

# ADVANCED ALGORITHM DESIGN

## Homework 3

December 4, 2024

### Problem 1

- (a) Let  $A, B$  be symmetric, real matrices with eigenvalues  $\lambda_1(A) \geq \lambda_2(A) \geq \dots \geq \lambda_n(A)$  (and similarly for  $B$ ). Prove that for every  $k$ ,  $\lambda_k(A) + \lambda_n(B) \leq \lambda_k(A+B) \leq \lambda_k(A) + \lambda_1(B)$ . Use this claim to establish that  $|\lambda_k(A+B) - \lambda_k(A)| \leq \max\{\lambda_1(B), |\lambda_n(B)|\}$ .
- (b) Let  $A$  be the adjacency matrix of a not necessarily regular graph  $G$  with  $m$  edges and  $n$  vertices with eigenvalues  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$ . Prove that  $\lambda_1 \geq 2m/n$ .

### Solution

- (a) Recall from the Courant-Fisher theorem that  $\lambda_k(M) = \max_{\substack{S \subseteq \mathbb{R}^n \\ \dim S = k}} \min_{\mathbf{x} \in S \setminus \{0\}} \frac{\mathbf{x}^\top M \mathbf{x}}{\|\mathbf{x}\|_2^2}$  for any symmetric

real symmetric matrix  $M$ . Define  $f_M(\mathbf{x}) := \frac{\mathbf{x}^\top M \mathbf{x}}{\|\mathbf{x}\|_2^2}$  (where  $\lambda_i$  means as usual). In particular,  $\lambda_1(M) \geq \mathbf{f}_M(\mathbf{x}) \geq \lambda_n(M)$ . Note that  $f_{A+B}(\mathbf{x}) = f_A(\mathbf{x}) + f_B(\mathbf{x})$ . Therefore,  $f_A(\mathbf{x}) + \lambda_1(B) \geq f_{A+B}(\mathbf{x}) \geq f_A(\mathbf{x}) + \lambda_n(B)$ . Taking max min with appropriate constraints preserves inequalities, whence  $\lambda_k(A) + \lambda_1(B) \geq \lambda_k(A+B) \geq \lambda_k(A) + \lambda_n(B)$ .

This gives  $\lambda_1(B) \geq \lambda_k(A+B) - \lambda_k(A) \geq \lambda_n(B)$ .

- If  $\lambda_n(B) \geq 0$  then  $|\lambda_k(A+B) - \lambda_k(A)| = \lambda_k(A+B) - \lambda_k(A) \leq \lambda_1(B) \leq \max\{\lambda_1(B), |\lambda_n(B)|\}$ .
- If  $\lambda_1(B) \geq 0 > \lambda_n(B)$  then  $|\lambda_k(A+B) - \lambda_k(A)| = \max\{\lambda_k(A+B) - \lambda_k(A), \lambda_k(A) - \lambda_k(A+B)\} \leq \max\{\lambda_1(B), -\lambda_n(B)\} = \max\{\lambda_1(B), |\lambda_n(B)|\}$ .
- If  $0 > \lambda_1(B)$  then  $|\lambda_k(A+B) - \lambda_k(A)| = \lambda_k(A) - \lambda_k(A+B) \leq -\lambda_n(B) \leq \max\{\lambda_1(B), |\lambda_n(B)|\}$ .

- (b)  $\lambda_1(A) \stackrel{\text{Courant-Fisher}}{=} \max_{\mathbf{x} \neq 0} \frac{\mathbf{x}^\top A \mathbf{x}}{\|\mathbf{x}\|_2^2} \geq \left( \frac{\mathbf{x}^\top A \mathbf{x}}{\|\mathbf{x}\|_2^2} \right)_{\mathbf{x}=\mathbf{1}} = \frac{\sum_{1 \leq i, j \leq n} A_{ij}}{(\sqrt{n})^2} = \frac{2m}{n}$  where  $\mathbf{1} \in \mathbb{R}^n$  has all 1's.

## Problem 2

Let  $R$  be a random symmetric matrix with uniformly random  $\pm 1$  entries. In this problem, for any  $\varepsilon \in (0, 1)$ , let  $S_\varepsilon$  be a finite set of  $N_\varepsilon$  unit vectors in  $\mathbb{R}^n$  such that for every unit vector  $u \in \mathbb{R}^n$ , there is a vector  $u' \in S$  such that  $\|u - u'\|_2 \leq \varepsilon$ .

