Question 1 (higher similarity ==> lower distance)

1. distance = 1-similarity
2. distance = 1/similarity
3. distance = -1*similarity

In [79]:

```
#Question 2

import numpy as np
import matplotlib.pyplot as plt

#to compute partial derivatives
delta = 0.005
scaling = 0.01

#other needed variables
gradient = []
stress = 0

#read in similarities
psychsimilarities = np.loadtxt(open("Assignment5-similarities.cs
v", "rb"), delimiter=",", skiprows=1)

#assign random values to the starting points on MDS grid
mdsdistances = np.random.uniform(0, 1, size=(21,2))

#matrix ==> array of MDS locations (x,y coordinates)
#[(football)[0.03,93.2], (soccer)[4,6.78], (basketball)[3.3,4.1]
]

#similarities ==> array from our data --> psychological distance
s
#* = startingsport
#[(football)[football-football, *football-soccer, football-bball
, football-golf],
#(soccer)[football-soccer, soccer-soccer, *soccer-bball, soccer-
golf]],
#(bball)[football-bball, bball-soccer, bball-bball, *bball-golf]
```

```
def stresscalc(mdsdistances, psychsimilarities):
    stress = 0
    mdsdistance = 0
    psychdistance = 0
    row = 0
    col = 1
    for row in range(0,20): #for each sport
        #compare sport to each remaining sport
        c = col
        for c in range(c,20):
            psychdistance = 1-psychsimilarities[row][c]
            mdsdistance = np.sqrt(np.square(mdsdistances[row][0]
- mdsdistances[c][0]) + np.square(mdsdistances[row][1] - mdsdist
ances[c][1]))
            stress += np.square(psychdistance-mdsdistance)
        col += 1
    return stress

#QUESTION 3
def findgradient(mdsdistances, psychsimilarities, delta):
    gradient= np.copy(mdsdistances)

    #Find the partial derivative by changing x and keeping y & c
hanging y and keeping x constant.
    for i in np.arange(len(mdsdistances) -1): #for all coordinat
es in our grid

        #FIRST SOLVE FOR X
        coordinatesmodplus = np.copy(mdsdistances)
        coordinatesmodminus = np.copy(mdsdistances)

        coordinatesmodplus[i][0]+= delta #changing x value, and
keeping y the same
        fpdx = stresscalc(coordinatesmodplus, psychsimilarities)
#f(changed concept x, y remains)

        coordinatesmodminus[i][0]-=delta #changing x value, keep
ing y the same
        fmdx=stresscalc(coordinatesmodminus, psychsimilarities)
#f(changed concept x, y remains)

        partialderivativex=(fpdx-fmdx)/(2*delta)

        gradient[i][0]=partialderivativex #update that part of t
```

```
he gradient with the partial derivative found for element i of v
alues

        #THEN SOLVE FOR Y
        coordinatesmodplus = np.copy(mdsdistances)
        coordinatesmodminus = np.copy(mdsdistances)

        coordinatesmodplus[i][1]+= delta #changing y value, and
keeping x the same
        fpdy = stresscalc(coordinatesmodplus, psychsimilarities)
#f(changed concept y, x remains)

        coordinatesmodminus[i][1]-=delta #changing y value, keep
ing x the same
        fmdy=stresscalc(coordinatesmodminus, psychsimilarities)
#f(changed concept y, x remains)

        partialderivativey=(fpdy-fmdy)/(2*delta)

        gradient[i][1]=partialderivativey #update that part of t
he gradient with the partial derivative found for element i of v
alues

    return gradient

# def gradientcheck(gradient):
#     passed = []
#     for i in range(len(gradient)):
#         if gradient[i][0] <= 0.1:
#             passed.append(1)
#         if gradient[i][1] <= 0.1:
#             passed.append(1)
#     return sum(passed)

#QUESTION 4
names = ['football', 'baseball', 'basketball', 'tennis',
         'softball', 'canoeing', 'handball', 'rugby',
         'hockey', 'icehockey', 'swimming', 'track',
         'boxing', 'volleyball', 'lacrosse', 'skiing',
         'golf', 'polo', 'surfing', 'wrestling', 'gymnastics']

xpoints = []
ypoints = []
stressvals = []
iterations= 0
```

```
#PLOT RANDOM POINTS FIRST
for i in range(len(mdsdistances)):
    xpoints.append(mdsdistances[i][0])
    ypoints.append(mdsdistances[i][1])

fig, ax = plt.subplots()
ax.scatter(xpoints,ypoints)
for i, txt in enumerate(names):
    ax.annotate(txt, (xpoints[i], ypoints[i]))


gradient = findgradient(mdsdistances, psychsimilarities, delta)
stress = stresscalc(mdsdistances, psychsimilarities)
print(stress)
# checkval = gradientcheck(gradient)
while stress >= 10:
    for i in range(len(gradient)):
        mdsdistances[i][0] += (-scaling * gradient[i][0])
        mdsdistances[i][1] += (-scaling * gradient[i][1])
        xpoints[i] = (mdsdistances[i][0])
        ypoints[i] = (mdsdistances[i][1])
    gradient = findgradient(mdsdistances, psychsimilarities, del
ta)
    stress = stresscalc(mdsdistances, psychsimilarities)
    stressvals.append(stress)
    iterations += 1
#     checkval = gradientcheck(gradient)
#     print("checkval", checkval)
    print(stress)

fig, ax = plt.subplots()
ax.scatter(xpoints,ypoints)
for i, txt in enumerate(names):
    ax.annotate(txt, (xpoints[i], ypoints[i]), fontsize = 10)
```

