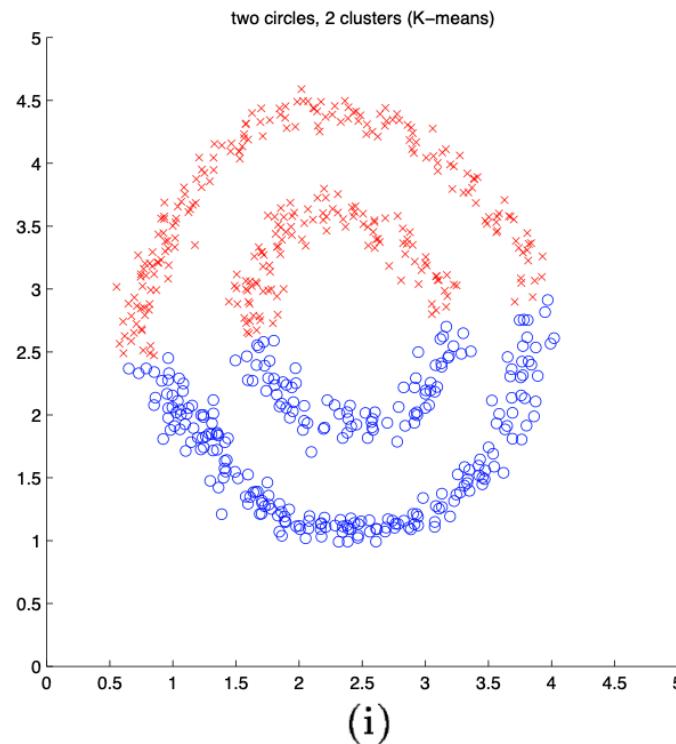


# TFIP-AI – Advanced Machine Learning

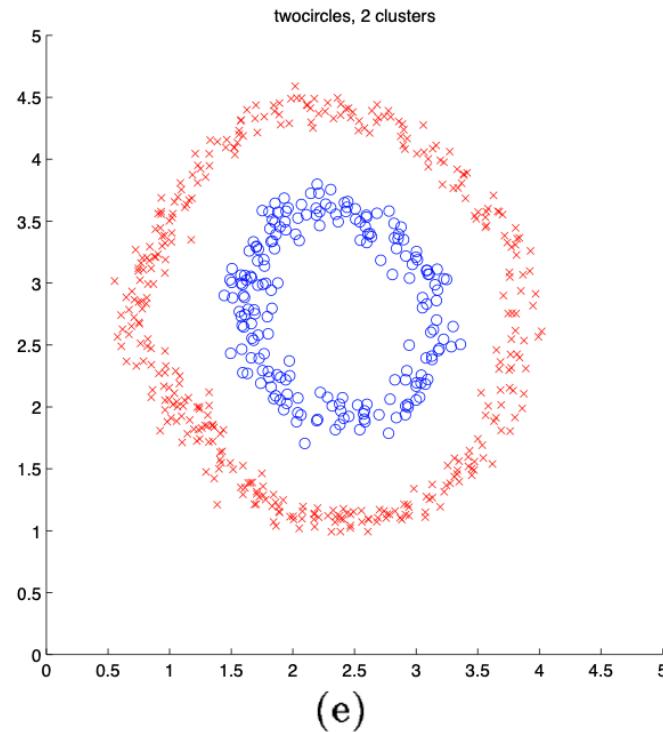
Unit 2 Spectral Clustering

