

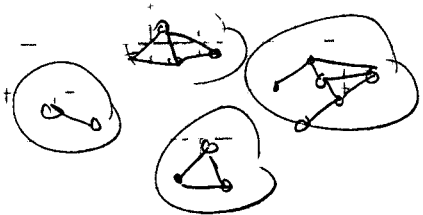
③

# 1.5 Spectral clustering (cont.)

Recall:  $W_{n \times n}$ ,  $W = W^T$  symmetric  
 $D = \text{diag}\{d_1, \dots, d_n\}$  where  $d_i = \sum_j w_{ij}$  and  $w_{ij} \geq 0$   
 $L_{\text{un}} = D - W$

$L_{\text{rw}} = I - P$ ,  $P = D^{-1}W$

If the graph has  $k$  connected components,



Then the eigenspace of  $L_{\text{un}}$   
 --- associated with eigenvalue  
 zero equals  
 ---  $\text{span}\{\mathbf{1}_A, \dots, \mathbf{1}_{A_k}\}$

What if  $L_{\text{rw}}$ ?

$L_{\text{rw}} = \underline{\Psi} (I - \Lambda) \underline{\Psi}^T$   
 $P = \underline{\Psi} \Lambda \underline{\Psi}^T$   
 $\underline{\Psi}^T D \underline{\Psi} = I$   
 $\underline{\Psi} = [\psi_1, \dots, \psi_n]^T, \psi_k^T D \psi_k = 1$   
 $\psi_k^T D \psi_\ell = 0$  if  $k \neq \ell$   
 and  $P \psi_k = \lambda_k \psi_k$

If  $f$  is eigenvector of  $L_{\text{un}}$  with  $\lambda = 0$ ,  
 $L_{\text{un}} f = 0 \cdot f$  and  $(D - W) f = 0$ .

If  $f$  is eigenvector of  $L_{\text{rw}}$  w/  $\lambda = 0$ ,  
 $D^{-1} (D - W) f = 0$  and  $(D - W) f = 0$

$\psi_1 = C_1 \mathbf{1}_A, \dots, \psi_k = C_k \mathbf{1}_{A_k}$

$\underline{\Psi}_{n,1:4} = \begin{bmatrix} c_1 & 0 & 0 & 0 \\ \vdots & & & \\ z_1 & 0 & 0 & 0 \\ 0 & c_2 & 0 & 0 \\ 0 & 0 & c_3 & 0 \\ 0 & 0 & 0 & c_4 \end{bmatrix} \begin{matrix} \} n_1 \\ \} n_2 \\ \} n_3 \\ \} n_4 \end{matrix}$   
 $\psi_1 = [c_1 -]$   
 $\psi_2 = [-c_2 -]$   
 $k=4$

What are the constants?

$C_1 = \sqrt{\frac{1}{\sum_{i \in C_1} d_i}}$

$C_1 = \{1, \dots, n_1\}$

$C_2 = \{n_1 + 1, \dots, n_1 + n_2\}$

If  $k=2$ ,  $\underline{\Psi}_{n,1:2} = \begin{bmatrix} c_1 & 0 \\ 0 & c_2 \end{bmatrix} \begin{matrix} n_1 \\ n_2 \end{matrix}$

Need  $\tilde{\Psi}_{:,1} = \begin{bmatrix} c \\ \vdots \\ c \end{bmatrix}, \tilde{\Psi}_{:,2} = \begin{bmatrix} c \\ \vdots \\ c \end{bmatrix} = \tilde{\Psi}_2$

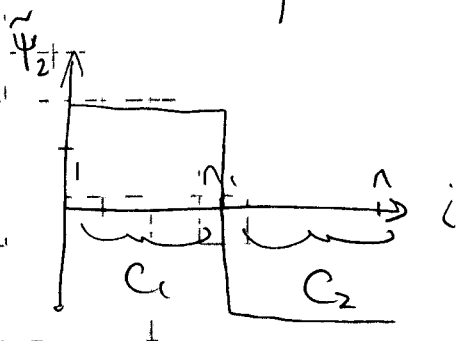
$\tilde{\Psi}_2 = \alpha \psi_1 + \beta \psi_2$   
 $\tilde{\Psi}_2^T D \tilde{\Psi}_2 = 1 \Rightarrow \alpha^2 + \beta^2 = 1$   
 $\tilde{\Psi}_2^T D \tilde{\Psi}_1 = 0 \Rightarrow \tilde{\Psi}_2^T d = 0$   
 Since  $d = \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix}$  so  $\alpha(\psi_1^T d) + \beta(\psi_2^T d) = 0$

and  $\alpha \sqrt{\sum_{i \in C_1} d_i} + \beta \sqrt{\sum_{i \in C_2} d_i} = 0$