30.7756268582338
29.2340216796795
27.950080655913332
26.797115332417903
25.7273829643099
24.753166713246255
23.899104262761337
23.149025005780473
22.464751510929926
21.82702609440978
21.245103733498063
20.729425551870214
20.27616324728105
19.871781088943944
19.500433616240073
19.148348445214474
18.805494981843612
18.46539979021808
18.1234927155003
17.77387645426199
17.404145117891545
16.990280785698285
16.507569884263116
15.963318548250355
15.393851918303206
14.832622896517655
14.297015673402099
13.790391489399273
13.312754270345803
12.867907450615105
12.458351663800737
12.083811203507201
11.742988033710164
11.434044704289366
11.154896928787386
10.90357157851574
10.678330974627256
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10.142638826810842
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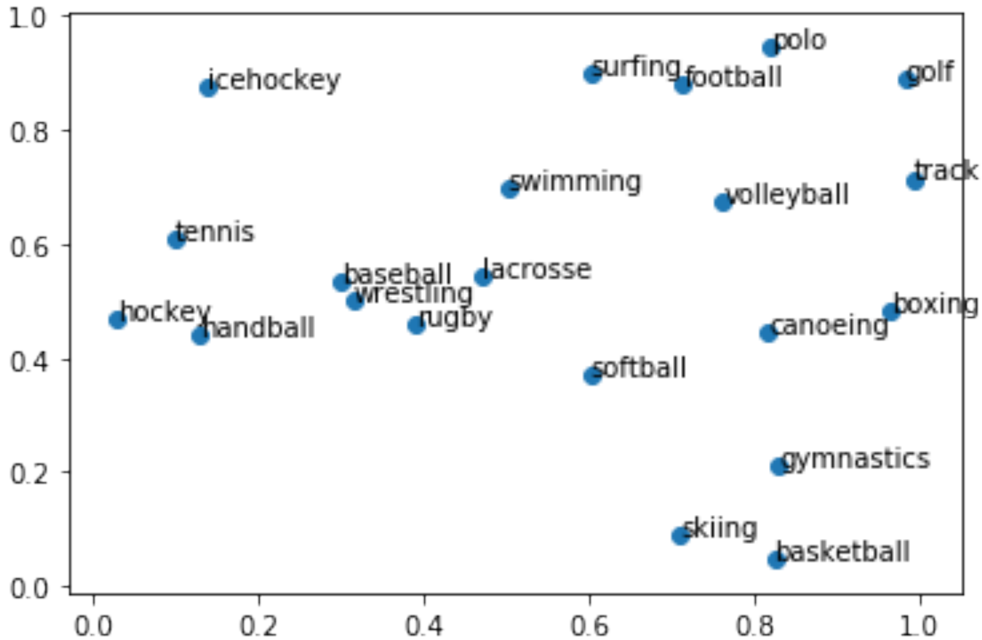
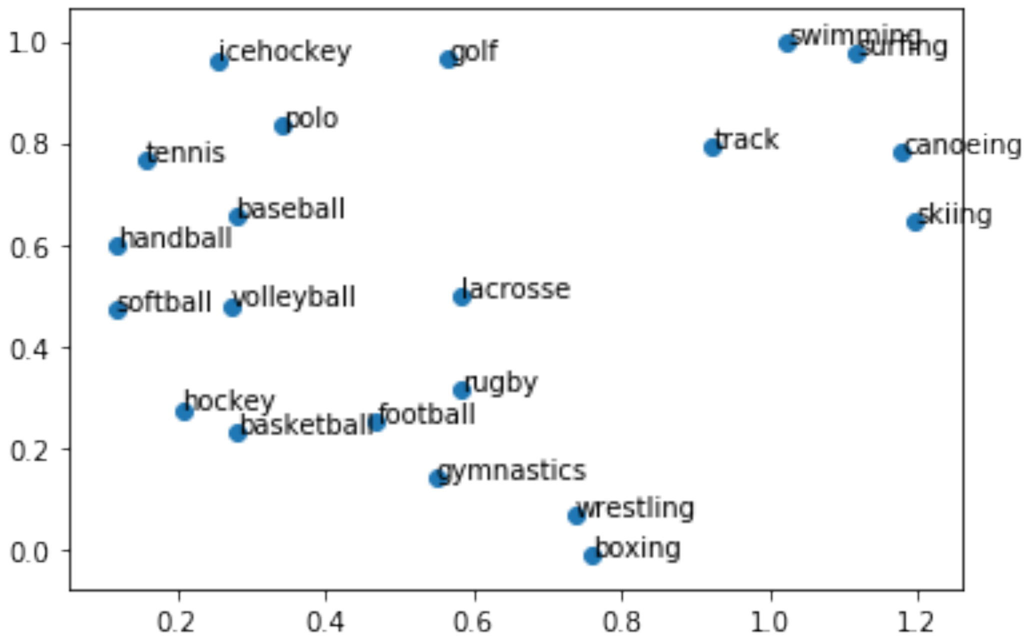
9.88474301386693





4.[20pts, HELP] Write the code that follows a gradient in order to find positions that minimize the stress – be sure to take small steps in the direction of the gradient (e.g. 0.01*gradient). Plot the sport names at the resulting coordinates. Do the results agree with your intuitions about how this domain might be organized? Why or why not?

The results are in line with what my intuition is about how sports might be organized. For example, all of the water-related (or snow-related) sports (i.e. canoeing, surfing, swimming, skiing) are clustered together. In addition, the "fighting" sports (i.e. wrestling, boxing) are clustered together, and the sports that require a ball are also clustered in the same region of the graph.

1. [5pts, SOLO] Make a scatter plot of the the pairwise distances MDS found vs. people's reported distances. Briefly describe what good and bad plots would look like and whether yours is good or bad.

In [48]:

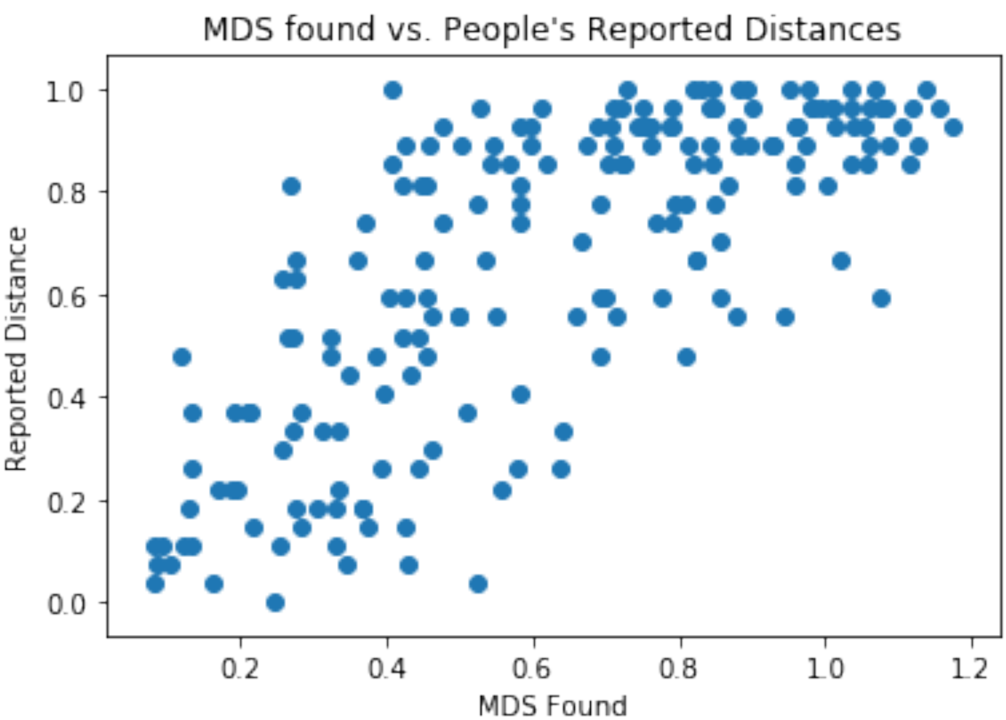
```
#QUESTION 5
psydist = []
mdsdist = []

col = 1
for row in range(0,20): #for each sport
    #compare sport to each remaining sport
    c = col
    for c in range(c,20):
        psydist.append(1-psychsimilarities[row][c])
    col += 1

col = 1
for row in range(0,20): #for each sport
    #compare sport to each remaining sport
    c = col
    for c in range(c,20):
        mdsdist.append(np.sqrt(np.square(mdsdistances[row][0] - mdsdistances[c][0]) + np.square(mdsdistances[row][1] - mdsdistances[c][1])))
    col += 1

print(len(psydist))
print(len(mdsdist))
plt.scatter(mdsdist, psydist)
plt.title("MDS found vs. People's Reported Distances")
plt.xlabel("MDS Found")
plt.ylabel("Reported Distance")
plt.show()
```

```
[[ 0.45059588  0.93361779]
 [ 0.81299194  0.65675009]
 [ 0.71540539  1.00355779]
 [ 1.04467129  0.5215493 ]
 [ 0.87695297  0.80640709]
 [ 0.22328299  0.00331391]
 [ 0.99462255  0.82237336]
 [ 0.40094204  0.77095533]
 [ 0.53313084  0.93879966]
 [ 0.64772708  0.42566199]
 [ 0.35188643 -0.01920809]
 [ 0.22421169  0.27792082]
 [ 0.07756792  0.95150369]
 [ 0.79692732  0.91311267]
 [ 0.44537676  0.67625818]
 [ 0.4174001  -0.07519789]
 [ 1.01292908  0.24162153]
 [ 0.91208671  0.49659232]
 [ 0.28573642 -0.06717961]
 [ 0.06969944  0.75515676]
 [ 0.02962239  0.03530635]]
190
190
```



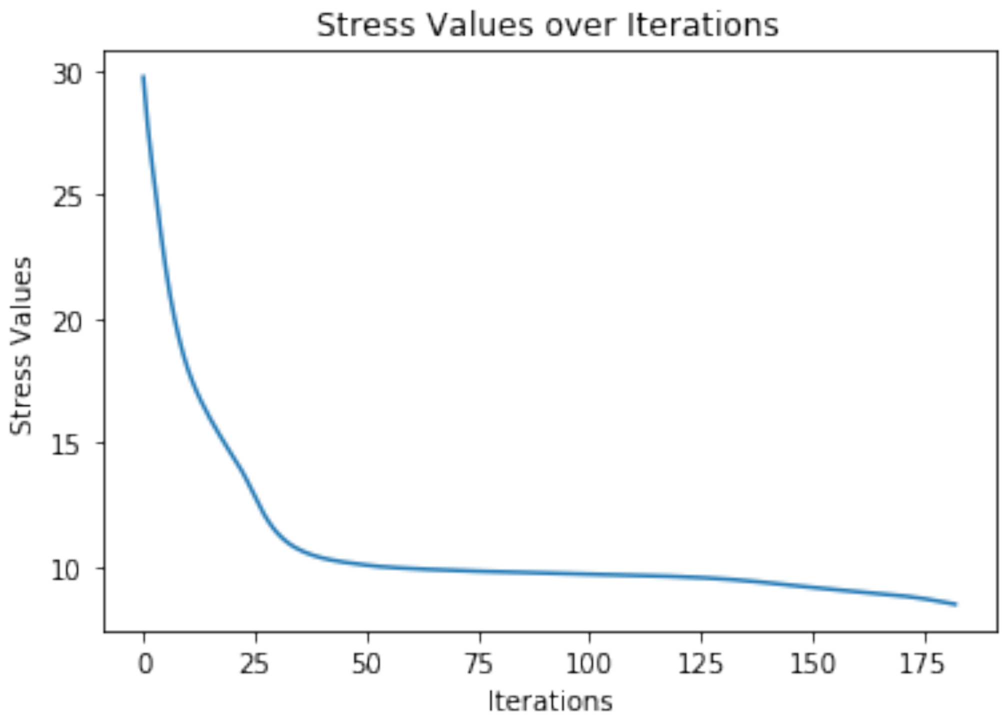
A good plot has a trend, meaning the x values and y values increase or decrease with some sort of consistent relationship. In this case, a good plot would have a positive correlation, meaning as people's reported distances increased, my MDS plots found should have also increased. This is somewhat represented in my graph but there are definitely some outliers. For example, one point was reported at a near 1 distance by people psychologically, but my MDS found it to be at ~0.4 distance value.

1. [5pts, SOLO] Plot the stress over iterations of your MDS. How should you use this plot in order to figure out how many iterations are needed?

In [54]:

```
#QUESTION 6

plt.plot((np.arange(iterations)), stressvals)
plt.title("Stress Values over Iterations")
plt.xlabel("Iterations")
plt.ylabel("Stress Values")
plt.show()
```



This plot can be used to figure out how many iterations are needed by looking at where the stress values begin to plateau, which is around a stress value of ~9. By the looks of my graph, my stress values continue to decrease even after 175 iterations, meaning I should probably run my program for longer. However, for the purpose of this assignment and on piazza/from advice from GSI's, I was told a stress value of around 10 is sufficient.

