

Construction of base graphs in Neuhel-Naor.

Reminder 4: If $K: X \times X \rightarrow [0, +\infty[$ symmetric kernel and $A = [a_{ij}]$ is a symmetric stochastic matrix, then

$$\gamma^+(A, K) = \inf \{ \gamma^+ > 0 : \forall x_1, \dots, x_n \in X \quad \forall y_1, \dots, y_n \in X$$

$$\frac{1}{n} \sum_{i,j} K(x_i, y_j) \leq \frac{\gamma^+}{n} \sum_{i,j} a_{ij} K(x_i, y_j) \}$$

If $G = (X, E)$ is a d -regular graph and $A_G = \frac{1}{d} [E(u, v)]_{u, v \in V}$, then the normalized adjacency matrix,

$$\gamma^+(G, K) = \gamma^+(A_G, K) = \inf \{ \gamma^+ > 0 : \forall f, g: V \rightarrow X \quad \frac{1}{|V|} \sum_{u, v \in V} K(f(u), g(v))$$

$$\leq \frac{\gamma^+}{|V| \cdot d} \sum_{(u, v) \in E} K(f(u), g(v)) \}$$

Goal: to build $G_n = (V_n, E_n)$ 3-regular graphs so that $|V_n| \rightarrow \infty$ and $\forall (X, \|\cdot\|_X)$ superreflexive $\forall p \geq 1 \quad \sup_n \gamma^+(G_n, \|\cdot\|_X^p) < \infty$

Preliminaries: $(X, \|\cdot\|_X)$ normed space and $f: \{1, \dots, n\} \rightarrow X$, $\|f\|_{L_p^n(X)} = \left(\frac{1}{n} \sum_{i=1}^n \|f(i)\|_X^p \right)^{1/p}$

and $A \otimes \text{Id}_X: L_p^n(X) \rightarrow L_p^n(X)$ and $L_p^n(X)_0 = \{ f \in L_p^n(X) : \sum_{i=1}^n f(i) = 0 \}$

$$f \mapsto (i \mapsto \sum_j a_{ij} f(j))$$

Remark: $L_p^n(X)_0$ stable under $A \otimes \text{Id}_X$ because A is stochastic:

$$\sum_i g(i) = \sum_i \left(\sum_j a_{ij} f(j) \right) = \sum_j \left(\sum_i a_{ij} \right) f(j) = \sum_j f(j) = 0$$

and $\lambda_X^{(n)}(A) := \|A \otimes \text{Id}_X\|_{B(L_p^n(X)_0)}$

N.B.: If $X = \mathbb{R}$, $p=2$, $\lambda_{\mathbb{R}}^{(n)}(A) = \max_{i \geq 2} |\lambda_i(A)| = \lambda(A)$ and $\gamma^+(A, \|\cdot\|_2^2) = \frac{1}{1 - \lambda(A)}$

(i.e., $K(x, y) = |x - y|^2$) $= \gamma^+(A, \|\cdot\|_4^2)$

Lemma 6.1.: $\gamma_+(A, \|\cdot\|_X^p) \leq \left(1 + \frac{4}{1 - \lambda_X^{(p)}(A)} \right)^{1/p}$

Remark: There is a converse estimate when X is K -convex: see Lemma 6.6 of the paper.

Proof: $\left(\frac{1}{n} \sum_i \sum_j \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}} \leq \|f - g\|_X + \left(\frac{1}{n^2} \sum_i \sum_j \|f_0(i) - g_0(j)\|_X^p \right)^{\frac{1}{p}}$