# Spectral clustering

K-means

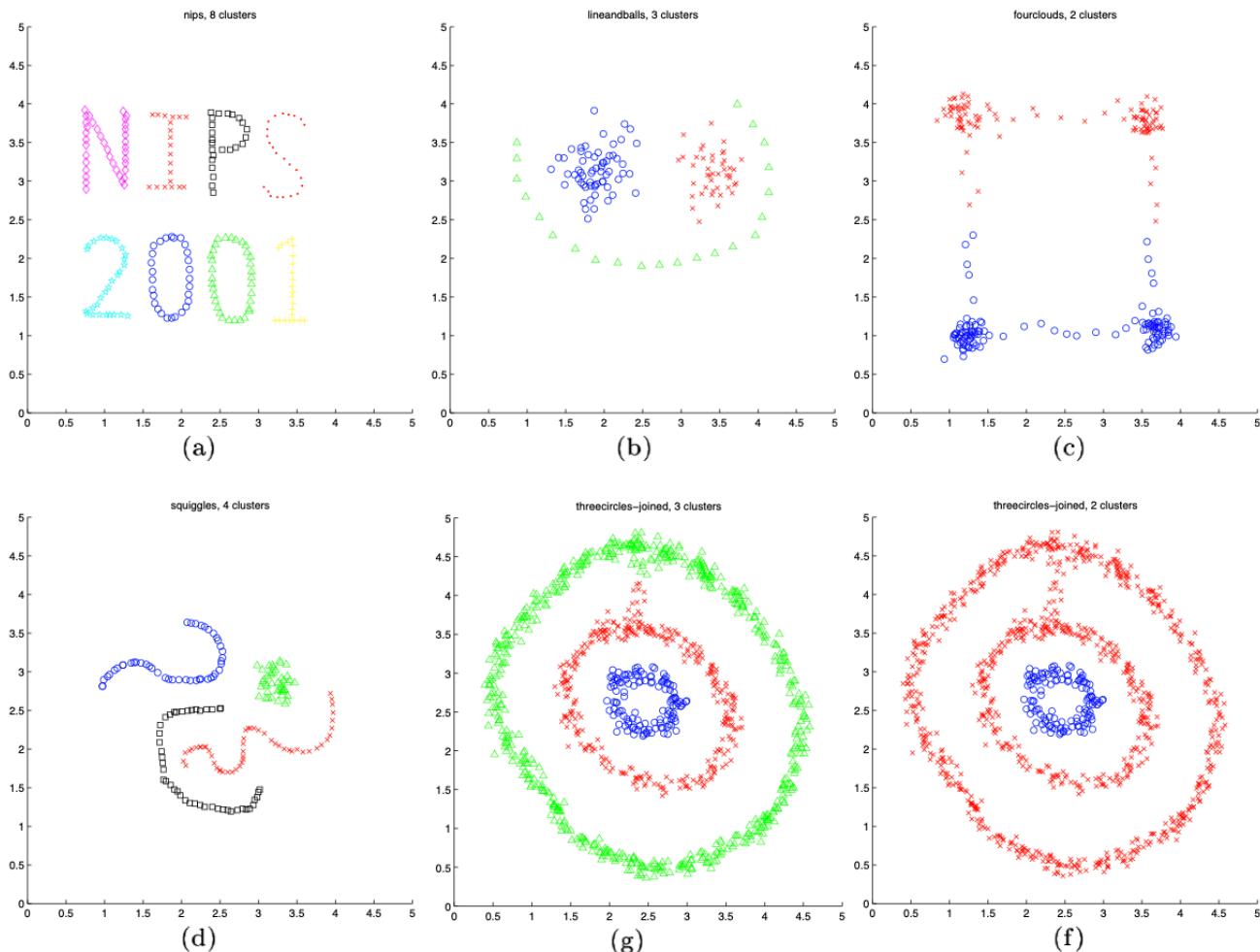


Spectral clustering



[Shi & Malik '00; Ng, Jordan, Weiss NIPS '01]

