



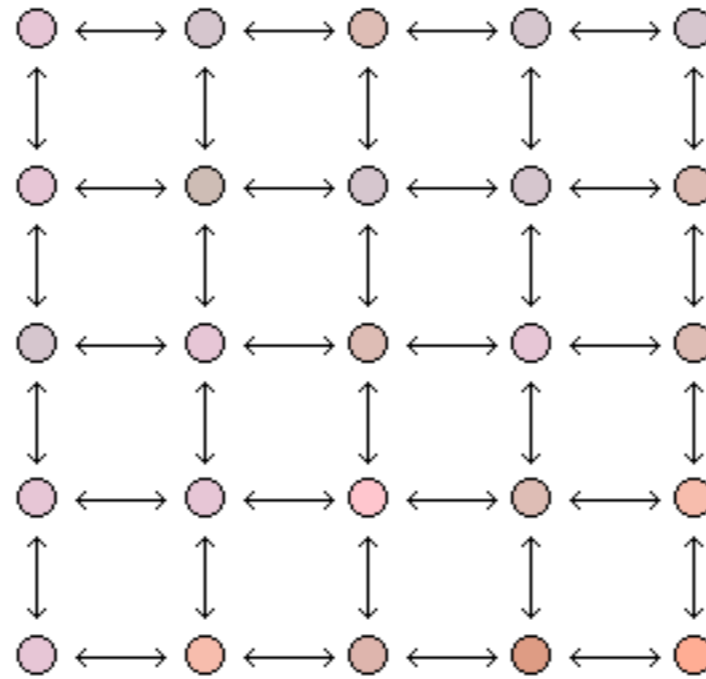
# **CS 556: Computer Vision**

## **Lecture 20**

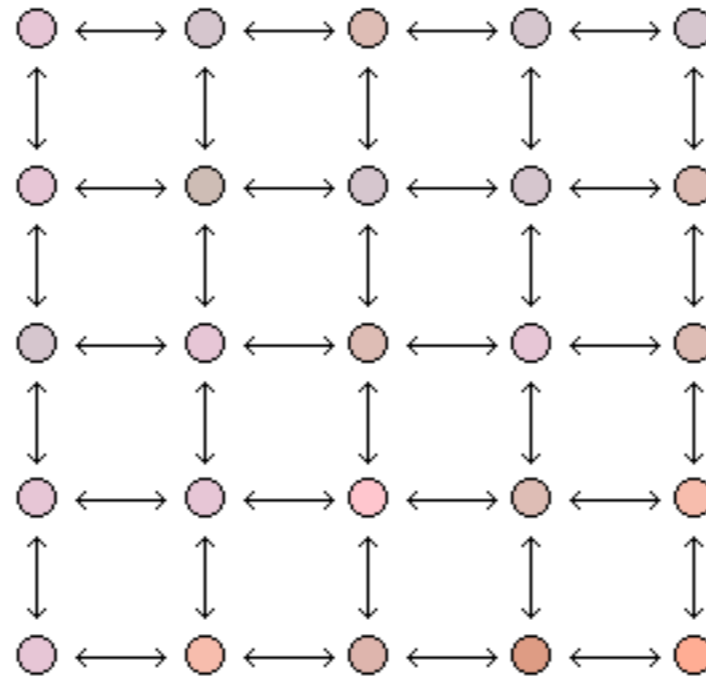
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# Perceptual Grouping as Graph-based Clustering

