

# Hypercontractivity

We work on the hypercube  $\{-1, 1\}^n$ .

Noise operator  $T_e$   $e \in [-1, 1]$

For  $f: \{-1, 1\}^n \rightarrow \mathbb{R}$   $(T_e f)(x) = \mathbb{E} f(y)$  where  $y \sim N_e(x)$

$\|T_e f\|_p \leq \|f\|_p$

$\|T_e f\|_p^p = \mathbb{E}_x |T_e f|^p = \mathbb{E}_x \left| \mathbb{E}_{y \sim N_e(x)} f(y) \right|^p$   $n \rightarrow 2^p$   
convex

$\leq \mathbb{E}_x \mathbb{E}_{y \sim N_e(x)} |f(y)|^p = \|f\|_p^p$

$y$  uniform on  $\{-1, 1\}^n$

$T_e$  is contractive on  $L^p$ .

## Hypercontractivity Theorem

If  $1 \leq p \leq q \leq \infty$ ,  $0 \leq e \leq \sqrt{\frac{p-1}{q-1}}$  then  $\forall f: \{-1, 1\}^n \rightarrow \mathbb{R}$

$\|T_e f\|_q \leq \|f\|_p$  (HC)

enough to check this case.

① Why this implies the KKL theorem?

KKL theorem: If  $f: \{-1, 1\}^n \rightarrow [-1, 1]$  then

$\max_i \text{Inf}_i(f) \geq \frac{c \log n}{n} \text{Var}(f)$

$\text{Inf}_i(f) = \mathbb{P}(f(x^{(i)}) \neq f(x))$   
 $x$  with  $i$ th bit flipped.

$= \|D_i f\|_2^2 = \|D_i f\|_p^p \quad \forall p$

$D_i f = \frac{f(x^{(i \rightarrow 1)}) - f(x^{(i \rightarrow -1)})}{2}$

$D_i w_s = \begin{cases} 0 & \text{if } i \neq s \\ w_s & \text{if } i = s \end{cases}$

Write  $f = \sum_{S \subset [n]} \hat{f}_S w_S$

$\text{Inf}_i f = \sum_{S \ni i} \hat{f}_S^2$

$T_e f = \sum_{S \subset [n]} e^{|S|} \hat{f}_S w_S$

We use (HC) for  $e = \frac{1}{2}$   $q=2$   $\sqrt{p-1} = \frac{1}{2} \Rightarrow p = \frac{5}{4}$

$\forall g \quad \|T_{\frac{1}{2}} g\|_2 \leq \|g\|_{5/4}$  Apply this to  $g = D_i f$

$\|T_{\frac{1}{2}} D_i f\|_2 \leq \|D_i f\|_{5/4} = \text{Inf}_i(f)^{4/5}$

$\text{Var}(f) = \sum_{S \neq \emptyset} \hat{f}_S^2$

For  $M \in \mathbb{N}$  to be defined  $(M \sim \log n)$

$1 = \sum_{1 \leq |S| \leq M} \hat{f}_S^2 \leq \sum_{1 \leq |S| \leq M} |S| \hat{f}_S^2$

$\leq 4^M \sum_{1 \leq |S| \leq M} 4^{-|S|} |S| \hat{f}_S^2$

$T_{\frac{1}{2}} D_i = D_i T_{\frac{1}{2}}$

$\|T_{\frac{1}{2}} D_i f\|_2^2 = \sum_{S \ni i} \left( T_{\frac{1}{2}} \hat{f}_S \right)_i^2$

$\leq \sum_{S \ni i} |S| \hat{f}_S^2$

$= 4^M \sum_{1 \leq |S| \leq M} \|T_{\frac{1}{2}} D_i f\|_2^2$

$$\|T_{\frac{1}{2}} D_i f\|_2^2 = \sum_{s \geq i} \binom{1}{4} |s| \hat{f}_s^2 = 4^M \sum_{i=1}^n \|T_{\frac{1}{2}} D_i f\|_2^2 \leq 4^n \sum_i (I_{\geq i} f)^2$$

