

$$\Rightarrow \mathbb{E} \left[\sup_{t \in T} |X_t| \right] \leq \mathbb{E} \left[\sup_{t \in T} |X_t - X_{n(t)}| + \sum_{n=1}^N |X_{n(t)} - X_{n-1(t)}| \right] \quad \text{Triangle inequality}$$

$$\leq \mathbb{E} \left[\sup_{t \in T} |X_t - X_{n(t)}| \right] + \sum_{n=1}^N \mathbb{E} \left[\sup_{t \in T} |X_{n(t)} - X_{n-1(t)}| \right]$$

$$V_{\text{eff}} = \left[\frac{1}{2} \sum_{i,j} \left(\frac{\partial \phi_i}{\partial x_j} \right)^2 \right] = \left[\frac{1}{2} \sum_{i,j} \left(\frac{\partial \phi_i}{\partial x_j} \right)^2 \right]$$

$$\mathbb{E} \left[\sup_{t \in T} |X_{n+1}(t) - X_{n-1}(t)| \right] = \mathbb{E} \left[\frac{d(\bar{r}_n(t), \bar{r}_{n-1}(t))}{\lambda} \cdot \frac{\lambda}{d(\bar{r}_n(t), \bar{r}_{n-1}(t))} |X_{n+1}(t) - X_{n-1}(t)| \right]$$

$$\leq \frac{3 \cdot 2^{-n}}{\lambda} \mathbb{E} \left[\sup_{t \in T} \frac{\lambda (X_{n+1}(t) - X_{n-1}(t))}{d(\bar{r}_n(t), \bar{r}_{n-1}(t))} \right] = \frac{3 \cdot 2^{-n}}{\lambda} \mathbb{E} \left[\sup_{t \in T} \log \exp(\dots) \right]$$

$$\begin{aligned} & \leq \frac{3 \cdot 2^{-n}}{\lambda} \mathbb{E} \left(\sup_{t \in T} \exp \left(\frac{\lambda |X_{n,t} - X_{n-1,t}|}{d(\pi_n(t), \pi_{n-1}(t))} \right) \right) \\ & \exp(\sup) = \sup(\exp) \end{aligned}$$

$$\hookrightarrow \leq \frac{2 \cdot 2^{-n}}{\lambda} \log \left[\mathbb{E} \left(\sup_{\substack{t_1 \in T_n \\ t_2 \in T_{n-1}}} \exp \left(\frac{\lambda |X_{n+1}(t_1) - X_{n+1}(t_2)|}{d(\pi_n(t_1), \pi_{n-1}(t_2))} \right) \right) \right]$$

$$\leq \frac{3 \cdot 2^{-n}}{\lambda} \log \mathbb{E} \left[|T_n| \cdot |T_{n-1}| \exp \left(\frac{\lambda |X_{n+1} - X_{n-1}(t)|}{d(r_{n+1}, r_{n-1}(t))} \right) \right] \xrightarrow{|T_{n-1}| \leq (T_n)}$$

$$\leq \frac{3 \cdot 2^{-n}}{\lambda} \log \mathbb{E} \left[|T_n|^2 e^{\frac{4(\lambda)}{\lambda}} \right] = 3 \cdot 2^{-n} \left[\frac{4(\lambda) + 2 \log |T_n|}{\lambda} \right]$$

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$$\sup_{\lambda \in \mathbb{R}^+} \left\{ \frac{\psi(\lambda t)}{\lambda} \right\} = \psi^*(1) \quad \xrightarrow{\text{Thus}} \sup_{\substack{t_n, \\ n_{n-1} \in T}} \left\{ |X_{t_n+1} - X_{t_{n-1}+1}| \right\} \leq 3 \cdot 2^{-n} \cdot \psi^*(1) (2\log |T_n|)$$

$$\Rightarrow \mathbb{E} \left[\sup_{t \in T} X_t \right] \leq \int_{N \rightarrow \infty} \mathbb{E} |X_t - X_{t_N}| + \sum_{n=1}^N \sup_{\substack{t \in T \\ t_{n-1} \in T}} |X_{t_n+1} - X_{t_{n-1}+1}|$$

$$\Rightarrow \mathbb{E} \left[\sup_{t \in T} X_t \right] \leq \int_{N \rightarrow \infty} \sum_{n=1}^N 3 \cdot 2^{-n} \psi^*(2\log |T_n|) \leq 2 \cdot 3 \int_0^\infty \psi^*(2\log N(T_d, \varepsilon)) d\varepsilon$$

|T_n| → the covering number

which finally reduces to $\mathbb{E} \left[\sup_{t \in T} X_t \right] \leq 6 \int_0^\infty \psi^*(2\log N(T_d, \varepsilon)) d\varepsilon$ P.S.V.