- Prove that for every unit vector  $u$  and  $t \geq 0$ ,  $\mathbb{P}[|u^\top R u| \geq t] \leq 2 \exp \left\{ \frac{-t^2}{2} \right\}$ .
- Prove that  $\mathbb{P}[\exists u \in S_\varepsilon \text{ s.t. } |u^\top R u| \geq t] \leq 2N_\varepsilon \exp \left\{ \frac{-t^2}{2} \right\}$ .
- Prove that for every unit vector  $u$ , and any  $\pm 1$ -entry matrix  $B$ ,  $|u^\top B u| \leq n^C$  for some  $C > 0$ . What's the smallest  $C$  for which you can establish this claim?
- In this part, you can assume without proof that for every  $\varepsilon > 0$ , there is an  $S_\varepsilon$  of size  $N_\varepsilon \leq \left(\frac{c}{\varepsilon}\right)^n$ . Using this and the results of the previous parts, argue that  $\mathbb{P}[\|R\|_2 \geq \mathcal{O}(\sqrt{n \log n})] \leq \frac{1}{n}$ .
- (Extra credit) Prove the assumption in part (d). That is, prove that there is an  $S_\varepsilon$  as described in part (2) of size  $(c/\varepsilon)^n$  for some  $c > 0$ .

## Solution

- Note that  $u^\top R u = \sum_{1 \leq i, j \leq n} R_{ij} u_i u_j$ . We will use Höfdding bound<sup>1</sup> with the  $n^2$  random variables  $X_{ij} := R_{ij} u_i u_j$ . Note that  $|X_{ij}| = |u_i u_j|$  because  $R_{ij} \in \{\pm 1\}$ . So  $X_{ij} \in [a_{ij}, b_{ij}]$  where  $a_{ij} := -|u_i u_j|$ ,  $b_{ij} := |u_i u_j|$ . The denominator in the exponential of our Höfdding bound becomes  $\sum_{1 \leq i, j \leq n} (b_{ij} - a_{ij})^2 = \sum_{1 \leq i, j \leq n} 4u_i^2 u_j^2 = 4 \sum_i u_i^2 \sum_j u_j^2 = 4$  because  $\|u\|_2^2 = 1$ . Noting that  $\sum_{i,j} \mathbb{E}[X_{ij}] = \sum_{i,j} u_i u_j \mathbb{E}[R_{ij}] = 0$  we get,
 
$$\mathbb{P}[|u^\top R u| \leq t] = \mathbb{P}\left[\left|\sum_{i,j} X_{ij}\right| \leq t\right] \leq 2 \exp \left\{ \frac{-2t^2}{\sum_{1 \leq i, j \leq n} (b_{ij} - a_{ij})^2} \right\} = 2 \exp \left\{ \frac{-2t^2}{4} \right\} = 2 \exp \left\{ \frac{-t^2}{2} \right\}.$$
- Let the  $(N =) N_\varepsilon$  vectors in  $S_\varepsilon$  be  $u_1, \dots, u_N$ . Then  $\mathbb{P}[\exists u \in S_\varepsilon \text{ s.t. } |u^\top R u| \geq t] = \mathbb{P}\left[\bigcup_{u \in S_\varepsilon} \{|u^\top R u| \geq t\}\right] \stackrel{\text{union bound}}{\leq} \sum_{u \in S_\varepsilon} \mathbb{P}[|u^\top R u| \geq t] \leq \sum_{u \in S_\varepsilon} 2 \exp \left\{ \frac{-t^2}{2} \right\} = 2N_\varepsilon \exp \left\{ \frac{-t^2}{2} \right\}.$
- Recall that for any  $x \in \mathbb{R}^n$  we have  $\|x\|_1 \leq \sqrt{n} \|x\|_2$ . If  $B \in \{\pm 1\}^{n \times n}$  and  $u \in \mathbb{R}^n$  has  $\|u\|_2 = 1$  then  $|u^\top B u| = \left| \sum_{i,j \in [n]} B_{ij} u_i u_j \right| \leq \sum_{i,j \in [n]} |B_{ij} u_i u_j| = \sum_i |u_i| \sum_j |u_j| = \|u\|_1^2 \leq n \|u\|_2^2 = n^1$ . So  $C = 1$  works.  
We will show that this is the best  $C$  (by showing that  $C = 1$  is attained). This is because when  $B = \mathbf{1}\mathbf{1}^\top$  (which is the matrix of all 1) and  $u = \frac{1}{\sqrt{n}}$  (which is the vector with each entry  $1/\sqrt{n}$ ) then  $\|u\|_2 = n \cdot \frac{1}{n} = 1$  and  $|u^\top B u| = \left| \sum_{i,j} u_i u_j \right| = n^2 \cdot \frac{1}{n} = n$ .