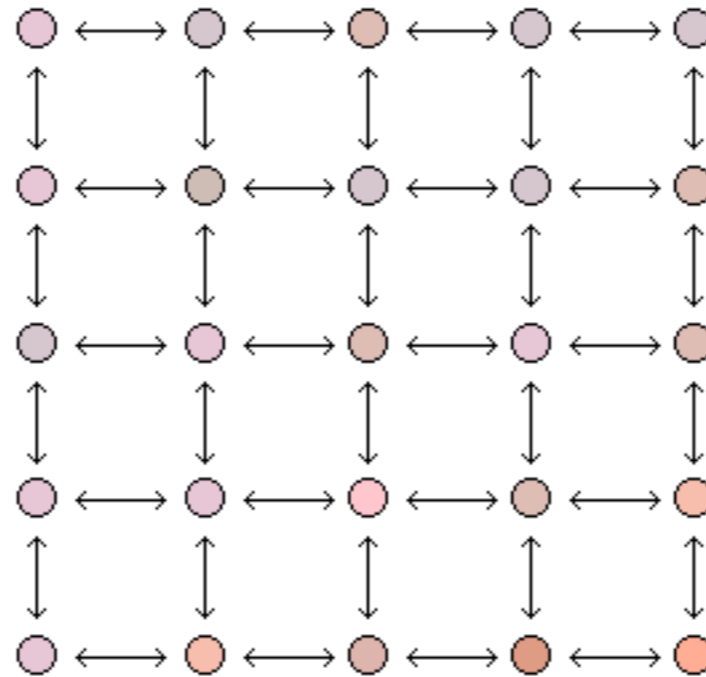


# Perceptual Grouping as Graph-based Clustering



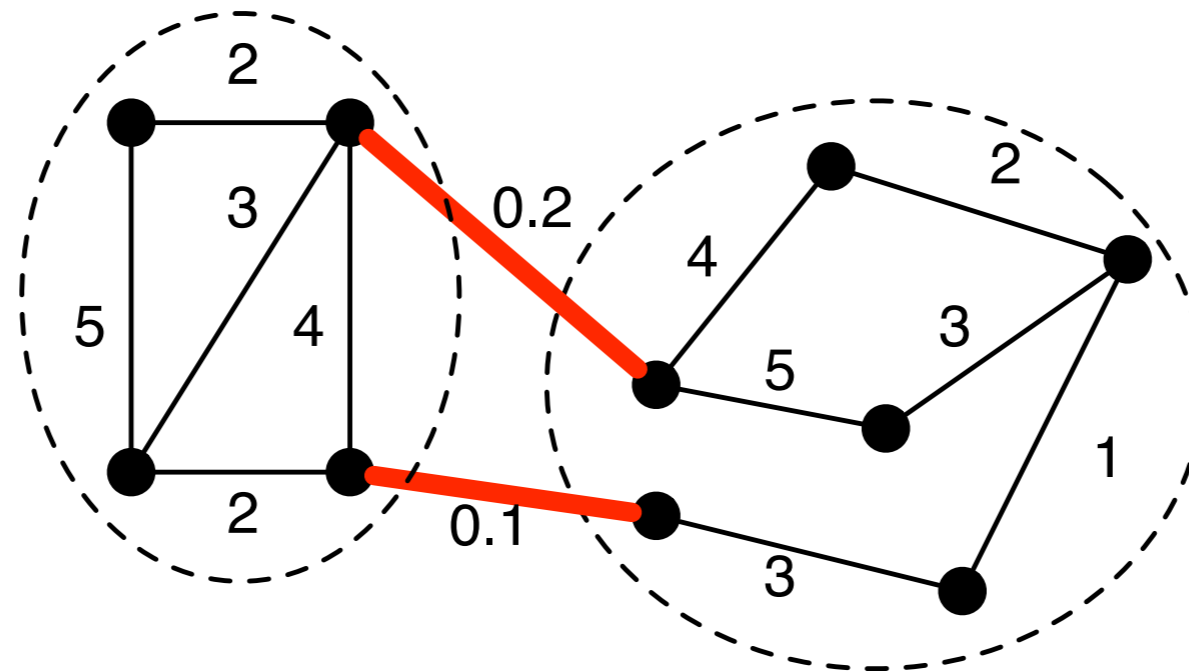
- Image elements are represented by a graph

# Perceptual Grouping as Graph-based Clustering



- Image elements are represented by a graph
- Grouping = Graph partitioning into subgraphs

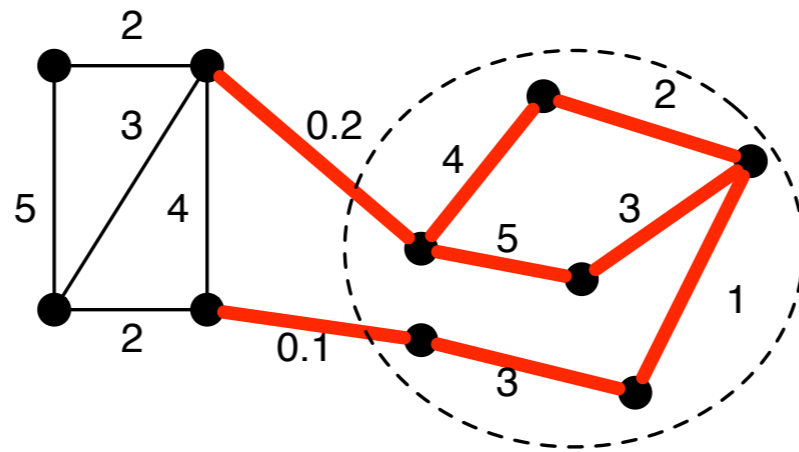
# Normalized-Cut Clustering



- Find two partitions  $G_1$  and  $G_2$  of graph  $G$
- So that the following criterion is minimized:

$$\min_{G_1, G_2} \text{Ncut}(G_1, G_2) = \frac{\text{cut}(G_1, G_2)}{\text{vol}(G_1)} + \frac{\text{cut}(G_2, G_1)}{\text{vol}(G_2)}$$

# Volume of a Subgraph



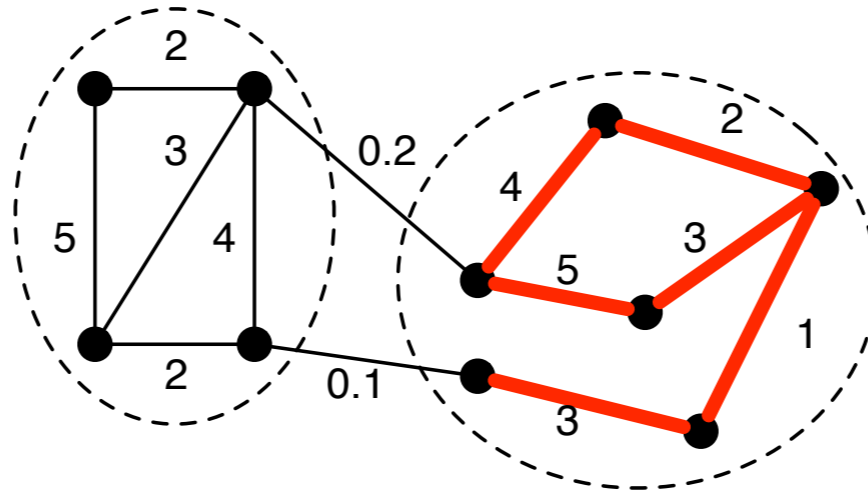
$$D = \begin{bmatrix} d_1 & 0 & 0 & \dots \\ 0 & d_2 & 0 & \\ \vdots & & & \\ \dots & 0 & 0 & d_N \end{bmatrix}$$

$$\mathbf{1}_{G_1} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$\swarrow$   
 $G_1$   
 $\nwarrow$

$$\Rightarrow \text{vol}(G_1) = \mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}$$