⊕ $S = u^T (A^T A) u = \sum_{i=1}^n u^T a_i a_i^T u = \sum_{i=1}^n \langle a_i, u \rangle \cdot \langle a_i, u \rangle = \sum_{i=1}^n z_i^2$ = 20/2

$\mathbb{P}[u^T A^T A u \geq \alpha] \xrightarrow{\lambda \in \mathbb{R}^+} \leq e^{-\lambda \alpha} \mathbb{E} \left[e^{\lambda u^T A^T A u} \right] = e^{-\lambda \alpha} \mathbb{E} \left[e^{\lambda z^T z} \right]^m$ $A \in \mathbb{R}^{m \times n}$

$$\Rightarrow \mathbb{E} \left[e^{\lambda z^T z} \right] = \mathbb{E} \left[e^{\lambda a^T u u^T a} \right] = \frac{1}{(2\pi)^{n/2}} \int_{\mathbb{R}^n} e^{\pm \lambda a^T u u^T a} e^{-\frac{a^T a}{2}} da$$

$$= \frac{1}{(2\pi)^{n/2}} \int \exp \left(\pm \frac{1}{2} a^T (I \pm 2\lambda u u^T) a \right) da = |I \pm 2\lambda u u^T|^{-1/2}$$

→ eigenvalues of $I \pm 2\lambda u u^T \rightarrow \begin{cases} \psi_{||u}: 1 \pm 2\lambda u^T u \\ \psi_{\perp u}: 1 \end{cases} \rightarrow \det(I \pm 2\lambda u u^T) = 1 \pm 2\lambda u^T u$

thus $\Rightarrow \mathbb{E} \left[e^{\pm \lambda z^T z} \right] = (1 \mp 2\lambda u^T u)^{-1/2}$ which suggests

$$\mathbb{P}[u^T A^T A u \geq \alpha] \leq \begin{cases} e^{-\lambda \alpha} \left[(1 - 2\lambda u^T u)^{-1/2} \right]^m \\ e^{+\lambda \alpha} \left[(1 + 2\lambda u^T u) \right]^{-m/2} \end{cases}$$

we can pick the better bound with respect to the given α .

⊕ $\mathbb{P} \left[\left| \frac{1}{m} u^T A^T A u - u^T u \right| \geq \varepsilon u^T u \right] = \mathbb{P} \left[\frac{1}{m} u^T A^T A u - u^T u \geq \varepsilon u^T u \right] + \mathbb{P} \left[\frac{1}{m} u^T A^T A u - u^T u \leq -\varepsilon u^T u \right]$

$$= \mathbb{P} \left[u^T A^T A u \geq m(1 + \varepsilon) u^T u \right] + \mathbb{P} \left[u^T A^T A u \leq m(1 - \varepsilon) u^T u \right]$$

$$\leq \underbrace{e^{-\lambda_1 m(1+\varepsilon)u^T v}}_{f_1} (1-2\lambda_1 u^T v)^{-m/2} + e^{\lambda_2 m(1-\varepsilon)u^T v} (1+2\lambda_2 u^T v)^{-m/2} \quad \text{--- } 2(1-\varepsilon)u^T v$$

$$\inf_{\lambda_1} f_1(\lambda_1) = \inf_{\lambda_1} \left\{ e^{-\lambda_1 a} (1-2\lambda_1 u^T v)^{-m/2} \right\} \rightarrow \frac{\partial f_1}{\partial \lambda_1} = -a e^{-\lambda_1 a} (1-2\lambda_1 u^T v)^{-m/2} + e^{-\lambda_1 a} (1-2\lambda_1 u^T v)^{-\frac{m}{2}-1} u^T v = 0$$

$$\rightarrow m u^T v = a(1-2\lambda_1 u^T v) \rightarrow \lambda_1^* = \frac{a - m u^T v}{2a u^T v} \rightarrow a = (1+\varepsilon)u^T v \rightarrow \lambda_1^* = \frac{\varepsilon}{2(1+\varepsilon)u^T v}$$

$$\text{So: } \mathbb{P}\left[u^T A^T A v \geq m(1+\varepsilon)u^T v\right] \leq e^{-\frac{m\varepsilon}{2}} \left(1 - \frac{\varepsilon}{1+\varepsilon}\right)^{-m/2} = \left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2} \quad (*)$$

likewise we can do the same thing for $\inf_{\lambda_2} f_2(\lambda_2)$.