1. [5pts, SOLO] Run the MDS code you wrote 10 times and show small plots, starting from random initial positions. Are they all the same or not? Why?

After running MDS 10 times it can be seen that the graphs are not all the same. This is due to a couple factors, including that the points are all starting from random initial positions. This means that their locations on the graph will vary depending on where they started that round of MDS. In addition, the method of gradient descent we are using does not account for local vs global minima of the stress function. If the gradient descent method finds a local minimum, this will also cause the resulting graph to look differently.

In [80]:

```
#Question 7

import numpy as np
import matplotlib.pyplot as plt

#to compute partial derivatives
delta = 0.005
scaling = 0.01

#other needed variables
gradient = []
stress = 0

#read in similarities
psychsimilarities = np.loadtxt(open("Assignment5-similarities.csv", "rb"), delimiter=",", skiprows=1)

#assign random values to the starting points on MDS grid
mdsdistances = np.random.uniform(0, 1, size=(21,2))

def stresscalc(mdsdistances, psychsimilarities):
```

```
def stresscalc(mdsdistances, psychsimilarities):
    stress = 0
    mdsdistance = 0
    psychdistance = 0
    row = 0
    col = 1
    for row in range(0,20): #for each sport
        #compare sport to each remaining sport
        c = col
        for c in range(c,20):
            psychdistance = 1-psychsimilarities[row][c]
            mdsdistance = np.sqrt(np.square(mdsdistances[row][0] - mdsdistances[c][0]) + np.square(mdsdistances[row][1] - mdsdistances[c][1]))
            stress += np.square(psychdistance-mdsdistance)
        col += 1
    return stress

def findgradient(mdsdistances, psychsimilarities, delta):
    gradient= np.copy(mdsdistances)

    #Find the partial derivative by changing x and keeping y & changing y and keeping x constant.
    for i in np.arange(len(mdsdistances) -1): #for all coordinates in our grid

        #FIRST SOLVE FOR X
        coordinatesmodplus = np.copy(mdsdistances)
        coordinatesmodminus = np.copy(mdsdistances)

        coordinatesmodplus[i][0]+= delta #changing x value, and keeping y the same
        fpdx = stresscalc(coordinatesmodplus, psychsimilarities) #f(changed concept x, y remains)

        coordinatesmodminus[i][0]-=delta #changing x value, keeping y the same
        fmdx=stresscalc(coordinatesmodminus, psychsimilarities) #f(changed concept x, y remains)

        partialderivativex=(fpdx-fmdx)/(2*delta)

        gradient[i][0]=partialderivativex #update that part of the gradient with the partial derivative found for element i of values
```

```
        #THEN SOLVE FOR Y
        coordinatesmodplus = np.copy(mdsdistances)
        coordinatesmodminus = np.copy(mdsdistances)

        coordinatesmodplus[i][1]+= delta #changing y value, and
keeping x the same
        fpdy = stresscalc(coordinatesmodplus, psychsimilarities)
#f(changed concept y, x remains)

        coordinatesmodminus[i][1]-=delta #changing y value, keep
ing x the same
        fmdy=stresscalc(coordinatesmodminus, psychsimilarities)
#f(changed concept y, x remains)

        partialderivativey=(fpdy-fmdy)/(2*delta)

        gradient[i][1]=partialderivativey #update that part of t
he gradient with the partial derivative found for element i of v
alues

    return gradient

def gradientcheck(gradient):
    passed = []
    for i in range(len(gradient)):
        if gradient[i][0] <= 0.1:
            passed.append(1)
        if gradient[i][1] <= 0.1:
            passed.append(1)
    return sum(passed)

names = ['football', 'baseball', 'basketball', 'tennis',
         'softball', 'canoeing', 'handball', 'rugby',
         'hockey', 'icehockey', 'swimming', 'track',
         'boxing', 'volleyball', 'lacrosse', 'skiing',
         'golf', 'polo', 'surfing', 'wrestling', 'gymnastics']

xpoints = []
ypoints = []
stressvals = []
iterations= 0

#PLOT RANDOM POINTS FIRST
for i in range(len(mdsdistances)):
```

```
    xpoints.append(mdsdistances[i][0])
    ypoints.append(mdsdistances[i][1])

# fig, ax = plt.subplots()
# ax.scatter(xpoints,ypoints)
# for i, txt in enumerate(names):
#     ax.annotate(txt, (xpoints[i], ypoints[i]))
n = 0

while n < 10:
    mdsdistances = np.random.uniform(0, 1, size=(21,2))
    gradient = findgradient(mdsdistances, psychsimilarities, del
ta)
    stress = stresscalc(mdsdistances, psychsimilarities)
    print(stress)
    checkval = gradientcheck(gradient)
    while stress >= 10:
        for i in range(len(gradient)):
            mdsdistances[i][0] += (-scaling * gradient[i][0])
            mdsdistances[i][1] += (-scaling * gradient[i][1])
            xpoints[i] = (mdsdistances[i][0])
            ypoints[i] = (mdsdistances[i][1])
        gradient = findgradient(mdsdistances, psychsimilarities,
delta)
        stress = stresscalc(mdsdistances, psychsimilarities)
       # checkval = gradientcheck(gradient)
        print(stress)
    print('NEW STRESS:', stress)

    fig, ax = plt.subplots()
    ax.scatter(xpoints,ypoints)
    for i, txt in enumerate(names):
        ax.annotate(txt, (xpoints[i], ypoints[i]), fontsize = 10
)
    n += 1
```

```
31.342938590553423
28.149608085375842
25.87853143113200
24.10320061974803
22.47113474020452
20.856952093264567
19.63727693994673
18.731238250451458
```

