Statistical Data Analysis

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Why is partitioning hard?

Problem

Partition vertex set into two parts (*graph bisection*).

n vertices into parts of sizes n_1 and n_2 ($n_1 + n_2 = n$):

- $\frac{n!}{n_1!n_2!}$ possibilities (half of it if order is ignored and $n_1 = n_2$)
- using Stirling's formula $n! \approx \sqrt{2\pi n}(n/e)^n$ we get

$$\frac{n!}{n_1!n_2!} \approx \frac{n^{n+1/2}}{n_1^{n_1+1/2} n_2^{n_2+1/2}}$$

- for a balanced partition ($n_1 \approx n_2$):

roughly $\frac{2^{n+1}}{\sqrt{n}}$ possibilities

Therefore, exhausitive search is usually unfeasible.

Arbitrary number of classes

Methods for graph bisection can be generalised (other ways are possible):

- number of vertices: n
- number of classes: k = number of subsets or clusters
- define $l = k - 2^{\lfloor \log_2 k \rfloor}$
- for $r = 1, \ldots, l$ (ascending order) apply graph bisection method with

$$n_1^{(r)} = n - \frac{r \cdot n}{k} \quad \text{and} \quad n_2^{(r)} = \frac{n}{k}$$

- apply (equally sized) graph bisection $\lfloor \log_2 k \rfloor$ times to the $n - \frac{l \cdot n}{k}$ vertices in the large class
- results in k classes of (almost) same size $\frac{n}{k}$

Graph cuts

Given a graph $G = (V, E, \omega)$.

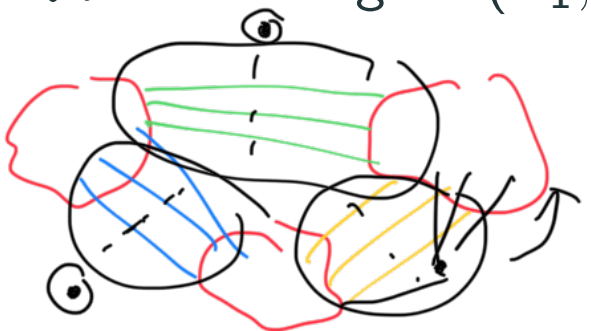
- for disjoint $A, B \subset V$ define the *cut size*

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

- for a partition $\mathcal{A} = A_1, A_2, \ldots, A_k$ define

$$\text{cut}(A_1, A_2, \ldots, A_k) = \sum_{i=1}^{k} \text{cut}(A_i, \overline{A}_i)$$

- basic problem: find $\mathcal{A}$ minimizing $\text{cut}(A_1, A_2, \ldots, A_k)$



Types of methods (usually heuristics)

Local

- Kernighan-Lin algorithm
- Fiduccia-Mattheyses algorithm
- ...

Global

- Spectral clustering
- ...

Kernighan-Lin algorithm

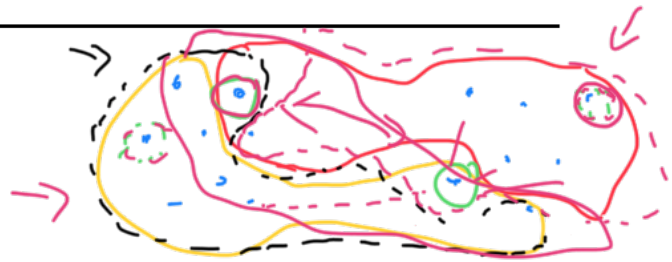
The algorithm (Kernighan and Lin in 1970) works as follows:

Algorithm: Partition vertex set into two parts (Kernighan & Lin)

Input: Graph $G = (V, E)$, positive integers n_1, n_2

1 Choose random partition V_1, V_2 of V with $|V_l| = n_l$;
2 **repeat**
3 minPair $\leftarrow \sum \omega_{ij} + 1$;
4 **for** ($i \in V_1, j \in V_2$, *neither i nor j has been swapped before*)
5 **if** $\text{cut}((V_1 \setminus \{i\}) \cup \{j\}, (V_2 \setminus \{j\}) \cup \{i\}) <$ minPair **then**
6 minPair $\leftarrow \text{cut}((V_1 \setminus \{i\}) \cup \{j\}, (V_2 \setminus \{j\}) \cup \{i\})$;
7 $i_0 \leftarrow i, j_0 \leftarrow j$;
8 **end**
9 $V_1 = (V_1 \setminus \{i_0\}) \cup \{j_0\}, V_2 = (V_2 \setminus \{j_0\}) \cup \{i_0\}$ (swap i_0 and j_0)
10 **until** *no pair of unused vertices exists*;
11 Pick partition (from the different V_1, V_2) with smallest cut size;