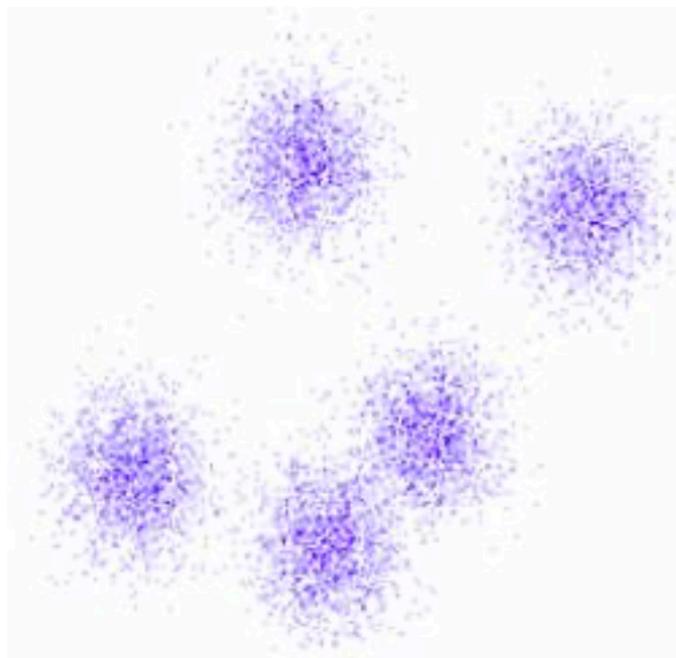
# Spectral clustering cont...



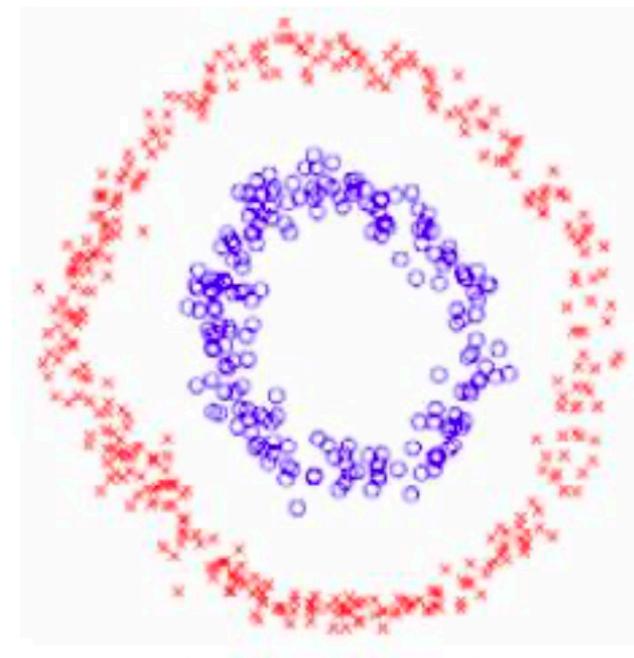
[Figures from Ng, Jordan, Weiss NIPS '01]

# Data Clustering

- Two different criteria
  - Compactness, e.g., k-means, mixture models
  - Connectivity, e.g., spectral clustering



**Compactness**



**Connectivity**

# Graph Clustering

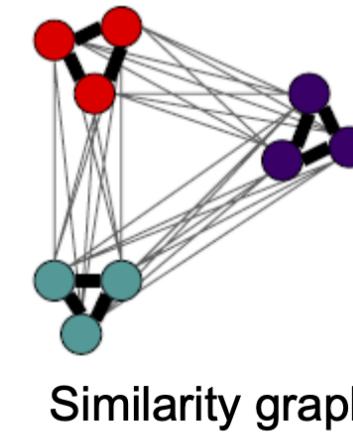
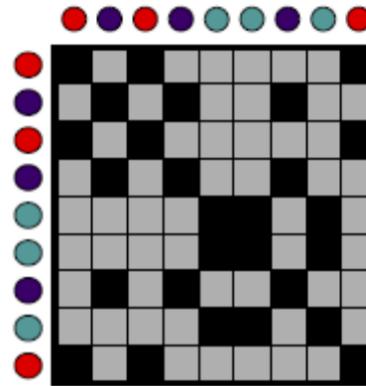
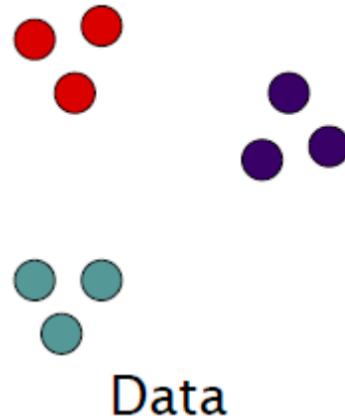
**Goal:** Given data points  $X_1, \dots, X_n$  and similarities  $w(X_i, X_j)$ , partition the data into groups so that points in a group are similar and points in different groups are dissimilar.

