

Extremal and Probabilistic Graph Theory
Lecture 14
April 19th, Tuesday

Recall (*Erdős – Gallai*).

$$ex(n, \{C_{t+1}, C_{t+2}, \dots\}) \leq \frac{t(n-1)}{2}.$$

Definition 14.1 A walk of length k in a graph G is an alternating sequence $(v_0, e_1, v_1, \dots, v_{k-1}, e_k, v_k)$ where $v_i \in V(G)$ and $e_i = \{v_{i-1}, v_i\} \in E(G)$.

Note. In this definition, a walk is an **ordered** sequence.

Definition 14.2 A walk is non-backtracking if $e_i \neq e_{i+1}, 1 \leq i \leq k-1$.

Definition 14.3 Let $A = (a_{ij})_{n \times n}$ be the adjacency matrix of the graph G s.t

$$a_{ij} = \begin{cases} 1 & \text{if } ij \in E(G), \\ 0 & \text{otherwise.} \end{cases}$$

Fact. For $u, v \in V(G)$ and the adjacency matrix A of G , $(A^k)_{uv}$ is the number of walks from u to v of length k in G .

Proof. Exercise (Hint: matrix multiplication and induction). ■

Notation 14.4 For $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n x_i y_i$.

Theorem 14.5 Let A be a symmetric matrix and let \mathbf{x} be a unit vector of \mathbb{R}^n s.t all entries of A and \mathbf{x} are non-negative, then $\langle A^k \mathbf{x}, \mathbf{x} \rangle \geq \langle A \mathbf{x}, \mathbf{x} \rangle^k$.

Proof. Since A is symmetric, there exists a matrix X s.t $D = X^{-1}AX = \text{diag}(\lambda_1, \dots, \lambda_n)$ where λ_i is the eigenvalue of A and X consists of the eigenvectors X_1, \dots, X_n which form an orthonormal basis of \mathbb{R}^n . So $AX_i = \lambda_i X_i$. Let $\mathbf{x} = \sum_{i=1}^n a_i X_i$, where $\sum_{i=1}^n a_i^2 = 1$. Then $\langle A \mathbf{x}, \mathbf{x} \rangle = \sum_{i=1}^n \lambda_i a_i^2$. Since $A = XDX^{-1}$, we have $A^k = XD^k X^{-1}$ and $\langle A^k \mathbf{x}, \mathbf{x} \rangle = \sum_{i=1}^n \lambda_i^k a_i^2$. By Jensen's inequality ($f(x) = x^k$ is convex),

$$\langle A^k \mathbf{x}, \mathbf{x} \rangle = \sum_{i=1}^n \lambda_i^k a_i^2 \geq \left(\sum_{i=1}^n \lambda_i a_i^2 \right)^k = \langle A \mathbf{x}, \mathbf{x} \rangle^k.$$

Note. This proof only works when k is even as some λ_i^k may be negative when k is odd.

Case 1. \mathbf{x} has a zero entry.

Without losing generality, say $x_1 = 0$. Let $\mathbf{y} \in \mathbb{R}^{n-1}$ be obtained from \mathbf{x} by deleting x_1 , and let $B \in \mathbb{R}^{(n-1) \times (n-1)}$ be obtained from A by deleting the 1st row and 1st column. By induction on n , $\langle B^k \mathbf{y}, \mathbf{y} \rangle \geq \langle B \mathbf{y}, \mathbf{y} \rangle^k$. Note that $\langle A \mathbf{x}, \mathbf{x} \rangle = \langle B \mathbf{y}, \mathbf{y} \rangle$, and $\langle A^k \mathbf{x}, \mathbf{x} \rangle \geq \langle B^k \mathbf{y}, \mathbf{y} \rangle$ (A exercise from linear algebra). So

$$\langle A^k \mathbf{x}, \mathbf{x} \rangle \geq \langle B^k \mathbf{y}, \mathbf{y} \rangle \geq \langle B \mathbf{y}, \mathbf{y} \rangle^k = \langle A \mathbf{x}, \mathbf{x} \rangle^k.$$

Case 2. All entries of \mathbf{x} are positive.