Output: Partition V_1, V_2 of V



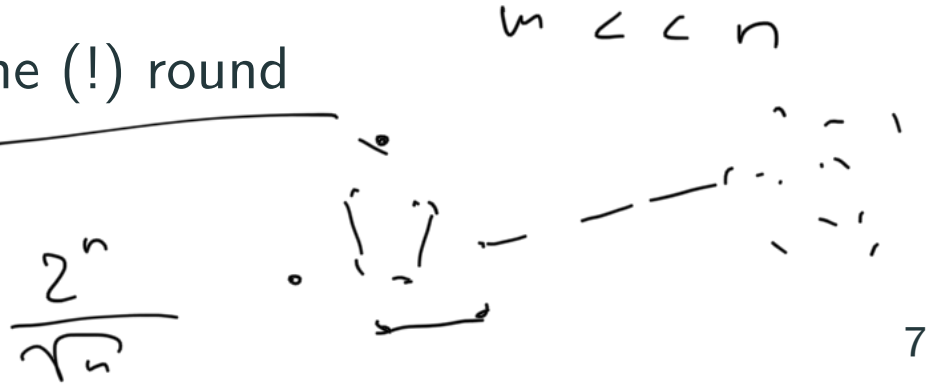
Runtime of Kernighan-Lin algorithm

At first glance we get:

- $0 \leq \min\{n_1, n_2\} \leq \frac{n}{2} \rightsquigarrow \mathcal{O}(n)$ swaps (worst case)
- $\frac{n}{2} \cdot \frac{n}{2}$ of considered pairs per swap (worst case)
- cut size change (swap i and j):

$$\sum_{v \in N(i) \cap V_1} \omega_{iv} + \sum_{v \in N(j) \cap V_2} \omega_{jv} - \sum_{v \in N(i) \cap V_2} \omega_{iv} - \sum_{v \in N(j) \cap V_1} \omega_{jv} + \omega_{ij}$$

- evaluating this expression costs $\mathcal{O}(m/n)$, where $m = |E|$, if stored in adjacency list
- $\rightsquigarrow$ runtime is $\mathcal{O}(m \cdot n^2)$ for one (!) round



Notes on the Kernighan-Lin algorithm

- swapping every round avoids local minima
- usually the algorithm is repeated several times with last output as input
- first partition is random $\rightsquigarrow$ sometimes algorithm is started more than once to get other (hopefully better) results
- convergence rate unknown
- for larger number of classes (i.e. $k \geq 3$) optimum might not be reached if applied
- Generalisation to hypergraphs: Fiduccia-Mattheyses algorithm

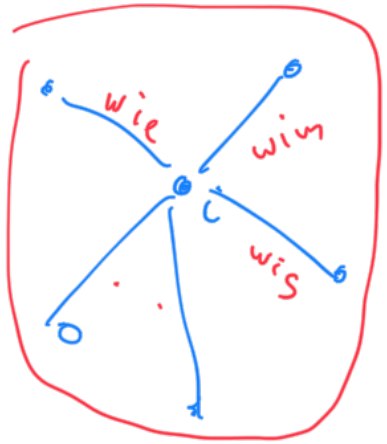
Spectral clustering

- mathematical foundation by Donath & Hoffman and Fiedler in 1973
- applications in various fields/for various problems
  - image segmentation
  - educational data mining
  - entity resolution
  - speech separation
  - ...