① where $\bar{f} = \frac{1}{n} \sum_i f(i)$ and $f_0 = f - \bar{f} \in L_p^n(X)$. (This is just the triangular $\leq$)

$$\leq \|f - \bar{f}\|_X + \left(\frac{1}{n^2} \sum_i \sum_j 2^{p/q} (\|f_0(i)\|_X^p + \|g_0(j)\|_X^p) \right)^{\frac{1}{p}}$$

$$= \|f - \bar{f}\|_X + 2^{\frac{p-1}{p}} \left(\frac{1}{n} \sum_i (\|f_0(i)\|_X^p + \|g_0(i)\|_X^p) \right)^{\frac{1}{p}}$$

$$(a+b)^p \leq \frac{a^p+b^p}{2} \cdot 2^p$$

$$(a+b)^p \leq 2^{p-1}(a^p+b^p)$$

and $\|f - \bar{f}\|_X = \left\| \frac{1}{n} \sum_i f(i) - g(i) \right\|_X = \left\| \frac{1}{n} \sum_i \sum_j a_{ij} f(i) - g(j) \right\|_X$

$$= \left\| \frac{1}{n} \sum_i \sum_j a_{ij} (f(i) - g(j)) \right\|_X \leq \left(\frac{1}{n} \sum_i \sum_j a_{ij} \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}}$$

(this is Jensen's inequality with $\mu(\{(i,j)\}) = \frac{1}{n} a_{ij}$)

Define $B = \begin{bmatrix} 0 & A \\ A & 0 \end{bmatrix}$, $h = f_0 \oplus g_0 \in L_p^{2n}(X)$.

$$(1-\lambda) \|h\|_{L_p^{2n}(X)} = \|h\|_{L_p^{2n}(X)} - \left(\frac{\lambda^p \|f_0\|_{L_p^n(X)}^p + \lambda^p \|g_0\|_{L_p^n(X)}^p}{2} \right)^{\frac{1}{p}}$$

$$\leq \|h\|_{L_p^{2n}(X)} \left(\frac{1}{2} \|A \oplus I_X\|_X (f_0) + \frac{1}{2} \|A \oplus I_X\|_X (g_0) \right)^{\frac{1}{p}}$$

$$= \|h\|_{L_p^{2n}(X)} - \| (B \oplus Id_X)(h) \|_{L_p^{2n}(X)} \leq \| (Id - B \oplus Id_X)(h) \|_{L_p^{2n}(X)}$$

$$= \left(\frac{1}{2n} \sum_i \|f_0(i) - \sum_j a_{ij} g(j)\|_X^p + \frac{1}{2n} \sum_j \|g_0(j) - \sum_i a_{ij} f(i)\|_X^p \right)^{\frac{1}{p}}$$

as A is stochastic and symmetric,

$$\leq \left(\frac{1}{n} \sum_i \sum_j a_{ij} \|f_0(i) - g_0(j)\|_X^p \right)^{\frac{1}{p}}$$

$$\leq \|f - g\|_X + \frac{1}{n} \left(\sum_i \sum_j a_{ij} \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}}$$

Let us ~~summarize~~ summarize: we had to bound ① and $\|h\| = \left(\frac{1}{2n} \sum_i (\|f_0(i)\|_X^p + \|g_0(i)\|_X^p) \right)^{\frac{1}{p}}$

$$\leq \left(\frac{1}{n} \sum_i \sum_j a_{ij} \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}} \leq \frac{2^{1/p}}{1-\lambda} \cdot 2 \cdot \left(\frac{1}{n} \sum_i \sum_j a_{ij} \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}}$$

Finally, ① $\leq \left(1 + 2^{\frac{p-1}{p}} \cdot \frac{2^{1/p} \cdot 2}{1-\lambda} \right) \left(\frac{1}{n} \sum_i \sum_j a_{ij} \|f(i) - g(j)\|_X^p \right)^{\frac{1}{p}}$

thus $\gamma^+ \leq \left(1 + \frac{4}{1-\lambda_p(A)} \right)^{\frac{1}{p} \cdot \frac{1}{1-\lambda}}$

Theorem (Corollary 7.4) $\forall \delta \in]0, 1[\forall p \in]1, \infty[\exists n_0(p, \delta) \exists (H_n^p(\delta))_{n \geq n_0(p, \delta)}$