$$\arg\min_{\lambda_2} f_2(\lambda_2) = \lambda_2^* = \frac{a - m u^T v}{2a u^T v} \rightarrow a = u(1-\varepsilon)u^T v \rightarrow \lambda_2^* = \frac{\varepsilon}{2(1-\varepsilon)u^T v}$$

$$\mathbb{P}\left[u^T A^T A v \geq m(1+\varepsilon)u^T v\right] \leq e^{-\frac{m\varepsilon}{2}} \cdot \left(1 - \frac{\varepsilon}{1-\varepsilon}\right)^{-m/2} = \left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2}$$

$$\mathbb{P}\left[u^T A^T A v \geq m(1-\varepsilon)u^T v\right] \leq e^{-\frac{m\varepsilon}{2}} \left(1 - \frac{\varepsilon}{1-\varepsilon}\right)^{-m/2} = \left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2} \quad (**)$$

$$(*), (**) \text{ implies that } \mathbb{P}\left[\left|\frac{1}{m}u^T A^T A v - u^T v\right| \geq \varepsilon u^T v\right] \leq \left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2} + \left((1-\varepsilon)e^{\varepsilon}\right)^{m/2}$$

$$\text{since } \varepsilon < a \rightarrow (1+\varepsilon)e^{-\varepsilon} \geq (1-\varepsilon)e^{\varepsilon} \rightarrow \mathbb{P}[- \geq -] \leq 2\left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2}$$

$$\text{now since } (1+\varepsilon)e^{-\varepsilon} \leq e^{-\frac{\varepsilon^2}{2} + \frac{\varepsilon^3}{3}} \rightarrow \left((1+\varepsilon)e^{-\varepsilon}\right)^{m/2} \leq e^{-m\left(\frac{\varepsilon^2}{4} - \frac{\varepsilon^3}{6}\right)}$$

which finally suggest that

$$\blacksquare \text{ Q.E.D. } \mathbb{P}\left[\left|\frac{u^T A^T A v}{m} - u^T v\right| \geq \varepsilon u^T v\right] \leq 2e^{-m\left(\frac{\varepsilon^2}{4} - \frac{\varepsilon^3}{6}\right)}$$

$$T = \left\{ \frac{e_k}{\sqrt{1+\log k}}, k \in [n] \right\} \quad W(T) = \mathbb{E} \left[\sup_{t \in T} \{t^T X\} \right]; X \sim \mathcal{N}(0, I_n) \quad \text{30/5}$$

$$y_t = t^T X$$

$$\rightarrow \mathbb{E}[e^{\lambda(y_t - y_s)}] = \mathbb{E}[e^{\lambda(t-s)^T X}] \leq \mathbb{E}[e^{\frac{\lambda^2}{2} \|t-s\|_2^2}] \rightarrow \text{it's } \|t-s\|_2^2 = y_t - y_s$$

so we do an ε -covering where $\varepsilon \geq \frac{1}{\sqrt{\log k}} \rightarrow k \geq e^{\frac{1}{\varepsilon^2}}$

$k \geq N(\varepsilon, T, d) \geq P(2\varepsilon, T, d) \rightarrow$ if we do ε -packing $\rightarrow k \geq e^{\frac{1}{4\varepsilon^2}}$

therefore $\int_0^\infty \sqrt{\log N(T, d, \varepsilon)} d\varepsilon \geq \int_1^\infty \sqrt{\frac{1}{4\varepsilon^2}} d\varepsilon = \frac{1}{2} \int_1^\infty \frac{d\varepsilon}{\varepsilon} = \infty$ which doesn't converge.

therefore $\int_0^\infty \sqrt{\log N(T, d, \varepsilon)} d\varepsilon$ is not a good bound!