**Similarity Graph:**  $G(V, E, W)$

$V$  – Vertices (Data points)

$E$  – Edge if similarity  $> 0$

$W$  - Edge weights (similarities)



Partition the graph so that edges within a group have large weights and edges across groups have small weights.

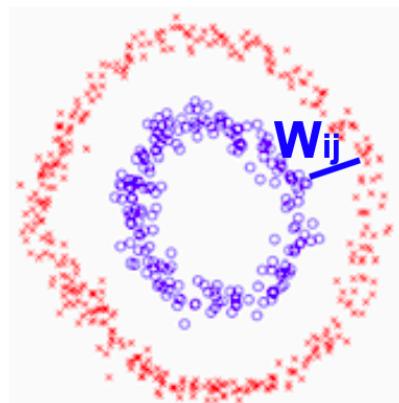
# Similarity graph construction

Similarity Graphs: Model local neighborhood relations between data points

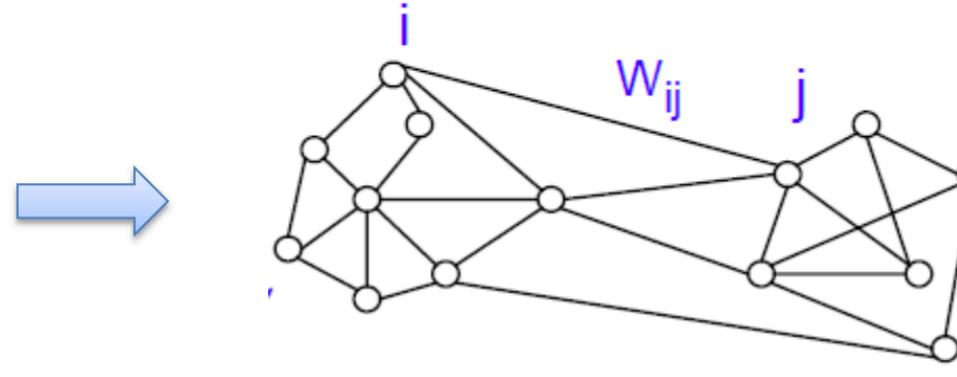
E.g. Gaussian kernel similarity function

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$$

→ Controls size of neighborhood



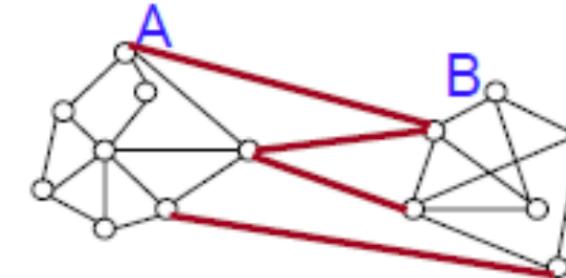
Data clustering



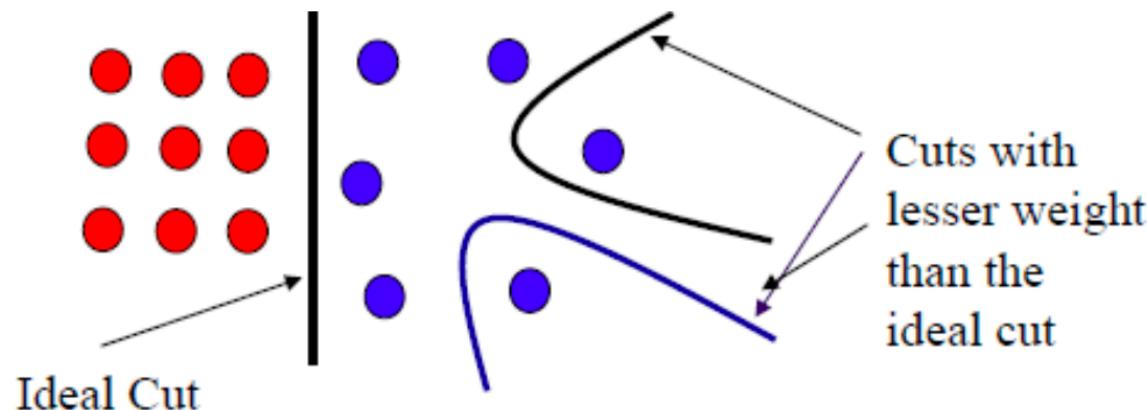
# Partitioning a graph into two clusters