If  $\exists i: I_{\geq i}(f) \geq \frac{\text{Var}(f)}{n^{3/4}}$   
 then  $\text{OK} \left( \frac{1}{n^{3/4}} \geq \frac{c \log n}{n} \right)$

otherwise  $\sum_{1 \leq |s| \leq n} \hat{f}_s^2 \leq 4^n n \frac{\text{Var}(f)^{8/5}}{n^{6/5}} = 4^n n^{-1/5} \text{Var}(f) \left[ \frac{\text{Var}(f)}{n} \right]$

choose  $n$  such that  $4^n n^{-1/5} = n^{-1/10} \quad [n \sim c \log n]$

$$\sum_{1 \leq |s| \leq M} \hat{f}_s^2 \leq n^{-1/10} \text{Var}(f)$$

and since  $\text{Var}(f) = \sum_{1 \leq |s|} \hat{f}_s^2$  we get that

$$\sum_{|s| > M} \hat{f}_s^2 \geq \left(1 - \frac{1}{n^{1/10}}\right) \text{Var}(f)$$

$$\begin{aligned} \max_i I_{\geq i}(f) &\geq \frac{1}{n} \sum_i I_{\geq i}(f) = \frac{1}{n} \sum_s |s| \hat{f}_s^2 \\ &\geq \frac{1}{n} \sum_{|s| > M} |s| \hat{f}_s^2 \\ &\geq \frac{M}{n} \sum_{|s| > M} \hat{f}_s^2 \geq \frac{M}{n} \cdot \frac{1}{2} \text{Var}(f) \\ &\geq \frac{c \log n}{n} \text{Var}(f) \end{aligned}$$

Proof of (Hc)

**Proof** by induction on  $n$ .  
 induction step: quite easy  
 $n=1$ : very tricky

inductive step  $n \rightarrow n+1$   
 more generally  $[n] = I \cup J$  (disjoint union)  
 (Hc)  $\{[-1, 1]^I\} \Rightarrow$  (Hc)  $\{[-1, 1]^n\}$  "extension property"

$$f: [-1, 1]^n \rightarrow \mathbb{R} \quad f(x_I, x_J) \quad \begin{matrix} x_I \in [-1, 1]^I \\ x_J \in [-1, 1]^J \end{matrix}$$

$$\begin{aligned} T_e f &= T_e^I T_e^J f = T_e^J T_e^I f \\ \|T_e f\|_q^q &= \mathbb{E} |T_e f|^q = \mathbb{E}_I \mathbb{E}_J |T_e^I T_e^J f|^q \\ &\stackrel{\text{Hc}_J}{\leq} \mathbb{E}_I \left( \mathbb{E}_J |T_e^I f|^q \right)^{q/P} \\ &= \mathbb{E}_I |T_e^I f|^q \quad \left\| \right\|_{L^r}^{r=\frac{q}{P}} \end{aligned}$$

*on this fixed  $x_I$*

$r = \frac{q}{P} \geq 1$   
 $L^r([-1, 1]^J)$

$$\|T_e f\|_{L^p}^p \leq \mathbb{E}_J \|T_e^I f\|_{L^p}^p \stackrel{1}{=} \mathbb{E}_J \|T_e^I f\|_{L^p}^p = \mathbb{E}_J \left( \mathbb{E}_I \|T_e^I f\|_{L^p}^p \right)^{\frac{1}{p}}$$

$$\stackrel{MC}{\text{in } I} \rightarrow \leq \mathbb{E}_J \left( \mathbb{E}_I \|f\|_{L^p}^p \right)^{\frac{1}{p}} = \mathbb{E}_J \mathbb{E}_I \|f\|_{L^p}^p = \|f\|_{L^p}^p$$

n=1 tricky - we only prove for  $q=2$   $p=1+e^2$  (implies  $p \geq 1+e^2$ ).

take  $f: [-1,1] \rightarrow \mathbb{R}$

$$a = \mathbb{E} f = \frac{f(1)+f(-1)}{2} \quad b = \frac{f(1)-f(-1)}{2} \quad f = a \tilde{w}_\phi + b \tilde{w}_{\phi^3}$$

$$T_e f = a \tilde{w}_\phi + e b \tilde{w}_{\phi^3}$$

$$\|T_e f\|_{L^2}^2 = a^2 + e^2 b^2 \stackrel{?}{\leq} \|f\|_{L^2}^2$$

need to prove

$$\left( a^2 + e^2 b^2 \right)^{\frac{1+e^2}{2}} \leq \frac{(a+b)^{1+e^2} + (a-b)^{1+e^2}}{2}$$