However, it's obvious that $W(T) < \infty$, when $n \rightarrow \infty$: $W(T) < \infty$

$$\begin{aligned} W(T) &= \mathbb{E} \left[\sup_{t \in T} t^T X \right] = \mathbb{E} \left[\max_{1 \leq k \leq n} \left\{ \frac{X_k}{\sqrt{1+\log k}} \right\} \right] \leq \int_0^\infty \mathbb{P} \left[\max_k \frac{|X_k|}{\sqrt{1+\log k}} \geq t \right] dt \\ &\leq \int_0^T 1 dt + \int_T^\infty \mathbb{P} \left[\max_k \frac{|X_k|}{\sqrt{1+\log k}} \geq t \right] dt \leq T + \int_T^\infty \sum_{k=1}^n \mathbb{P} \left[|X_k| \geq t \sqrt{1+\log k} \right] dt \\ &\leq T + \sum_{k=1}^n \int_T^\infty 2e^{-\frac{t^2}{2(1+\log k)}} dt \quad \text{Union Bound} \\ &\leq T + c \sum_{k=1}^n e^{-\frac{T^2}{2} \log k} < \infty \quad \text{Q.E.D.} \end{aligned}$$

$c = e^{-\frac{T^2}{2}} \quad \left(\forall t \geq T, e^{-\frac{t^2}{2}} \geq e^{-\frac{T^2}{2}} \right)$

now, $T + c \sum_{k=1}^n e^{-\frac{T^2}{2} \log k}$ is Bounded and it's far better than

$\int_0^\infty \sqrt{\log N(\varepsilon, T, d)} d\varepsilon$ which is not bounded and not tight.

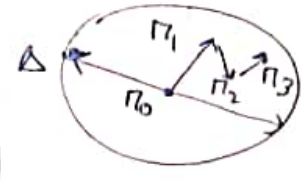
$$X_t - X_s \sim d(s, t) \text{ subg} \quad \Delta = \text{diam}(T) = \sup_{s, t} d(s, t) \quad : 4 D/2$$

since in the optimal case we can cover a the set with only a point and Δ -covering, like the thing that Dr. Yasser did, we define:

$$n \in \{1, 2, \dots\} \rightarrow \varepsilon_n = 2^{-n} \cdot \Delta : T_n : \Delta, 2^{-n} \text{ covering and } n_{\text{alt}} \text{ is our quantifier}$$

$$\Rightarrow |X_t - X_s| = \left| X_s - X_{n_0(s)} + \sum_{n=1}^N (X_{n_n(s)} - X_{n_{n-1}(s)}) - \sum_{n=1}^N (X_{n_n(t)} - X_{n_{n-1}(t)}) - (X_t - X_{n_0(t)}) \right|$$

triangle inequality $\rightarrow \sum_{n \in \{1, \dots, N\}} \left(|X_s - X_{n_n(s)}| + \sum_{n=1}^N |X_{n_n(s)} - X_{n_{n-1}(s)}| \right)$



$$\Rightarrow \sup_{t, s \in T} |X_t - X_s| \leq \sup_{t, s \in T} \left\{ \sum_{n \in \{1, \dots, N\}} |X_s - X_{n_n(s)}| + \sum_{n=1}^N |X_{n_n(s)} - X_{n_{n-1}(s)}| \right\}$$

$$\leq 2 \left(\sup_{t \in T} |X_t - X_{n_0(t)}| + \sum_{n=1}^N \sup_{t \in T} |X_{n_n(t)} - X_{n_{n-1}(t)}| \right)$$

probabilistic chaining $\Delta, 2^{-n} \sim \text{subg}$ $3\Delta 2^{-n} \sim \text{subg}$

$$\mathbb{P} \left[\sup_{t \in T} |X_{n_{\text{alt}}(t)} - X_{n_{n-1}(t)}| \leq 6\Delta \cdot 2^{-n} \sqrt{\log |N_n|} + 3\Delta 2^{-n} u_i \right] \geq 1 - e^{-\frac{u_i^2}{2}} \quad (\text{de})$$

$$\Rightarrow \mathbb{P} \left(\exists n : \sup_{t \in T} |X_{n_{\text{alt}}(t)} - X_{n_{n-1}(t)}| \leq 6\Delta \cdot 2^{-n} \sqrt{\log |N_n|} \right) \geq 1 - \mathbb{P}[\exists n \dots]$$

$$\geq 1 - \sum_{i=1}^N \mathbb{P} \left[\sup_{t \in T} \dots \right] \geq 1 - \sum_{i=1}^N e^{-\frac{u_i^2}{2}}$$

Union Bound

$$\stackrel{e^x \geq 1+x}{\geq} 1 - \sum_{i=1}^{\infty} e^{-\frac{u_i^2}{2}} = 1 - 2e^{-\frac{u^2}{2}} e^{-2} \frac{e^{-2}}{1-e^{-2}} \geq 1 - \frac{1}{3} e^{-\frac{u^2}{2}}$$

$$\text{from AM-GM} \rightarrow u_i^2 = u^2 + 4i \leq (u + 2\sqrt{i})^2$$

thus we've Proven that with probability of at least "1- δ " where $\delta = \frac{1}{3} e^{-\frac{u^2}{2}}$

$$\mathbb{P} \left[\sup_{t \in T} |X_s - X_t| \leq 2 \sum_{n=1}^{\infty} 6\Delta 2^{-n} \sqrt{\log |N_n|} + 3\Delta 2^{-n} u_i \right] \geq 1 - \frac{1}{3} e^{-\frac{u^2}{2}}$$

