

Tuesday, April 17

Lanczos!

Spectral graph theory!

## Krylov Subspace

$$K = \{z^{(0)}, A z^{(0)}, A^2 z^{(0)}, \dots, A^{m-1} z^{(0)}\}$$

Power method just uses last vector. Can we do better?

## Lanczos Method

$z^{(0)} \sim \mathcal{N}(0, I)$  initial start

Compute  $Q \in \mathbb{R}^{d \times m}$ , an orthonormal basis for  $K$

Form  $T = Q^T A Q$  ( $T$  is tridiagonal, prove for hw)

Let  $z$  be top eigenvector of  $T$

Return  $y^* = Q z$

Analysis:

1.  $y^* = Qz$  is the best vector in  $K$  i.e.,

$$\begin{aligned} y^* &= \operatorname{argmin}_y \|x - Xy\|_F^2 \\ &= \operatorname{argmin}_y \|X\|_F^2 - \|Xy\|_F^2 = \end{aligned}$$

2. There is a very "good" vector  $w$  in  $K$ . All  $w$  in  $K$

$$\begin{aligned} w &= \alpha_1 z^{(0)} + \alpha_2 A z^{(0)} + \dots + \alpha_m A^{m-1} z^{(0)} \\ &= p(A) z^{(0)} \\ &= \sum_{i=1}^d p(\lambda_i) v_i v_i^T z^{(0)} \\ &= \sum_{i=1}^d p(\lambda_i) v_i c_i^{(0)} \end{aligned}$$

Goal: Find  $p(\lambda)$  s.t.  $p(\lambda_j)$  small for  $j \neq i$  but  $p(\lambda_i)$  large

Answer: Chebyshev polynomial!

Claim: There is degree  $m = O(\sqrt{1/\epsilon} \log \frac{d}{\epsilon})$

Chebyshev  $p$  where  $p(1) = 1$  but

$|p(\lambda)| \leq \epsilon$  for  $0 \leq \lambda \leq 1 - \gamma$

# Spectral Graph Theory

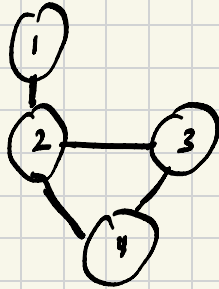
Graph data:

↳ social networks

↳ internet

$G = (V, E)$   
graph vertices edges  
( $n$ ) ( $m$ )

← assume undirected  
for now



$$V = \{1, 2, 3, 4\}$$

$$E = \{(1, 2), (2, 3), (2, 4), (3, 4)\}$$

**Adjacency Matrix**

$$A \in \mathbb{R}^{n \times n}$$

$$[A]_{ij} = \begin{cases} 1 & \text{if } (ij) \in E \text{ or } (ji) \in E \\ 0 & \text{else} \end{cases}$$

$$A = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \end{matrix}$$

**Degree Matrix**

$$D \in \mathbb{R}^{n \times n}$$

$$[D]_{i,i} = \sum_{j=1}^n [A]_{i,j}$$

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}$$

## Laplacian

$$L = D - A$$

$$L = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 3 & -1 & -1 \\ 0 & -1 & 2 & -1 \\ 0 & -1 & -1 & 2 \end{bmatrix}$$

Fun Facts:

↳ If  $L$  has  $k$  eigenvalues equal to 0, then  $G$  has  $k$  connected components

↳ Sum of cubes of eigenvalues equals number of triangles times 6

## Edge-Incidence Matrix

$$B \in \mathbb{R}^{m \times n}$$

$$B_{(i,j),k} = \begin{cases} 1 & \text{if } k=i \\ -1 & \text{if } k=j \\ 0 & \text{else} \end{cases}$$

Show:

$$\hookrightarrow L = B^T B$$

$$\hookrightarrow = \sum_{i=1}^m b_i b_i^T \quad \text{where } b_i \text{ is } i\text{th row of } B$$