$$\|f\|_{L^p}^p = \left( \frac{(a+b)^p + (a-b)^p}{2} \right)^{\frac{1}{p}}$$

We can assume  $a \geq 0$   $a \geq b$  (otherwise flip)  $a=1$   
 $b \geq 0$

$$b \leq x \quad (1+e^2 x^2)^{\frac{1+e^2}{2}} \stackrel{?}{\leq} \frac{(1+x)^{1+e^2} + (1-x)^{1+e^2}}{2} \quad 0 \leq x \leq 1$$

$$0 \leq x \leq 1 \quad (1+x)^2 \leq 1+2x+x^2$$

$b \geq 0$

$\leq 1 + e^2 x^2 \frac{1+e^2}{2} \leq 1 + \frac{x^2}{2} e^{2(1+e^2)}$  when expanded in Taylor series, all  $+O(x^2)$  coefficients are  $\geq 0$ .

cf  $\cosh(t) \leq \exp(t^2/2)$   
 used in Chernoff

GAUSSIAN hypercontractivity

GAUSS space

$(\mathbb{R}^n, \sigma_n)$  standard Gaussian measure  $N(0, Id_n)$

A pair  $(X, Y)$  of random variables in  $\mathbb{R}^n$  is a pair of  $\rho$ -correlated standard Gaussians if  $\rho \in [-1, 1]$

- $(X, Y)$  is jointly Gaussian
  - $X \sim N(0, Id_n)$
  - $Y \sim N(0, Id_n)$
- $$\mathbb{E}[X_i Y_j] = \begin{cases} \rho & \text{if } i=j \\ 0 & \text{otherwise} \end{cases}$$

Prototype:  $z_1, z_2$  iid  $N(0, Id_n)$

$(z_1, \rho z_1 + \sqrt{1-\rho^2} z_2)$  is a pair of  $\rho$ -correlated standard Gaussians.

We define the GAUSSIAN mix operators on  $L^2(\sigma_n)$ .

$$(T_\rho f)(z) = \mathbb{E} f(\rho z + \sqrt{1-\rho^2} z')$$

We define  $\tau$

$$f \in C^1(\mathbb{R}^n) \quad z \in \mathbb{R}^n$$

$$(U_e f)(z) = \mathbb{E} f(ez + \sqrt{1-e^2} z)$$

$$\mathbb{E}_{z_n} U_e f = \mathbb{E}_{\substack{z \sim N(0, I_{2n}) \\ z' \sim N(0, I_{2n}) \\ z \perp z'}} f(ez + \sqrt{1-e^2} z') = \mathbb{E}_{z_n} f$$

$U_e \approx T_e$

$$(U_e U_{e'} f)(z) = \mathbb{E} [ f(e(e'z + \sqrt{1-e'^2} z_1) + \sqrt{1-e^2} z_2) ]$$

$$= \mathbb{E} [ f(ee'z + \sqrt{1-ee'^2} z) ]$$

$$U_e U_{e'} = U_{ee'}$$

More usually  $e \leftarrow e^{-t}$

$$P_t = U_{e^{-t}}$$

$$P_t P_{t'} = P_{t+t'}$$

$(P_t)_{t \geq 0}$  is called the ORNSTEIN-UHLENBECK semigroup.

complete  $\begin{matrix} \uparrow \\ \text{wise} \end{matrix}$   $\begin{matrix} \uparrow \\ \text{to mix} \end{matrix}$   $\begin{matrix} \uparrow \\ \text{[0,1]} \end{matrix}$

As before

$$\|U_e f\|_{L^p} \leq \|f\|_{L^p}$$

$\forall f \in L^p$   $U_e f$  is smooth ( $C^\infty$ )  $\forall e \in ]-1, 1[$ .

GAUSSIAN hypercontractivity theorem

$$\forall f \in L^p(\mathbb{R}^n)$$

$$q \geq p \quad 0 \leq e \leq \sqrt{\frac{p-1}{q-1}}$$

$$\|U_e f\|_{L^q} \leq \|f\|_{L^p}$$

Proof Take  $f$  continuous, compactly supported (enough by density)

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\forall N \in \mathbb{N} \quad g_N: [-1, 1]^n \rightarrow \mathbb{R}$$

$$g_N(x_1^1, \dots, x_N^1; x_1^2, \dots, x_N^2, \dots, x_1^N, \dots, x_N^N)$$

$$= f\left(\frac{x_1^1 + \dots + x_N^1}{\sqrt{N}}, \frac{x_1^2 + \dots + x_N^2}{\sqrt{N}}, \dots, \frac{x_1^N + \dots + x_N^N}{\sqrt{N}}\right)$$

