

Lecture 12

Last time

- ▷ Distances continued.
- ▷ Davis-Kahan $\sin \theta$ Theorem

Today

- ▷ Proof of Davis-Kahan $\sin \theta$.
- ▷ Wedin's theorem
- ▷ Community detection

Proof of Davis-Kahan: We will prove a slightly more general bound on

$$\|U^\top U^*\| \leftarrow \text{Any rotationally invariant norm.}$$

The final bound will follow from Lemma $\text{\textcolor{violet}{4}}$ (Lecture 10). Assume condition

1) holds true. **WLOG** we can assume that $a = -b \leq 0$. Otherwise, we can modify

$$M^* \leftarrow M^* - \frac{a+b}{2} I_n \text{ and } M \leftarrow M - \frac{a+b}{2} I_n.$$

You can check that this doesn't change the eigenvectors, it only shifts eigenvalues. Thus, we get

$$\underbrace{\|L^*\|_{\text{op}}}_{\max_{i \in [r]} |\lambda_i^*|} \leq b \quad \text{and} \quad \underbrace{\sigma_{\min}(L_\perp)}_{\min_{i \in [n] \setminus [r]} |\lambda_i|} \geq b + \Delta.$$

We will use these to control $\|U_{\perp}^T U^*\|$.
The next decomposition will be useful:

$$U_{\perp}^T (M - M^*) U^* = \Lambda_{\perp} U_{\perp}^T U^* - U_{\perp}^T U^* \Lambda^*.$$

Thus, by noting $EU^* = (M - M^*)U^*$, yields

$$\begin{aligned} \|U_{\perp}^T EU^*\| &\stackrel{\text{Reverse triangle ineq.}}{\geq} \|\Lambda_{\perp} U_{\perp}^T U^*\| - \|U_{\perp}^T U^* \Lambda^*\| \\ &\geq \sigma_{\min}(\Lambda_{\perp}) \cdot \|U_{\perp}^T U^*\| - \|U_{\perp}^T U^*\| \cdot \|\Lambda^*\|_{\text{op}} \end{aligned}$$

Fact $\star$ in Lecture 10

$$\begin{aligned} &\geq (b + \Delta - b) \|U_{\perp}^T U^*\| \\ &= \Delta \|U_{\perp}^T U^*\|. \end{aligned}$$

Consequently,

$$\|U_{\perp}^T U^*\| \leq \underbrace{\|U_{\perp}^T EU^*\|}_{\Delta} \stackrel{\text{Fact } \star}{\leq} \|U_{\perp}^T\|_{\text{op}} \underbrace{\|EU^*\|}_{\Delta} \stackrel{\|U_{\perp}^T\|_{\text{op}} = 1}{=} \underbrace{\|EU^*\|}_{\Delta}$$

When $\|\cdot\| = \|\cdot\|_{\text{op}}$, we can apply Fact $\star$ once more to derive $\|\sin \Theta\|_{\text{op}} \leq \frac{\|E\|_{\text{op}}}{\Delta}$.

When $\|\cdot\| = \|\cdot\|_F$, we do the same and note $\|U^*\|_F = \sqrt{r}$, which gives $\|\sin \Theta\|_F \leq \frac{\sqrt{r} \|E\|_{\text{op}}}{\Delta}$.

The proof with condition 2) is similar and we leave it as an exercise.

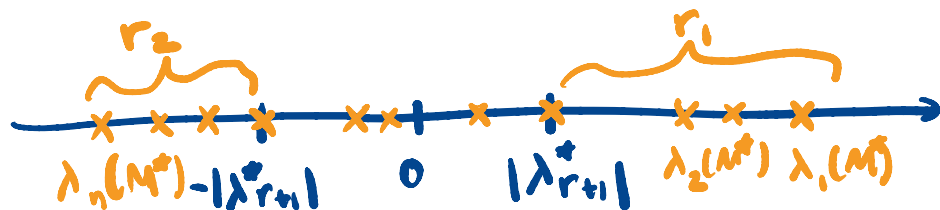
□

Proof of Corollary (:) : We shall prove that the the eigenvalues satisfies condition 2). Let $\lambda_i(M^*)$ (resp. $\lambda_i(M)$) be the i th largest eigenvalue of M^* (resp. M) sorted by value (as opposed to absolute value).

By Weyl's ineq.

$$(w) \quad |\lambda_i(M) - \lambda_i(M^*)| \leq \|E\|_{op} \quad \forall i \in [n]$$

Let $r_1 = \# \{ i \mid \lambda_i(M) \geq |\lambda_{r_1+1}^*| \}$ and $r_2 = \# \{ i \mid \lambda_i(M) \leq -|\lambda_{r_2+1}^*| \}$. That is



By construction, $r = r_1 + r_2$. Using (w) together with triangle inq we get that for i s.t. $i \in [r_1]$ or $i > n - r_2$ we have

$$\begin{aligned} |\lambda_i(M)| &\geq |\lambda_i(M^*)| - \|E\|_{op} \\ &\geq |\lambda_r^*| - (1 - 1/\sqrt{2})(|\lambda_r^*| - |\lambda_{r+1}^*|) \\ &= \frac{1}{\sqrt{2}}|\lambda_r^*| + (1 - 1/\sqrt{2})|\lambda_{r+1}^*| \\ &\stackrel{\text{Convex combination with more weight on the smallest value.}}{\geq} \frac{1}{\sqrt{2}}|\lambda_{r+1}^*| + (1 - 1/\sqrt{2})|\lambda_r^*| \\ &= |\lambda_{r+1}^*| + (1 - 1/\sqrt{2})(|\lambda_r^*| - |\lambda_{r+1}^*|) \\ &\geq |\lambda_{r+1}^*| + \|E\|_{op}. \end{aligned}$$