By re-normalization, we may assume that the largest eigenvalue of A is $\lambda = 1$, with a non-negative unit eigenvector $\mathbf{z} \in \mathbb{R}^n$, i.e $A\mathbf{z} = \mathbf{z}$. (By *Perron – Frobenius* Theorem).

If \mathbf{x} is an eigenvector of A with $\lambda = 1$, then it is clear that

$$\langle A^k \mathbf{x}, \mathbf{x} \rangle = \langle \mathbf{x}, \mathbf{x} \rangle = 1 = \langle A\mathbf{x}, \mathbf{x} \rangle^k.$$

So we may assume that \mathbf{x} is not such a thing. Then there exist a unit vector $\mathbf{y} \in \mathbb{R}^n$ which is orthogonal to \mathbf{z} s.t $\mathbf{x} = \alpha\mathbf{z} + \beta\mathbf{y}$, with $\alpha^2 + \beta^2 = 1$, where $\alpha, \beta \geq 0$ (\mathbf{x}, \mathbf{z} are non-negative).

Claim 1. $\langle A\mathbf{y}, \mathbf{y} \rangle < 1$.

Proof. Suppose that $\langle A\mathbf{y}, \mathbf{y} \rangle = 1$. Then $\langle A\mathbf{x}, \mathbf{x} \rangle = \alpha^2 \langle A\mathbf{z}, \mathbf{z} \rangle + \beta^2 \langle A\mathbf{y}, \mathbf{y} \rangle = \alpha^2 + \beta^2 = 1$. But $\langle A\mathbf{x}, \mathbf{x} \rangle = \sum_{i=1}^n \lambda_i a_i^2 \leq \max\{\lambda_1, \dots, \lambda_n\} = 1$. This implies $\lambda = 1$, and \mathbf{x} is an eigenvector of $\lambda = 1$. This is a contradiction. ■

We can select a non-negative unit vector $\mathbf{w} \in \mathbb{R}^n$ s.t \mathbf{w} has a zero entry and $\mathbf{w} = \alpha'\mathbf{z} + \beta'\mathbf{y}$, where $0 \leq \alpha' \leq \alpha, 0 \leq \beta', \alpha'^2 + \beta'^2 = 1$. By Case 1, we have $\langle A^k \mathbf{w}, \mathbf{w} \rangle \geq \langle A\mathbf{w}, \mathbf{w} \rangle^k$.

Let $f : [0, 1] \rightarrow \mathbb{R}$ by

$$f(t) = 1 - t^k + \frac{\langle A^k \mathbf{y}, \mathbf{y} \rangle - 1}{\langle A\mathbf{y}, \mathbf{y} \rangle - 1} (t - 1).$$

Then $f'' \leq 0$, which means f is convex on $[0, 1]$. And $f(1) = 0$.

Claim 2. $f(\langle A\mathbf{x}, \mathbf{x} \rangle) = \langle A^k \mathbf{x}, \mathbf{x} \rangle - \langle A\mathbf{x}, \mathbf{x} \rangle^k$. Similarly, $f(\langle A\mathbf{w}, \mathbf{w} \rangle) = \langle A^k \mathbf{w}, \mathbf{w} \rangle - \langle A\mathbf{w}, \mathbf{w} \rangle^k$.

