## (AP)Affinity Propagation algorithm

#### **Overview:**

In statistics and data mining, affinity propagation (AP) is a clustering algorithm based on the concept of "message passing" between data points. Unlike clustering algorithms such as k-means or k-medoids, affinity propagation does not require the number of clusters to be determined or estimated before running the algorithm. Similar to k-medoids, affinity propagation finds "exemplars," members of the input set that are representative of clusters

### Algo:

1-compute similarities

2-compute responsibilities

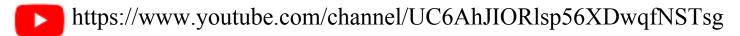
3-compute availabilities



delphi & c++ programmation For more information:

contact us at: fb ..gitH ..or .. yt







x: set of data points

N: size of dataset .. where  $...0 \le i \le N$  &  $0 \le k \le N$  availability, similarity, responsibility matrix = NxN

## 1- Similarity Equation:

$$S(i,k) = - \|x_i - x_{k_{A}}\|_{Progs\ Angedevil\ AD}^{M.Aaek\ Progs\ Angedevil\ AD}$$

M.Aaek\ Progs\ Angedevil\ AD

M.Aaek\ Progs\ Angedevil\ AD

M.Aaek\ Progs\ Angedevil\ AD

Diagonal s(i,i), initialized to the median similarity

# 2-Responsibility Equation: responsibilities matrix initialized to 0

$$\begin{array}{c} \text{MAaek Progs Angedevil AD} \\ \text{Wil AD} \\ \text{At } r(i,k)_{\text{gedevil AD}} s(i,k) \overset{\text{M.Aaek}}{-} \max_{k \neq k'} \{a(i,k') \overset{\text{M.Aaek}}{+} s(i,k')\}_{\text{gedevil AD}} \\ \text{MAaek Progs Angedevil AD} \\ \text{Wil AD} \\ \text{Wil AD} \end{array}$$

#### 3-Availabilities:

$$a(i,k) \leftarrow \min \left( O_{A,r}(k,k) + \sum_{i' \notin (i,k)} \max(O,r(i',k)) \right) for i \neq k$$

M.Aaek Progs Ange

a(k,k) diagonal:

M.Aaek Progs Angedevil AD  $a(k,k) \leftarrow \sum_{M.Aaik \neq k_{ogs Angedevil AD}} max(0, r(i', k))$ 

M.Aaek Progs Angedevil AD

## finally,

algorithm terminate if clusters unchanged after infinite number of iteration (use break to finaliz the iteration loop), or after predetermined number of iteration is reached

exemplar extracted from diagonal sum of r & a, where r(i,i) + a(i,i) > 0

## lets explain the 3 equation with exemple:

dataset = one dimension 0.90, 0.15, 0.62, 0.8, 0.27, 0.18, 0.30 len ... N = 7

compute similarities:

as we know

$$s(i,k) = - ||xi - xk||^2$$

$$0 \le i \le N$$

$$0 \le k \le N$$

$$s(0,0) = -(0.90-0.90)^2 = 0.0$$

$$s(0,1) = -(0.90-0.15)^2 = -0.56$$

$$s(0,2) = -(0.90-0.62)^2 = -0.08$$

$$s(6,6) = -(0.30-0.30)^2 = 0.0$$
  
put result in Matrix NxN

fill Diagonal(s(i,i) with median value of similarity matrix:

```
0.00, -0.56, -0.08, -0.01, -0.40, -0.52, -0.36,
-0.56, 0.00, -0.22, -0.42, -0.01, -0.00, -0.02,
-0.08, -0.22, 0.00, -0.03, -0.12, -0.19, -0.10,
-0.01, -0.42, -0.03, 0.00, -0.28, -0.38, -0.25,
-0.40, -0.01, -0.12, -0.28, 0.00, -0.01, -0.00,
-0.52, -0.00, -0.19, -0.38, -0.01, 0.00, -0.01,
-0.36, -0.02, -0.10, -0.25, -0.00, -0.01, 0.00
```

before calc median value we must sort the matrix:

0,00 0,00 0,00 0,00 0,00 0,00 0,00

0,00 0,00 0,00 0,00 -0,01 -0,01 -0,01

-0,01 -0,01 -0,01 -0,01 -0,01 -0,02 -0,02

-0,03 -0,03 -0,08 -0,08 -0,10 -0,10 -0,12

-0,12 -0,19 -0,19 -0,22 -0,22 -0,25 -0,25

-0,28 -0,28 -0,36 -0,36 -0,38 -0,38 -0,40

-0,40 -0,42 -0,42 -0,52 -0,52 -0,56 -0,56

median = sorted\_similarities(N/2,N/2) = -0.08

#### final similarities matrix:

- we done with similarities matrix. lets move to responsibilities and availabilities

these two matrix, must updated continuouly as long as the algorithm not terminated, therfore we have to determine the number of iteration, or use an infinite loop and break if clusters, unchanged

```
for i=0 to infinite
responsibilities(...)
availabilities(...)
if curent clusters = previous clusters ..break
```

## -responsibility:

```
r(i,k) = s(i,k) - max(s(i,k')+a(i,k')) where k not equal k'
compute max value in s(i,k')+a(i,k')
```

$$0 \le i \le N$$
,  $0 \le k \le N$ ,  $0 \le k' \le N$   
for  $i = 0$ ,  $k = 0$ ,  $k' = 0$ 

k = k' ..we know that k must not equal to k' ..so this step will bypassed

#### move to

```
for i = 0, k = 0, k' = 1
k<>k' ... fine
s(i,k') = -0.56 \dots v(alue from similarities matrix)
a(i,k') = 0 ... availability is not yet filled ... is initialized to 0 for first use
s+k=-0.56
```

for 
$$i = 0$$
,  $k = 0$ ,  $k' = 2$   
 $k <> k'$  ... fine

$$s(i,k') = -0.08$$

$$s(1,K') = -0.08$$

$$a(i,k') = 0$$

$$s+k=-0.08$$

for 
$$i = 0$$
,  $k = 0$ ,  $k' = 3$   
 $k < k'$  ... fine  
 $s(i,k') = -0.01$   
 $a(i,k') = 0$   
 $s+k=-0.01$ 

max value in : -0.56 , -0.08 , -0.01 , -0.40 , -0.52 , -0.36 is -0.01 maxval = -0.01

$$r(i,k) = s(i,k) - maxval = -0.08 - (-0.01) = -0.07$$

#### continue:

s+k=-0.36

for 
$$i = 0$$
,  $k = 1$ ,  $k' = 0$   
 $k < > k'$  ... fine  
 $s(i,k') = -0.08$   
 $a(i,k') = 0$   
 $s+k=-0.08$ 

-----

for 
$$i = 0$$
,  $k = 1$ ,  $k' = 1$   
 $k = k'$  ... bypass

-----

for 
$$i = 0$$
,  $k = 1$ ,  $k' = 2$   
 $k <> k'$  ... fine  
 $s(i,k') = -0.08$   
 $a(i,k') = 0$   
 $s+k=-0.08$ 

```
_____
```

for 
$$i = 0$$
,  $k = 1$ ,  $k' = 3$   $k <> k'$  ... fine  $s(i,k') = -0.01$   $a(i,k') = 0$   $s+k=-0.01$ 

.

#### .continue until

-----

for 
$$i = 0$$
,  $k = 1$ ,  $k' = 6$   $k <> k'$  ... fine  $s(i,k') = -0.36$   $a(i,k') = 0$   $s+k=-0.36$ 

max value in : -0.08, -0.08, -0.01, -0.40, -0.52, -0.36 is -0.01 maxval = -0.01

$$r(i,k) = s(i,k) - maxval = -0.56 - (-0.01) = -0.55$$

continue until

for 
$$i = 6$$
,  $k = 6$ ,  $k' = 6$ 

put all result in matrix, and before do that, we need apply dump factor on result, where dump factor [0...1]

ex: dump factor = 0.3

new matrix = (1-dump factor) \* current matrix + dump factor \* previous matrix for matrix[0][0] = (1-0.3)\*0.07 - 0.3\*0 = -0.05

responsibilities matrix:

now compute availabilities:

a(i,k) = min(0,-0.03) = -0.03 < -----

#### -availabilities:

```
a(i,k) = min(0, r(k,k) + sum(max(0,r(i',k)))) i not equal to k and i' not belong to (i,k)
compute max value in 0,r(i',k)
0 \le i \le N, 0 \le k \le N, 0 \le i' \le N
for i = 0, k = 0, k' = 0
i = i' bypass
for i = 0, k = 0, i' = 1
i⇔i' ... fine
r(i',k) = -0.39...(value from responsibilities matrix)
max(0,-0.39) = 0
for i = 0, k = 0, i' = 2 i <> i'
... fine
r(i',k) = -0.03
max(0,-0.03) = 0
-----
for i = 0, k = 0, i' = 3 i<>i'
... fine
r(i',k) = 0.02
max(0,0.02) = 0.02
for i = 0, k = 0, i' = 4
i⇔i' ... fine
r(i',k) = -0.28
max(0,-0.28) = 0
for i = 0, k = 0, i' = 5
i⇔i' ... fine
r(i',k) = -0.36
max(0,-0.36) = 0
for i = 0, k = 0, i' = 6
i⇔i' ... fine
r(i',k) = -0.25
max(0,-0.25) = 0
sum all result : 0+0+0.02+0+0+0 = 0.02
add sum to r(k,k) ... r(k,k) = r(0,0) = -0.05
-0.05 + 0.02 = -0.03
```

```
now set diagonal a(k,k) a(k,k) = sum(max(0,r(i',k))) sum(max(0,r(i',k))) = 0.02
a(k,k) = 0.02
```

dont forgot to apply dump factor to availabilities matrix ....... continue until

for 
$$i = 6$$
,  $k = 6$ ,  $i' = 6$ 

you get as result:

#### availabilities matrix

```
0.01, -0.03, -0.02, -0.01, -0.03, -0.03, -0.03, -0.02, 0.00, -0.02, 0.00, -0.03, -0.03, -0.04, -0.03, -0.02, -0.03, 0.00, 0.00, -0.03, -0.03, -0.03, -0.03, -0.03, -0.03, -0.03, -0.02, 0.06, -0.03, -0.03, -0.03, -0.02, -0.02, 0.00, 0.01, -0.03, -0.04, -0.02, -0.04, -0.02, 0.00, -0.03, 0.01, -0.03, -0.03, -0.02, -0.02, -0.04, -0.02, -0.04, -0.02, -0.04, -0.02, -0.04, -0.03, 0.00
```

we done with the first iteration ..... calc availabilities + responsibilities & extract exemplar from diagonal. availabilities + responsibilities matrix:

```
-0.04, -0.42, -0.07, 0.04, -0.30, -0.39, -0.28, -0.42, -0.05, -0.18, -0.30, -0.04, -0.03, -0.05, -0.05, -0.17, -0.03, 0.03, -0.09, -0.14, -0.08, -0.02, -0.32, -0.04, 0.01, -0.22, -0.29, -0.20, -0.30, -0.04, -0.11, -0.20, -0.05, -0.04, -0.03, -0.38, -0.03, -0.16, -0.27, -0.04, -0.05, -0.04, -0.05, -0.07, -0.05, -0.04, -0.05, -0.07, -0.05, -0.04, -0.05, -0.07, -0.05, -0.04, -0.05, -0.05, -0.05, -0.05, -0.04, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05, -0.05
```

check if any elemnent of the diagonal = positive?

```
-0.04, -0.42, -0.07, 0.04, -0.30, -0.39, -0.28, -0.42, -0.05, -0.18, -0.30, -0.04, -0.03, -0.05, -0.05, -0.17, -0.03, 0.03, -0.09, -0.14, -0.08, -0.02, -0.32, -0.04, 0.01, -0.22, -0.29, -0.20, -0.30, -0.04, -0.11, -0.20, -0.05, -0.04, -0.03, -0.38, -0.03, -0.16, -0.27, -0.04, -0.05, -0.04, -0.05, -0.04, -0.27, -0.05, -0.04, -0.05, -0.04, -0.27, -0.05, -0.04, -0.05, -0.04, -0.05, -0.05, -0.09, -0.17, -0.03, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.09, -0.17, -0.03, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.04, -0.05, -0.05, -0.04, -0.05, -0.05, -0.05, -0.05, -0.05
```

