:
```

```
In [19]: def compute_full_gradient(p):
         # Numerically compute the full gradient of stress at a position p
         # This should return a matrix whose elements are the gradient of stress at p with res
             full_gradient=np.zeros((np.array(p).shape))
             for i in range(21):
                 for j in range(2):
                     full_gradient[i,j]=compute_gradient(p,i,j,delta=0.001)
             return full_gradient
```

```
In [20]: compute_full_gradient(pos)
```

```
365.2927557780574
365.3016039383682
365.2809488038164
365.31341845432473
365.2955737210888
365.2987857239974
365.27726666012404
```

365.31710358325415
365.27734630167345
365.31702470925677
365.30010329632387
365.2942540589594
365.28159635514385
365.31277158318477
365.28683370143926
365.30753128417734
365.2752846722249
365.31908331684343
365.31508917390056
365.27927700768987
365.29112843466487
365.3032234083214
365.29600075972115
365.2983582381439
365.283970205107
365.31039977568946
365.3012985984743
365.29305585013606
365.30232323829546
365.29204433556663
365.28345289482013
365.31091279938437
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365.285294232108
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365.3254782934502
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```
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365.3651530145552
365.22922243680534
365.29109586228003
365.3032589718543
365.29583986658724
365.29851243540907
```

```
Out[20]: array([[ -4.42408016, -16.23482525],
                [ -1.60600145, -19.91846157],
                [-19.83920379,   2.92461868],
                [-15.58761402, -10.34879137],
                [-21.89932231,  17.90608311],
                [ -6.04748683,  -1.17873921],
                [-13.21478529,   4.12137417],
                [  5.13945136, -13.72995228],
                [ 62.4629462 , -11.8892876 ],
                [ 43.80736221,  28.29378069],
                [ -6.22689319,   1.29396073],
                [-48.78216202,   9.42235056],
                [  2.77829178,  21.37253979],
                [ 12.29985386, -41.35651155],
                [ 57.71643046, -15.9818803 ],
                [ 27.77211894, -21.19762778],
                [-25.03839819, -29.680795  ],
```

```
        [  3.26921014,  13.31103547],
        [-49.69719326,  16.24212425],
        [  3.19903035,  67.96528887],
        [ -6.08155479,  -1.33628441]])
```

```
In [21]: # Now go through and adjust the position to minimize the stress
         pos# start positions
         rate=0.01 #learning rate
         max_iters=1000
         iters=0# iternation counter
         cur=pos
```

```
In [22]: while iters< max_iters:
             cur = cur- rate * compute_full_gradient(cur) #Grad descent
             iters = iters+1  #iteration count
             #print("Iteration",iters,"\nX value is",cur) #Print iterations

         #print("The local minimum occurs at", cur)
```

