

Today

- Random Walk
- Hitting Set Lemma.
- Explicit Constructions

CSS. 413.1

Pseudorandomness

Lecture 10 (2021-9-23)

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Today - Random Walk on expanders

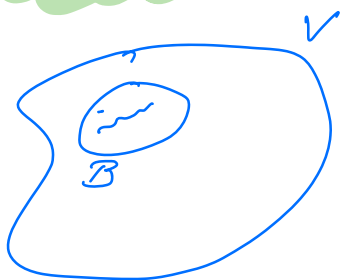
Hitting Set for Random walks on expanders

G - expander on N -vertices w/
spectral gap $1-\lambda$ w/ $\lambda < 1$
where $\lambda = \max\{\lambda_2, |\lambda_n|\}$.

M - corresponding RW Matrix.

$B \subseteq V$

$\pi(B) = \mu$



x_1, \dots, x_t - random walk
of length t starting from
an initial vertex $x_1 \sim \pi$

Then

$$(*) \dots P_{x_1, \dots, x_t} \left[\bigwedge_{i \in [t]} (x_i \in B) \right] \leq \mu (\mu + \lambda(t-\mu))^{t-1}$$

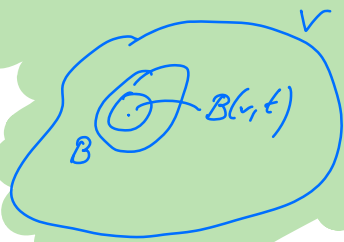
Remarks:

① G - complete graph w/ self loops
 M_{ind}
 $(x) \leq \mu^t$; $\lambda = 0$ ✓

② Application to Derandomization

Thm [Karp-Pippenger-Sipser]

G is an N -vertex D -regular
 $(\frac{N}{2}, A)$ -vertex expander for some $A > 1$



$$B \subseteq V, |B| \leq N/2$$

\Downarrow

$$\Pr_{v \leftarrow \pi} [B(v, t) \subseteq B] \leq \frac{\mu}{A^t}$$

KPS \rightarrow RP error reduction

$$\frac{1}{2} \rightarrow \delta$$

$$(a). \mu = \frac{1}{2} \dots \frac{\mu}{A^t} \leq \delta \quad ; \quad t = O\left(\frac{\log(\frac{1}{\delta})}{\log A}\right)$$

$$(b). \# \text{ repetitions: } |B(v, t)| \leq (D+1)^t \\ = \text{poly}(n) \\ \text{provided } t = O(\log n)$$

Concl: Reduce error $\frac{1}{2} \rightarrow \frac{1}{poly(n)}$

w/o paying any additional randomness.

Qn: Can we reduce error further say to inverse exponential (or possibly paying a few extra random bits)

YES. By Hitting Set Lemma.

RP error reduction

error: $\delta \rightarrow \frac{1}{2}$

$\pi(B) = \frac{1}{2}$.

$$P_n[\text{walk} \in B] \leq \mu(\mu + \lambda(1-\mu))^{t-1}$$

$$= \frac{1}{2} \left(\frac{1+\lambda}{2}\right)^{t-1}$$

$$\leq \left(\frac{1+\lambda}{2}\right)^t = c^t$$

for some

$$c < 1$$

t -step.

error: $\frac{1}{2} \rightarrow \exp(-t)$

random coins = $\log N + (t-1) \log D$

iterations = t .

Rewriting in terms of δ

error: $\frac{1}{2} \rightarrow \delta$ ($\delta = \exp(-t)$)

AKS: $\left\{ \begin{array}{l} \# \text{ random coins} = n + O(\log \frac{1}{\delta}) \\ \# \text{ iterations} = O(\log \frac{1}{\delta}) \end{array} \right.$

KPS: $\left\{ \begin{array}{l} \# \text{ random coins} = n \\ \# \text{ iterations} = \text{poly}(\frac{1}{\delta}) \end{array} \right.$

Ind.: $\left\{ \begin{array}{l} \# \text{ random coins} = O((\log \frac{1}{\delta}) n) \\ \# \text{ iterations} = O(\log(\frac{1}{\delta})) \end{array} \right.$

What about BPP error reduction.