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<sup>1</sup>If  $X_1, \dots, X_n$  are independent with  $X_i \in [a_i, b_i]$  then  $\mathbb{P}\left[\sum_{i \in [n]} (X_i - \mathbb{E}[X_i])\right] \leq 2 \exp \left\{ \frac{-2t^2}{\sum_{i \in [n]} (b_i - a_i)^2} \right\}$

(d) Let  $\mathbb{S}^{n-1}$  be the collection of all unit vectors in  $\mathbb{R}^n$ .

**Lemma 1**

$$\frac{\max_{\mathbf{u} \in S_\varepsilon} |\mathbf{u}^\top R \mathbf{u}|}{1 - 2\varepsilon} \geq \max_{\mathbf{u} \in \mathbb{S}^{n-1}} |\mathbf{u}^\top R \mathbf{u}| = \|R\|_2.$$

*Proof.* Say  $\mathbf{x} \in \mathbb{S}^{n-1}$  is an eigenvector for the largest (in magnitude) eigenvalue of  $R$ . Let this eigenvalue be  $\lambda$ . So  $\|R\|_2 = |\lambda|$ . But  $\exists \mathbf{y} \in S_\varepsilon$  such that  $\|\mathbf{y} - \mathbf{x}\|_2 \leq \varepsilon$ . Then  $|\mathbf{x}^\top R \mathbf{x} - \mathbf{y}^\top R \mathbf{y}| = |\mathbf{x}^\top R(\mathbf{x} - \mathbf{y}) - (\mathbf{y} - \mathbf{x})^\top R \mathbf{y}| \leq |\mathbf{x}^\top R(\mathbf{x} - \mathbf{y})| + |(\mathbf{y} - \mathbf{x})^\top R \mathbf{y}| \leq \|\mathbf{x} - \mathbf{y}\|_2 \|R\|_2 (\|\mathbf{x}\|_2 + \|\mathbf{y}\|_2) = 2\|R\|_2 \|\mathbf{x} - \mathbf{y}\|_2 = 2\varepsilon |\lambda|$ .

Thus  $\max_{\mathbf{u} \in S_\varepsilon} |\mathbf{u}^\top R \mathbf{u}| \geq |\mathbf{y}^\top R \mathbf{y}| \geq |\mathbf{x}^\top R \mathbf{x}| - |\mathbf{x}^\top R \mathbf{x} - \mathbf{y}^\top R \mathbf{y}| \geq |\lambda| - 2\varepsilon |\lambda| = |\lambda| (1 - 2\varepsilon)$ .  $\blacksquare$

Then  $\mathbb{P}[\|R\|_2 \geq t] \leq \mathbb{P}\left[\frac{\max_{\mathbf{u} \in S_\varepsilon} |\mathbf{u}^\top R \mathbf{u}|}{1 - 2\varepsilon} \geq t\right] = \mathbb{P}\left[\max_{\mathbf{u} \in S_\varepsilon} |\mathbf{u}^\top R \mathbf{u}| \geq t(1 - 2\varepsilon)\right] =$   
 $\mathbb{P}\left[\exists \mathbf{u} \in S_\varepsilon \text{ s.t. } |\mathbf{u}^\top R \mathbf{u}| \geq t(1 - 2\varepsilon)\right] \stackrel{(b)}{\leq} 2N_\varepsilon \exp\left\{\frac{-t^2(1 - 2\varepsilon)^2}{2}\right\} \leq 2\left(\frac{c}{\varepsilon}\right)^n \exp\left\{\frac{-t^2(1 - 2\varepsilon)^2}{2}\right\}$   
 where the first inequality is true because it's more probable for a larger quantity to be  $\geq t$ . Take  $\varepsilon = \frac{\log n}{n}$  so that  $1 - 2\varepsilon \geq \frac{1}{2}$  for large  $n$ . Take  $t = \alpha\sqrt{n \log n}$ . Then  $2\left(\frac{c}{\varepsilon}\right)^n \exp\left\{\frac{-t^2(1 - 2\varepsilon)^2}{2}\right\} \leq$   
 $2\left(\frac{cn}{\log n}\right)^n \exp\left\{\frac{-\alpha^2 n \log n}{8}\right\} = 2\left(\frac{cn}{\log n}\right)^n n^{\frac{-\alpha^2 n}{8}} = 2\left(\frac{c}{n^{\frac{\alpha^2}{8} - 1} \log n}\right)^n \leq \frac{1}{n}$  by choosing large constant  $\alpha$ .