18.02571557251666
17.4266267667201
16.888479855793516
16.425117315752036
16.032557816133224
15.694566306692632
15.397127246681586
15.131205935041729
14.892048241942275
14.67664637799215
14.482034957346178
14.304930220336084
14.141849308117278
13.989599451462965
13.846026014805355
13.710259041870891
13.58208042497738
13.461277128602639
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13.24046805607119
13.139856585812977
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12.378990262922645
12.335566921243462
12.295626263704028
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12.16400099022353
12.136519770784888
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11.862425264730824
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11.823946974740062
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11.784569874772071
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11.722938423975462
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11.538605923478801
11.513485153473262
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11.435896629380723
11.40942391420283
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11.219066385764675
11.191181985311712
11.162978849759737
11.134329863753761
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11.043632346701115
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9.978483820819106
NEW STRESS: 9.978483820819106
33.6219566024969
31.096891838182067
29.1736315747589
27.615607273434406
26.359881624843485
25.35143396452544
24.544111670843613
23.85687741850006
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22.855877231201685
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21.450671503258793
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19.71816272626383
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19.207339225912076
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18.170831858386258
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18.07665761679936
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17.691744078483705
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16.942705216115677
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16.400692486443013
16.240410097930642
16.067201888621327
15.879648801853467
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15.221181721806259
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14.120792956453451
13.822281431741358
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12.540470841132421
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12.020911926295428
11.870862892315156
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11.384651861419501
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10.457498371803114
10.206987335332583
9.968411308634911

```
NEW STRESS: 9.968411308634911
28.970014787935384
27.10980580156949
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23.550682137087303
22.022190606002344
20.555028397451235
19.456929804967896
18.591332519787535
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16.9869002891223
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15.754233252742072
15.181288578249436
14.63268825888342
14.128963913628033
13.664256702290512
13.233447306168504
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12.459335286297005
12.108038928210997
11.77766072032106
11.467776843398031
11.178967173924747
10.91229860065104
10.668355725729038
10.446095991757407
10.243125134503677
10.058746998195742
9.892534737573737
NEW STRESS: 9.892534737573737
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33.11980888773937
30.978629755821416
29.13606640660183
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25.943552689085433
24.458037742139425
22.937769784472675
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14.495707078751481
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```

```
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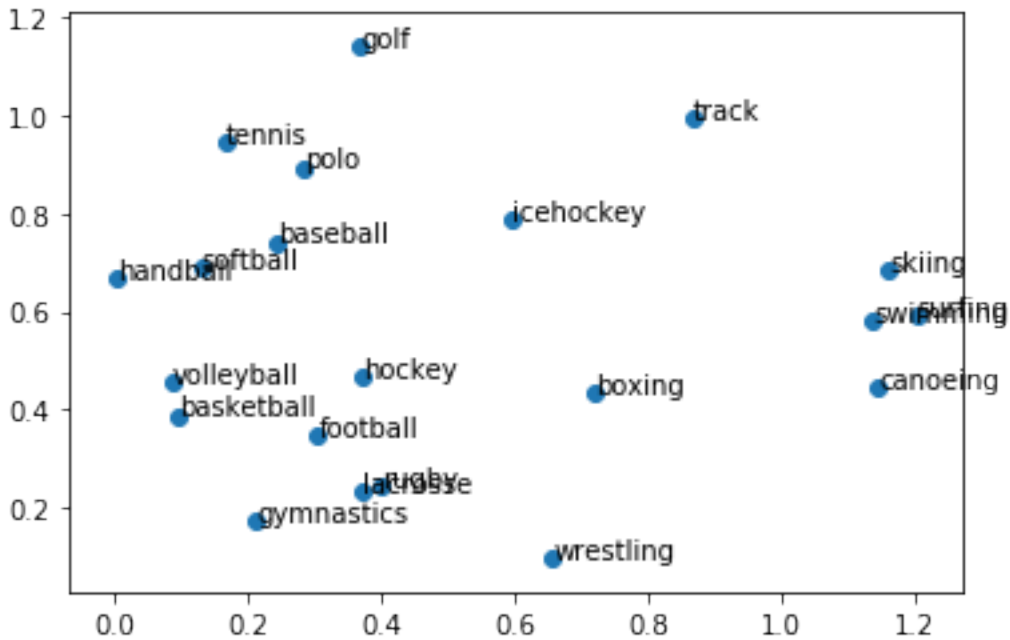