Now since

$$2 \sum_{n=1}^{\infty} 6 \Delta 2^{-n} + 3 \Delta 2^{-n} u_i = 12 \sum_{n=1}^{\infty} \Delta 2^{-n} \sqrt{\log N(2^{-n} \Delta)} + 3 \Delta 2^{-n} u_i$$

: 40, 2, 1, 1

Therefore we get

$$\begin{aligned} \Rightarrow \sup_{s, t \in T} \{ |x_t - x_s| \} &\leq 24 \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon + 3 \Delta \sum_{n=1}^{\infty} 2^{-n} (u + 2\sqrt{n}) \\ &\leq 24 \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon + 3u \text{diam}(T) + 6 \sum_{n=1}^{\infty} 3 \Delta 2^{-n} \sqrt{n} \\ &\leq C \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon + C_2 u \text{diam}(T) + C_3 \text{diam}(T) \end{aligned}$$

In order to cover the set T with $\text{diam } T$, we only need one element from the set T . Thus

$$\begin{cases} N(T, d, \frac{\text{diam}(T)}{2}) \geq 2 \rightarrow 2^{-n} \Delta \leq C \sqrt{\log N(T, d, \Delta 2^{-n})} 2^{-n} \Delta \\ \Rightarrow \sum_{n=1}^{\infty} \Delta 2^{-n} \leq C \sum_{n=1}^{\infty} \sqrt{\log N(T, d, \Delta 2^{-n})} 2^{-n} \Delta \leq C \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon \end{cases}$$

Riemann integral by $\lim_{n \rightarrow \infty}$

It suffices if $\Delta 2^{-n} = o(1)$

thus finally we've proven that

$$\exists C: \sup_{t, s} |x_t - x_s| \leq C \left[\int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon + u \text{diam}(T) \right]$$

with probability of at least $1 - \frac{1}{3} e^{-\frac{u^2}{2}}$

which is better than $1 - 7e^{-u^2/2}$

Q.E.D.

$$\mathbb{E}[e^{\lambda(X_t - X_s)}] \leq \exp\left(\frac{\lambda^2 d(s, t)^2}{2}\right) \quad |X_t - X_s| \leq C \cdot d(s, t) \quad \text{--- 50/2}$$

Again, we consider the same approach, we take the $\Delta \cdot 2^n$ coming, which suggests:

$$\begin{aligned} \sup_{t \in T} \{X_t\} &= \sup_{t \in T} \left\{ X_t - X_{\pi_L(t)} + \sum_{i=k+1}^L X_{\pi_i(t)} - X_{\pi_{i-1}(t)} + X_0 \right\} \\ \text{Triangle} \quad &\leq \sup_{t \in T} \{X_t - X_{\pi_L(t)}\} + \sum_{i=k+1}^L \sup_{t \in T} \{X_{\pi_i(t)} - X_{\pi_{i-1}(t)}\} + X_0 \leq C \cdot \sup_{t \in T} \underbrace{d(t, \pi_L(t))}_{\substack{\dots + \dots \\ d(t, \pi_L(t))}} \end{aligned}$$

$$d(t, \pi_L(t)) \leq 2^{-L} = 2\delta \rightarrow \delta = 2^{-L-1}$$

$$\Rightarrow \sup_{t \in T} X_t \leq 2\delta C + \sum_{i=k+1}^L \sup_{t \in T} \{X_{\pi_i(t)} - X_{\pi_{i-1}(t)}\}$$

as we did before:

$$\xrightarrow{\forall i} \mathbb{E} \left[\sup_{t \in T} X_{\pi_i(t)} - X_{\pi_{i-1}(t)} \right] \leq \mathbb{E} \left[\sup_{t_1, t_2} \{X_{t_1} - X_{t_2}\} \right] \leq \sqrt{2(3 \cdot 2^i)^2 \log |N_i| / |N_{i-1}|}$$

$$\Rightarrow \sum_{i=k+1}^L \sup_{t \in T} \{X_{\pi_i(t)} - X_{\pi_{i-1}(t)}\} \leq 6 \sum_{i=k+1}^L 2^{-i} \sqrt{\log |N_i|} \leq 12 \int_{\delta}^{\infty} \sqrt{\log N(\varepsilon, T, d)} d\varepsilon$$

$$\xrightarrow{\forall \delta} \mathbb{E} \left[\sup_{t \in T} X_t \right] \leq 2\delta \mathbb{E}[C] + 12 \int_{\delta}^{\infty} \sqrt{\log N(\varepsilon, T, d)} d\varepsilon$$