(e) Consider the following algorithm for any given input  $\varepsilon > 0$  to find a set  $S_\varepsilon \subseteq \mathbb{S}^{n-1}$ .

**Input:**  $\varepsilon > 0$ , dimension  $n$

**Output:** a number  $N$  and points  $\mathbf{v}_1, \dots, \mathbf{v}_N \in \mathbb{S}^{n-1}$  such that every point in  $\mathbb{S}^{n-1}$  is  $\varepsilon$ -close to some  $\mathbf{v}_i$ .

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1: begin
2:    $N \leftarrow 1$ 
3:    $\mathbf{v}_1 \leftarrow (1, 0, \dots, 0) \in \mathbb{R}^n$ 
4:    $S \leftarrow B_\varepsilon^o(\mathbf{v}_1) \cap \mathbb{S}^{n-1}$   $\triangleright$  points in  $\mathbb{S}^{n-1}$  which are at distance  $< \varepsilon$  from  $\mathbf{v}_1$ 
5:   while  $N \geq 1$  do
6:      $\mathbf{v}_N \leftarrow$  any point in  $\mathbb{S}^{n-1} \setminus S$ 
7:      $S \leftarrow S \cup (B_\varepsilon(\mathbf{v}_2) \cap \mathbb{S}^{n-1})$ 
8:     if  $S = \mathbb{S}^{n-1}$  then  $\triangleright$  check if  $\mathbb{S}^{n-1}$  has been covered
9:       break
10:    else
11:       $N \leftarrow N + 1$ 
12:    end if
13:  end while
14:  return  $N, S_\varepsilon = \{\mathbf{v}_1, \dots, \mathbf{v}_N\}$ 
15: end

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Now we prove that this algorithm actually gives  $S_\varepsilon$  and  $N_\varepsilon$  as desired. In what follows,  $B, B^o$

will respectively denote closed and open balls.

If the above algorithm terminates with answer  $N, S_\varepsilon$ , then  $\mathbb{S}^{n-1} \subseteq \bigcup_{i=1}^N B_\varepsilon^o(\mathbf{v}_i) \subseteq \bigcup_{i=1}^N B_\varepsilon(\mathbf{v}_i)$ .

### Claim 2

The above algorithm terminates.

*Proof.* Suppose the algorithm goes on forever. So we get a sequence of points  $\mathbf{v}_1, \mathbf{v}_2, \dots$  such that  $\mathbb{S}^{n-1} \subseteq \bigcup_{i \in \mathbb{N}} B_\varepsilon^o(\mathbf{v}_i)$ . Since  $\mathbb{S}^{n-1}$  is compact there is a finite  $N$  such that  $\mathbb{S}^{n-1} \subseteq \bigcup_{i=1}^N B_\varepsilon^o(\mathbf{v}_i)$ . This is a contradiction to our original assumption. ■

Next we note that just by how our algorithm is designed, if  $\mathbf{x}, \mathbf{y} \in S_\varepsilon$  then  $\|\mathbf{x} - \mathbf{y}\|_2 \geq \varepsilon$ . This is because a new point (line 6) is always chosen so that it is not in the  $\varepsilon$ -ball around any of the previously chosen points, and distance is symmetric.

Further  $S_\varepsilon$  is maximal in the sense that if  $S' \supsetneq S_\varepsilon$  is a collection of points in  $\mathbb{S}^{n-1}$ , there will be two points in  $S'$  which are at most  $\varepsilon$ -close to each other. This is by our breaking criterion on line 8. Simply put,  $S_\varepsilon$  covers  $\mathbb{S}^{n-1}$  with  $\varepsilon$ -balls.

### Claim 3

If  $\mathbf{x}, \mathbf{y} \in S_\varepsilon$  are distinct, then  $B_{\frac{\varepsilon}{2}}^o(\mathbf{x}) \cap B_{\frac{\varepsilon}{2}}^o(\mathbf{y}) \cap \mathbb{S}^{n-1} = \emptyset$ .