**Min-cut:** Partition graph into two sets A and B such that weight of edges connecting vertices in A to vertices in B is minimum.

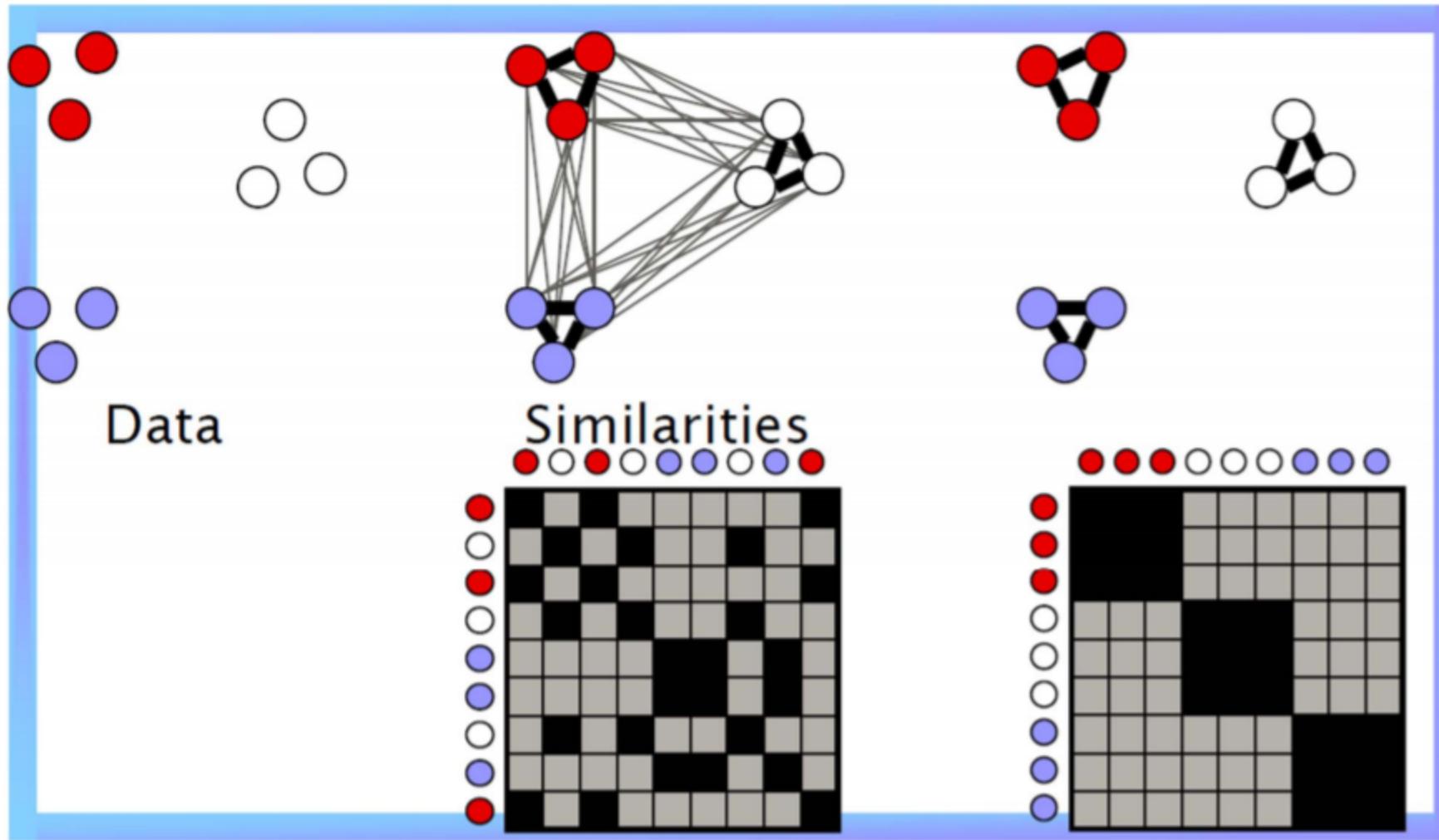
$$\text{cut}(A, B) := \sum_{i \in A, j \in B} w_{ij}$$



