

Spectral Graph Theory

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- Various graph properties have linear algebraic interpretations
- Several applications: clustering, clique detection, pagerank, graph property testing

Graphs and associated matrices

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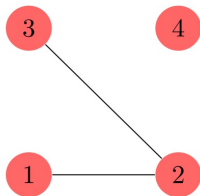
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 - Laplacian $L = D - A$

An example



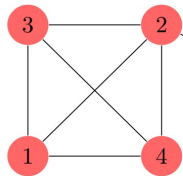
$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$L = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

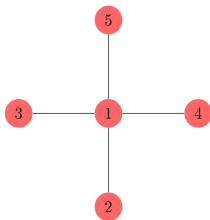
Some well-known graphs

Complete graph



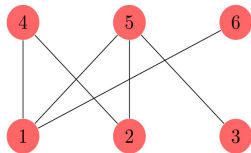
$$A = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

Star graph



$$A = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Bipartite graph



$$A = \begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

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 - Number of paths, triangles
 - Presence of cliques

Powers of the adjacency matrix: counting number of edges

- Let $A \in \{0, 1\}^n$ be the adjacency matrix of a graph $G = (V, E)$ and a_i be its columns. Then

$$\begin{aligned}(A^2)_{ii} &= (A^\top A)_{ii} \\ &= \|a_i\|_2^2 = d_i\end{aligned}$$

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- This gives

$$\text{Tr}(A^2) = \sum_{i=1}^n d_i = 2|E|$$

Powers of the adjacency matrix: paths between nodes

- Number of paths N_{ij} of length 2 between nodes i and j :

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- In general $(A^k)_{ij}$ counts the number of paths of length k between nodes i and j

Graph spectra: Bipartite graphs

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- The spectrum of a bipartite graph is symmetric around zero

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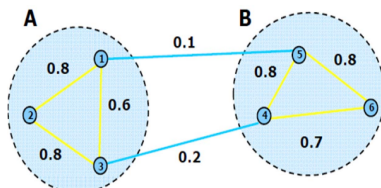
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$$A \begin{bmatrix} -v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0 & B \\ B^\top & 0 \end{bmatrix} \begin{bmatrix} -v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} Bv_2 \\ -B^\top v_1 \end{bmatrix} = -\lambda \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

Graphs with clusters



- Adjacency matrix has a block diagonal structure (roughly)

$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

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- The all ones vector is an eigenvector with eigenvalue equal to the size of each component
- The next eigenvector reveals component labels

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ -1 \\ -1 \\ -1 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 1 \\ 1 \\ -1 \\ -1 \\ -1 \end{bmatrix}$$

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- This idea can be extended to more general settings (more components, noisy observations of the adjacency matrix)

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- Has direct application to community detection in large graphs
- Lot of recent work in analyzing spectral algorithms in the stochastic block model setting
- Several other interesting connections: graph coloring and chromatic number, grouping graphs with similar spectra

The stochastic block model

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For $n \in \mathbb{N}$ and $p, q \in (0, 1)$, let $\mathcal{G}(n, p, q)$ be the class of random graphs where

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- each vertex v is assigned a label $\sigma_v \in \{+1, -1\}$ (independently and uniformly at random)
- each possible edge (u, v) is included with probability p if $\sigma_u = \sigma_v$ and with probability q if $\sigma_u \neq \sigma_v$

Clustering in networks

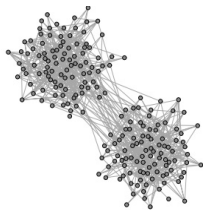


Figure 1: A random graph $G \sim \mathcal{G}(200, \frac{1}{20}, \frac{1}{200})$

- The expected adjacency matrix has a block structure

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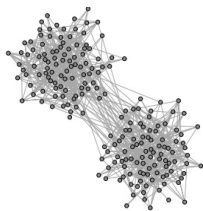


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- For example, with $n = 4$:

$$\mathbb{E}[A] = \begin{bmatrix} p & p & q & q \\ p & p & q & q \\ q & q & p & p \\ q & q & p & p \end{bmatrix}$$

References

- Luca Trevisan. *Lecture Notes on Expansion, Sparsest Cut, and Spectral Graph Theory*.
- Daniel Spielman. *Spectral Graph Theory, Combinatorial Scientific Computing, Chapman and Hall/CRC Press, 2011*.

Thank you