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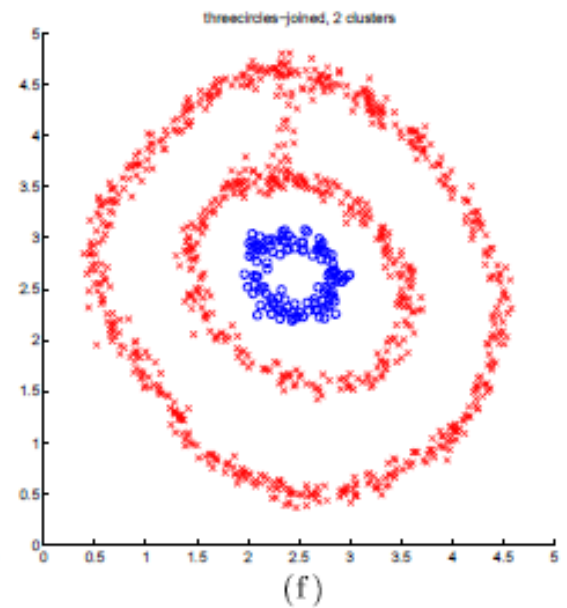
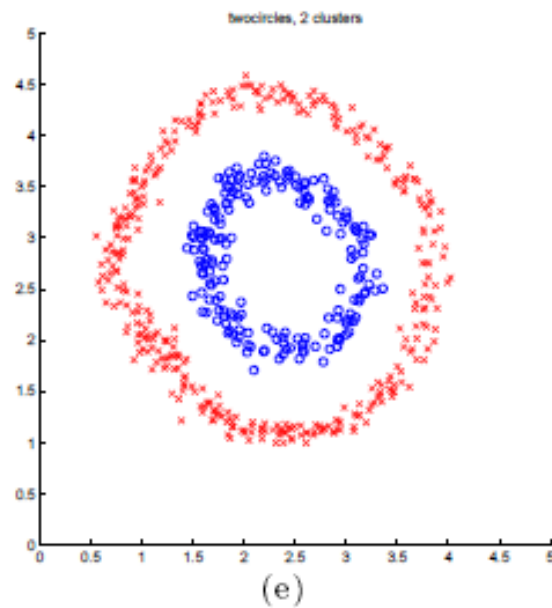
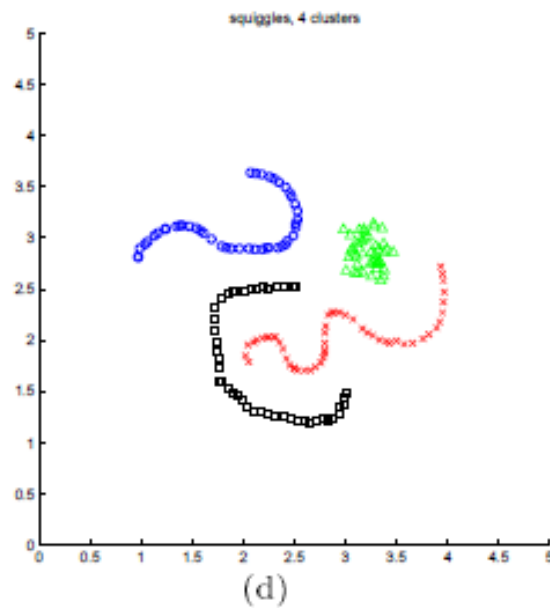
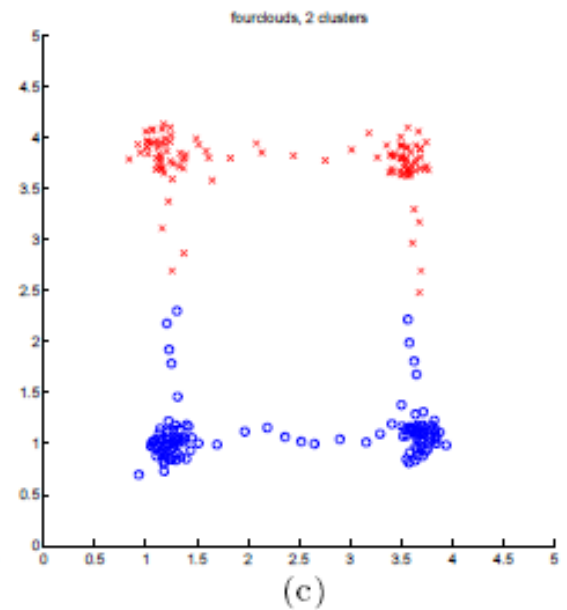
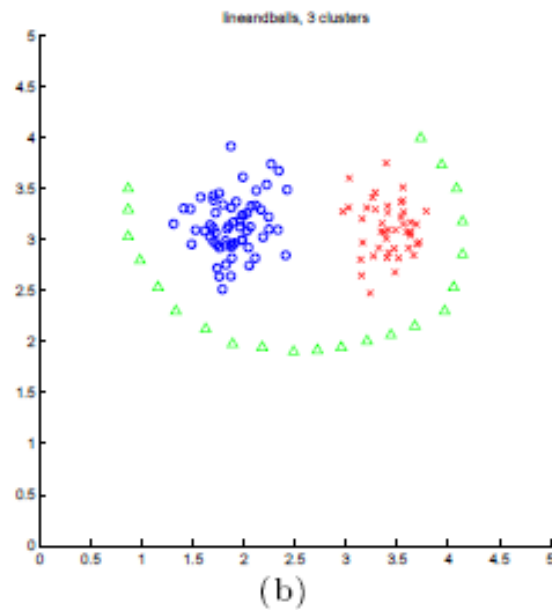
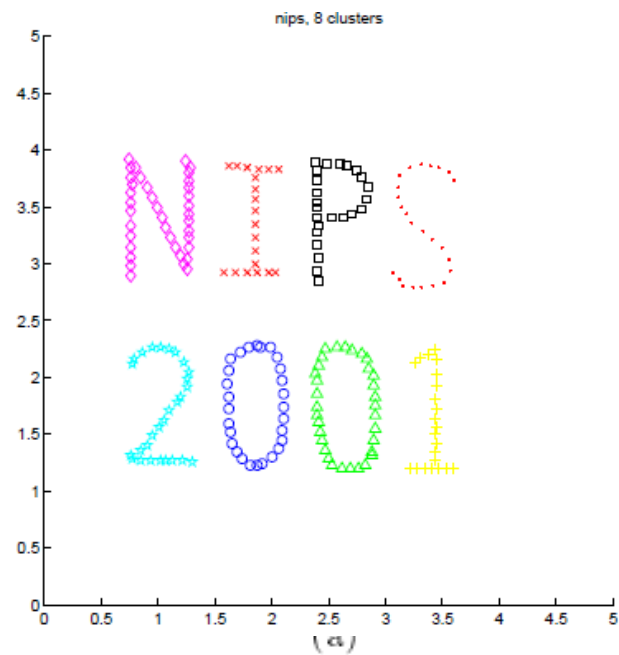
## Spectral Clustering