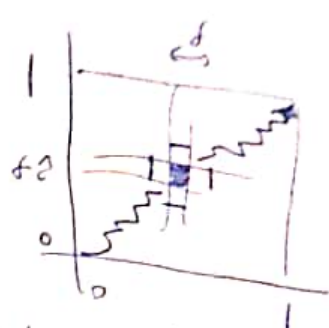
we can find the tightest bound by applying infimum over the R.H.S. of the inequality, which suggests

$$\mathbb{E} \left[\sup_{t \in T} X_t \right] \leq \inf_{\delta} \left\{ 2\delta \mathbb{E}[C] + 12 \int_{\delta}^{\infty} \sqrt{\log N(\varepsilon, T, d)} d\varepsilon \right\} \quad \text{--- d.s.p.}$$

$$(I) |f(x_1) - f(x_2)| \leq \|f - g\|_{\infty}$$

$$\{x_i - x_n\} \stackrel{iid}{\sim} P_X$$

$\approx 60 \frac{1}{2}$



$$W_1(P_n, P) = \sup_{f \in 1-Lip} \left\{ \mathbb{E}_n[f(X)] - \mathbb{E}_P[f(X)] \right\}$$

we did as we did in the class for functions, we make a grid of width & length δ . So now we want to find the covering functions with δ -width grid $\rightarrow N(\epsilon, \square) \leq \left(\frac{2}{\epsilon}\right) \cdot \prod_{i=1}^{1/\delta-1} \frac{2(i+1)}{3} \cdot 5 = \left(\frac{2}{\epsilon}\right) \cdot 5^{\frac{1}{\delta}-1} \frac{2^{\frac{1}{\delta}-1}}{3^{\frac{1}{\delta}-1}}$

$$\log N(\epsilon, \square) \leq (\log 3) \left(\frac{1}{\epsilon}\right)^2 + (\log 5) \left(\frac{1}{\epsilon}\right) + \log \frac{2}{\epsilon} \leq C \cdot \left(\frac{1}{\epsilon}\right)^2$$

$$\leq \left(\frac{2}{\epsilon}\right) 5^{\frac{1}{\epsilon}} 3^{\frac{1}{\epsilon} 2}$$

each square is neighboring 5 squares.

$$\rightarrow N(\epsilon) \leq \exp\left(C \left(\frac{1}{\epsilon}\right)^2\right)$$

(II)

$$N(\epsilon) \geq N_{\text{one dimensional}} \geq \prod_{i=1}^{1/\delta-1} 3^{i-1}$$

Q.E.D.

$$\hookrightarrow \int \sqrt{\log N(\epsilon)} d\epsilon \geq \int C \left(\frac{1}{\epsilon} + 1\right) d\epsilon \text{ which is clearly diverging.} = \infty$$

$$(III) \text{ let } Z_f = \frac{1}{n} \sum_{i=1}^n f(x_i) - \mathbb{E}f(x_i)$$

here we do the exact same thing as we did in lectures!

$$\rightarrow \mathbb{E}[W_1(P_n, P)] = \mathbb{E} \left[\sup_{f \in \mathcal{F}} Z_f \right]$$

$$\Rightarrow |Z_f - Z_g| = \left| \frac{1}{n} \sum_{i=1}^n (f(x_i) - g(x_i)) - \mathbb{E}_P[f(X)] + \mathbb{E}_P[g(X)] \right|$$

$$\leq \mathbb{E}_P[|f(X) - g(X)|] + \frac{1}{n} \sum_{i=1}^n |f(x_i) - g(x_i)| \leq 2 \|f - g\|_{\infty}$$

$$\Rightarrow \mathbb{E}[W_1(P_n, P)] = \mathbb{E} \left[\sup_{f \in \mathcal{F}} Z_f \right] \leq \inf_{\delta} \left\{ 4\delta\sqrt{n} + 12 \int_{\delta}^{\infty} \sqrt{\log N(F, \|\cdot\|_{\infty}, \frac{1}{\sqrt{n}}, \epsilon)} d\epsilon \right\}$$