# Association within a Subgraph

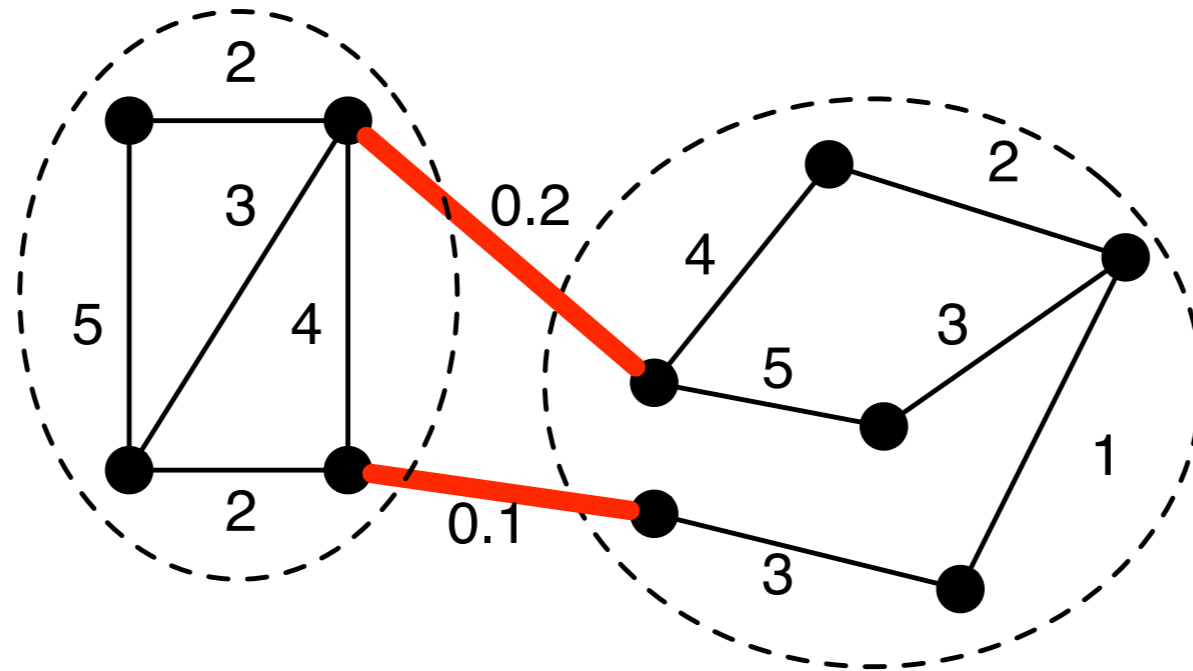


adjacency  
matrix

$$A = \begin{matrix} & & & & j \\ & & & & \vdots \\ & & & & a_{ij} \\ i & \left[ \begin{array}{c} \dots \\ \dots \\ \dots \end{array} \right] \end{matrix}$$

$$\text{assoc}(G_1) = \sum_{i,j \in G_1} a_{ij} = \mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}$$

# Cut between Two Graph Partitions



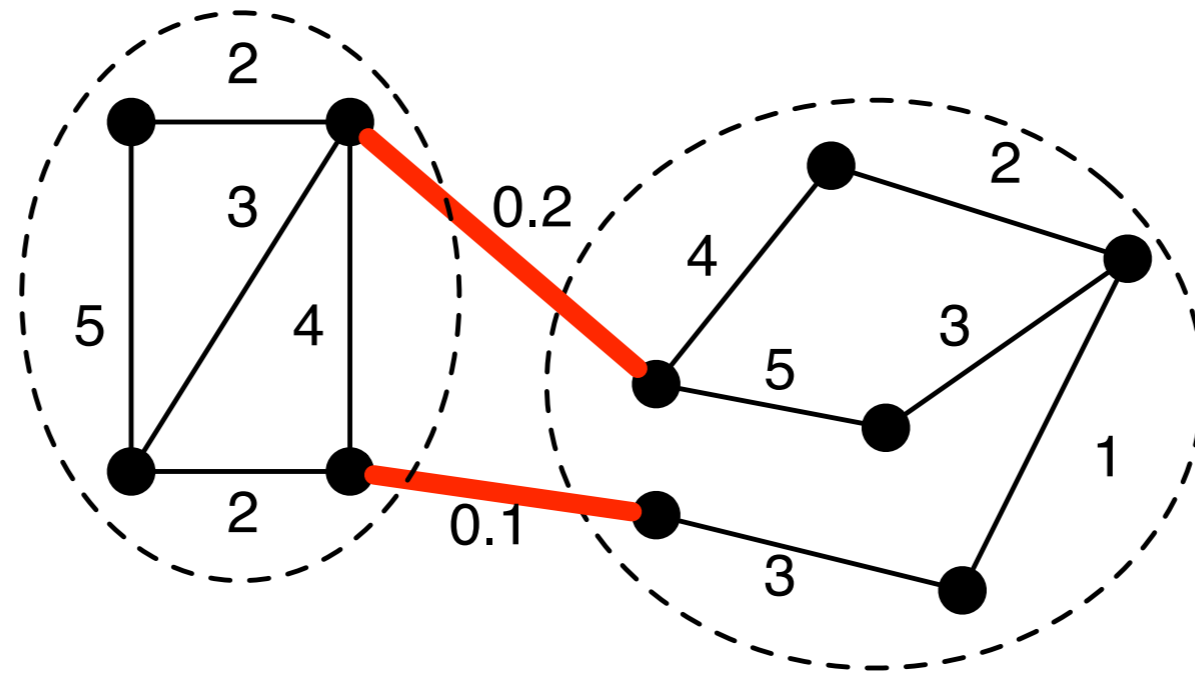
$$\text{cut}(G_1, G_2) = \text{vol}(G_1) - \text{assoc}(G_1)$$

$$= \mathbf{1}_{G_1}^T D \mathbf{1}_{G_1} - \mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}$$