**Dr. K. V Dakshinamurthy**  
President, INSOF

<https://charlesmartin14.wordpress.com/2012/10/09/spectral-clustering/>

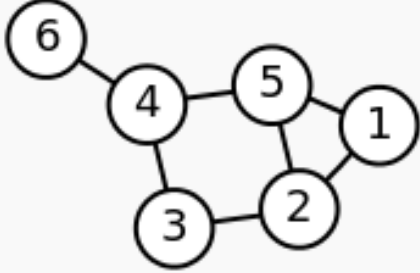
<http://ai.stanford.edu/~ang/papers/nips01-spectral.pdf>

# SPECTRAL CLUSTERING



# WHEN AFFINITY IS MORE IMPORTANT



Labeled graph	Degree matrix	Adjacency matrix	Laplacian matrix
	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

The elements of  $L$  are given by

$$L_{i,j} := \begin{cases} \deg(v_i) & \text{if } i = j \\ -1 & \text{if } i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise} \end{cases}$$

where  $\deg(v_i)$  is degree of the vertex  $i$ .

- The number of times 0 appears as an eigenvalue in the Laplacian is the number of [connected components](#) in the graph.
- The smallest non-zero eigenvalue of  $L$  is called the [spectral gap](#).
- The second smallest eigenvalue of  $L$  is the [algebraic connectivity](#) (or [Fiedler value](#)) of  $G$ .