Chernoff Bound for RW on expanders

G -expander on N -vertices w/
spectral gap $1-\lambda$ w/ $\lambda < 1$

where $\lambda = \max\{|\lambda_2|, |\lambda_n|\}$

M -corresponding RW Matrix.

$B \subseteq V$

$\pi(B) = \mu$



X_1, \dots, X_t - random walk
of length t starting from
an initial vertex $X \sim \pi$

Then

$$P_{x_1, \dots, x_t} \left[\frac{\#\{e \in [t] \mid X_e \in B\}}{t} - \mu > \varepsilon \right] \leq 2 \exp(- (1-\tilde{\alpha}) \varepsilon^2 t)$$

Problem Set 2: Weaker version of Chernoff bd (using the hitting set lemma)

Proof of hitting set lemma:

$$(*) = P_{x_1, \dots, x_t} \left[\bigwedge_{e \in [t]} (X_e \in B) \right]$$

$$= \sum_{v_1, \dots, v_t \in B} P_{x_1=v_1, x_2=v_2, \dots, x_t=v_t}$$

$$= \sum_{v_1, \dots, v_t \in B} \pi(v_1) M(v_1, v_2) M(v_2, v_3) \dots M(v_{t-1}, v_t)$$

$$\mathbb{1}_B = \mathbb{1}_{[v \in B]} \quad B \quad v \setminus B$$

$$P = \text{Diag}(\mathbb{1}_B) = \begin{array}{c|c} B & v \setminus B \\ \hline B & \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} \\ v \setminus B & \end{array}$$

$$\begin{aligned}
 (*) &= \sum_{v_1, \dots, v_\ell \in V} \pi(v_1) P(v_1, v_1) M(v_1, v_2) P(v_2, v_2) \\
 &\quad \cdot M(v_2, v_3) P(v_3, v_3) \dots P(v_{\ell-1}, v_{\ell-1}) \\
 &\quad \cdot M(v_{\ell-1}, v_\ell) P(v_\ell, v_\ell)
 \end{aligned}$$

$$= \sum_{v \in V} \pi(v) (P(MP)^{\ell-1} \mathbb{1})(v) \quad \left(\begin{array}{l} \text{Moving} \\ \text{to } \pi\text{-inner} \\ \text{product} \end{array} \right)$$

$$\begin{aligned}
 (*) &= \langle P(MP)^{\ell-1} \mathbb{1}, \mathbb{1} \rangle_\pi \\
 &= \langle P(MP)^{\ell-1} \mathbb{1}, \mathbb{1}_B \rangle_\pi \quad \left(\begin{array}{l} \text{since} \\ \text{supp}(P(MP)^{\ell-1} \mathbb{1}) \\ \subseteq B \end{array} \right) \\
 &= \langle P(MP)^{\ell-1} \mathbb{1}_B, \mathbb{1}_B \rangle_\pi \quad \left(\begin{array}{l} \text{since } P\mathbb{1} \\ = P\mathbb{1}_B \end{array} \right)
 \end{aligned}$$

$$\leq \| P(MP)^{\ell-1} \mathbb{1}_B \|_{2,\pi} \cdot \| \mathbb{1}_B \|_{2,\pi} \quad \left(\begin{array}{l} \text{Applying Cauchy} \\ \text{Schwarz} \end{array} \right)$$

$$= \| P(MP)^{\ell-1} \mathbb{1}_B \|_{2,\pi} \cdot \sqrt{\mu}$$

$$= \| (PMP)^{\ell-1} \mathbb{1}_B \|_{2,\pi} \cdot \sqrt{\mu} \quad \left(\begin{array}{l} \text{since} \\ P^2 = P \end{array} \right)$$

What is the 2-norm of $(PMP)^{\ell-1} \mathbb{1}_B$?