$$= \mathbf{1}_{G_1}^T (D - A) \mathbf{1}_{G_1}$$



# Cut between Two Graph Partitions



$$\text{cut}(G_1, G_2) = \mathbf{1}_{G_1}^T (D - A) \mathbf{1}_{G_2}$$

$$\text{cut}(G_2, G_1) = \mathbf{1}_{G_2}^T (D - A) \mathbf{1}_{G_1}$$

# Normalized-Cut Objective Function

$$\min_{G_1, G_2} \frac{\text{cut}(G_1, G_2)}{\text{vol}(G_1)} + \frac{\text{cut}(G_2, G_1)}{\text{vol}(G_2)}$$

# Normalized-Cut Objective Function

$$\min_{G_1, G_2} \frac{\text{cut}(G_1, G_2)}{\text{vol}(G_1)} + \frac{\text{cut}(G_2, G_1)}{\text{vol}(G_2)}$$

$$\min_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T (D - A) \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T (D - A) \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$

# Normalized-Cut Objective Function

$$\min_{G_1, G_2} \frac{\text{cut}(G_1, G_2)}{\text{vol}(G_1)} + \frac{\text{cut}(G_2, G_1)}{\text{vol}(G_2)}$$

$$\min_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T (D - A) \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T (D - A) \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T A \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$

# Normalized-Cut Objective Function

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T A \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$

↓

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T D^{-1} A \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T D^{-1} A \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$

# Normalized-Cut Objective Function

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T A \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$



$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T \underbrace{D^{-1} A}_{\text{normalized Laplacian}} \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T \underbrace{D^{-1} A}_{\text{normalized Laplacian}} \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$

normalized  
Laplacian

# Normalized-Cut Objective Function

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T A \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T D \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T A \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T D \mathbf{1}_{G_2}}$$



$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T \underbrace{D^{-1} A}_{\text{normalized Laplacian}} \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T \underbrace{D^{-1} A}_{\text{normalized Laplacian}} \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$

normalized  
Laplacian



$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T L \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T L \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$

# Normalized-Cut Linearization

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T L \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T L \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$



$$X = [0 \ 0 \ 1 \ 0 \ 1 \ \dots \ 0 \ 1 \ 1 \ 0]^T$$

indicator vector for nodes that  
belong to a subgraph



# Normalized-Cut Linearization

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T L \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T L \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$



$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in \{0, 1\}^n$        $X_{G_2} \in \{0, 1\}^n$

$$\|X_{G_1}\| \neq 0$$

$$\|X_{G_2}\| \neq 0$$

# Normalized-Cut Linearization

$$\max_{G_1, G_2} \frac{\mathbf{1}_{G_1}^T L \mathbf{1}_{G_1}}{\mathbf{1}_{G_1}^T \mathbf{1}_{G_1}} + \frac{\mathbf{1}_{G_2}^T L \mathbf{1}_{G_2}}{\mathbf{1}_{G_2}^T \mathbf{1}_{G_2}}$$



$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in \{0, 1\}^n$        $X_{G_2} \in \{0, 1\}^n$

$$\|X_{G_1}\| \neq 0$$

$$\|X_{G_2}\| \neq 0$$

$$X_{G_1}^T X_{G_2} = 0$$

orthogonality

# Normalized-Cut Relaxation

$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in [0, 1]^n$      $X_{G_2} \in [0, 1]^n$

$$\|X_{G_1}\| \neq 0 \quad \|X_{G_2}\| \neq 0$$

$$X_{G_1}^T X_{G_2} = 0$$

# How to Solve Normalized-Cut?

$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in [0, 1]^n$      $X_{G_2} \in [0, 1]^n$

$$\|X_{G_1}\| \neq 0 \quad \|X_{G_2}\| \neq 0$$

$$X_{G_1}^T X_{G_2} = 0$$

# How to Solve Normalized-Cut?

## Approximation I

$$\max_{X_{G_1}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}}$$

subject to:  $X_{G_1} \in [0, 1]^n$

$$\|X_{G_1}\| \neq 0$$

# How to Solve Normalized-Cut?

## Approximation II

$$\max_{X_{G_1}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}}$$

subject to:  $\|X_{G_1}\| \neq 0$

# How to Solve Normalized-Cut?

$$\max_{X_{G_1}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}}$$

subject to:  $\|X_{G_1}\| \neq 0$

# How to Solve Normalized-Cut?

$$\max_{X_{G_1}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}}$$

subject to:  $\|X_{G_1}\| \neq 0$

Rayleigh-Ritz theorem

$X_{G_1} =$  eigenvector of the largest eigenvalue of  $L$



# How to Solve Normalized-Cut?

$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in [0, 1]^n$      $X_{G_2} \in [0, 1]^n$