$d_n^p(\delta)$ -regular such that (i) $|V(H_n^p(\delta))| = m_n = 2^{D_n}$, $D_n \geq \frac{n}{10}$

(ii) $d_n^p(\delta) \leq e^{(\log m_n)^{1-\delta}}$

and $\forall (X, \|\cdot\|_X)$ K -convex Banach space $\exists \delta_0^p(X) \forall \delta < \delta_0^p(X) \sup \gamma^+(H_n^p(\delta), \|\cdot\|_X) \leq \delta^n$

③:

Lemma 7.3 $\forall K, p > 1 \exists n(K, p) \exists \delta(K, p) \in]0, 1[\exists (H_n(K, p))_{n \geq n(K, p)}$
 $d_n^p(K, p)$ -regular $d_n(K, p) \leq e^{(\log m_n)^{1-\delta(K, p)}}$ with $m_n = |V(H_n(K, p))| = 2^{D_n}$
 for $D_n \geq \frac{n}{10}$
 and for any X K -curve with $K(X) \leq K$, for all $n \geq n(K, p)$, $\chi(H_n(K, p), \|\cdot\|_X^p) \leq g^n$

For 7.3 $\Rightarrow$ 7.4, see the paper.

Reminder 2: If $A \subset \{1, \dots, n\}$ and $w_A: \mathbb{F}_2^n \rightarrow X$
 $x \mapsto x_{-1} \sum_{i \in A} x_i$ and $f \in L^p(\mathbb{F}_2^n, X)$,

$$e^{z\Delta} f = \sum_{A \subset \{1, \dots, n\}} e^{z|A|} \hat{f}(A) w_A$$

$$R_z(u) = \prod_{j=1}^n (1 + (-1)^{u_j} e^z) = (1 - e^z)^{\sum x_j} (1 + e^z)^{n - \sum x_j}$$

$$= \sum_{A \subset \{1, \dots, n\}} e^{z|A|} (-1)^{\sum_{i \in A} x_i} : e^{z\Delta} f = R_z * f.$$

Then $(e^{z\Delta} f)(y) = \sum_{w \in \mathbb{F}_2^n} \left(\frac{1 - e^z}{2} \right)^{\sum y_j - w_j} \left(\frac{1 + e^z}{2} \right)^{n - \sum y_j - w_j} \cdot f(w)$

$$= \sum_{w \in \mathbb{F}_2^n} \left(\frac{1 - e^z}{2} \right)^{\|y - w\|_1} \left(\frac{1 + e^z}{2} \right)^{n - \|y - w\|_1} f(w)$$

because we just work modulo 2.

In particular, $(e^{-t\Delta} \delta_n)(y) = \left(\frac{1 - e^{-t}}{2} \right)^{\|y\|_1} \left(\frac{1 + e^{-t}}{2} \right)^{n - \|y\|_1}$

$\tau_t = \frac{1 - e^{-t}}{2}$; $\mathcal{E}^n = \tau_t^{4n} \mathbb{E}^n (1 - \tau_t)^{(1 - 4\tau_t)n}$ and $e_t^n: \{0, \dots, n\} \rightarrow \mathbb{N}$
 $k \mapsto \left\lfloor \frac{\tau_t^k (1 - \tau_t)^{n-k}}{\sigma_t^n} \right\rfloor$

Lemma 7.2: Action of $e^{-t\Delta}$ and Poincaré inequalities: let $t \in]0, \frac{1}{4}[$, $p \geq 1, n \geq 2^{13}$
 so that $\tau_t \geq \left(\frac{1 - \log 18n}{18n} \right)^{1/2}$; $G_t^n = (\mathbb{F}_2^n, \mathcal{E}_t^n)$, $V(G_t^n) = \mathbb{F}_2^n$: for all $x, y \in \mathbb{F}_2^n$
 the edge (x, y) appears $e_t^n(\|x - y\|_1)$ times: G_t^n is d_t^n -regular, $\frac{1}{3\sigma_t^n} \leq d_t^n \leq \frac{1}{\sigma_t^n}$.