*Proof.* Suppose  $\mathbf{p} \in \mathbb{S}^{n-1} \cap B_{\frac{\varepsilon}{2}}^o(\mathbf{x}) \cap B_{\frac{\varepsilon}{2}}^o(\mathbf{y})$  and say  $\mathbf{y}$  was picked after  $\mathbf{x}$  in the algorithm. Then  $\|\mathbf{x} - \mathbf{y}\|_2 \leq \|\mathbf{x} - \mathbf{p}\|_2 + \|\mathbf{p} - \mathbf{y}\|_2 \leq \varepsilon$ . Moreover equality here occurs only when  $\|\mathbf{p} - \mathbf{x}\|_2 = \|\mathbf{p} - \mathbf{y}\|_2 = \frac{\varepsilon}{2}$  which means  $\mathbf{p} \notin B_{\frac{\varepsilon}{2}}^o(\mathbf{x})$  which is a contradiction. So it must happen that  $\|\mathbf{x} - \mathbf{y}\|_2 < \varepsilon$  which contradicts the constructive step in line 6 because this indicated that  $\mathbf{y}$  was picked in the  $\varepsilon$ -ball around  $\mathbf{x}$ . ■

### Claim 4

If  $\mathbf{x} \in \bigcup_{i \in [N]} B_\varepsilon(\mathbf{v}_i) \subseteq \mathbb{R}^n$  then  $\|\mathbf{x}\|_2 \leq 1 + \frac{\varepsilon}{2}$ .

*Proof.* Say  $\mathbf{x} \in B_\varepsilon(\mathbf{v}_i)$  for some  $i$ . Then  $\|\mathbf{x}\|_2 \leq \|\mathbf{v}_i\|_2 + \|\mathbf{x} - \mathbf{v}_i\|_2 \leq 1 + \varepsilon$ . ■

Denote  $V_n := \text{vol}(\mathbb{D}^n)$ ,  $A_n := \text{area}(\mathbb{S}^{n-1})$ . These are respectively the  $n$ -dimensional volume of  $D^n$  (the solid unit ball with  $\mathbb{S}^{n-1} = \partial \mathbb{D}^n$ ) and the  $(n-1)$ -dimensional volume (area) of  $\mathbb{S}^{n-1}$ . By claim 4,  $\bigcup_{i \in [N]} B_\varepsilon(\mathbf{v}_i) \subseteq \mathbb{R}^n \subseteq B_{1+\frac{\varepsilon}{2}}(0)$ .  $\text{vol}(B_{1+\frac{\varepsilon}{2}}(0)) = (1 + \frac{\varepsilon}{2})^n V_n$ . So

$\text{vol}\left(\bigcup_{i \in [N]} B_\varepsilon(\mathbf{v}_i)\right) \leq V_n (1 + \frac{\varepsilon}{2})^n$ . Claim 3 says the above union is almost disjoint (the intersections form a set of measure 0). Hence  $\text{vol}\left(\bigcup_{i \in [N]} B_\varepsilon(\mathbf{v}_i)\right) = \sum_{i=1}^N \text{vol}(B_\varepsilon(\mathbf{v}_i)) = \sum_{i=1}^N \varepsilon^n V(n) = NV_n \varepsilon^n$ . These prove that  $N \varepsilon^n \leq (1 + \frac{\varepsilon}{2})^n \implies N \leq (\frac{1}{\varepsilon} + \frac{1}{2})^n = \left(\frac{(2+\varepsilon)/2}{\varepsilon}\right)^n \leq \left(\frac{2}{\varepsilon}\right)^n$ .

### Problem 3

Let  $G$  be a graph on  $n$  vertices ( $n$  is even) chosen as follows:

1. Pick an arbitrary  $S$  of size  $n/2$ ,
2. For each pair  $i, j$  of vertices such that  $i, j \in S$  or  $i, j \notin S$ , include  $\{i, j\}$  in  $G$  with probability  $p$ ,
3. For each pair  $i, j$  such that  $i \in S, j \notin S$  or  $i \notin S, j \in S$ , include  $\{i, j\}$  in  $G$  with probability  $q$ .

Suppose that  $p - q > c$  for some fixed constant  $c > 0$ .

Consider the following algorithm:

1. pick a vertex  $v$ ,
2. Output  $\hat{S}$  obtained by including in  $\hat{S}$  the  $n/2$  vertices that have the fewest common neighbors with  $v$ .