Laplacian matrix (and another graph definition)

The degree matrix $D(G)$ is given by

$$d_{ij} = \begin{cases} \sum_{l \in N(i)} w_{il} & \text{if } i = j, \\ 0 & \text{else.} \end{cases}$$



Laplacian matrix:

$$L(G) = D(G) - W(G)$$

We also need:

$$\text{vol}(A) = \sum_{ij \in E, i,j \in A} \omega_{ij} \text{ for } A \subset V \text{ (no double counting!)}$$

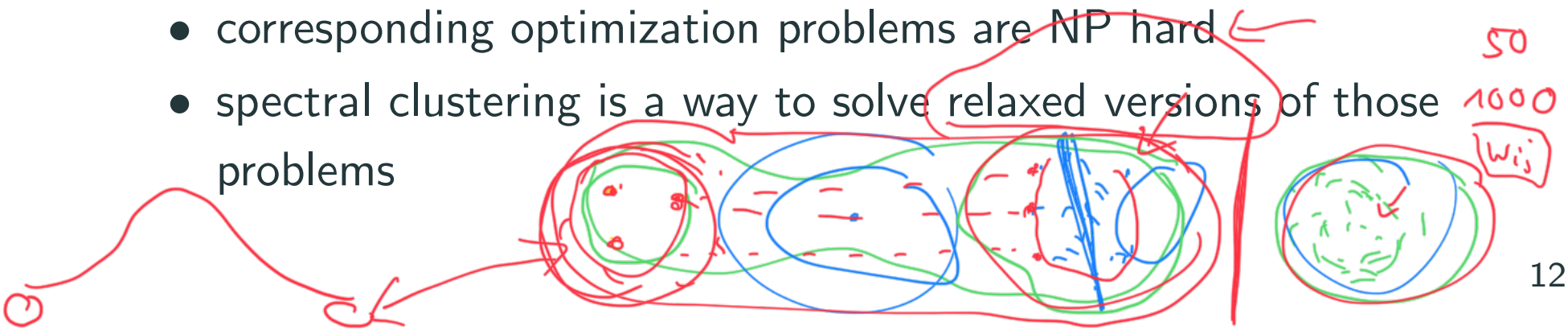
Spectral clustering and graph cuts

Clustering corresponds to finding cuts in graphs (see next slides; other interpretations possible), there are (usually) two types:

- RatioCut (balanced by number of vertices in each cluster)
- NCut (balanced by sum of edge weights in each cluster)

Formalization of RatioCut and NCut

- $\text{RatioCut}(A_1, A_2, \ldots, A_k) = \sum_{i=1}^{k} \frac{\text{cut}(A_i, \overline{A}_i)}{|A_i|}$
  - $\sum_{i=1}^{k}(1/|A_i|)$ is minimized if all A_i have the same size
  - hence minimizing RadioCut balances clusters by their number of vertices (as desired)
- $\text{NCut}(A_1, A_2, \ldots, A_k) = \sum_{i=1}^{k} \frac{\text{cut}(A_i, \overline{A}_i)}{\text{vol}(A_i)}$
  - $\sum_{i=1}^{k}(1/\text{vol}(A_i))$ is minimized if all $\text{vol}(A_i)$ coincide
  - hence minimizing NCut balances clusters by their edge weights (as desired)
- corresponding optimization problems are NP hard
- spectral clustering is a way to solve relaxed versions of those problems



Useful properties of the Laplacian

Proposition: The Laplacian matrix $L\ (= D - W)$ satisfies the following properties:

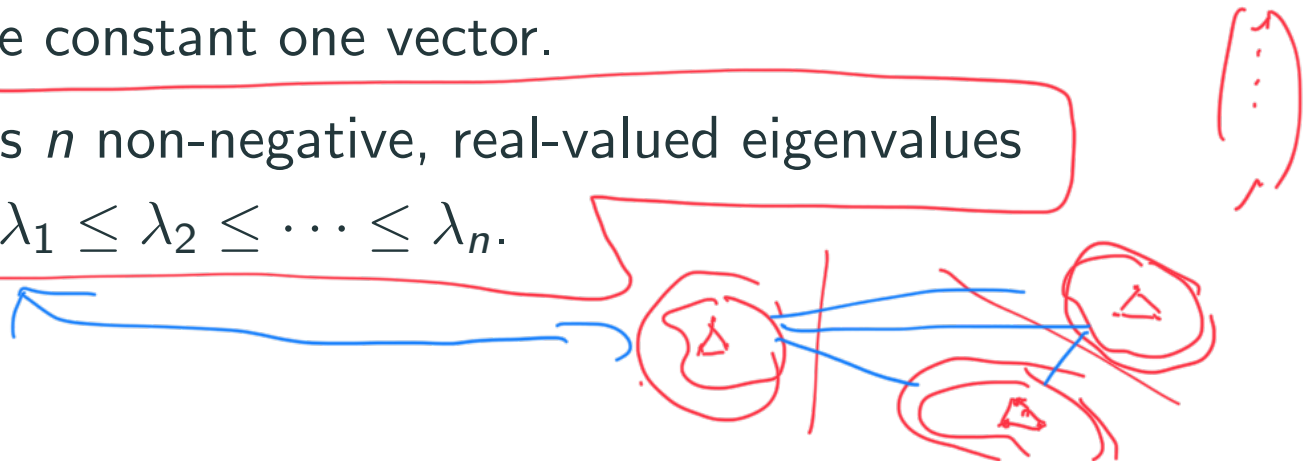
i For every vector $f \in \mathbb{R}^n$ we have