For all metric space (X, d_X) , $\frac{1}{3|\mathcal{E}_t^n|} \sum_{\mathcal{E}_t^n} d_X(f(x), g(y))^p \leq \frac{1}{2^n} \sum_{x, y \in \mathbb{F}_2^n} (e^{-t\Delta} \chi_y / d_X(x, y))^p$
 $\leq \frac{1}{|\mathcal{E}_t^n|} \sum_{\mathcal{E}_t^n} d_X(f(x), g(y))^p$

End of talk: 7.2 $\Rightarrow$ 7.3.

Claim: Here's a linear subspace V_n of $\mathbb{F}_2^n$ so that $D_n = \dim(V_n) \geq \frac{n}{40}$
 $d_n = \min_{x \in V_n, x \neq 0} \|x\|_1 \geq \frac{n}{10}$

It's a "good linear code"

Proof: Let V be the k -dimensional linear subspace of $\mathbb{F}_2^n$ such that

$$(*) = \left| \left\{ x \in \mathbb{F}_2^n : \exists v \in V \|x - v\|_1 \leq \frac{n}{10} \right\} \right| \leq 2^k \cdot \sum_{\ell \leq \frac{n}{10}} \binom{n}{\ell} = 2^k A_n$$

We have $A_n = 2^n P\left[\sum_i X_i \leq \frac{n}{10}\right]$ X_i independent Bernoulli

"facts of life"

$$= 2^n P\left[\sum \varepsilon_i > \frac{4n}{5}\right] \quad \varepsilon_i \text{ --- Rademacher.}$$

$$\text{Then } P\left[\sum \varepsilon_i > a\right] \leq e^{-\frac{a^2}{n}} \text{ and } A_n \leq 2^k e^{-\frac{8n}{25}} \text{ and } (*) \leq 2^k e^{-\frac{8n}{25}}$$

Pick $h \in \left[\frac{n}{10}, \frac{8n}{25}\right]$ and V k -dimensional and note that $(*) \leq 2^k \Rightarrow \exists v \in \mathbb{F}_2^n \|v\|_1 \geq \frac{n}{10}$.

$$V_n = \text{span}(V \cup \{v_0\}), \min_{v \in V_n} \|v\|_1 \geq \frac{n}{10}$$

Define: $H_n = H_n(h, p)$, $V(H_n) = \mathbb{F}_2^n / V_n^\perp$, $V_n^\perp = \{x \in \mathbb{F}_2^n : \forall y \in V_n \sum_i x_i y_i = 0 \pmod{2}\}$
and $|V(H_n)| = 2^{h_n}$ and $h_n = \dim V_n \geq \frac{n}{10}$.

The number of edges joining $x + V_n^\perp$ and $y + V_n^\perp$
= _____ with one end in $x + V_n^\perp$ and the other end in $y + V_n^\perp$, divided by $|V_n^\perp|$, makes

$$\frac{1}{|V_n^\perp|} \sum_{(u,v) \in V_n^\perp \times V_n^\perp} e^n(\|u - v\|_1) = \sum_{u \in V_n^\perp} e^n(\|u - y + u\|_1)$$

$$\text{and the degree at } x = u + V_n^\perp \text{ is } \sum_{y \in V_n^\perp} \left(\sum_{u \in V_n^\perp} \|u - y + u\|_1 \right) = \sum_{z \in \mathbb{F}_2^n} e^n(\|u - z\|_1) = d_x^n \text{ (by 7.21)}$$

Let $\pi: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n / V_n^\perp$ be the quotient map and X be a B -space:

If $f \in L^p(\mathbb{F}_2^n / V_n^\perp, X)$, we get $\pi f: \mathbb{F}_2^n \rightarrow X$ $\left(\begin{matrix} \mathbb{F}_2^n \xrightarrow{\pi} \mathbb{F}_2^n / V_n^\perp \\ x \mapsto f(\pi(x)) \end{matrix} \right) \in L^p(\mathbb{F}_2^n, X)$ constant on cosets.