Prove that for large  $n$ , with probability at least 0.99 over the draw of  $G$ ,  $\hat{S}$  either equals  $S$  or  $V \setminus S$ .

### Solution

For any vertex  $v$  in  $G = (V = [n], E)$ , denote by  $N(v)$  the neighbors of  $v$  in  $G$ . Say  $n = 2k$ . Denote  $T := V \setminus S$ . Then  $|T| = |S| = k$ . Let's proceed as the hint suggests.

Assume  $v \in S$  WLOG (otherwise replace  $S$  with  $T$ ). Let  $u$  be an arbitrary vertex. Denote  $X_u := |N(u) \cap N(v)|$ . Note that  $X_u = \sum_{x \in V} \mathbf{1}[x \in N(u) \cap N(v)] = \sum_{x \in V} \mathbf{1}_{x \in N(u)} \cdot \mathbf{1}_{x \in N(v)}$  because the events  $\{x \in N(u)\}, \{x \in N(v)\}$  are independent. This can be further split as  $X_u = \sum_{x \in S \setminus \{u, v\}} \mathbf{1}_{x \in N(u)} \cdot \mathbf{1}_{x \in N(v)} + \sum_{x \in T \setminus \{u, v\}} \mathbf{1}_{x \in N(u)} \cdot \mathbf{1}_{x \in N(v)} \implies \mathbb{E}[X_u] = \sum_{x \in S \setminus \{u, v\}} \mathbb{P}[x \in N(u)] \cdot \mathbb{P}[x \in N(v)] + \sum_{x \in T \setminus \{u, v\}} \mathbb{P}[x \in N(u)] \cdot \mathbb{P}[x \in N(v)] = p \sum_{x \in S \setminus \{u, v\}} \mathbb{P}[x \in N(u)] + q \sum_{x \in T \setminus \{u, v\}} \mathbb{P}[x \in N(u)]$ .

- Say  $u \in S$ . Then  $\mathbb{E}[X_u] = (k-2)p^2 + kq^2$ .
- Say  $u \in T$ . Then  $\mathbb{E}[X_u] = (k-1)pq + (k-1)pq = 2(k-1)pq$ .

Denote  $b := (k-2)p^2 + kq^2$  and  $a := 2(k-1)pq$ . One observes that  $d := b - a = (k-1)(p-q)^2 + q^2 - p^2$ . It is important to note that  $b \leq k(p^2 + q^2) \leq 2k$  and  $d \geq (k-1)c^2$ .

So far we learnt that, in expectation, vertices in  $S$  has higher number of common neighbors with  $v$  than those in  $T$ . So if  $X_i$ 's are well concentrated in  $(t, \infty)$  for  $i \in S$ , and  $X_j$ 's are well concentrated in  $(-\infty, t)$  where  $t \in (a, b)$  (where  $t \in (a, b)$ ) then  $X_i \geq X_j \forall i \in S, j \in T$ . So  $\hat{S}$  would be  $T$ .

For  $i \in S \setminus \{v\}$  let  $A_i$  be the event  $\{X_i \leq t\}$ . For  $j \in T$  let  $B_j$  be the event  $\{X_j \geq t\}$ . We are interested in the event  $E := \left( \bigcup_{i \in S \setminus \{v\}} A_i \right) \cup \left( \bigcup_{j \in T} B_j \right)$ . But  $\mathbb{P}[E] = \sum_{i \in S \setminus \{v\}} \mathbb{P}[A_i] + \sum_{j \in T} \mathbb{P}[B_j] = \sum_{i \in S \setminus \{v\}} \mathbb{P}[A_i] + \sum_{j \in T} \mathbb{P}[B_j]$ .