Proof. It is the same to verify

$$\frac{\langle A^k \mathbf{y}, \mathbf{y} \rangle - 1}{\langle A\mathbf{y}, \mathbf{y} \rangle - 1} = \frac{\langle A^k \mathbf{x}, \mathbf{x} \rangle - 1}{\langle A\mathbf{x}, \mathbf{x} \rangle - 1}.$$

Hint: $\langle A\mathbf{x}, \mathbf{x} \rangle = \alpha^2 \langle A\mathbf{z}, \mathbf{z} \rangle + \beta^2 \langle A\mathbf{y}, \mathbf{y} \rangle = 1 + \beta^2(\langle A\mathbf{y}, \mathbf{y} \rangle - 1)$. Similarly, $\langle A^k \mathbf{x}, \mathbf{x} \rangle = 1 + \beta^2(\langle A^k \mathbf{y}, \mathbf{y} \rangle - 1)$. ■

Claim 3. $\langle A\mathbf{w}, \mathbf{w} \rangle \leq \langle A\mathbf{x}, \mathbf{x} \rangle \leq 1$.

Proof. We have $\langle A\mathbf{x}, \mathbf{x} \rangle = 1 + \beta^2(\langle A\mathbf{y}, \mathbf{y} \rangle - 1)$. $\langle A\mathbf{w}, \mathbf{w} \rangle = 1 + \beta'^2(\langle A\mathbf{y}, \mathbf{y} \rangle - 1)$. Since $\beta^2 \leq \beta'^2$, by Claim 1, we can prove $\langle A\mathbf{w}, \mathbf{w} \rangle \leq \langle A\mathbf{x}, \mathbf{x} \rangle \leq 1$. ■

By Claim 2 and Claim 3 we have

$$\langle A^k \mathbf{x}, \mathbf{x} \rangle - \langle A\mathbf{x}, \mathbf{x} \rangle^k = f(\langle A\mathbf{x}, \mathbf{x} \rangle) \geq \min\{f(\langle A\mathbf{w}, \mathbf{w} \rangle), f(1) = 0\} \geq 0.$$

Now the proof of theorem 14.5 is finished. ■

Corollary 14.6 *A graph G of average degree d has at least nd^k walks of length k .*

Proof. Take A as the adjacency matrix of G , and $\mathbf{x} = \frac{1}{\sqrt{n}}\mathbf{1}$. By theorem 1, $\langle A^k \mathbf{x}, \mathbf{x} \rangle \geq \langle A\mathbf{x}, \mathbf{x} \rangle^k$. Here, $\langle A\mathbf{x}, \mathbf{x} \rangle = 2e/n = d$, and $\langle A^k \mathbf{x}, \mathbf{x} \rangle = \#\{k\text{-walks}\}/n$, this implies $\#\{k\text{-walks}\} \geq nd^k$. This is tight for any d -regular graphs (easy to verify). ■

Theorem 14.7 *Let G be a n -vertex graph with average degree d , where the smallest degree of vertices is at least 2 ($\delta(G) \geq 2$). Then G has at least $nd(d-1)^{k-1}$ non-backtracking walks of length k with equality iff G is a d -regular graph.*

Proof. In next lecture. ■

Here we introduce some definitions related to theorem 14.7.

Definition 14.8 Consider each edge $uv \in E(G)$ as a pair of directed edges \vec{uv} and \vec{vu} . Let A be a $nd \times nd$ matrix indexed by all directed edges.

$$(A)_{\vec{uv}, \vec{wz}} = \begin{cases} 1 & \text{if } u \neq z \text{ and } v = w, \\ 0 & \text{otherwise.} \end{cases}$$

Definition 14.9 Let P be defined by

$$(P)_{\vec{uv}, \vec{wz}} = \begin{cases} 1/(d(v) - 1) & \text{if } u \neq z \text{ and } v = w, \\ 0 & \text{otherwise.} \end{cases}$$

The matrix P is the transition matrix of a random walk. Let $\mathbf{x} = \frac{1}{nd} \mathbf{1} \in \mathbb{R}^{nd}$, then $\mathbf{x}P = \mathbf{x}$.

Definition 14.10 A non-backtracking random walk is defined as following: If at step t , the walk is at the edge \vec{uv} , then at step $t + 1$, we move to an edge \vec{vz} , where z is a random neighbor of v (but not u).