$$f^T L f = \frac{1}{2} \sum_{i,j=1}^{n} w_{ij} (f_i - f_j)^2.$$

ii L is symmetric and positive semi-definite.

iii The smallest eigenvalue of L is 0, the corresponding eigenvector is the constant one vector.

iv L has n non-negative, real-valued eigenvalues $0 = \lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$.



Useful properties of the Laplacian

Proof:

i By the definition of d_i,

$$f^T L f = f^T D f - f^T W f = \sum_{i=1}^{n} d_i f_i^2 - \sum_{i,j=1}^{n} f_i f_j w_{ij}$$

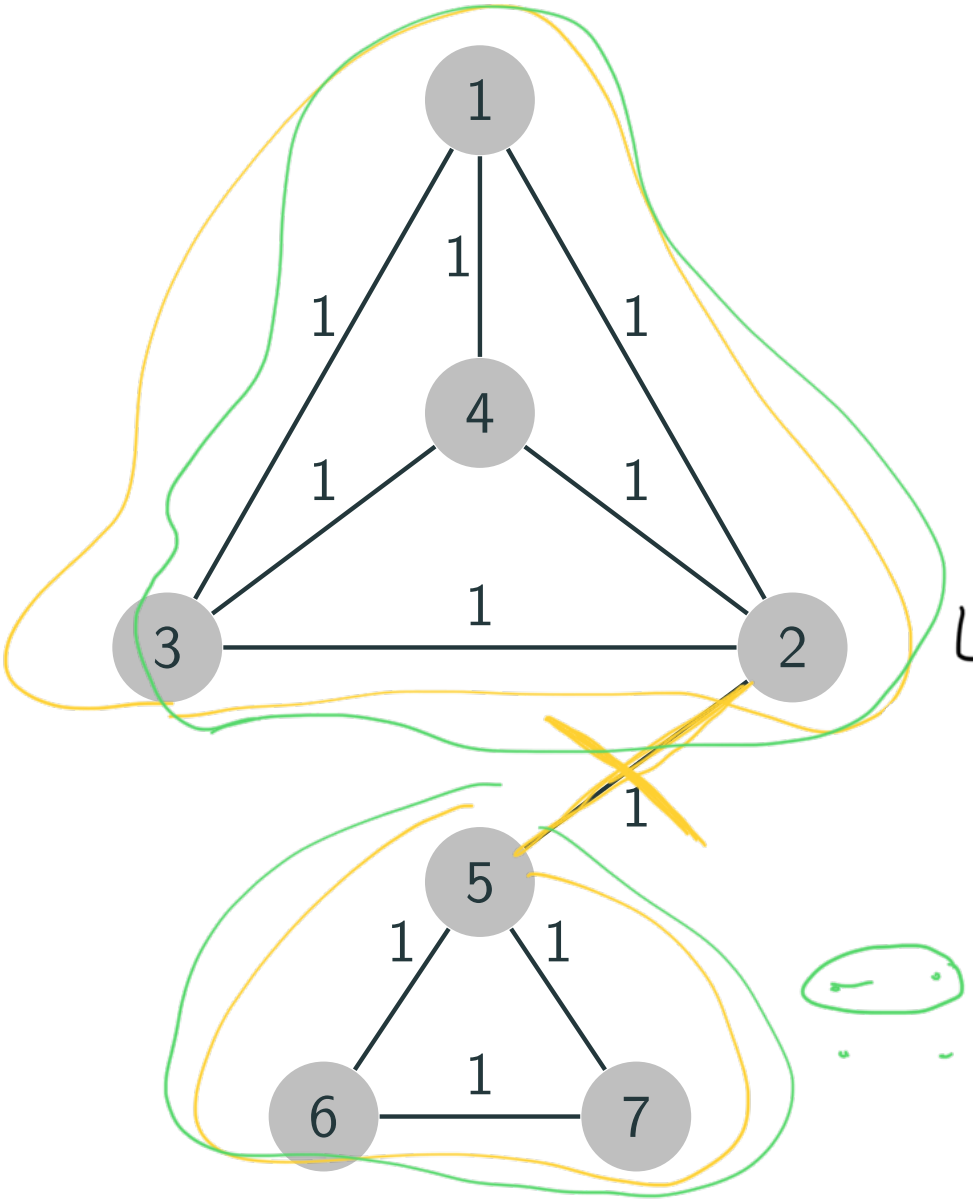
$$= \frac{1}{2}\left(\sum_{i=1}^{n} d_i f_i^2 - 2 \sum_{i,j=1}^{n} f_i f_j w_{ij} + \sum_{j=1}^{n} d_j f_j^2 \right) = \frac{1}{2} \sum_{i,j=1}^{n} w_{ij} (f_i - f_j)^2 .$$