# Affinity/Adjacency in continuous sense

$$W(i, j) = e^{-d(x_i, x_j)/2\sigma^2}$$

$$d(x_i, x_j) = \|x_i - x_j\|^2 \quad \text{One possible definition}$$

$$W(i, i) = 0$$

$$d(x_i, x_j) = d(x_j, x_i) \quad \text{Mandatory condition}$$

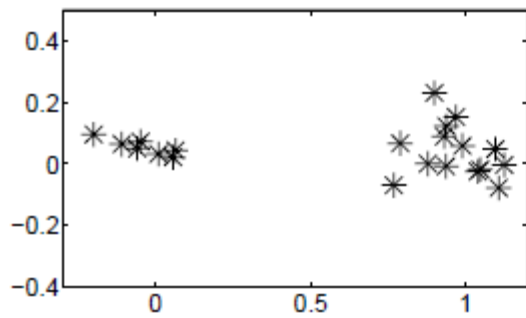


The **symmetric normalized Laplacian matrix** is defined as:<sup>[1]</sup>

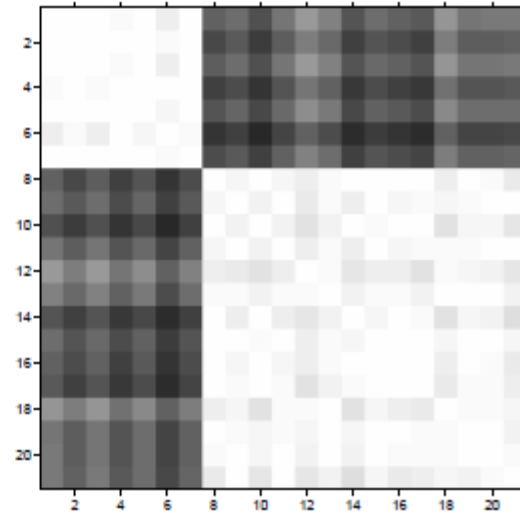
$$L^{\text{sym}} := D^{-1/2} L D^{-1/2} = I - D^{-1/2} A D^{-1/2},$$

The elements of  $L^{\text{sym}}$  are given by

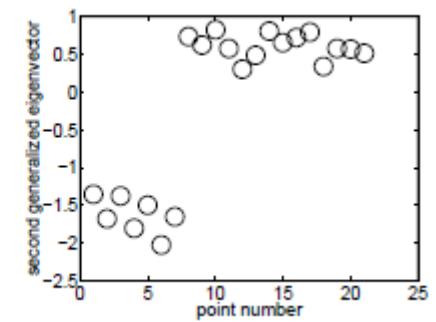
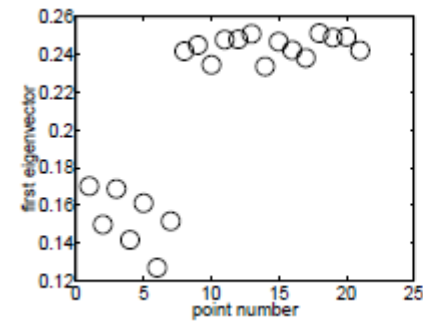
$$L_{i,j}^{\text{sym}} := \begin{cases} 1 & \text{if } i = j \text{ and } \deg(v_i) \neq 0 \\ -\frac{1}{\sqrt{\deg(v_i) \deg(v_j)}} & \text{if } i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise.} \end{cases}$$