For a general operator $M: \mathbb{R}^V \rightarrow \mathbb{R}^V$

$$\|M\|_{2,\pi} = \max \frac{\|Mx\|_{2,\pi}}{\|x\|_{2,\pi}}$$

- largest eigenvalue of M .
(if one exists)

Obs: (1) $\|M_1 + M_2\| \leq \|M_1\| + \|M_2\|$

(2) $\|M_1 \cdot M_2\| \leq \|M_1\| \cdot \|M_2\|$

Coming back to the proof

$$\|(PMP)^{t-1} \frac{1_B}{2,\pi}\| \leq \|(PMP)^{t-1}\|_{2,\pi} \cdot \left\| \frac{1_B}{2,\pi} \right\|$$

(defn of $\|M\|$)

$$= \|(PMP)^{t-1}\|_{2,\pi} \cdot \sqrt{\mu}$$

$$\leq \|PMP\|_{2,\pi}^{t-1} \cdot \sqrt{\mu}$$

$$(*) \leq \|PMP\|_{2,\pi}^{t-1} \cdot \mu$$

Qn: What is $\|PMP\|_{2,\pi}$?

Suffices to show

$$\|PMP\|_{2,\pi}$$

$$\leq \mu + \lambda(1-\mu)$$

$$= (1-\lambda)\mu + \lambda$$

Warmup Case: M - independent random
coin.

G - complete graph w/ self
loops

$$M_{\text{ind}} = \begin{bmatrix} \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \end{bmatrix} \quad (P M_{\text{ind}} = \pi)$$

since
 p - prob dist

$$= J T T \quad (J \text{ is all } 1\text{'s matrix})$$

$$T = \text{Diag}(\pi)$$

$$P M_{\text{ind}} P = \begin{bmatrix} I & O \\ O & O \end{bmatrix} \begin{bmatrix} \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \end{bmatrix} \begin{bmatrix} I & O \\ O & O \end{bmatrix}$$

$$= \begin{bmatrix} \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \\ \text{---} \pi \text{---} \\ O & O \end{bmatrix}$$

Rank 1 matrix $P M_{\text{ind}} P \cdot \mathbb{1}_B = \pi(B) \cdot \mathbb{1}_B$

$\mathbb{1}_B$ is the e-vector for $P M_{\text{ind}} P$
w/ eigenvalue $\pi(B) = \mu$.

$$\| P M_{\text{ind}} P \|_{2, \pi} = \mu.$$

What we want is $\|PMP\|_{2,2}$

(not $\|PM_{ind}P\|_{2,2}$)

Idea: Write M as a combination
of M_{ind} & error matrix

$$M: \begin{aligned} v_1 &\rightarrow \mathbb{1} \\ v_2 &\rightarrow \lambda_2 v_2 \\ v_3 &\rightarrow \lambda_3 v_3 \\ &\vdots \\ v_n &\rightarrow \lambda_n v_n. \end{aligned}$$

$$M_{ind}: \begin{aligned} v_1 &\rightarrow v_1 \\ v_2 &\rightarrow 0 \\ &\vdots \\ v_n &\rightarrow 0 \end{aligned}$$

$$M_E: \begin{aligned} v_1 &\rightarrow \lambda_1 v_1 \\ v_2 &\rightarrow \lambda_2 v_2 \\ v_3 &\rightarrow \lambda_3 v_3 \\ &\vdots \\ v_n &\rightarrow \lambda_n v_n. \end{aligned}$$

$$M = (I - \tilde{\lambda}) M_{ind} + M_E$$

Matrix
Decomposition
of RW matrix

$$\|M_E\|_{2,2}: x \mapsto M_E x.$$

$$x = \sum \alpha_i v_i \quad \|x\|_{2,2}^2 = \sum \alpha_i^2.$$

$$M_E x = \alpha_1 \lambda_1 v_1 + \sum_{i=2}^n \alpha_i \lambda_i v_i.$$

$$\|M_E x\|_{2,\pi}^2 = \alpha_1^2 \lambda^2 + \sum_{c=2}^n \alpha_c \lambda_c^2 \leq \lambda^2 (\sum \alpha_c^2) = \lambda^2 \|x\|_{2,\pi}^2$$