By the CLT  $\lim_{N \rightarrow \infty} \|g_N\|_{L^q} = \|f\|_{L^q(\mathbb{R}^n)}$

(ii)  $\forall g_N \quad \|T_e g_N\|_{L^q} \leq \|g_N\|_{L^q}$

$$\|T_e g_N\|_{L^q}^q = \mathbb{E}_{x_j^i} | \mathbb{E}_{y_j^i \sim N_e(x_j^i)} f\left(\frac{y_1^1 + \dots + y_N^1}{\sqrt{N}}, \dots, \frac{y_1^N + \dots + y_N^N}{\sqrt{N}}\right) |^q$$

$\uparrow$   
e-correlated random bits

$\dots + y^i \dots$  CLT  $\rightarrow$  uncorrelated standard gaussian



$$(*) U_e h_\alpha = e^{-|\alpha|} h_\alpha$$

Theorem If  $Q$  is a polynomial in  $n$  variables of degree  $k$

Then  $\forall q \geq 2 \quad \|Q\|_{L^q(\mathbb{R}^n)} \leq (q-1)^{k/2} \|Q\|_{L^2(\mathbb{R}^n)}$

Proof  $U_e h_\alpha = e^{-|\alpha|} h_\alpha$  allows to define  $U_e$  on polynomials  $\forall e \in \mathbb{R}$ .

$$U_e U_{e'} = U_{ee'} \quad \forall e, e' \in \mathbb{R}$$

$$Q = U_e \left[ U_{\frac{1}{e}} Q \right] \quad p=2 \quad e = \frac{1}{\sqrt{q-1}}$$

HC  $\Rightarrow \quad \|Q\|_{L^q} \leq \|U_{\frac{1}{e}} Q\|_{L^2}$

$$\| \sum c_\alpha h_\alpha \|_{L^2} = \left( \sum c_\alpha^2 \right)^{1/2}$$

$$Q = \sum c_\alpha h_\alpha \quad U_{\frac{1}{e}} Q = \sum c_\alpha \left(\frac{1}{e}\right)^{|\alpha|} h_\alpha$$

$$\|Q\|_{L^2} = \left( \sum c_\alpha^2 \right)^{1/2} \quad \|U_{\frac{1}{e}} Q\|_{L^2} = \left( \sum c_\alpha^2 \left(\frac{1}{e}\right)^{2|\alpha|} \right)^{1/2} = \left( \sum c_\alpha^2 (q-1)^{|\alpha|} \right)^{1/2}$$

Since  $\deg(Q) \leq k$ , the non-vanishing  $c_\alpha$  correspond to  $|\alpha| \leq k$

$$\|Q\|_{L^q} \leq \|U_{\frac{1}{e}} Q\|_{L^2} \leq (q-1)^{k/2} \left( \sum c_\alpha^2 \right)^{1/2} = (q-1)^{k/2} \|Q\|_{L^2}$$

Corollary

$z_1, \dots, z_n$  iid  $N(0,1)$   
 $X = Q(z_1, \dots, z_n) \quad \deg Q \leq k$

Then  $\mathbb{P}(|X - \mathbb{E}X| \geq t \sqrt{\text{Var} X}) \leq \exp\left(-\frac{k}{2e} t^{2/k}\right) \quad \forall t \geq (2e)^{k/2}$

Proof

Identify  $X$  with  $Q: (\mathbb{R}^n, \mathcal{Z}_n) \rightarrow \mathbb{R}$

Assume  $\mathbb{E}X = 0 \quad \text{Var} X = 1$

$$\mathbb{P}(|X| \geq t) = \mathbb{P}(|X|^q \geq t^q) \leq t^{-q} \|X\|_{L^q}^q \quad \|X\|_{L^2} = 1$$

$$\leq t^{-q} (q-1)^{kq/2}$$

$$\leq t^{-q} q^{kq/2}$$

$$= \left(\frac{q^{k/2}}{t}\right)^q$$

$$= e^{-\frac{k}{2e} t^{2/k}}$$

$$q = \frac{t^{2/k}}{e}$$

$$\frac{q^{k/2}}{t} = e^{-\frac{k}{2} t^{2/k}}$$

$$t \geq (2e)^{k/2} \Leftrightarrow t \geq (2e)^{k/2}$$