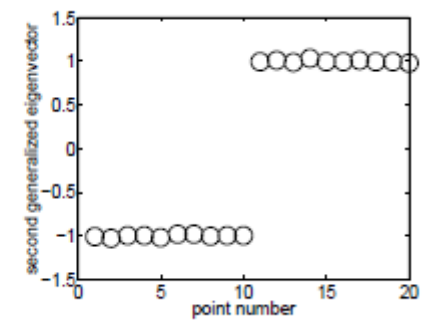
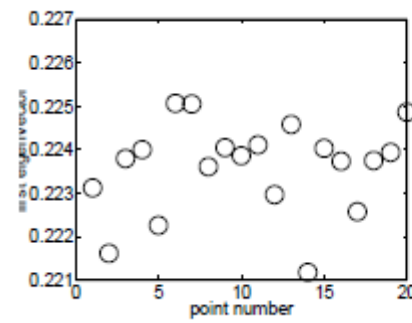
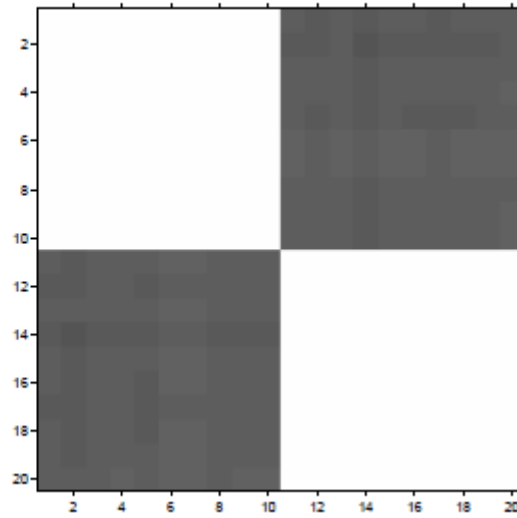
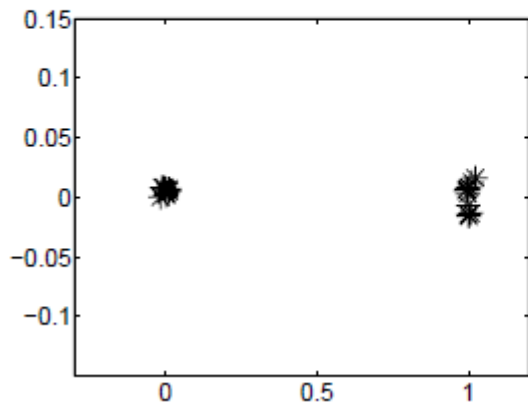
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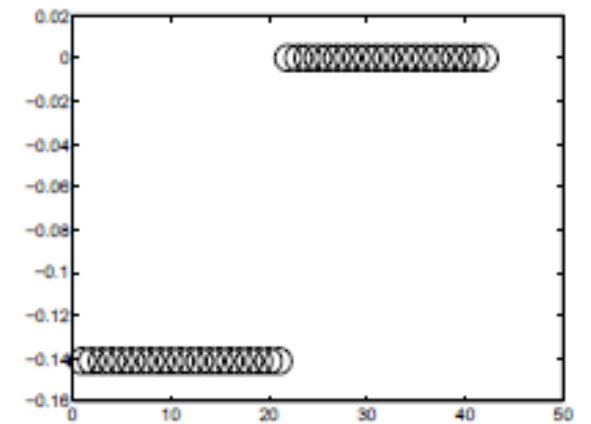
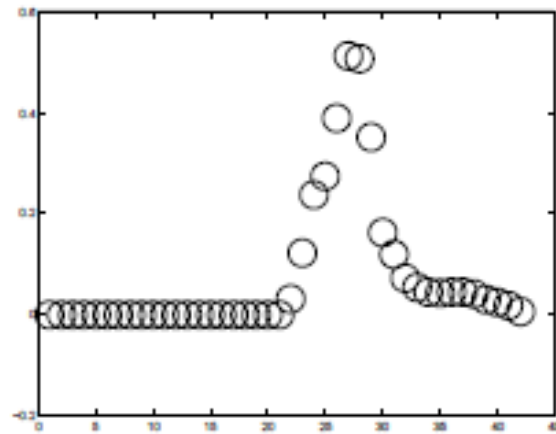
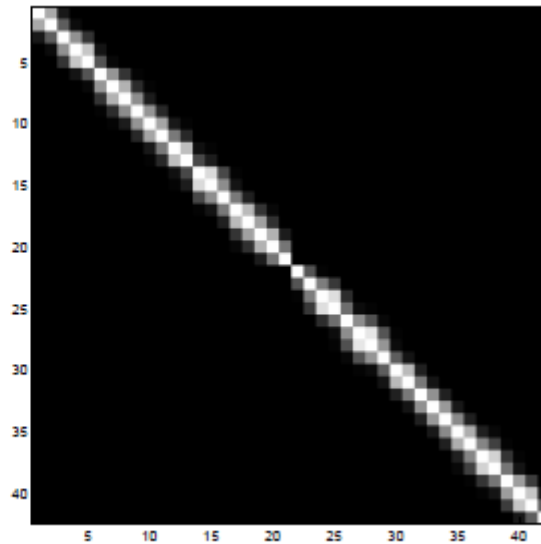
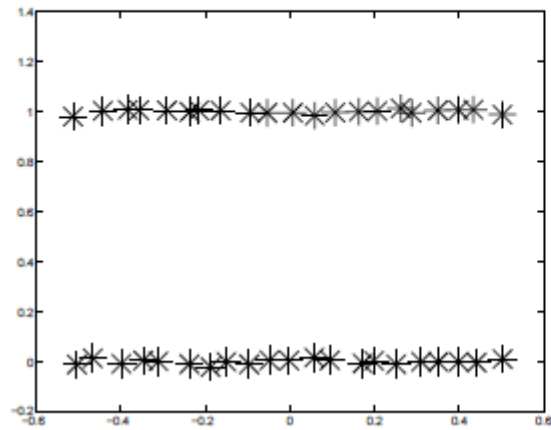