$$\leq \inf_{\delta \geq 0} \left\{ 4\delta\sqrt{n} + \frac{12}{\sqrt{n}} \int_{\delta}^{\infty} \frac{C}{\epsilon} d\epsilon \right\} \leq C' \inf_{\delta \geq 0} \left\{ \delta\sqrt{n} + \frac{1}{\sqrt{n}} \int_{\delta}^{\infty} \frac{d\epsilon}{\epsilon} \right\}$$

$$= \frac{C'}{\sqrt{n}} \left(1 + \log(2\sqrt{n}) \right) \leq \frac{C'' \log n}{\sqrt{n}} \quad \text{Q.E.D.} \quad \square$$

$X = \{X_1, \dots, X_m\}$ $X_i \sim N(0, I_n)$ $m \geq \exp(cn)$, by definition:

$$\text{CH}(A) = \{y \in \mathbb{R}^n, \exists a_1, \dots, a_m \in [0, 1] : \sum a_i |z_i|, y = \sum a_i X_i\}$$

$$f(u) = \sup_{X \in \text{CH}(A)} u^T X = \max_{X \in A} u^T X = \max_{1 \leq i \leq n} u^T X_i = Y_u \quad \text{which is a process with index } u$$

let $r_+ = \sup_{\|u\|=1} \{Y_u\}$, $r_- = \inf_{\|u\|=1} \{Y_u\}$, now consider an ε -convex on the

surface of $B_1 \Rightarrow r_+ \leq \max_{1 \leq i \leq n} u_i^T X_i \leq \max_{1 \leq i \leq n} u_i^T X_i + \varepsilon |X_i|$

$$r_+ \leq \max_{1 \leq i \leq n} \{u_i^T X_i\} + \varepsilon \cdot \max_{1 \leq i \leq n} |X_i| \Rightarrow r_+ \leq \frac{1}{1-\varepsilon} \max_{1 \leq i \leq n} u_i^T X_i$$

$$\Rightarrow \mathbb{P}(r_+ \geq t) \leq \mathbb{P}\left[\frac{\max_{1 \leq i \leq n} \{u_i^T X_i\}}{1-\varepsilon} \geq t\right] = \mathbb{P}\left[\max_{1 \leq i \leq n} u_i^T X_i \geq (1-\varepsilon)t\right]$$

$$\leq m |N_\varepsilon| e^{-\frac{t^2(1-\varepsilon)^2}{2}} \leq m \left(\frac{3}{\varepsilon}\right)^n e^{-\frac{t^2(1-\varepsilon)^2}{2}}$$

$$\Rightarrow \mathbb{P}(r_+ \geq t) \leq \exp\left(\log m + n \log \frac{3}{\varepsilon} - \frac{1}{2}(1-\varepsilon)^2 t^2\right) \quad \left| \begin{array}{l} m \geq e^{cn} \\ n \leq \frac{1}{c} \log m \end{array} \right.$$

$$\mathbb{P}(r_+ \geq t) \Big|_{t = \frac{\log m}{1-\varepsilon}} \leq \exp\left(\log m + n \log \frac{3}{\varepsilon} - \frac{1}{2} \frac{(1-\varepsilon)^2}{(1-\varepsilon)^4} (\log m)^2\right)$$

$$\Rightarrow \mathbb{P}(r_+ \geq \frac{\log m}{1-\varepsilon}) \leq \exp\left(\left(1 + \frac{1}{c} \log \frac{3}{\varepsilon}\right) \log m - \frac{1}{c} \log^2(m)\right) \xrightarrow{\text{let } \varepsilon = 3e^{-\alpha c}} \exp(\log m (1 + \alpha - \frac{1}{2} \log m))$$

$\rightarrow \log m \gg 2(1+\alpha)$ as for large enough m , ~~will suffice~~ will suffice.

