

Spectral and Algebraic Graph Theory 462/562

formerly grad course numbered AMTH 561/CPSC 662
Spectral = eigvals and eigvecs

U grad/grad => I assume less.

Grads get extra homework problems

More applied/CS focus

But still very mathy

Can find lecture notes from previous years.

Writing a book now. The book will have
details I cannot cover in class.

I will distribute my handwritten notes, when I
have them.

Assignments: 5-6. Probably 6. Can work in small groups
(for now). No tests or exam.

Occasional recommended exercises, especially for
this lecture.

Prereqs: linear algebra. graph theory. some probability.
proof-based exposition. endurance

Today: Intro, overview, a proof or two.

Get used to my notation.

Please interrupt when necessary.

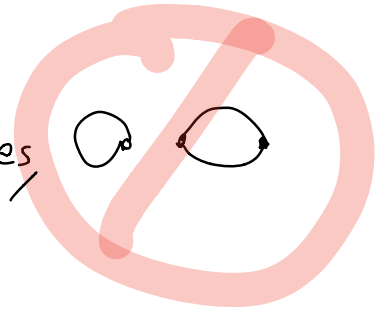
Graphs. $G = (U, E)$ E is set of pairs of U .

Write edges as (a, b) , although $\{a, b\}$ would be better.

$$(a, b) = (b, a)$$

Undirected.

No self-loops or multi-edges,
usually.



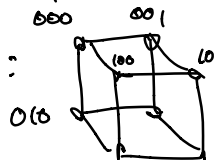
Might be weights on edges. If so, almost always positive.

Sources: social networks, comm. networks, etc.
abstract like

path on n vertices. $U = \{1, \dots, n\}$

$$E = \{(a, a+1) : 1 \leq a < n\}$$

ring: path plus edge $(1, n)$

hypercube:  $U = \{0, 1\}^d$

$$(a, b) \in E \text{ if } |\{i : a(i) \neq b(i)\}| = 1$$

random.

edge (a, b) appears with probability p ,
independently chosen.

Matrices for graphs.

Adjacency. M . row/cols labeled by V .

$$M(a,b) = \begin{cases} 1 & (a,b) \in E \\ 0 & \text{o.w.} \end{cases}$$

Is using matrix as a spreadsheet

Very surprising eigenvalues or eigenvectors should matter.

Diffusion Operator / walk Matrix.

Let D = diagonal matrix of degrees.

$$d = M \cdot \mathbb{1} \quad D = \text{diag}(d)$$

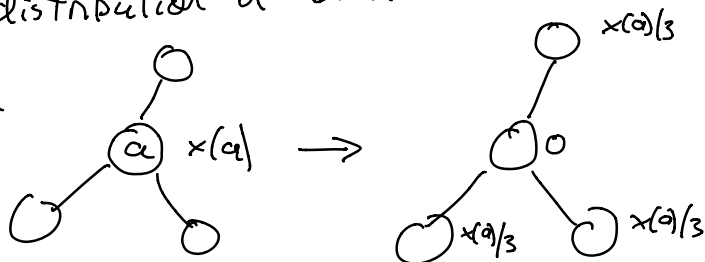
$$W = D^{-1}M$$

Let $p \in \mathbb{R}^V$ be a vector s.t. $p(a)$ = amount of stuff at vertex a .

If stuff at a moves to neighbors of a , evenly,

then new distribution of stuff is

$$q^T = p^T D^{-1} M$$



Total amount of stuff, $p^T \mathbb{1}$, is conserved

$$\text{because } q^T \mathbb{1} = p^T D^{-1} M \mathbb{1} = p^T D^{-1} d = p^T \mathbb{1}$$

Expect spectra of W to matter.

Laplacian $L = D - M$

defines a natural quadratic form:

$$\text{for } x \in \mathbb{R}^V, \quad x^T L x = \sum_{(a,b) \in E} w_{a,b} (x(a) - x(b))^2$$

e.g. $0 \text{---} 1 \text{---} 3$ $x = [0, 1, 3]$ $x^T L x = 1^2 + 2^2 = 5$

Spectral Theory

ψ is an eigenvector of M of eigenvalue λ if

$$M\psi = \lambda\psi$$

Theorem Every real symmetric $n \times n$ matrix M

has n real eigenvalues $\mu_1 \geq \mu_2 \geq \dots \geq \mu_n$

and n orthonormal eigenvectors ψ_1, \dots, ψ_n

$$\left(\psi_i^T \psi_j = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{o.w.} \end{cases} \right)$$

$$\text{s.t. } M\psi_i = \mu_i \psi_i$$

Note: ψ_1, \dots, ψ_n not uniquely defined.

Examples in Jupyter

Course topics

Graph structure: cuts, coloring, indep sets,
partitioning, local partitioning

The zoo: fundamental examples

Estimating eigenvalues

Random walks.

Physical models: springs & resistors

Effective resistance and elimination

Expanders - extremal combinatorics
relation to codes and pseudo randomness

Sparsification

Solving Laplacian equations
and computing eigenvectors.

Def The Rayleigh Quotient of x with respect to M is $\frac{x^T M x}{x^T x}$

Theorem If M is symmetric and x maximizes $\frac{x^T M x}{x^T x}$ then $Mx = \mu_1 x$.

Will expand $x = \sum_{i=1}^n c_i \psi_i$, where $c_i = \psi_i^T x$

Why? well $x = \sum x(i) \delta_i$, where δ_i is ebasec in direction i , and $x(i) = \delta_i^T x$.

$$\text{And, } \sum_i c_i \psi_i = \sum_i \psi_i \cdot \psi_i^T x = \left(\sum_i \psi_i \psi_i^T \right) x = I x = x$$

Claim $x^T M x = \sum_i c_i^2 \mu_i$, where $c_i = \psi_i^T x$

proof

$$\begin{aligned} x^T M x &= \left(\sum_i c_i \psi_i \right)^T M \left(\sum_j c_j \psi_j \right) \\ &= \left(\sum_i c_i \psi_i \right)^T \left(\sum_j c_j \lambda_j \psi_j \right) \end{aligned}$$

$$\text{as } \psi_i^T \psi_j = \begin{cases} 1 & i=j \\ 0 & \text{o.w.} \end{cases}$$

$$= \sum_i c_i^2 \lambda_i$$

proof of theorem for all x

$$\frac{x^T M x}{x^T x} = \frac{\sum_i c_i^2 \mu_i}{\sum c_i^2} \leq \frac{\sum_i c_i^2 \mu_1}{\sum_i c_i^2}$$

$$\text{as } c_i^2 \geq 0 \text{ and } \mu_1 \geq \mu_i, \forall i$$

$$= \mu_1$$

and, equality only holds if $c_i^2 = 0$ for $\mu_i < \mu_1$