b



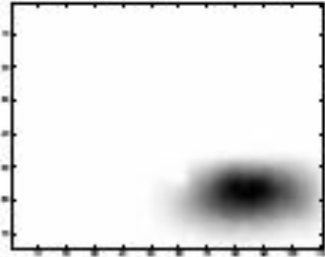




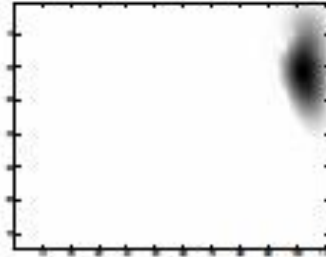




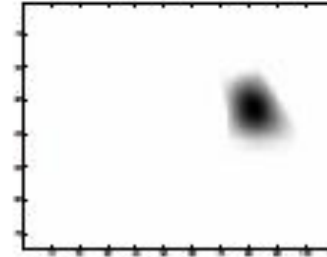
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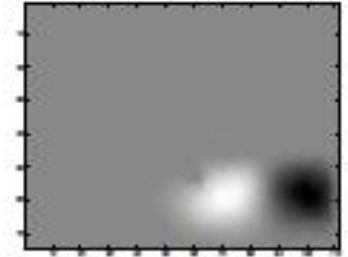
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c



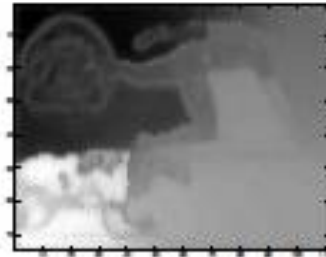
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e



f



g



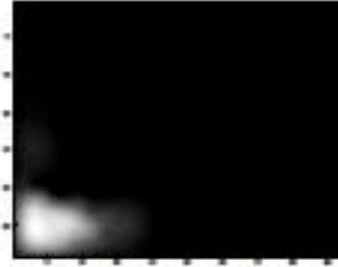
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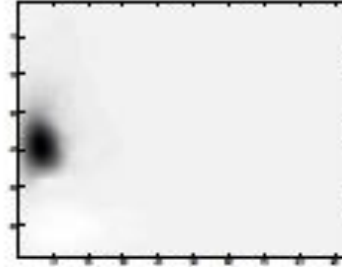
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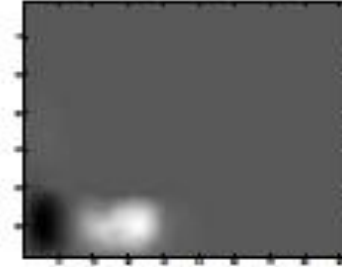
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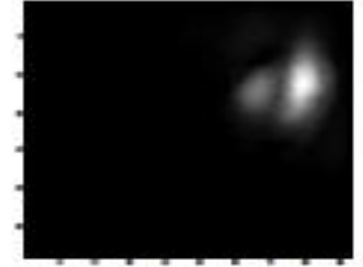
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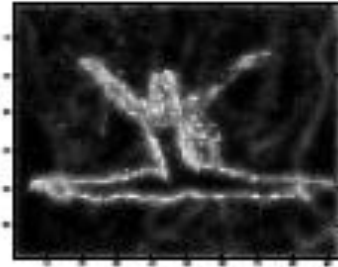
c