~~1.2.2~~

$$\mathbb{P}[\|A\|_{op} \geq c(\sqrt{p} + \sqrt{q} + t)] \leq e^{-t^2}$$

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$$\begin{aligned} \Rightarrow \mathbb{E}[\|A\|_{op}] &= \int_0^\infty \mathbb{P}[\|A\|_{op} \geq t] dt = \int_0^{c\sigma(\sqrt{p} + \sqrt{q})} \mathbb{P}[\|A\|_{op} \geq t] dt + \int_{c\sigma(\sqrt{p} + \sqrt{q})}^\infty \mathbb{P}[\|A\|_{op} \geq t] dt \\ &\leq \int_0^\infty 1 dt + \int_{c\sigma(\sqrt{p} + \sqrt{q})}^\infty \mathbb{P}[\|A\|_{op} \geq c\sigma(\sqrt{p} + \sqrt{q}) + t] dt \quad \text{shifting} \\ &\leq c\sigma(\sqrt{p} + \sqrt{q}) + c\sigma \frac{\sqrt{\pi}}{2} \leq c\sigma'(\sqrt{p} + \sqrt{q}) \rightarrow \boxed{\mathbb{E}[\|A\|_{op}] \leq c\sigma\sqrt{p} + c\sigma\sqrt{q}} \end{aligned}$$

Now we formulate

$$\Rightarrow \|A\|_{op} = \sup_{(u,v) \in B_m \times B_n} u^T A v = \sup_{(u,v) \in B_m \times B_n} \left\{ \sum_{i,j} u_i v_j A_{ij} \right\} \quad \text{by:}$$

$$\begin{aligned} \Rightarrow \mathbb{E}[e^{\lambda u^T A v}] &= \mathbb{E}\left[e^{\sum_{i,j} u_i v_j A_{ij}}\right] = \prod_{i,j} \mathbb{E}[e^{\lambda u_i v_j A_{ij}}] \leq e^{\frac{\lambda^2 \sigma^2}{2} \sum_{i,j} u_i^2 v_j^2} \\ &\leq \exp\left(\frac{\lambda^2 \sigma^2}{2} \|u\|_2^2 \|v\|_2^2\right) = e^{\frac{\lambda^2 \sigma^2}{2}} \end{aligned}$$

$$\forall (u,v) \in B_m \times B_n \rightarrow u^T A v \sim \sigma^2 \text{ subg}$$

In the days we get:

$$\mathbb{P}\left[\sup_{u,v \in B_m \times B_n} \{u^T A v\} \geq t\right] \leq \mathbb{P}\left[\max_{u,v \in B_m \times B_n} \{u^T A v\} \geq (1-2\varepsilon)t\right] \leq |N_1| |N_2| \cdot e^{-\frac{t^2}{2\sigma^2} (1-2\varepsilon)^2}$$

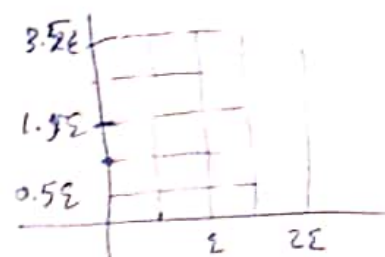
We know that balls in \mathbb{R}^d can be covered by $(\frac{3}{\varepsilon})^d$. thus

$$|N_1| \leq \left(\frac{3}{\varepsilon}\right)^n, \quad |N_2| \leq \left(\frac{3}{\varepsilon}\right)^m \quad \text{which leads to:}$$

$$\mathbb{P}\left[\|A\|_{op} \geq t\right] \leq \exp\left[\underbrace{-\frac{t^2 (1-2\varepsilon)^2}{2\sigma^2}}_{\leq -u^2} + \ln\left(\frac{3}{\varepsilon}\right)(m+n)\right]$$

$$\Rightarrow \boxed{\mathbb{P}[\|A\|_{op} \geq c\sigma(\sqrt{m} + \sqrt{n} + u)] \leq e^{-u^2}} \quad \text{Q.E.D.}$$

we need to introduce a covering. if we take a 2-dim grid: $2D^2$
 with $\frac{\epsilon}{2}$ distances. now if we're given a function, we need to give
 a function that covers the given function



the number of functions:

$$\rightarrow \left(\frac{1}{(\epsilon/2)} \right)^{(2)} = \left(\frac{2}{\epsilon} \right)^2$$

this is a good ϵ -covering. thus $N(\epsilon, \mathcal{F}, \|\cdot\|_\infty) \leq \left(\frac{2}{\epsilon} \right)^2$.

since in each step we have three choices, we get

$$N(\mathcal{F}, \|\cdot\|_\infty, \epsilon) = \frac{1}{\epsilon} \times 3^{\lceil \frac{2}{\epsilon} \rceil}$$

since the function we introduced. was 1-Lipschitz, for one exterior

Coverage. So due to $N(\mathcal{F}, \|\cdot\|_\infty, \epsilon) \leq N^{\text{ext}}(\mathcal{F}, \|\cdot\|_\infty, \epsilon/2)$. Q.E.D.