We will take  $t = \frac{a+b}{2}$  so that  $t = b(1 - \frac{b-a}{2b}) = a(1 + \frac{b-a}{2a})$ . Recall the lower and upper tail Chernoff bounds for a random variable  $X$  which is a sum of (finitely many) independent 0/1 random variables:

- $\mathbb{P}[X \leq \mathbb{E}[X](1 - \varepsilon)] \leq \exp\left\{-\frac{\varepsilon^2 \mathbb{E}[X]}{2}\right\}$ . Using this for  $A_i$  (with  $i \in S$ ) gives

$$\begin{aligned} \mathbb{P}[A_i] &= \mathbb{P}\left[X_i \leq \frac{a+b}{2}\right] = \mathbb{P}\left[X_i \leq b\left(1 - \frac{b-a}{2b}\right)\right] \\ &\leq \exp\left\{-\frac{(b-a)^2}{8b}\right\} = \exp\left\{-\frac{d^2}{8b}\right\} \leq \exp\left\{-\frac{d^2}{12b}\right\} \\ &\leq \exp\left\{-\frac{(k-1)^2 c^4}{12 \cdot 2k}\right\} \stackrel{\cdot k \geq 2 \Rightarrow k-1 \geq \frac{2k}{3}}{\leq} \exp\left\{-\frac{c^4 k}{54}\right\}. \end{aligned}$$

- $\mathbb{P}[X \geq \mathbb{E}[X](1 + \varepsilon)] \leq \exp\left\{-\frac{\varepsilon^2 \mathbb{E}[X]}{3(1+\varepsilon)}\right\}$ . Using this for  $B_j$  (with  $j \in T$ ) gives

$$\begin{aligned} \mathbb{P}[B_j] &= \mathbb{P}\left[X_i \geq \frac{a+b}{2}\right] = \mathbb{P}\left[X_i \leq a\left(1 + \frac{b-a}{2a}\right)\right] \\ &\leq \exp\left\{-\frac{(b-a)^2}{6(a+b)}\right\} \leq \exp\left\{-\frac{d^2}{12b}\right\} \\ &\leq \exp\left\{-\frac{(k-1)^2 c^4}{16 \cdot 2k}\right\} \stackrel{\cdot k \geq 2 \Rightarrow k-1 \geq \frac{2k}{3}}{\leq} \exp\left\{-\frac{c^4 k}{54}\right\}. \end{aligned}$$

Therefore  $\mathbb{P}[E] \leq (n-1) \exp\left\{-\frac{c^4 n}{108}\right\} \leq n \exp\left\{-\frac{c^4 n}{108}\right\}$ . Let  $C := \frac{c^4}{108}$ . We recall that  $e^x \geq 1 + x + x^2/2$  for  $x \geq 0$ . Hence  $e^{-x} \leq \frac{1}{1+x+x^2/2}$  on  $\mathbb{R}_{\geq 0}$ . Taking  $x = Cn > 0$  and  $n > \frac{200}{C^2}$  gives  $n \exp\{-Cn\} \leq \frac{n}{1+nC+n^2C^2/2} = \frac{1}{\frac{1}{n}+C+nC^2/2} \stackrel{[\cdot \frac{1}{n}+C>0]}{<} \frac{1}{nC^2/2} \frac{1}{100} = 0.01$ , whence  $\mathbb{P}[E^c] \geq 0.99$ . Recall that  $A_i^c$  (for  $i \in S$ ) was the event that the number of common neighbors of  $i, v$  is  $> \frac{a+b}{2}$ ,  $B_j^c$  (for  $j \in T$ ) was the event that the number of common neighbors of  $j, v$  is  $< \frac{a+b}{2}$ . So  $E^c$  is the event that every vertex in  $S$  has  $> \frac{a+b}{2}$  common neighbors with  $v$  and every vertex in  $T$  has  $< \frac{a+b}{2}$  common neighbors with  $v$ , hence it's a special case with  $\hat{S} = T$  which is a subset of the event that we are interested in. Therefore the chance that, over the draw of  $G$ , the  $n/2$  vertices with fewest common neighbors of  $v$  is at least  $\mathbb{P}[E^c] \geq 0.99$ .

## Problem 4

In the class, we saw that we can distinguish between a graph  $G \sim G(n, 1/2)$  and  $G \sim G(n, 1/2, k)$  (i.e.,  $G \sim G(n, 1/2)$  with an added  $k$ -clique) in polynomial time if  $k \geq c\sqrt{n}$  for some  $c > 0$ .

Find an algorithm that for any  $t \in \mathbb{N}$ , runs in time  $n^{\mathcal{O}(t)}$  and succeeds in the same goal for  $k \geq \sqrt{n/2^t}$ . (Hint: suppose you were given, in addition, a set  $S$  of  $t$  vertices in the planted clique if there was one. Can you now reduce the problem to graphs on a smaller number of vertices?)