d



e



f



g



h



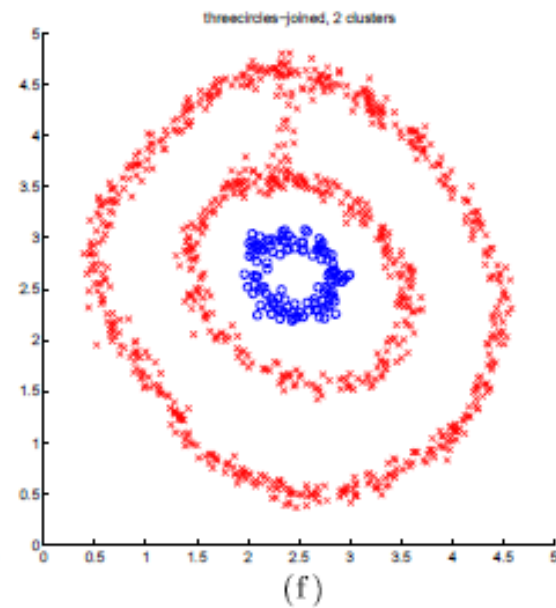
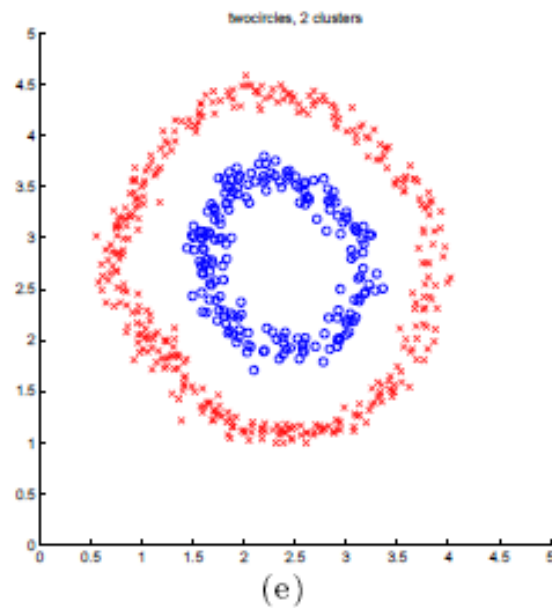
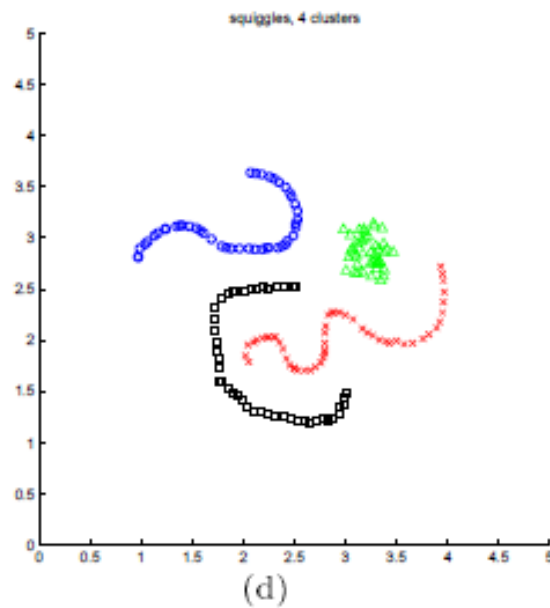
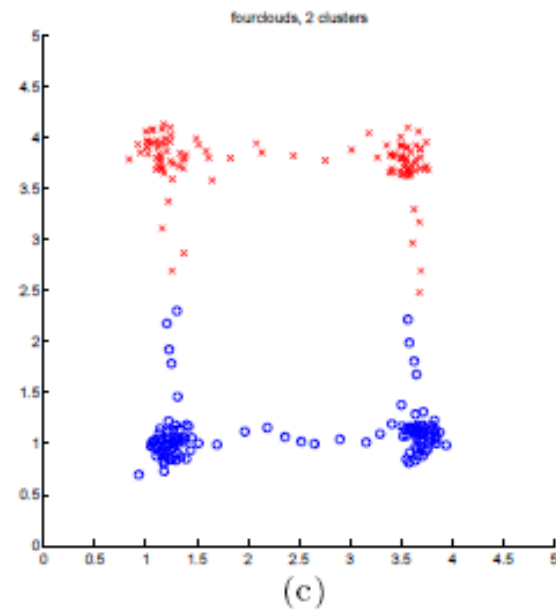
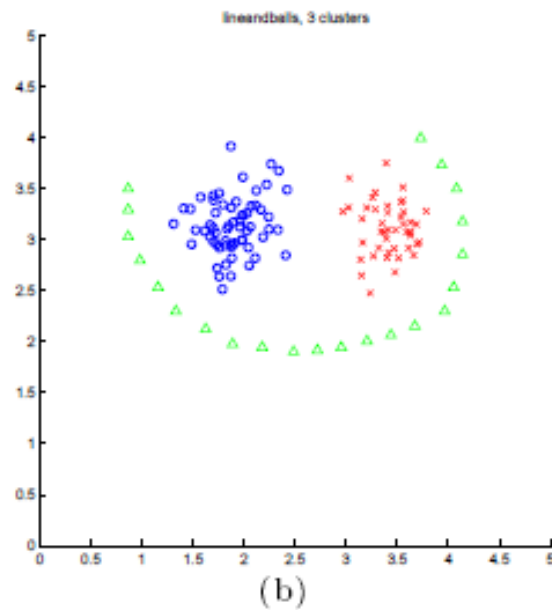
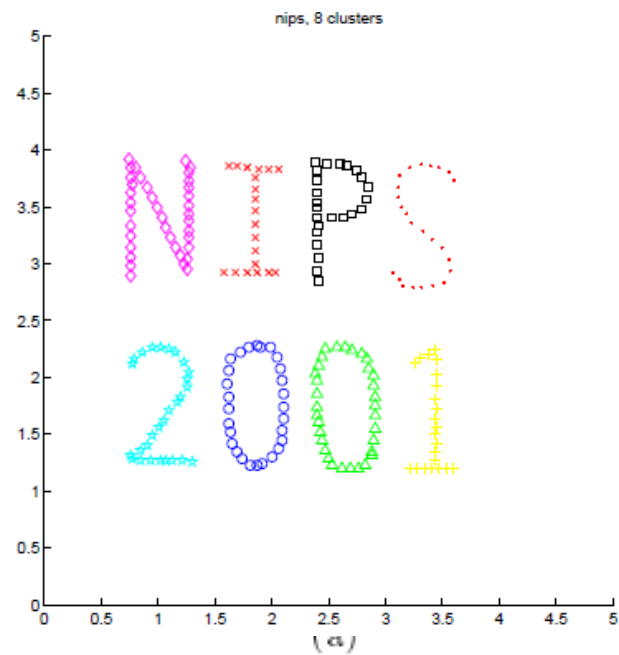
i