ii The symmetry of L follows directly from the symmetry of W and D. The positive semi-definiteness is a direct consequence of Part (i), which shows that $f^T L f \geq 0$ for all $f \in \mathbb{R}^n$.

iii All eigenvalues are real (symmetric matrix). The rest follows easily from Part (ii) and the defining equation of eigenvalues.

iv This is a direct consequence of (i)-(iii).

Graph cuts and spectral clustering



$$f^T L f = \frac{1}{2} \sum_{i,j=1}^{n} w_{ij} (f_i - f_j)^2$$

$$L(G) = \begin{pmatrix} 3 & -1 & -1 & -1 & 0 & 0 & 0 \\ -1 & 4 & -1 & -1 & -1 & 0 & 0 \\ -1 & -1 & 3 & 1 & 0 & 0 & 0 \\ -1 & -1 & -1 & 3 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & 2 \end{pmatrix}$$

Connectivity

Proposition: The number of connected components of a graph is equal to the multiplicity of the first eigenvalue (which is 0) of the graph Laplacian matrix.

Relaxation of RatioCut for $k = 2$

Goal is to solve

$$\min_{A \subset V} \text{RatioCut}(A, \overline{A})$$

Reformulation: for $A \subset V$ define $f = (f_1, \ldots, f_n) \in \mathbb{R}^n$ (some kind of indicator vector) via

$$f_i = \begin{cases} \sqrt{|\overline{A}|/|A|} & \text{if } v_i \in A, \\ -\sqrt{|A|/|\overline{A}|} & \text{if } v_i \in \overline{A}. \end{cases}$$

It can be shown that

$$f^T L f = |V| \, \text{RatioCut}(A, \overline{A})$$

Relaxation of RatioCut for $k = 2$

Proof:

$$2f^T Lf = \sum_{i,j=1}^{n} w_{ij}(f_i - f_j)^2$$

$$= \sum_{i \in A, j \in \overline{A}} w_{i,j} \left(\sqrt{\frac{|\overline{A}|}{|A|}} + \sqrt{\frac{|A|}{|\overline{A}|}} \right)^2 + \sum_{i \in \overline{A}, j \in A} w_{i,j} \left(-\sqrt{\frac{|\overline{A}|}{|A|}} - \sqrt{\frac{|A|}{|\overline{A}|}} \right)^2$$

$$= 2\mathrm{cut}(A, \overline{A}) \left(\frac{|\overline{A}|}{|A|} + \frac{|A|}{|\overline{A}|} + 2 \right)$$

$$= 2\mathrm{cut}(A, \overline{A}) \left(\frac{|A| + |\overline{A}|}{|A|} + \frac{|A| + |\overline{A}|}{|\overline{A}|} \right)$$

$$= 2|V| \cdot \mathrm{RatioCut}(A, \overline{A})$$

Relaxation of RatioCut for $k = 2$

Further, f is orthogonal to 1:

$$\sum_{i=1}^{n} f_i = \sum_{i \in A} \sqrt{\frac{|\overline{A}|}{|A|}} - \sum_{i \in \overline{A}} \sqrt{\frac{|A|}{|\overline{A}|}} = |A| \sqrt{\frac{|\overline{A}|}{|A|}} - |\overline{A}| \sqrt{\frac{|A|}{|\overline{A}|}} = 0.$$

Finally

$$\|f\|^2 = \sum_{i=1}^{n} f_i^2 = |A| \frac{|\overline{A}|}{|A|} + |\overline{A}| \frac{|A|}{|\overline{A}|} = |\overline{A}| + |A| = n.$$

Hence the minimization problem is equivalent to

$$\min_{A \subset V} f^T L f$$

subject to the given f.