- Easy to solve  $O(VE)$  algorithm
- Not satisfactory partition – often isolates vertices



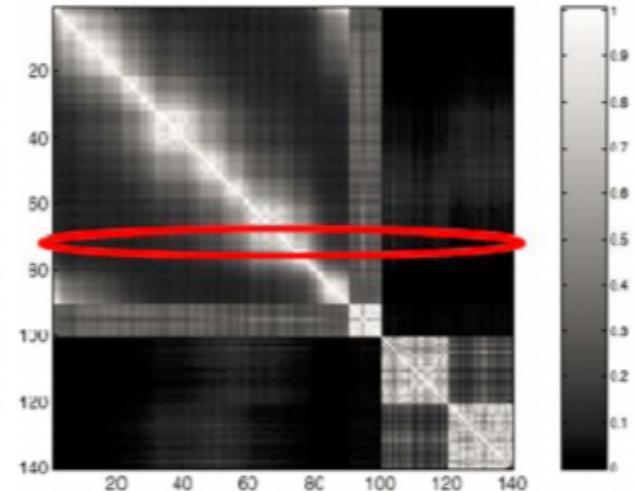
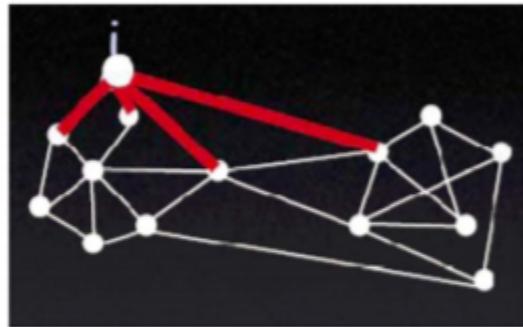
# Graph partitioning



# Graph Terminologies

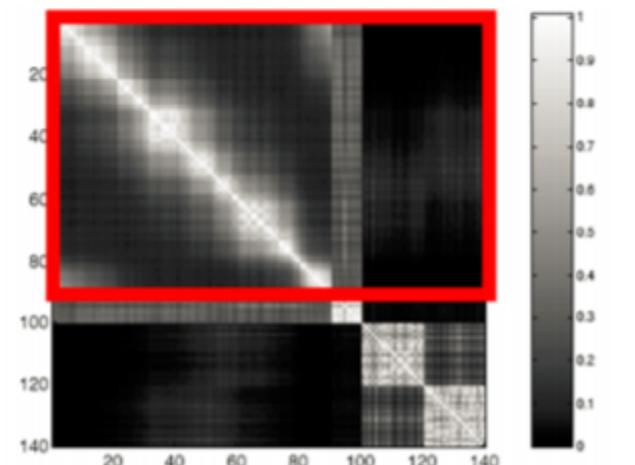
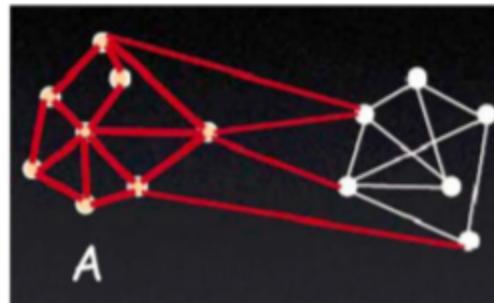
- Degree of nodes