# A spectral algorithm

Given a set of points  $S = \{s_1, \dots, s_n\}$  in  $\mathbb{R}^l$  that we want to cluster into  $k$  subsets:

1. Form the affinity matrix  $A \in \mathbb{R}^{n \times n}$  defined by  $A_{ij} = \exp(-\|s_i - s_j\|^2 / 2\sigma^2)$  if  $i \neq j$ , and  $A_{ii} = 0$ .
2. Define  $D$  to be the diagonal matrix whose  $(i, i)$ -element is the sum of  $A$ 's  $i$ -th row, and construct the matrix  $L = D^{-1/2} A D^{-1/2}$ .
3. Find  $x_1, x_2, \dots, x_k$ , the  $k$  largest eigenvectors of  $L$  (chosen to be orthogonal to each other in the case of repeated eigenvalues), and form the matrix  $X = [x_1 x_2 \dots x_k] \in \mathbb{R}^{n \times k}$  by stacking the eigenvectors in columns.
4. Form the matrix  $Y$  from  $X$  by renormalizing each of  $X$ 's rows to have unit length (i.e.  $Y_{ij} = X_{ij} / (\sum_j X_{ij}^2)^{1/2}$ ).
5. Treating each row of  $Y$  as a point in  $\mathbb{R}^k$ , cluster them into  $k$  clusters via K-means or any other algorithm (that attempts to minimize distortion).
6. Finally, assign the original point  $s_i$  to cluster  $j$  if and only if row  $i$  of the matrix  $Y$  was assigned to cluster  $j$ .





[http://www.cs.stanford.edu/~acoates/papers/coatesng\\_nntot2012.pdf](http://www.cs.stanford.edu/~acoates/papers/coatesng_nntot2012.pdf)

[http://www.cs.stanford.edu/~acoates/papers/CoatesLeeNg\\_nips2010\\_dlwkshp\\_singlelayer.pdf](http://www.cs.stanford.edu/~acoates/papers/CoatesLeeNg_nips2010_dlwkshp_singlelayer.pdf)

<http://fastml.com/the-secret-of-the-big-guys/>

# AN ADVANCED SPECTRAL FEATURE ENGINEERING

# This is hot!

- Do K-means clustering of the data
- For every point, create a hard cluster space representation

	Cluster 1	Cluster 2	...	Cluster 100	Target
Record 1	1	0	0	0	A
Record 2	0	0	..1..	0	B
...					A