On the other hand, if $r_1 < i \leq n - r_2$
we have

$$\begin{aligned} |\lambda_i(M)| &\leq |\lambda_i(M^*)| + |\lambda_i(M) - \lambda_i(M^*)| \\ &\leq |\lambda_{r+1}^*| + \|E\|_{op}. \end{aligned}$$

Thus, setting $b = |\lambda_{r+1}^*| + \|E\|_{op}$, gives
 $\{\lambda_{r+1}, \dots, \lambda_n\} \subseteq [-b, b]$

Using that $|\lambda_1^*| \geq \dots \geq |\lambda_n^*|$ yields
 $\{\lambda_1^*, \dots, \lambda_r^*\} \subseteq (-\infty, -|\lambda_{r+1}^*|] \cup [|\lambda_{r+1}^*|, \infty)$.

We can set $a = -b$ and

$$\Delta = |\lambda_r^*| - |\lambda_{r+1}^*| - \|E\|_{op} > (|\lambda_r^*| - |\lambda_{r+1}^*|) / \sqrt{2}.$$

Invoking Davis-Kahan with condition
2) gives the result. □

Wedin's $\sin \theta$ theorem

Wedin (1972) developed a parallel
perturbation result for singular vec-
tors. Assume $M = M^* + E \in \mathbb{R}^{n \times m}$
wLOG, assume $n < m$

$$M^* = \sum_{i=1}^r \lambda_i^* u_i^* v_i^{*T} = [U^* \ U_\perp^*] \begin{bmatrix} \Sigma^* & 0 & 0 \\ 0 & \Sigma_\perp^* & 0 \end{bmatrix} \begin{bmatrix} V^{*T} \\ V_\perp^{*T} \end{bmatrix},$$

$$M = \sum_{i=1}^r \lambda_i u_i v_i^T = [U \ U_\perp] \begin{bmatrix} \Sigma & 0 & 0 \\ 0 & \Sigma_\perp & 0 \end{bmatrix} \begin{bmatrix} V^T \\ V_\perp^T \end{bmatrix},$$

where $U^* = [u_1^*, \dots, u_r^*]$, $U_\perp^* = [u_{r+1}^*, \dots, u_n^*]$,
 $V^* = [v_1^*, \dots, v_r^*]$, $V_\perp^* = [v_{r+1}^*, \dots, v_n^*]$,
 $\Sigma^* = \text{diag}(\sigma_1^*, \dots, \sigma_r^*)$, and $\Sigma_\perp^* = \text{diag}(\sigma_{r+1}^*, \dots, \sigma_n^*)$.
 The matrices $U, U_\perp, V, V_\perp, \Sigma$ and $\Sigma_\perp$
 are defined analogously.

Theorem (Wedin's Sin Θ): Consider
 the setting in (♥). Assume $\|E\|_{op} \leq$
 $\sigma_r^* - \sigma_{r+1}^*/\sqrt{2}$. Then

$$\text{dist}_{op}(U, U^*) \vee \text{dist}_{op}^+(V, V^*) \leq 2 \frac{\|E^T U^*\|_{op} \vee \|E V^*\|_{op}}{\sigma_r^* - \sigma_{r+1}^*}.$$

$$\text{dist}_F(U, U^*) \vee \text{dist}_F^+(V, V^*) \leq 2 \frac{\|E^T U^*\|_F \vee \|E V^*\|_F}{\sigma_r^* - \sigma_{r+1}^*}.$$

The proof is similar in spirit to that
 of Davis-Kahan Sin Θ . If you are in
 terested it appears in **Spectral Methods
 for Data Science** by Chen, Chi, Fan & Ma

Section 2.4.3.

Community detection in networks

We will apply these perturbation results to analyze an spectral method for community detection.

We consider the so-called **stochastic block model** where we observe a random graph $G(n, p, q)$ with n nodes that can be split into two disjoint communities of size $n/2$ s.t.

$$P((v_1, v_2) \text{ is an edge}) = \begin{cases} p & v_1, v_2 \text{ are in the same community,} \\ q & \text{otherwise.} \end{cases}$$

The goal is to identify the two communities from one draw of $G(n, p, q)$.

Consider the adjacency matrix of G given by

$$A_{ij} = \begin{cases} 1 & \text{if } (i,j) \text{ is an edge} \\ 0 & \text{otherwise.} \end{cases}$$

In expectation this matrix has a block structure. Assuming the first community is $[n/2]$, we have

$$\mathbb{E} A = \begin{bmatrix} p \cdots p & q \cdots q \\ p \cdots p & q \cdots q \\ \hline q \cdots q & p \cdots p \\ q \cdots q & p \cdots p \end{bmatrix}$$

Check that this matrix is rank 2 with $\lambda_1 = \frac{p+q}{2}$, $\lambda_2 = \frac{p-q}{2}$,

$$u_1 = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \quad \text{and} \quad u_2 = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ -1 \end{bmatrix} \Bigg\}^{n/2}$$

Key Insight: Thus, if A is close to $\mathbb{E} A$ we could use its second eigen vector to identify the communities.