0.01 = positive

$$(3,3) = 0.01$$

exemplar = 0.01

keep updating availabilities & responsibilities by passing to iteration 2,3,4....until n

check result in iteration 2:

exemplar = 0.05

currnt exemplars not = previous exemplar

$$0.05 \text{ not} = 0.01$$

continue iteration to check if exemplar change nor not ... if not change ... break the iteration loop

#### next iteration

exemplar = 0.10,0.00,0.00currnt exemplars not = previous exemplar 0.10,0.00,0.00 not = 0.05

## continue iteration : after 48 iteration we get

```
-0.16, -1.29, -0.27, 0.16, -0.94, -1.22, -0.82,

-1.38, 0.00, -0.53, -0.89, -0.03, -0.03, -0.00,

-0.27, -0.44, -0.11, 0.11, -0.24, -0.41, -0.16,

-0.62, -1.43, -0.62, 0.41, -1.13, -1.37, -1.02,

-1.25, -0.19, -0.55, -0.82, -0.03, -0.21, -0.16,

-1.53, -0.16, -0.72, -1.06, -0.21, -0.03, -0.19,

-0.91, 0.00, -0.25, -0.49, -0.03, -0.03, -0.00,
```

exemplars: 0.00, 0.41

#### next iteration

```
-0.16, -1.29, -0.27, 0.16, -0.94, -1.22, -0.82, -1.38, 0.00, -0.53, -0.89, -0.03, -0.03, -0.00, -0.27, -0.44, -0.11, 0.11, -0.24, -0.41, -0.16, -0.62, -1.43, -0.62, 0.41, -1.13, -1.37, -1.02, -1.25, -0.19, -0.55, -0.82, -0.03, -0.21, -0.16, -1.53, -0.16, -0.72, -1.06, -0.21, -0.03, -0.19, -0.91, 0.00, -0.25, -0.49, -0.03, -0.03, -0.00,
```

exemplar 0.00 position = 1 exemplar 0.41 position = 3

for each k
if similarities[i][1] > similarities[i][3] ... dataset(i) is belong to cluster(1)
if similarities[i][1] < similarities[i][3] ... dataset(i) is belong to cluster(3)

#### similarities

### for i=0 -0.56 < -0.01 dataset(0) -> cluster 3

lets consider another exemple this time we work on 2-D ...points(x,y)

len: 25

$$(0,0)$$
  $(0,2)$   $(0,4)$   $(0,6)$   $(1,1)$ 

$$(1,3)$$
  $(1,5)$   $(2,0)$   $(2,2)$   $(2,4)$ 

$$(2,6)$$
  $(3,1)$   $(3,3)$   $(3,5)$   $(4,0)$ 

$$(4,2)$$
  $(4,4)$   $(4,6)$   $(5,1)$   $(5,3)$ 

similarities after setting diagonal:

-16 -4 -16 -36 -2 -10 -26 -4 -8 -20 -40 -10 -18 -34 -16 -20 -32 -52 -26 -34 -50 -36 -40 -52 -72 -4 -16 -4 -16 -2 -2 -10 -8 -4 -8 -20 -10 -10 -18 -20 -16 -20 -32 -26 -26 -34 -40 -36 -40 -52 -16 -4 -16 -4 -10 -2 -2 -20 -8 -4 -8 -18 -10 -10 -32 -20 -16 -20 -34 -26 -26 -52 -40 -36 -40 -36 -16 -4 -16 -26 -10 -2 -40 -20 -8 -4 -34 -18 -10 -52 -32 -20 -16 -50 -34 -26 -72 -52 -40 -36 -2 -2 -10 -26 -16 -4 -16 -2 -2 -10 -26 -4 -8 -20 -10 -10 -18 -34 -16 -20 -32 -26 -26 -34 -50 -10 -2 -2 -10 -4 -16 -4 -10 -2 -2 -10 -8 -4 -8 -18 -10 -10 -18 -20 -16 -20 -34 -26 -26 -34 -26 -10 -2 -2 -16 -4 -16 -26 -10 -2 -2 -20 -8 -4 -34 -18 -10 -10 -32 -20 -16 -50 -34 -26 -26 -4 -8 -20 -40 -2 -10 -26 -16 -4 -16 -36 -2 -10 -26 -4 -8 -20 -40 -10 -18 -34 -16 -20 -32 -52 -8 -4 -8 -20 -2 -2 -10 -4 -16 -4 -16 -2 -2 -10 -8 -4 -8 -20 -10 -10 -18 -20 -16 -20 -32 -20 -8 -4 -8 -10 -2 -2 -16 -4 -16 -4 -10 -2 -2 -20 -8 -4 -8 -18 -10 -10 -32 -20 -16 -20 -40 -20 -8 -4 -26 -10 -2 -36 -16 -4 -16 -26 -10 -2 -40 -20 -8 -4 -34 -18 -10 -52 -32 -20 -16 -10 -10 -18 -34 -4 -8 -20 -2 -2 -10 -26 -16 -4 -16 -2 -2 -10 -26 -4 -8 -20 -10 -10 -18 -34 -18 -10 -10 -18 -8 -4 -8 -10 -2 -2 -10 -4 -16 -4 -10 -2 -2 -10 -8 -4 -8 -18 -10 -10 -18 -34 -18 -10 -10 -20 -8 -4 -26 -10 -2 -2 -16 -4 -16 -26 -10 -2 -2 -20 -8 -4 -34 -18 -10 -10 -16 -20 -32 -52 -10 -18 -34 -4 -8 -20 -40 -2 -10 -26 -16 -4 -16 -36 -2 -10 -26 -4 -8 -20 -40 -20 -16 -20 -32 -10 -10 -18 -8 -4 -8 -20 -2 -2 -10 -4 -16 -4 -16 -2 -2 -10 -8 -4 -8 -20 -32 -20 -16 -20 -18 -10 -10 -20 -8 -4 -8 -10 -2 -2 -16 -4 -16 -4 -10 -2 -2 -20 -8 -4 -8 -52 -32 -20 -16 -34 -18 -10 -40 -20 -8 -4 -26 -10 -2 -36 -16 -4 -16 -26 -10 -2 -40 -20 -8 -4 -26 -26 -34 -50 -16 -20 -32 -10 -10 -18 -34 -4 -8 -20 -2 -2 -10 -26 -16 -4 -16 -2 -2 -10 -26 -34 -26 -26 -34 -20 -16 -20 -18 -10 -10 -18 -8 -4 -8 -10 -2 -2 -10 -4 -16 -4 -10 -2 -2 -10 -50 -34 -26 -26 -32 -20 -16 -34 -18 -10 -10 -20 -8 -4 -26 -10 -2 -2 -16 -4 -16 -26 -10 -2 -2 -36 -40 -52 -72 -26 -34 -50 -16 -20 -32 -52 -10 -18 -34 -4 -8 -20 -40 -2 -10 -26 -16 -4 -16 -36 -40 -36 -40 -52 -26 -26 -26 -34 -20 -16 -20 -32 -10 -10 -18 -8 -4 -8 -20 -2 -2 -10 -4 -16 -4 -16 -52 -40 -36 -40 -34 -26 -26 -32 -20 -16 -20 -18 -10 -10 -20 -8 -4 -8 -10 -2 -2 -16 -4 -16 -4 -72 -52 -40 -36 -50 -34 -26 -52 -32 -20 -16 -34 -18 -10 -40 -20 -8 -4 -26 -10 -2 -36 -16 -4 -16 As you see... a large matrix has been generated with len=625 where 25 \* 25 = 625