- Now, build a regression



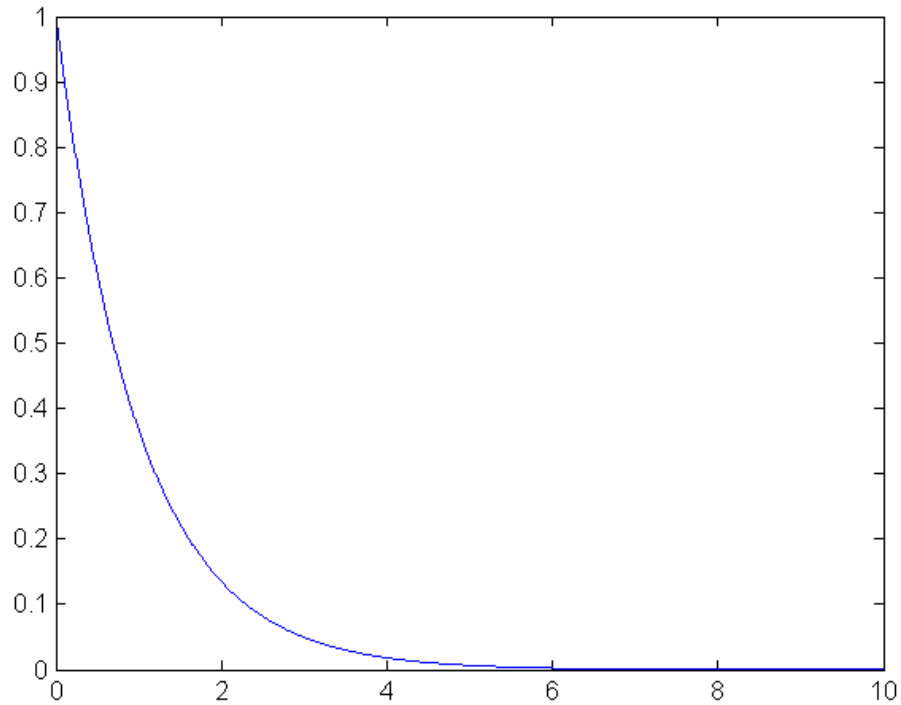
# This is hotter!

- Do K-means clustering of the data
- For every point, create a soft cluster space representation (  $\phi(r) = e^{-(\varepsilon r)^2}$  )

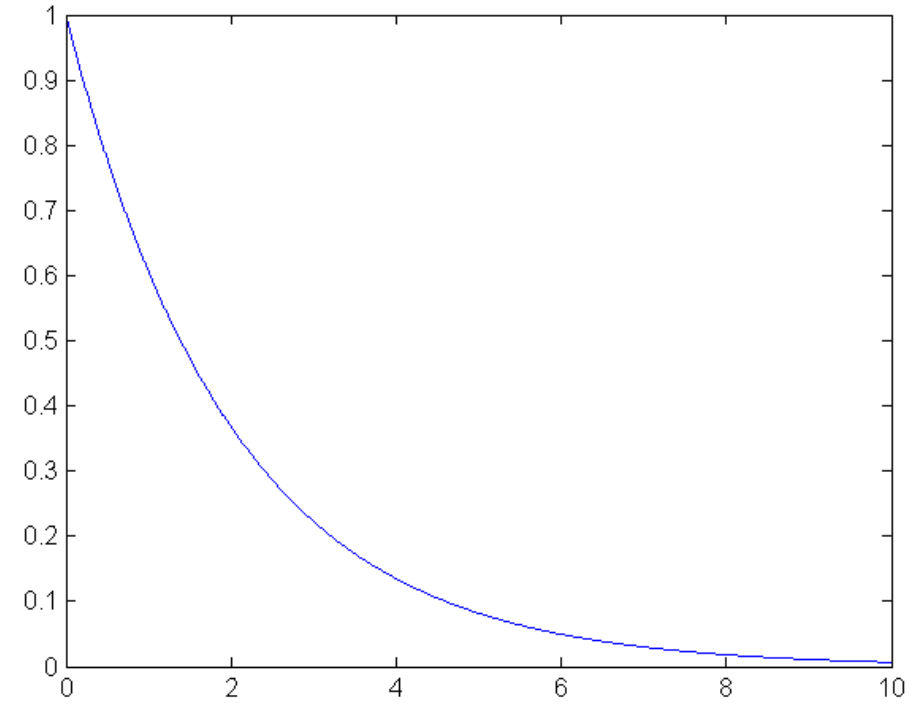
	Cluster 1	Cluster 2	...	Cluster 100	Target
Record 1	1	0	0, 0, 0, 1, 0, 0	0	A
Record 2	0	1	0, 0, 1, 0, 0, 0	0	B

- Now, build a regression

$e=1$



$e=0.5$



# A powerful method

- run rSofia K-means to find cluster centers (hundreds or thousands)
- map the data to these centers using RBF
- learn a linear model on the mapped data



# Will it get better with spectral k-means?

- R&D question



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