Relaxation of RatioCut for $k = 2$

This problem is NP-hard since the solution vector only takes two particular values.

Relaxing this problem is possible:

$$\min_{f \in \mathbb{R}^n} f^T L f \text{ subject to } f \perp 1, \|f\| = \sqrt{n}$$

The Rayleigh-Ritz theorem (see e.g. Strang - Linear algebra and its applications) gives the solution of this problem via an eigenvector corresponding to the second smallest eigenvalue of L.

Remark: Solution has to be transformed!

Special case ($k = 2$) of unnormalized spectral clustering

Algorithm: Unnormalized spectral clustering ($k = 2$)

Input: Weight matrix (or any similarity matrix) $S \in \mathbb{R}^{n \times n}$

1 Construct similarity graph G;
2 Compute $L(G)$;
3 Compute Eigenvectors X_1 and X_2 of $L(G)$;
4 Build $U \in \mathbb{R}^{n \times 2}$ with X_1 and X_2 as columns;
5 Rows of U are $y_1, y_2, \ldots, y_n \in \mathbb{R}^2$;
6 Cluster $y_1, y_2, \ldots, y_n$ into Clusters C_1 and C_2 (k-means);

Output: Clusters $A_1 = \{j : y_j \in C_1\}$ and $A_2 = \{j : y_j \in C_2\}$

Relaxation of RatioCut for $k > 2$ (sketch)

- Define k indicator vectors $h_j = (h_{1,j}, h_{2,j}, \ldots, h_{n,j})^T$ via

$$h_{i,j} = \begin{cases} 1/\sqrt{|A_j|} & \text{if } v_i \in A_j, \\ 0 & \text{else} \end{cases}$$

- Matrix $H \in \mathbb{R}^{n \times k}$ with columns $h_1, h_2, \ldots, h_k$ is orthogonal
- We have $h_i^T L h_i = \frac{\text{cut}(A_i, \overline{A}_i)}{|A_i|}$ and $h_i^T L h_i = (H^T L H)_{ii}$
- Together this yields $\text{RatioCut}(A_1, A_2, \ldots, A_k) = \text{tr}(H^T L H)$
- Hence the minimum of $\text{RatioCut}(A_1, A_2, \ldots, A_k)$ can be approximated by solving (the relaxed version)

$$\min_{H \in \mathbb{R}^{n \times k}} \text{tr}(H^T L H) \text{ subject to } H^T H = I$$

General case of unnormalized spectral clustering

Algorithm: Unnormalized spectral clustering

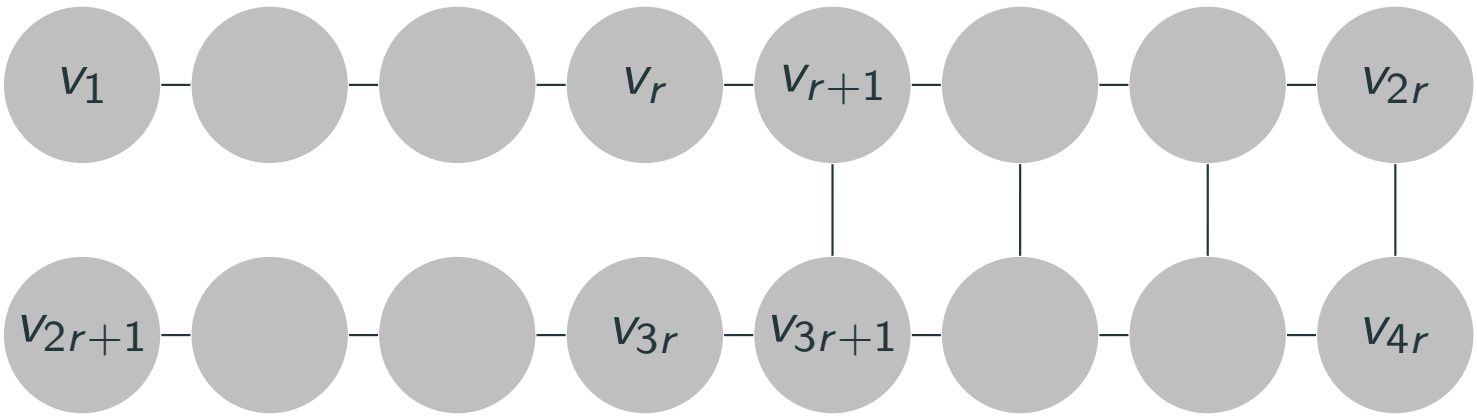
Input: Weight matrix (or any similarity matrix) $S \in \mathbb{R}^{n \times n}$, number k of clusters