Claim: let $f \in L^p(\mathbb{F}_2^n / V_n^\perp, X)$. (i.e., $\int_A f(u) du = 0$). Then $\pi f \in L^p(\mathbb{F}_2^n, X)$ with $\int_{\mathbb{F}_2^n} \pi f(u) du = 0$. $h_n = \min_{u \in V_n^\perp} \|u\|_1 \geq \frac{n}{10}$.

Proof: $V_n^\perp = V_n$. (exercise) - Let $\emptyset \neq A \subset \{1, \dots, n\}$ and $|A| \leq h_n$. Then $\chi_A \notin V_n^\perp$
so that $\exists v \in V_n^\perp \langle \chi_A, v \rangle \neq 0$ $\sum v_i = 1 \pmod{2}$

$$\pi f(\hat{A}) = \int_{\mathbb{F}_2^n} \pi f(u) w_A(u) du = \int_{\mathbb{F}_2^n} \pi f(u+v) w_A(u) du = \int_{\mathbb{F}_2^n} \pi f(u) w_A(u-v) du$$

$$= (-1)^{\sum v_i} \int_{\mathbb{F}_2^n} \pi f(u) w_A(u) du = -\pi f(\hat{A}). \text{ Therefore } \pi f(\hat{A}) = 0.$$

Remark: Theorem 5.1 $\Rightarrow$ ~~$\forall f \in L^p(\mathbb{F}_2^n)$~~ $\|e^{-t\Delta} \pi f\|_{B(L^p(\mathbb{F}_2^n / V_n^\perp, X))} \leq C e^{-A h_n \min(t, t^B)}$
(If f is K -convex with $K(x) \leq K$, then H is $A = A(K, p)$, $B = B(K, p) \geq 2$, $C = C(K, p)$, so that

$$\text{Here } \forall f \in L^p(\mathbb{F}_2^n / V_n^\perp, X), \|e^{-t\Delta} \pi f\|_{L^p(\mathbb{F}_2^n, X)} \leq C e^{-A h_n \min(t, t^B)}$$

$$\text{Pick } t = t(n, p, h) = \left(\frac{\log 2C}{h_n A} \right)^{1/B} \text{ then } C e^{-A h_n \min(t, t^B)} \leq \frac{1}{2}.$$

(5)

there is $n(K, p)$ such that for all $n > n(K, p)$ $\epsilon < \frac{1}{4}$ and $n > 2^{13}$

and $\frac{1-e^{-\epsilon}}{2} = \tau_\epsilon \geq \left(\frac{p \log 18n}{n} \right)^{1/2}$. Now remember, $B > 2$!

$$\text{We have degree} = d_\epsilon^n \leq \frac{1}{\tau_\epsilon^n} = \frac{1}{\tau_\epsilon^{4\tau_\epsilon n} (1-\tau_\epsilon)^{2-4\tau_\epsilon n}} \leq \frac{1}{\tau_\epsilon^{8\tau_\epsilon n}} \leq e^{(\log m_n)^{1-d(K,p)}}$$

We can apply Lemma 7.2: $e^{-t\Delta} \pi$

then $e^{-t\Delta} \pi$ is a stochastic symmetric operator on $L_p(\mathbb{F}_2^n / V_n^\perp)$

for $d(K,p) < \frac{1}{B}$,
 $B = B(K,p) > 2$.
 here is a check needed here.