$$d_i = \sum_j w_{i,j}$$



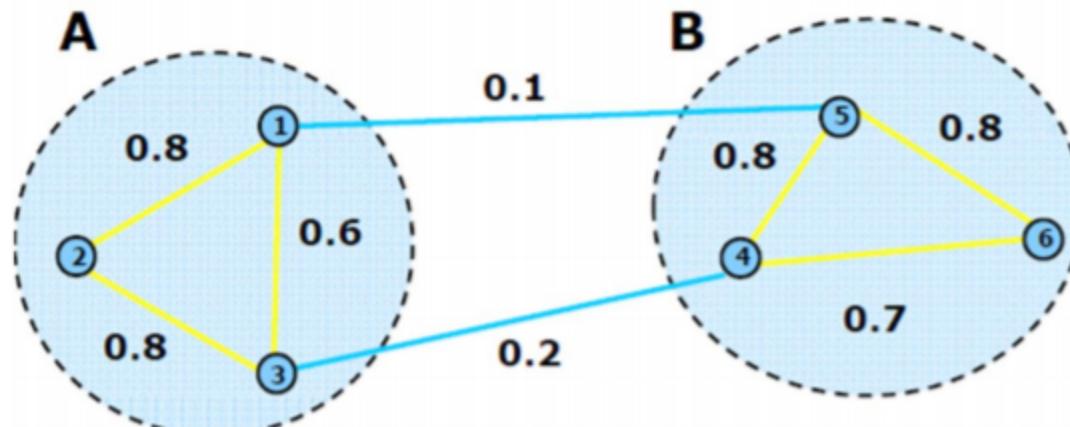
- Volume of a set

$$\text{vol}(A) = \sum_{i \in A} d_i, A \subseteq V$$



# Graph Cut

- Consider a partition of the graph into two parts A and B



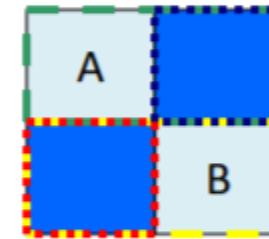
- $\text{Cut}(A, B)$ : sum of the weights of the set of edges that connect the two groups
- An intuitive goal is find the partition that minimizes the cut

$$\text{cut}(A, B) = \sum_{i \in A, j \in B} w_{ij} = 0.3$$

# Normalized Cut

- Consider the connectivity between groups relative to the volume of each group

$$Ncut(A, B) = \frac{\frac{cut(A, B)}{Vol(A)}}{+} \frac{\frac{cut(A, B)}{Vol(B)}}$$



$$Ncut(A, B) = cut(A, B) \frac{Vol(A) + Vol(B)}{Vol(A)Vol(B)}$$

Minimized when  $Vol(A)$  and  $Vol(B)$  are equal.  
Thus encourage balanced cut

# Solving NCut

- How to minimize  $Ncut$ ?

Let  $W$  be the similarity matrix,  $W(i, j) = W_{i,j}$ ;

Let  $D$  be the diag. matrix,  $D(i, i) = \sum_j W(i, j)$ ;

Let  $x$  be a vector in  $\{1, -1\}^N$ ,  $x(i) = 1 \Leftrightarrow i \in A$ .

- Relax the optimization problem into the continuous domain by solving generalized eigenvalue system:

$$\min_y y^T (D - W)y \text{ subject to } y^T D y = 1$$

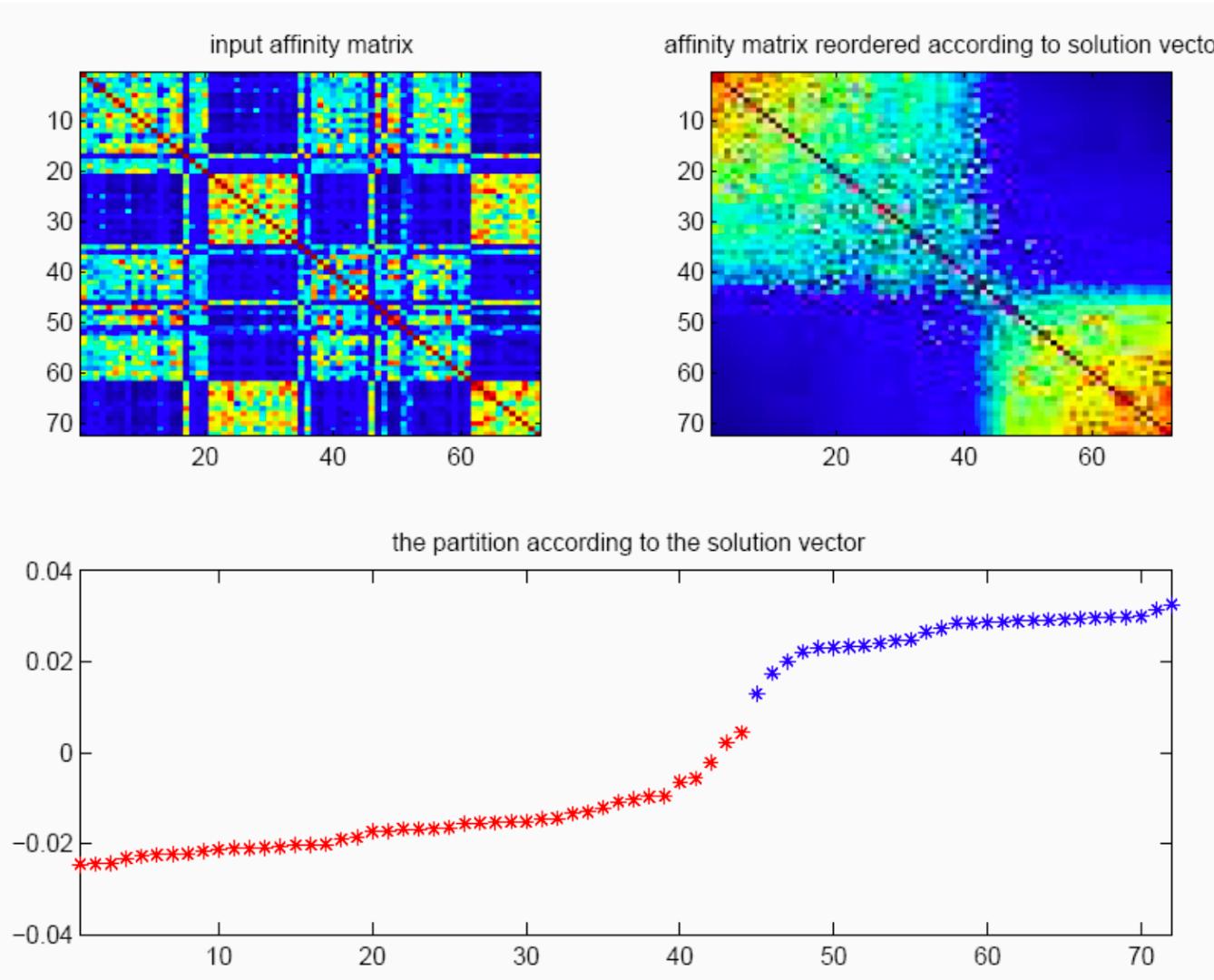
- Which gives:  $(D - W)y = \lambda Dy$
- Note that  $(D - W)\mathbf{1} = 0$ , so the first eigenvector is  $y_0 = \mathbf{1}$  with eigenvalue 0.
- The second smallest eigenvector is the real valued solution to this problem!!

## 2-way Normalized Cuts

1. Compute the affinity matrix  $W$ , compute the degree matrix ( $D$ ),  $D$  is diagonal and  
$$D(i, i) = \sum_{j \in V} W(i, j)$$
2. Solve  $(D - W)y = \lambda Dy$ , where  $D - W$  is called the Laplacian matrix
3. Use the eigenvector with the second smallest eigen-value to bipartition the graph into two parts.

# Example

Xing et al 2001



# Spectral clustering for segmentation