$$X_{G_1}^T X_{G_2} = 0$$

$X_{G_1}$  = eigenvector of the largest eigenvalue of  $L$

$$X_{G_2} = ?$$

# How to Solve Normalized-Cut?

$$\max_{X_{G_1}, X_{G_2}} \frac{X_{G_1}^T L X_{G_1}}{X_{G_1}^T X_{G_1}} + \frac{X_{G_2}^T L X_{G_2}}{X_{G_2}^T X_{G_2}}$$

subject to:  $X_{G_1} \in [0, 1]^n$      $X_{G_2} \in [0, 1]^n$

$$X_{G_1}^T X_{G_2} = 0$$

$X_{G_1}$  = eigenvector of the largest eigenvalue of  $L$

$X_{G_2}$  = eigenvector of the second largest  
eigenvalue of  $L$

# Ncuts: General Case

$$\min_{G_1, G_2, \dots, G_K} \sum_{k=1}^K \frac{\mathbf{1}_{G_k}^T (D - A) \mathbf{1}_{G_k}}{\mathbf{1}_{G_k}^T D \mathbf{1}_{G_k}}$$

cut

volume

# Ncuts: General Case

$$\min_{G_1, G_2, \dots, G_K} \sum_{k=1}^K \frac{\mathbf{1}_{G_k}^T (D - A) \mathbf{1}_{G_k}}{\mathbf{1}_{G_k}^T D \mathbf{1}_{G_k}}$$

← cut  
← volume

⇓ relaxation

$$\max_{X_1, \dots, X_K} \sum_{k=1}^K \frac{X_k^T D^{-1} A X_k}{X_k^T X_k}$$

s.t.

$$X_k \in [0, 1]^n \quad \forall k, l, \quad X_k^T X_l = 0$$

# Ncuts: General Case

Solution:

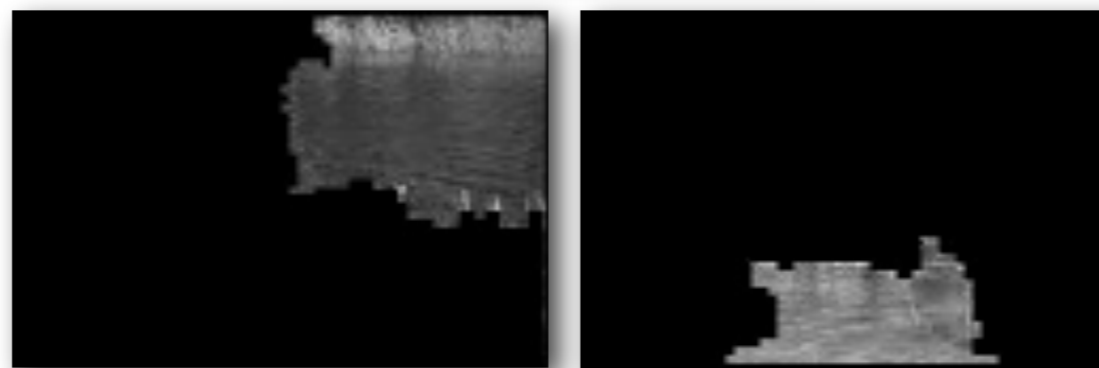
$K$  eigenvectors of  $D^{-1}A$

corresponding to

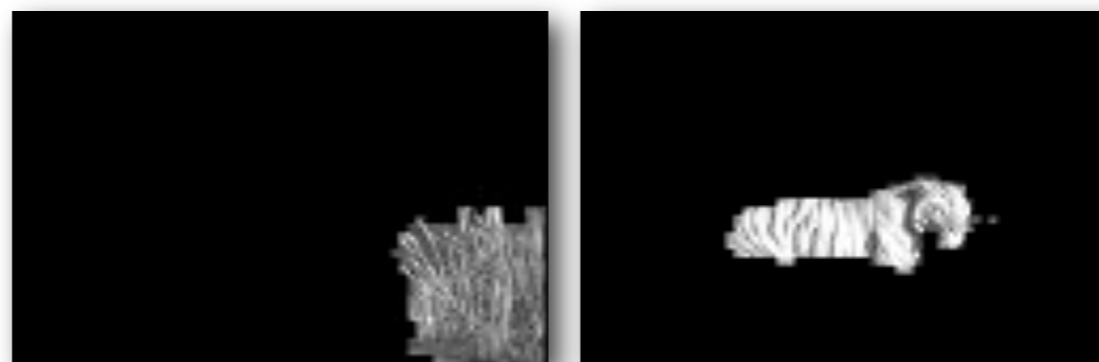
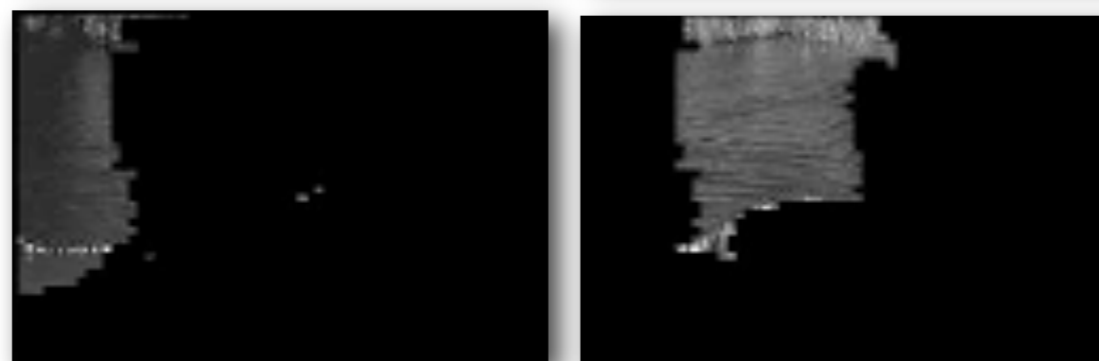
the  $K$  largest eigenvalues of  $D^{-1}A$

# Experiments -- Ncuts as Image Segmentation

input  
image



segments

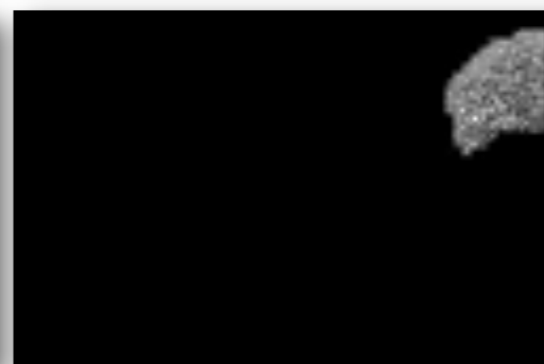
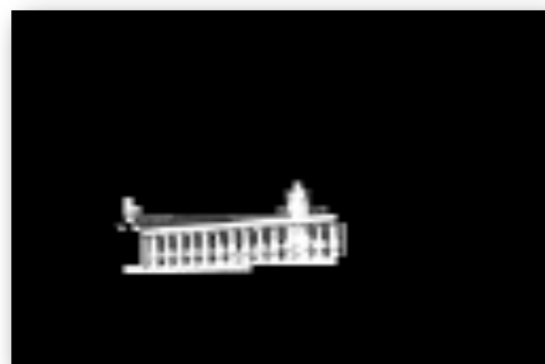
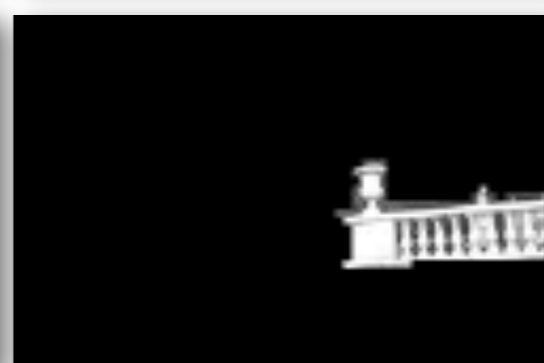


# Experiments -- Ncuts as Image Segmentation

input  
image



segments



# Experiments -- Ncuts as Image Segmentation





# Experiments -- Ncuts as Image Segmentation