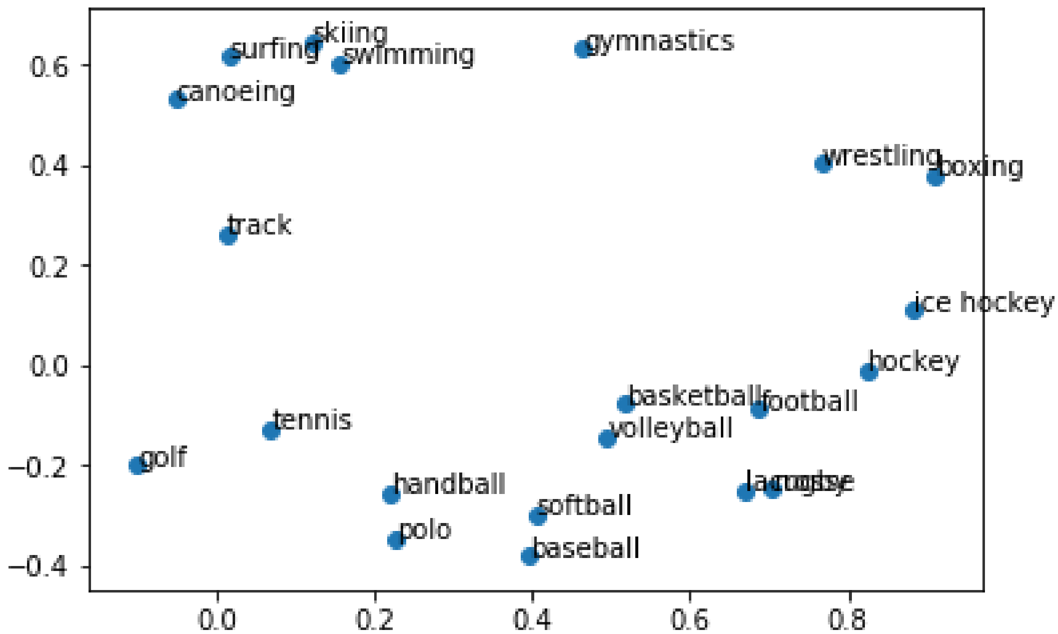
```
365.2927557780574
365.3016039383682
365.2809488038164
365.31341845432473
365.2955737210888
365.2987857239974
365.27726666012404
365.31710358325415
365.27734630167345
365.31702470925677
365.30010329632387
365.2942540589594
365.28159635514385
365.31277158318477
365.28683370143926
365.30753128417734
365.2752846722249
365.31908331684343
365.31508917390056
365.27927700768987
365.29112843466487
365.3032234083214
365.29600075972115
365.2983582381439
365.283970205107
365.31039977568946
365.3012985984743
365.29305585013606
365.30232323829546
```

```
9.389991372614626
9.389983920372261
9.38998392058927
9.389984852392093
9.389984852205798
9.389988231911722
9.389988231986443
9.389986847236099
9.389986847466215
9.389989759863276
9.389989760029493
9.389986597575582
9.389986597713953
9.389987915369044
9.389987915209414
9.389985781812012
9.389985782048797
9.389988738480868
9.389988738452688
```

```
In [23]: #plot example with annotation
         cur=np.transpose(cur)
         x=cur[0]
         y=cur[1]
         n=names

         fig, ax = plt.subplots()
         ax.scatter(x,y)


         for i, txt in enumerate(names):
             ax.annotate(txt, (x[i], y[i]))
```




```
In [24]: #Do the result agree with expectation?
         #Yes, the result pretty much meet the expectation with my psychological distance. Sin
         #in one cluster, boxing and Wrestling are indeed th most similar.
```

```
In [25]: #3. [5pts] Plot the stress over iterations of your MDS. How should you use this plot
         #how many iterations are needed?
         #I might need 2000-3000 iterations to capture the local minimum. The plot would be a
         #I decided to select the cut off when there are 2000 iterations.
```

```
In [28]: #4. [10pts] Run the MDS code you wrote 5 times and show small plots, starting from ra
         #positions. Are they all the same or not? Why?
         #No, they are not the same. Since gradient descent would help us find local minimum i
         #might converge at different local minimms.
         def mds():
             pos# start positions
             rate=0.01 #learning rate
             max_iters=1000
             iters=0# iternation counter
             cur=pos

             while iters< max_iters:
                 cur = cur- rate * compute_full_gradient(cur) #Grad descent
                 iters = iters+1  #iteration count
               # print("Iteration",iters,"\nX value is",cur) #Print iterations
```

```
cur=np.transpose(cur)
x=cur[0]
y=cur[1]
n=names

fig, ax = plt.subplots()
ax.scatter(x,y)


for i, txt in enumerate(names):
    ax.annotate(txt, (x[i], y[i]))
```

In [29]:
```
#5.If you wanted to find one best answer but had run MDS 5 times, how would you pick
#best? Why?
#I would pick the minimum of the stress out of all stresses generated. This would the
#plotted would be the closest to reported similarites.
```