$\alpha$  and  $\beta$  should have different signs bc ...

$$\tilde{\Psi}_2 = \alpha C_1 \mathbb{1}_{A_1} + \beta C_2 \mathbb{1}_{A_2}$$

$$\tilde{\Psi}_2(i) = \begin{cases} \alpha C_1 & \text{if } i \in C_1 \\ \beta C_2 & \text{if } i \in C_2 \end{cases}$$



We can use the signs of these to get the cluster, or more in general, we don't have to cut at zero but can tune to any cut-off

How to know  $k$  in spectral clustering

Remark Spectral gap heuristic

The first  $k$  eigen values will be close to one, then there will be a "gap" after  $k$ .

(missing a lot here...)

## Graph cut

def (cut)

$$A \cap B = \emptyset \text{ where } A, B \subseteq V = \{1, \dots, n\}$$

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

def (volume of set  $A$ )

$$\text{Vol}(A) = \sum_{i \in A} d_i \quad \text{sum of degrees}$$

def (normalized cut of partition  $C$ )

$$C = \{C_1, \dots, C_k\}$$

$$\text{NCut}(C) = \frac{\sum_{l=1}^k W(C_l, C_l^c)}{\text{Vol}(C_l)}$$

$$\text{where } A^c = V \setminus A$$

Proposition

$$\text{NCut}(C) = \sum_{l=1}^k \Psi_l^T L \Psi_l$$

$$\Psi_l = C_l \mathbb{1}_{C_l^c}, \quad l = 1, \dots, k$$

$$C_l = \frac{1}{\sqrt{\text{Vol}(C_l)}}$$

Proof

$$\begin{aligned} \Psi_l^T L \Psi_l &= \frac{1}{2} \sum_{i,j} w_{ij} (\Psi_l(i) - \Psi_l(j))^2 \\ &= \sum_{\substack{i \in C_l \\ j \in C_l^c}} w_{ij} \left( \frac{1}{\sqrt{\text{Vol}(C_l)}} - 0 \right)^2 \end{aligned}$$

$$= \sum_{\substack{i \in C_l \\ j \in C_l^c}} w_{ij} \frac{1}{\text{Vol}(C_l)} = \frac{W(C_l, C_l^c)}{\text{Vol}(C_l)}$$

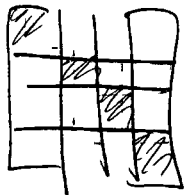
## Problem of min NCut

$$\min_C \text{NCut}(C) = \text{Tr}(H^T L H)$$

$$\sum \psi_l^T L \psi_l$$

introduce matrix  $H = \begin{bmatrix} \psi_1 & \dots & \psi_k \end{bmatrix}$

as defined  $\psi_l = C_l \mathbf{1}_{C_l}$

so we see  $H =$   as

Seen previously:  $H$  is a function of  $C$ .

(min NCut)

$$\begin{cases} \min_H \text{Tr}(H^T L H) & \text{where } L = L_{\text{un}} \\ H \text{ has the form above} \end{cases}$$

$$\psi_k^T D \psi_l = \delta_{kl} \Rightarrow H^T D H = I_k$$

spec-min-NCut

$$\begin{cases} \min_{H_{n \times k}} \text{Tr}(H^T L H) \\ \text{s.t. } H^T D H = I_k \end{cases}$$

Prop Solution of (spec-min-NCut) is the first  $k$  eigenvectors of  $L_{\text{rw}}$ , normalized to be  $\psi_k^T D \psi_k = 1$

## exercise

$$\text{RCut}(C) = \sum_{l=1}^k \frac{W(C_l, C_l^c)}{|C_l|}$$

$$|C_l| = \text{number of nodes in } C_l$$

spec-min-RCut  $\Leftrightarrow$  spectral clustering using  $L_{\text{rw}}$ .

Which Laplacian to use between:

- $L_{\text{un}}$
- $L_{\text{sym}}$
- $L_{\text{rw}}$

→ next class.