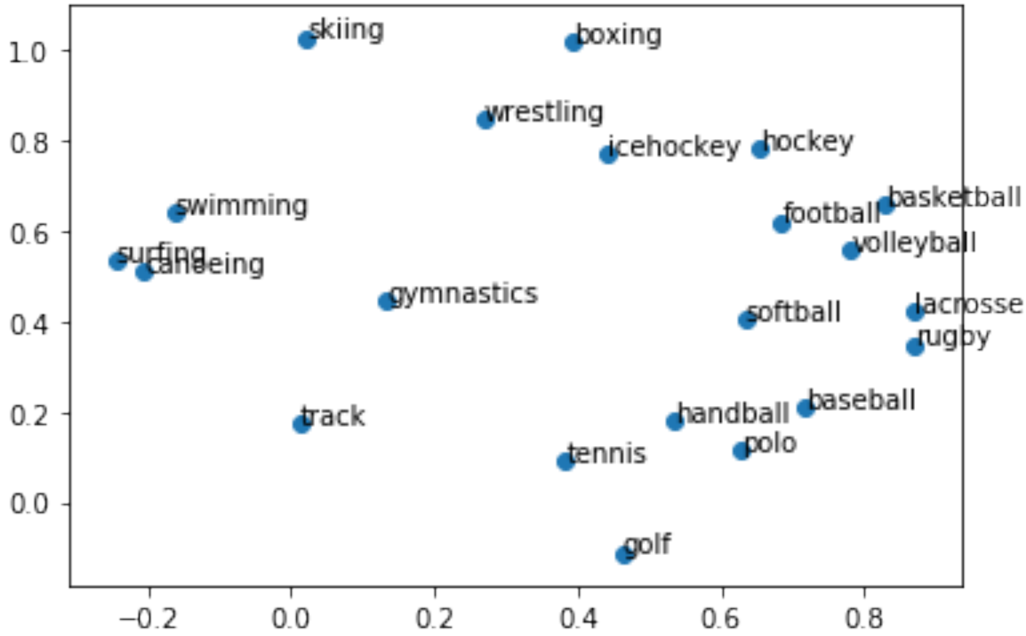
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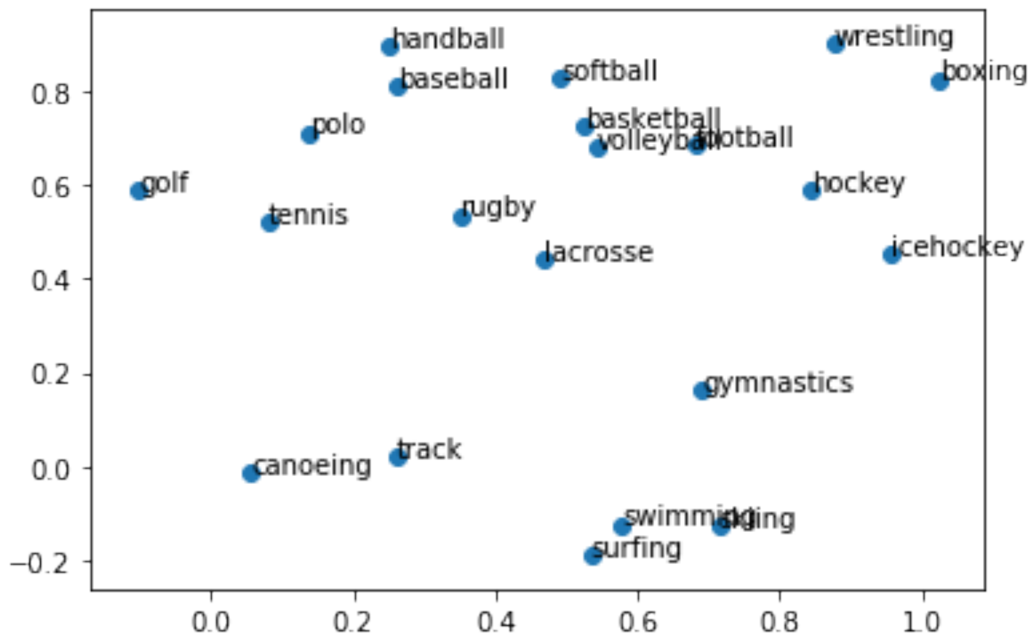
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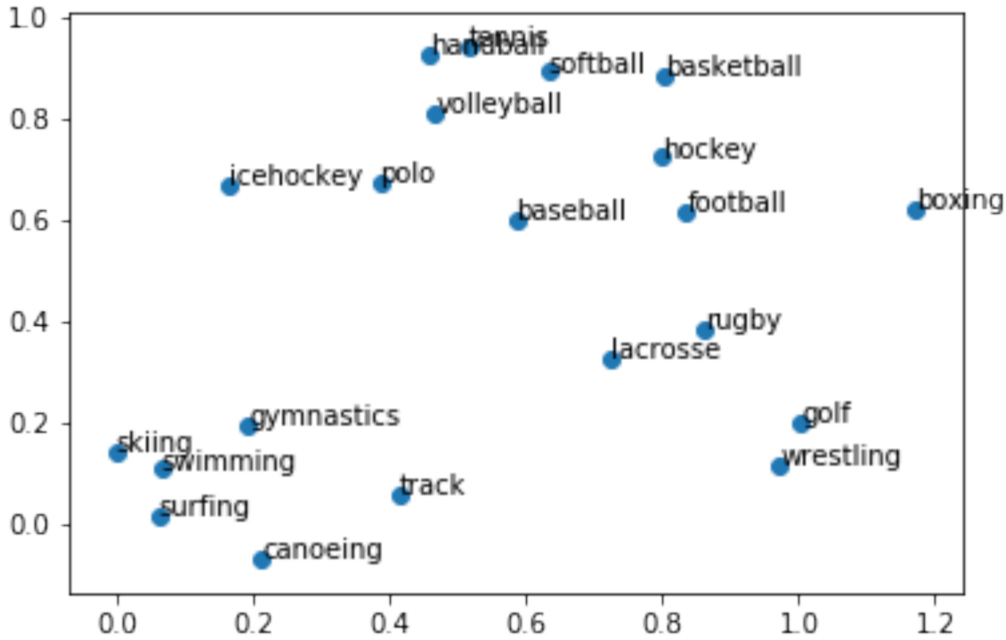
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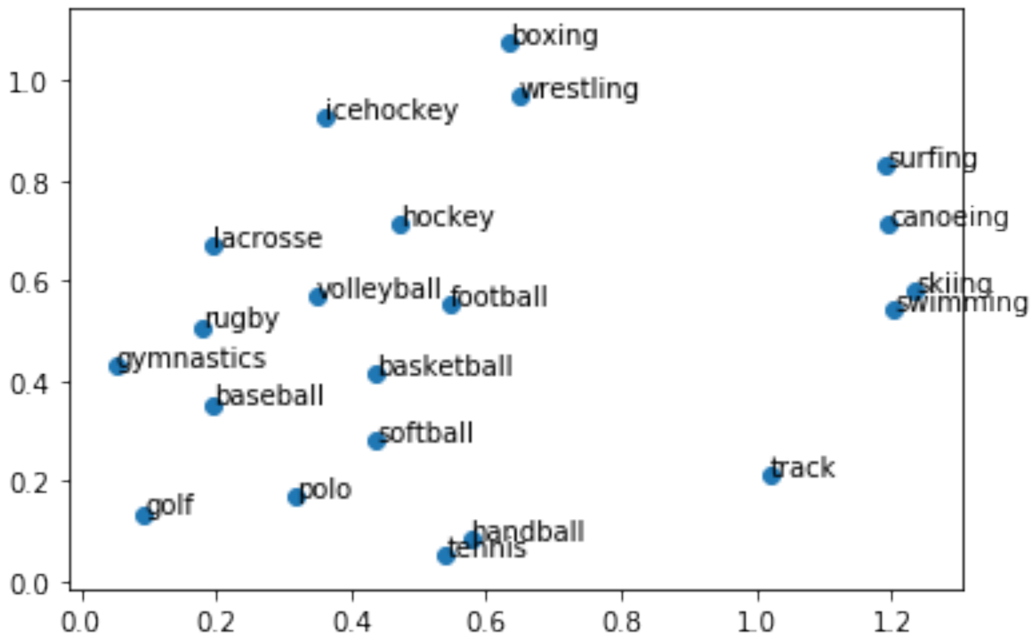
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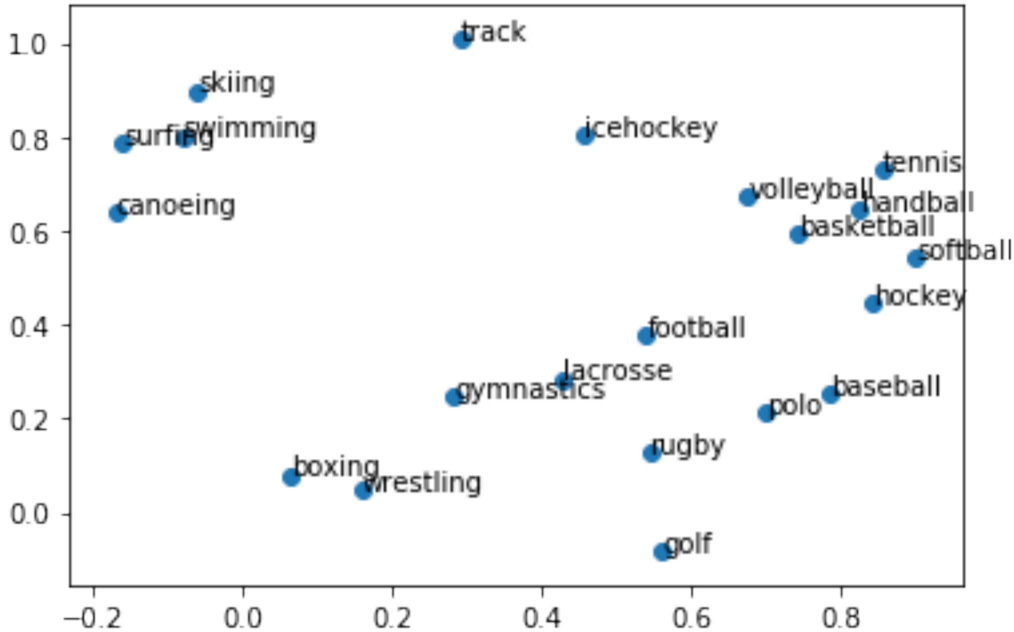
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polo
rugby
boxing
wrestling
golf
1.0
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0.4
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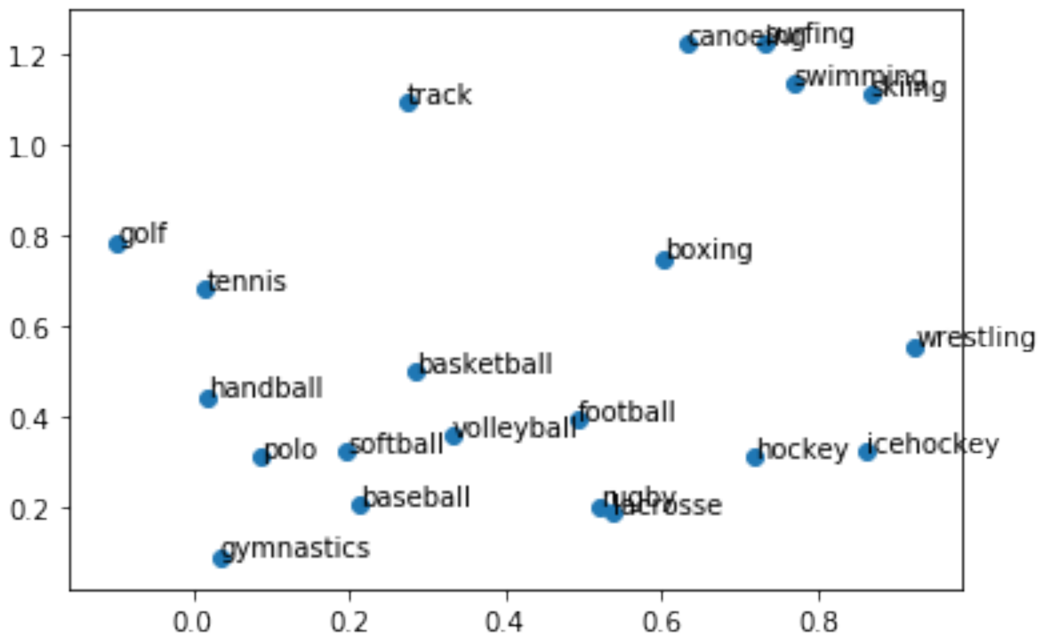
canoeing
surfing
swimming
skiing
track
golf
boxing
tennis
wrestling
basketball
handball
football
volleyball
softball
polo
hockey
icehockey
baseball
rugby
lacrosse
gymnastics
1.2
1.0
0.8