"assume that you input 1k set of data... the simlarities size = 1k \* 1k = 1mb

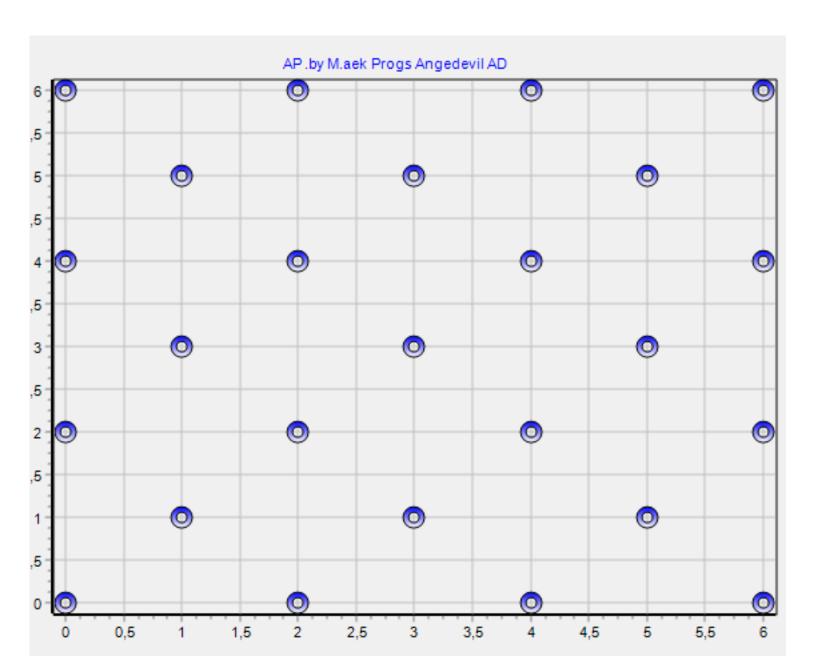
1mb set of data give you 1TB....1mb \*1mb = 1000000\*1000000 = 1000000000000

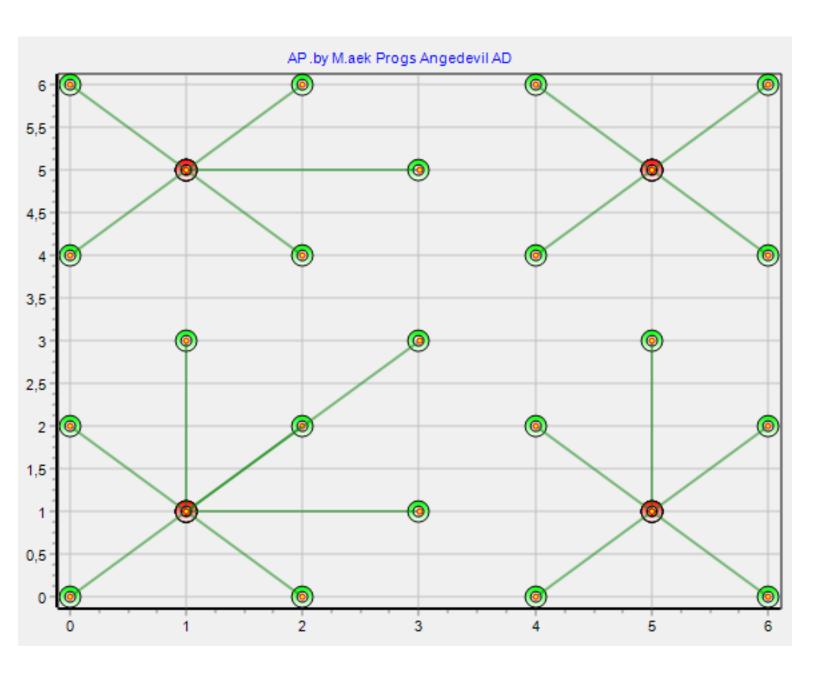
Space complexity is given by:  $O(N^2)$ 

algorithm therminate after 27 iteration .. exemplar table:

4,4,6,6,4, 4,6,4,4,6, 6,4,4,6,18, 18,20,20,18,18, 20,18,18,20,20

Time Complexity ....  $O(N^2i)$ 





red point i = exemplars

affinity propagation doesn't need to dertmine the number of cluster.
affinity propagation is better than kmeans & k medoids on error minimizing and outliers

## application:

- -The inventors of affinity propagation showed it is better for certain computer vision and computational biology tasks
- -Another recent application was in economics, when the affinity propagation was used to find some temporal patterns in the output multipliers of the US economy between 1997 and 2017
- .....and many other advantages