1 Construct similarity graph G;
2 Compute $L(G)$;
3 Compute Eigenvectors $X_1, X_2, \ldots, X_k$ of $L(G)$;
4 Build $U \in \mathbb{R}^{n \times k}$ with $X_1, X_2, \ldots, X_k$ as columns;
5 Rows of U are $y_1, y_2, \ldots, y_n \in \mathbb{R}^k$;
6 Cluster $y_1, y_2, \ldots, y_n$ into Clusters $C_1, C_2, \ldots, C_k$ (k-means);

Output: Clusters $A_1, A_2, \ldots, A_k$ with $A_i = \{j : y_j \in C_i\}$

Notes on spectral clustering

- faster ($\mathcal{O}(mn)$ or $\mathcal{O}(n^2)$ for the eigenvector calculation) than Kernighan-Lin
- quality of approximated solution can be arbitrarily far from exact solution (cockroach graphs for $k = 2$)



- other relaxations possible (and probably useful)
- any other clustering algorithm may be used instead of k-means

Computing eigenvalues

- find roots of characteristic polynomial (computationally expensive)
- power method: iterate (with any starting vector $X_{(0)}$)

$$X_{(l)} = A^l X_{(0)}$$

- power method converges to eigenvector X corresponding to (w.r.t. absolute value) largest eigenvalue
- power method is fast but
  - method does not work if $X_{(0)}$ is orthogonal to X (can be avoided by choosing all entries of $X_{(0)}$ to be positive, since X has only entries of same sign)
  - entries of $X_{(l)}$ become large during the iterative process (renormalization helps)
  - When are we done? (option is to start with two different vectors)

Computational complexity of the power method

Two aspects:

- complexity of one multiplication
- required number of multiplications

First aspect:

- n^2 multiplications if stored in adjacency matrix
- less if matrix is stored in adjacency lists and matrix is sparse
  - compute
    $$\sum_{j \in N(i)} X_{(l)_j}$$
    which gives the i-th entry of $X_{(l+1)}$
  - therefore a total of
    $$\sum_i d(i) = 2m$$
    operations (m being the number of edges in the graph)

Computational complexity of the power method

Second aspect:

- it can be shown that this is $\mathcal{O}(n)$
- we will come back to this

Total computational complexity is $\mathcal{O}(mn)$, which means

- $\mathcal{O}(n^2)$ if graph is sparse
- $\mathcal{O}(n^3)$ if graph is dense

$\rightsquigarrow$ use adjacency list

Computing other eigenvalues

We have

$$(\lambda_n I - L)X_i = (\lambda_n - \lambda_i)X_i$$

hence eigenvalues are reversed for matrix $\lambda_n I - L$

$\rightsquigarrow$ smallest eigenvalue can be calculated with power method

Computing other eigenvalues

Trick to compute second largest eigenvalue:

- X_n normalised eigenvector corresponding to largest eigenvalue λ_n
- choose starting vector X and define

$$Y = X - (X_n^T X) X_n$$

- we have

$$X_i^T Y = \begin{cases} 0 & \text{if } i = n, \\ X_i^T X & \text{otherwise} \end{cases}$$

- therefore

$$Y = \sum_{i=1}^{n-1} c_i X_i$$

  where $c_i = X_i^T Y$

$\rightsquigarrow$ use Y as starting vector for power method

Compute all eigenvalues and eigenvectors

Combining methods for given (symmetric) matrix A with eigenvectors X_i and eigenvalues λ_i:

- Find orthogonal matrix Q with $B = Q^T A Q$ being a tridiagonal matrix
  - $Q^T X_i$ is eigenvector of B
  - B can be found efficiently, e.g. by Householder algorithm or Lancosz algorithm
- compute eigenvalues and eigenvectors of B
  - these give eigenvalues and eigenvectors of A
  - can be done using for example the QL algorithm