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0.0
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0.4
0.6
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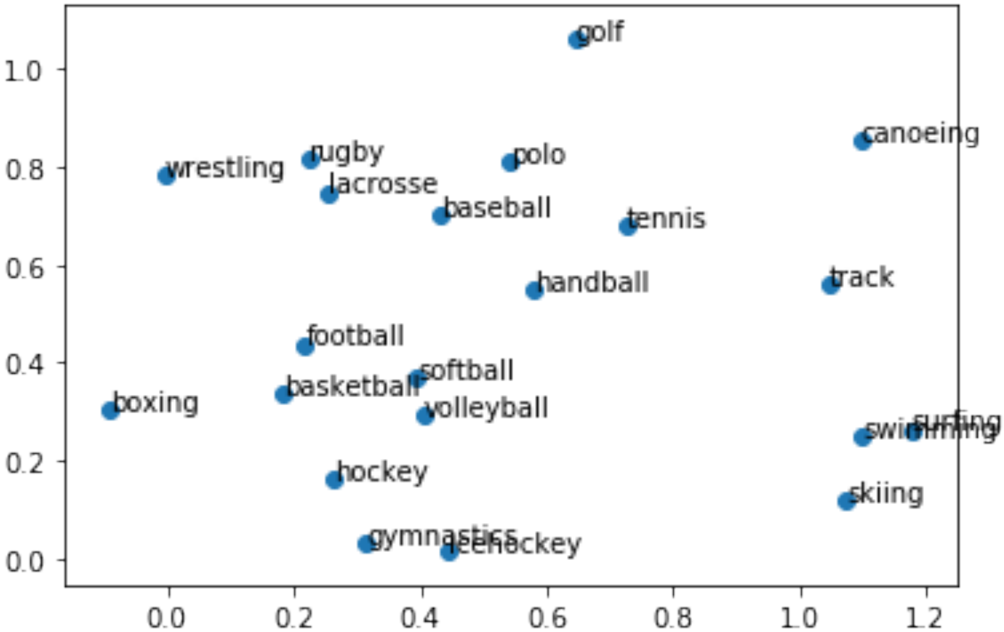
golf
canoeing
rugby
polo
wrestling
lacrosse
baseball
tennis
track
handball
football
softball
basketball
boxing
volleyball
surfing
swimming
hockey
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gymnastics
icehockey
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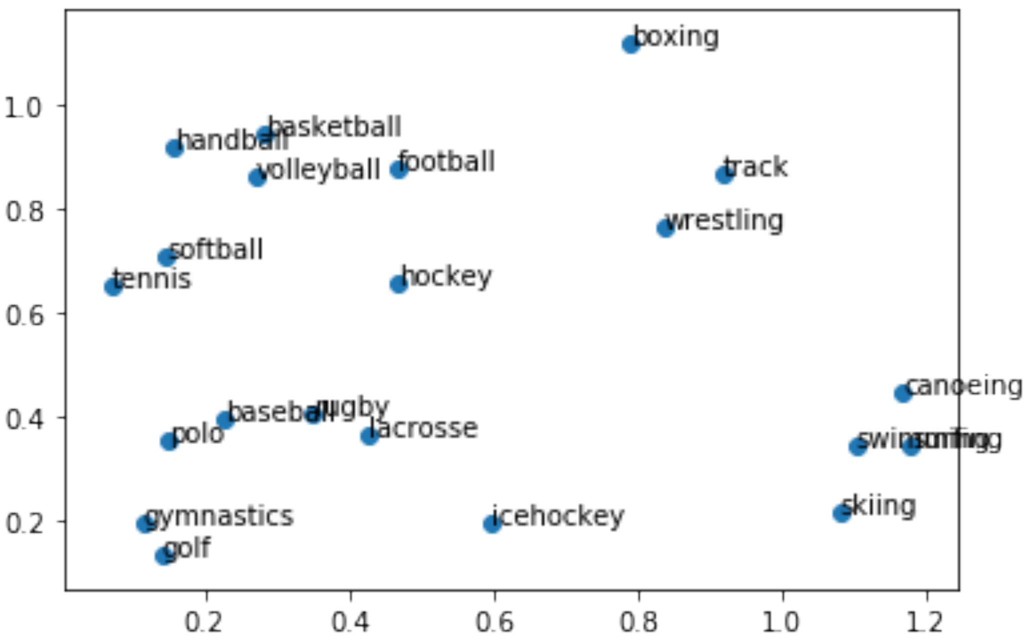
boxing
basketball
handball
football
volleyball
track
wrestling
softball
tennis
hockey
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baseball
rugby
lacrosse
polo
swimming
skiing
gymnastics
icehockey
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0.8
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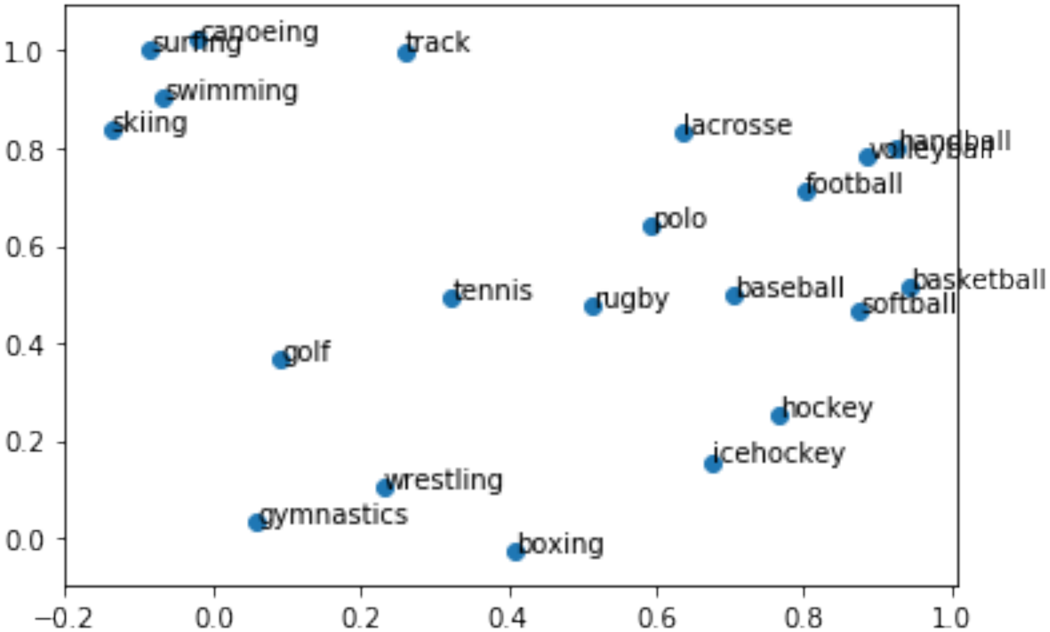