Thursday, April 9

Graph  $G = (V, E)$  with  $n$  nodes/vertices,  $m$  edges undirected

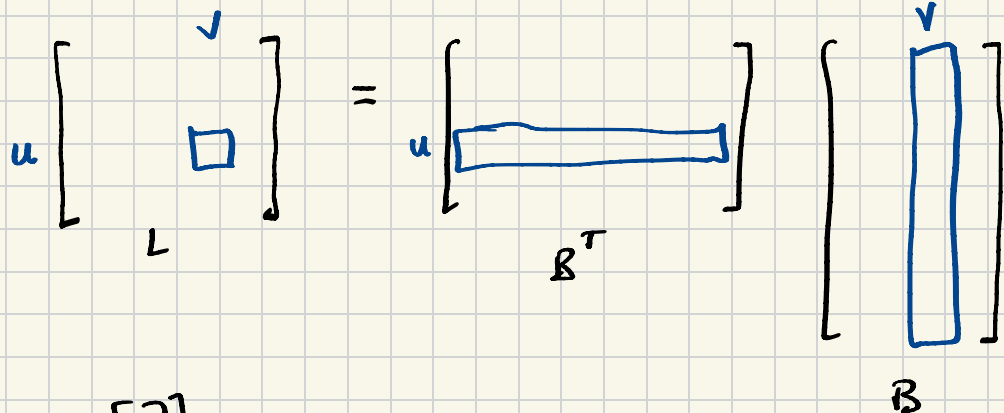
Adjacency Matrix:  $A \in \mathbb{R}^{n \times n}$   $[A]_{i,j} = \begin{cases} 1 & \text{if } (i,j) \in E \text{ or } (j,i) \in E \\ 0 & \text{else} \end{cases}$

Degree Matrix:  $D \in \mathbb{R}^{n \times n}$   $[D]_{i,i} = \sum_{j=1}^n [A]_{i,j} = \# \text{edges to } i$

Laplacian Matrix:  $L \in \mathbb{R}^{n \times n}$   $L = D - A$

Edge-incidence Matrix:  $B \in \mathbb{R}^{m \times n}$   $[B]_{(i,j),u} = \begin{cases} 1 & \text{if } i=u \\ -1 & \text{if } j=u \\ 0 & \text{else} \end{cases}$   
 $= \mathbb{1}[i=u] - \mathbb{1}[j=u]$

Claim:  $L = B^T B$



$$[B^T B]_{u,v} = \sum_{(i,j) \in E} [B^T]_{u,(i,j)} [B]_{(i,j),v}$$

$$= \sum_{(i,j) \in E} (\mathbb{1}[i=u] - \mathbb{1}[j=u]) (\mathbb{1}[i=v] - \mathbb{1}[j=v])$$

$$\text{if } u=v = \sum_{(i,j) \in E} \mathbb{1}[i=u] + \mathbb{1}[j=u] = \# \text{ edges to } u = [D]_{u,u} = [L]_{u,u}$$

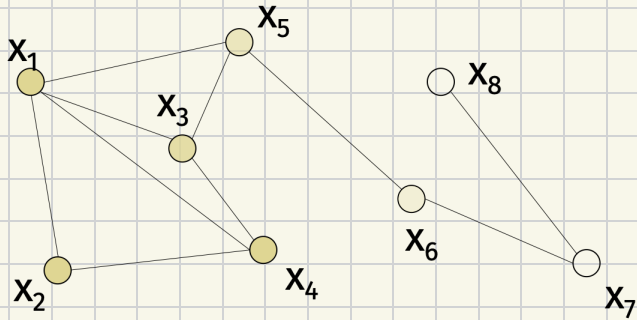
$$\text{if } u \neq v = -\mathbb{1}[i=u] \mathbb{1}[j=v] - \mathbb{1}[j=u] \mathbb{1}[i=v] = -[A]_{u,v} = [L]_{u,v}$$

## Insights

$$x^T L x = x^T B B^T x = \sum_{(i,j) \in E} \begin{bmatrix} +1 & \\ & -1 \end{bmatrix} \begin{bmatrix} x_i \\ x_j \end{bmatrix} \Big\|_2^2 = \sum_{(i,j) \in E} (x_i - x_j)^2 \geq 0$$

If  $B = U \Sigma V^T$  then  $L = V \Sigma^2 V^T$ .

Consider  $f(x) = x^T L x = \begin{cases} \text{small if } x \text{ "smooth" on graph} \\ \text{large if } x \text{ "jumpy"} \end{cases}$



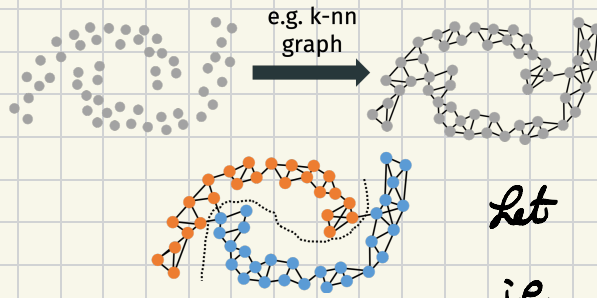
# Graph Partitioning

↳ understanding social networks

↳ clustering

↳ visualization

↳ Karate graph!! 😊



Let  $c \in \{-1, 1\}^n$  be "cut" vector.

$$\text{i.e. } c_i = \begin{cases} 1 & \text{if } i \in S \\ -1 & \text{else} \end{cases}$$

Goal: Find  $S$  and  $S^c = V \setminus S$  s.t.