## Solution

Let's first present the algorithm to the input graph  $G = (V = [n], E)$  which is as follows. We loop through all  $\binom{n}{t+1+z} = n^{\mathcal{O}(t)}$  subsets of  $V$  which are of size  $s := t+1+z$  and form a clique. For each such subset  $S \subseteq V$ , take the vertices in  $V$  connected to every vertex in  $S$  and call it  $\mathcal{N}_S$  and take  $\mathcal{A}_S$  to be the  $\pm 1$ -adjacency matrix of the subgraph of  $G$  induced by  $\mathcal{N}_S$ . We declare that " $G$  has a  $k$ -planted clique" if  $\|\mathcal{A}_S\|_2 > C\sqrt{|\mathcal{N}_S|}$  (this is the algorithm discussed in class). If this fails for every such subset  $S$ , we declare that there is "no planted clique".

In the above, we do  $n^{\mathcal{O}(1)}$  (where the  $\mathcal{O}$  is with respect to  $t$ ) computations per  $S \subseteq V$  of size  $t$ . The number of loops is  $n^{\mathcal{O}(t)}$  and checking if  $S$  forms a clique takes time of order  $t^2 < n^2$ . So the total running time of the above algorithm is  $n^{\mathcal{O}(t)}$ .

Let's now analyze why this algorithm works.

Let's first do the analysis assuming that the graph  $G = (V = [n], E)$  has a  $t$ -clique  $S \subseteq V$ . Now let's look at all those vertices in  $V \setminus S$  which are connected to each vertex in  $S$  and call it  $\mathcal{N} = \mathcal{N}_S$ . Let  $\mathbf{1}_{v \in \mathcal{N}}$  be the indicator variable that is 1 if  $v \in \mathcal{N}$ , and 0 otherwise. So  $|\mathcal{N}| = \sum_{v \in V \setminus S} \mathbf{1}_{v \in \mathcal{N}}$ . Now

$$\mathbb{E}[|\mathcal{N}|] = \sum_{v \in V \setminus S} \mathbb{E}[\mathbf{1}_{v \in \mathcal{N}}] = \sum_{v \in V \setminus S} \mathbb{P}[v \in \mathcal{N}] = (1 + o(1)) \frac{n-t}{2^t}.$$

We will see that the size of  $\mathcal{N}$  is well-concentrated around its mean. Note that  $\mathbf{1}_{v \in \mathcal{N}}$  (for  $v \in V \setminus S$ ) are all independent. Chernoff gives  $\mathbb{P}[|\mathcal{N}| \geq 2\mathbb{E}[|\mathcal{N}|]] \leq \exp\{-\mathcal{O}(\frac{n-t}{2^t})\}$ . So we can take  $|\mathcal{N}| = \frac{2n}{2^t}$  with probability exponentially (in  $n$ ) close to 1.

Recall that in class we have a constant  $C$  from lemma 2 in lecture 19 (second last page). Let  $z \in \mathbb{N}$  be such that  $2^z > C$ .

- Say  $G \sim G_{n, \frac{1}{2}, k}$ . Then the algorithm reaches some  $(t+1+z)$ -clique  $S$  for which  $\mathcal{N}_S$  contains a  $(k-s)$ -clique (recall  $s = t+1+z$ ). But  $k-s > \sqrt{\frac{n}{2^t}} - s > 2C\sqrt{\frac{2(n-s)}{2^s}} = 2C\sqrt{|\mathcal{N}_S|}$  with probability  $1 - \exp\{-\mathcal{O}(\frac{n-s}{2^s})\}$ . Therefore the failure chance in this case is inverse exponential in  $n$ .
- Say  $G \sim G_{n, \frac{1}{2}}$ . The chance that we get some  $S$  such that  $|\mathcal{N}_S|$  is  $> \frac{2n}{2^s}$  is inverse-exponential in  $\frac{n}{2^s}$ . Among the small  $|\mathcal{N}_S|$ 's, the success probability of the algorithm discussed in class is large because  $k-s \geq 2C\sqrt{|\mathcal{N}_S|}$ . By the lemma given on Ed discussion,  $\mathbb{P}[\mathcal{A}_S \leq C\sqrt{|\mathcal{N}_S|}] \leq C'' \exp\{-C'n/2^s\}$ . Therefore the chance that some  $S$  gives  $\|\mathcal{A}_S\|_2 > C\sqrt{|\mathcal{N}_S|}$  is (by union bound)  $\leq C'' \binom{n}{s} \exp\{-C'n/2^s\}$ .