there are 2 mistakes on page 58. let $s \in \mathbb{F}_2^n / V_n^\perp : (e^{-t\Delta} \pi)(s) = e^{-t\Delta} \pi_s$

$$\begin{aligned} \text{Let } y \in \mathbb{F}_2^n : (e^{-t\Delta} \pi_s)(y) &= \sum_{u \in \mathbb{F}_2^n} (e^{-t\Delta} \pi_{s+u})(y) = \sum_{u \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-y\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-y\|_1} \\ &= (e^{-t\Delta} \pi_{s'}) (y) \quad \text{if } y-y' \in V_n^\perp \end{aligned}$$

this does not depend on $y \in T$ (where $T \in \mathbb{F}_2^n / V_n^\perp$) symmetric in s and T .

$$q_{s,T} = \sum_{u \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-y\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-y\|_1} \quad \text{for } y \in T$$

$$q_{T,s} = \sum_{u \in V_n^\perp} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|y+u-x\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|y+u-x\|_1} = q_{s,T}.$$

$$\begin{aligned} \text{then } \sum_s q_{s,T} &= \sum_s \sum_{u \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-y\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-y\|_1} \\ &= \sum_{x \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-y\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-y\|_1} \\ &= \sum_{k=0}^n \binom{n}{k} \left(\frac{1-e^{-\epsilon}}{2} \right)^k \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-k} = 1 \end{aligned}$$

$Q = [q_{s,T}]$ is symmetric and stochastic

Theorem 5.1 : $\|Q \otimes \text{id}_X\|_{\mathcal{B}(L_p(\mathbb{F}_2^n / V_n^\perp), X)} = \lambda_X^{(p)}(Q) \leq \frac{1}{2}$

Lemma 6.1 $\Rightarrow \gamma^p(Q, \|\cdot\|_X^p) \leq g^p$ and finally, for $f, g : \mathbb{F}_2^n / V_n^\perp \rightarrow X$.

$$\begin{aligned} \frac{1}{|\mathbb{F}_2^n / V_n^\perp|^2} \sum_{s, T} \|f(s) - g(T)\|_X^p &\leq \frac{g^p}{|\mathbb{F}_2^n / V_n^\perp|} \sum_s \sum_T q_{s,T} \|f(s) - g(T)\|_X^p \\ &= \frac{g^p}{|\mathbb{F}_2^n / V_n^\perp|} \sum_T \sum_s \left(\sum_{u \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-v\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-v\|_1} \right) \|f(s) - g(T)\|_X^p \\ &= \frac{g^p}{|\mathbb{F}_2^n / V_n^\perp| \times |V_n^\perp|} \sum_T \sum_{v \in T} \sum_s \sum_{u \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-v\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-v\|_1} \|f(s) - g(T)\|_X^p \\ &= \frac{g^p}{2^n} \sum_{u \in \mathbb{F}_2^n} \sum_{v \in \mathbb{F}_2^n} \left(\frac{1-e^{-\epsilon}}{2} \right)^{\|u-v\|_1} \left(\frac{1+e^{-\epsilon}}{2} \right)^{n-\|u-v\|_1} \|f(u) - g(v)\|_X^p \end{aligned}$$

for all $v \in T$
 $\|f(s) - g(T)\|_X^p$
 $\|f(u) - g(v)\|_X^p$

$$\stackrel{\text{by 7.2}}{\leq} \frac{3 \cdot g^p}{|E_t^*|} \sum_{(u,v) \in E_t^*} \|\pi f(u) - \pi g(v)\|$$

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But in my new graph H_n ,

$$\begin{aligned} &= \frac{3 \cdot g^p}{|E_t^*|} \sum_s \sum_T \left(\sum_{u \in s} \sum_{v \in T} e_t^*(\|u-v\|_1) \right) \|f(s) - g(T)\|_X^p \\ &= \frac{3 \cdot g^p}{|E_t^*|} \sum_s \sum_T |V_n| E_n(s, T) \|f(s) - g(T)\|_X^p \\ &= \frac{3 \cdot g^p}{|E_t^*|} \sum_{(\pi) \in E_n} \|f(s) - g(T)\|_X^p \quad (\text{here } |E_n| = \frac{|E_t^*|}{|V_n|}) \end{aligned}$$

"Chernoff bounds/estimate"