1. Number of edges b/w  $S, S^c$  small

2.  $S, S^c$  are not too small

$$\begin{aligned} 1. c^T L c &= \sum_{(i,j) \in E} (c_i - c_j)^2 \\ &= 4 \cdot \# \text{ edges between } S, S^c \\ &= 4 \text{ cut}(S, S^c) \end{aligned}$$

$$2. |c^T \mathbf{1}| = |S| - |S^c|$$

## Computing the Optimal Cut

$$\min_{C \in \left\{ \frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}} \right\}^n} C^T L C \quad \text{s.t.} \quad C^T \mathbf{1} = 0$$

|| relax  
↓

$$\min_{C: \|C\|_2 = 1} C^T L C \quad \text{s.t.} \quad C^T \mathbf{1} = 0$$

## Eigen Perspective

$$\lambda_d = \min_{v: \|v\|_2 = 1} v^T L v \quad v_d = \operatorname{argmin}_{v: \|v\|_2 = 1} v^T L v$$

$$\lambda_{d+1} = \min_{\substack{v: \|v\|_2 = 1 \\ \langle v, v_d \rangle = 0}} v^T L v \quad v_{d+1} = \operatorname{argmin}_{\substack{v: \|v\|_2 = 1 \\ \langle v, v_d \rangle = 0}} v^T L v$$

Show:

↳ Smallest eigenvector of  $L$  is  $\frac{1}{\sqrt{n}} \mathbf{1}$

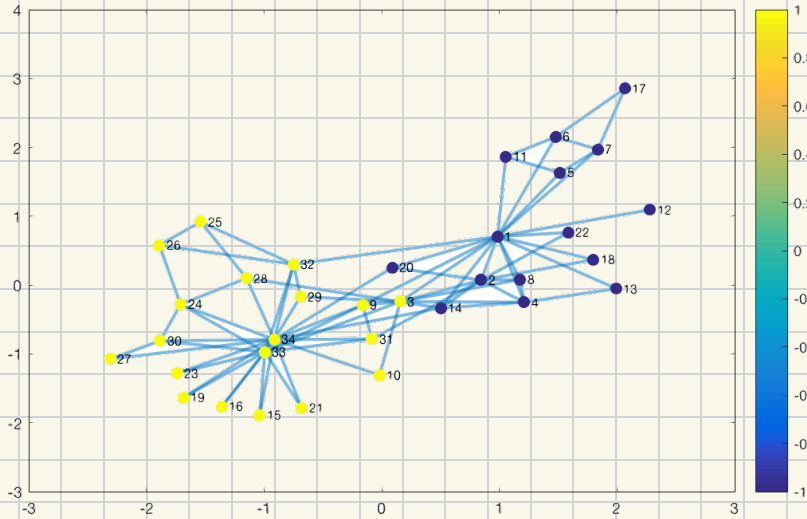
↳ Second smallest is solution to the relaxed problem

Strategy:

compute  $v_{n-1}$

use  $c = \text{sign}(v_{n-1})$

Time Complexity:



# Stochastic Block Model

Motivation: Interesting setting we can analyze

$$0 < q < p < 1$$

Group  $S$  and  $S^c$  partition  $V$  into two equal groups

$$\Pr(\text{edge } i,j) = \begin{cases} p & \text{if } i,j \in S \text{ or } i,j \in S^c \\ q & \text{else} \end{cases}$$

$$\mathbb{E}[A] = \begin{matrix} S \\ \left. \begin{array}{|c|} \hline \phantom{A} \\ \hline \end{array} \right\} \\ S^c \\ \left. \begin{array}{|c|} \hline \phantom{A} \\ \hline \end{array} \right\} \end{matrix} = \lambda_1 v_1 v_1^T + \lambda_2 v_2 v_2^T = \dots$$

Recall  $L = D - A$

i.e.  $\lambda_1$  eigenvalue of  $A$   
is bottom eigenvalue of  $L$