Hence $\|M_E x\|_{2,\pi} \leq \lambda$

Conclusion: M is a s.w matrix w/ spectral $1-\lambda$ then

$$M = (1-\lambda)M_{ind} + M_E$$

where $\|M_E\| \leq \lambda$

$$\begin{aligned} \|PMP\|_{2,\pi} &= \|P((1-\lambda)M_{ind} + M_E)P\|_{2,\pi} \\ &\leq (1-\lambda)\|PM_{ind}P\|_{2,\pi} + \|PM_E P\|_{2,\pi} \\ &= (1-\lambda)\mu + \|PM_E P\|_{2,\pi} \\ &\leq (1-\lambda)\mu + \|P\| \cdot \|M_E\| \cdot \|P\| \\ &\leq (1-\lambda)\mu + \|M_E\| \quad (\text{since } \|P\| \leq 1) \\ &\leq (1-\lambda)\mu + \lambda \end{aligned}$$

$$\begin{aligned} (*) &\leq \|PMP\|^{t-1} \cdot \mu \\ &= (\lambda + (1-\lambda)\mu)^{t-1} \cdot \mu \\ &= (\mu + \lambda(1-\mu))^{t-1} \mu \end{aligned}$$



Explicit Constructions of Expander Graphs

explicit: $\text{poly}(N)$ (mildly explicit)

super-explicit: Given $v \in [N]$, $c \in [D]$
can calculate the i -th nbr
of v in time $\text{poly}(\log N, \log D)$
(fully explicit).

Algebraic Construction
of explicit expander
graphs.

① m -tve integer

$$V = \mathbb{Z}/m\mathbb{Z} \times \mathbb{Z}/m\mathbb{Z}$$

$$\{(x, y) \mid x \in \{0, \dots, m-1\}\}$$

$$(x, y) \rightarrow (x, y), (x+1, y), (x, y+1), (x, x+y), (y, x) \\ (x-1, y), (x, y-1), (x, y-x), (y, -x)$$

\mathcal{G} -regular.

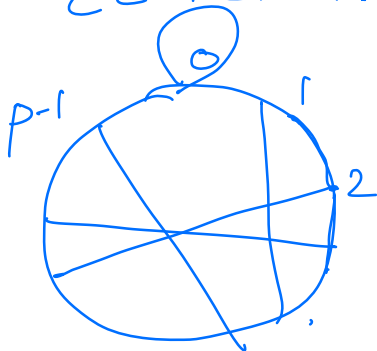
Margulis: $\exists \lambda < 1$, $\forall m$, the
above graph is $(1-\lambda)$ -spectral
expander

② $V = \mathbb{F}_p$ p - prime

3-regular graph.

$$x \rightarrow x+1, x-1, \sqrt{x}$$

(Convention: $\sqrt{0} = 0$)



$\frac{3}{16}$ Selberg Theorem.

$$\exists \lambda, \lambda < 1 \neq p.$$

this graph is a $(1-\lambda)$ -spectral expander.

③ Lubotzky - Philips - Sarnak.

p - prime $p \equiv 1 \pmod{4}$

q - prime power q - square \pmod{p}

$$q \neq p$$

$$\exists i \in \mathbb{F}_q, i^2 + 1 = 0.$$

$$A = \left\{ (a_0, a_1, a_2, a_3) \mid \begin{array}{l} a_0 - \text{odd positive} \\ a_1, a_2, a_3 - \text{even} \\ a_0^2 + a_1^2 + a_2^2 + a_3^2 = p \end{array} \right\}$$

$$|A| = p+1 = D(\text{degree})$$

Graph on $\mathbb{F}_q \cup \{\infty\}$ (i.e. $N=q+1$)
which is (A) -regular.

(a_0, a_1, a_2, a_3) -th nbr of $z \in \mathbb{F}_q \cup \{\infty\}$

$$\frac{(a_0 + ia_1)z + (a_2 + ia_3)}{(-a_2 + ia_3)z + (a_0 - ia_1)}$$

Thm [LPS]: \forall prime powers q .

[Morgenstern] G_q has spectral gap

$$1 - \lambda \text{ where } \lambda = \frac{2\sqrt{p}}{p+1}$$

$$= \frac{2\sqrt{D-1}}{D}$$

[Ramanujan Graphs]