

Overview

- Take Home final
- Two HWs
- Will need to scribe once

Topics

- Spectral Graph Theory I
 - LA Review
 - Graphs & Matrices
- Spectral Graph Theory II
 - Random Walks & Alg. App
 - Graph Partitioning
 - Spectral Clustering
- Iterative Algorithms Laplacian It. Systems
 - $Lx=b$ where L is
 - $\begin{pmatrix} 0 & 1 & \dots \end{pmatrix}$

a Laplacian

- Graph Sparsification

- Is there a graph $G' \approx G$
such that

G $\binom{n}{2}$ edges

G' $O(n)$ edges

Lecture:

Def: Undirected Graphs

$$G = (V, E)$$

[unordered pairs of
vertices $E \subseteq \binom{V}{2}$]

Def: Weighted Graph has an assoc.

weight vector $w \in \mathbb{R}^E$

Goal: - Study graphs as $G \mapsto M_G$

The action of $M_G : \mathbb{R}^n \mapsto \mathbb{R}^n$

$f(x) := M_G x$ is connected to
random walks & averaging

- Study the quadratic forms

$$\left. \begin{array}{l} g(x) = x^T M_G x \\ g : \mathbb{R}^n \mapsto \mathbb{R} \end{array} \right\} \begin{array}{l} \text{Convergence of R.W.} \\ \text{Graph Clustering} \end{array}$$

Key Insight: Move graphs from
combinatorial \rightarrow algebraic structure.

- Good math / good code.

Graph Matrices

Adjacency matrix

$$(A_G)_{ij} = \begin{cases} w_{ij} & \{i, j\} \in E \\ \dots & \dots \end{cases}$$

o (o o.w.

- zeros on the diagonal

- Symmetric

- Fact: $[A_G^k]_{ij} = \sum_{\substack{\text{k-len.} \\ \text{walks} \\ \text{from} \\ i \rightarrow j}} \text{product of weights of each path}$

- Rmk: If $w_{ij} = 1 \ \forall \ i, j$ then this quantity is just the number of k walks from $i \rightarrow j$

Degree Matrix

$$d_i = \sum_{j \sim i} w_{ij}$$

$$D_G = \text{diag}(d_1, \dots, d_n)$$

Consider: $W = A_G D_G^{-1}$ and

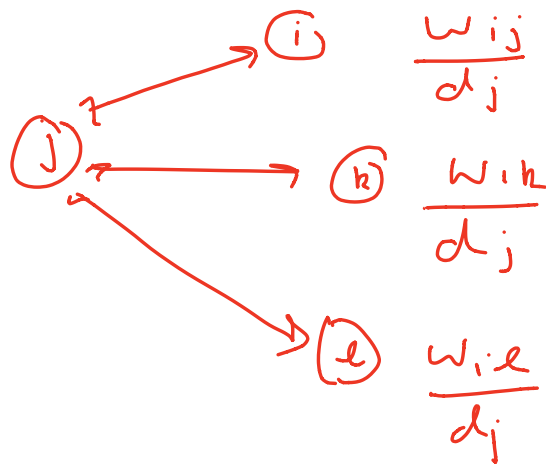
1.4 $\vec{v} \in \mathbb{R}^n$ h. ... and

we can define a probability distribution

Consider Random Walk Matrix

$$(W\vec{p})_i = \sum_{j \sim i} \frac{w_{ij}}{d_j} p_j$$

new prob distribution



Defines a new pdf in terms
of a Markov Chain

Fact: So W describes the transition
probability matrix of a
random walk on the graph

Laplacian Matrix

$$L = D - A$$

Def: $L_G := D_G - A_G$

- symmetric
- eigenvalues are positive
- D_G in some sense serves as an identity

Ex: Laplacian with one edge

$$\begin{matrix} & w_{ij} \\ i & \text{---} & j \end{matrix}$$

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

$$= w \begin{pmatrix} 1 \\ -1 \end{pmatrix} (1 \quad -1)$$

We call these x_{ij}

then $\text{rank}(L) \leq \# \text{edges}$.

Prop: L_G, L_H $V(G) = V(H)$

then $L_{G \oplus H} = L_G + L_H$

$$V(G \oplus H) = V(H) \cup V(G)$$

$$E(G \oplus H) = E(H) \cup E(G)$$

$$\vec{w}_{G \oplus H} = \vec{w}_G + \vec{w}_H$$

A different way to think of the Laplacian

$$L_G = \sum_{e \in E} w_e L_e$$

Rank 1 matrices

Then the quadratic form also looks like

$$x^T L_G x = \sum_{e \in E} w_e x^T L_e x = \sum_{e \in E} w_e (x_i - x_j)^2$$

Rmk: $w_e \geq 0 \Rightarrow x^T L_G x \geq 0$

Spectral Theorem

$$\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n \quad m \in \mathbb{R}^{n \times n} \quad m^T = m \quad \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$$

Thm. Let $M \in \mathbb{R}^{n \times n}$ then
it has an orthonormal basis of
eigenvectors

$$M = V \Lambda V^T$$