1. [5pts, SOLO] If you wanted to find one "best" answer but had run MDS 10 times, how would you pick the best? Why? Show a plot of the best and any code you used to find it.

In [ ]:

```
#QUESTION 8
psydist = []
mdsdist = []

mds1 = []
mds2 = []
mds3 = []
mds4 = []
mds5 = []
mds6 = []
mds7 = []
mds8 = []
mds9 = []
mds10 = []

def plot_distances(mdsdistances, psychsimilarities):
    col = 1
    for row in range(0,20): #for each sport
        #compare sport to each remaining sport
        c = col
        for c in range(c,20):
```

```
            psydist.append(1-psychsimilarities[row][c])
        col += 1

    col = 1
    for row in range(0,20): #for each sport
        #compare sport to each remaining sport
        c = col
        for c in range(c,20):
            mdsdist.append(np.sqrt(np.square(mdsdistances[row][0
] - mdsdistances[c][0]) + np.square(mdsdistances[row][1] - mdsdi
stances[c][1])))
        col += 1

    print(len(psydist))
    print(len(mdsdist))
    plt.scatter(mdsdist, psydist)
    plt.title("MDS found vs. People's Reported Distances")
    plt.xlabel("MDS Found")
    plt.ylabel("Reported Distance")
    plt.show()

# calc the trendline
z = numpy.polyfit(x, y, 1)
p = numpy.poly1d(z)
pylab.plot(x,p(x),"r--")
# the line equation:
print "y=%.6fx+(%.6f)"%(z[0],z[1])
```