

Lecture 21

①

$$d_T(x, y) = \sup_{C: \|C\|_2 \leq 1} d_C(x, y) : \text{Talagrand's convex distance}$$

Talagrand's Convex Distance Inequality

$$\mathbb{P}(X^n \in A) \mathbb{P}(d_T(X^n, A) > t) \leq e^{-t^2/4}$$

Corollary: For a function $f: \mathcal{X}^n \rightarrow \mathbb{R}$ which is Lipchitz in d_T , $\mathbb{P}(f(X^n) > \mathbb{E}f(X^n) + t) \leq 2 \cdot e^{-t^2/4}$

$$\hookrightarrow f(x) \leq \sup_{y \in A} f(y) + d_T(x, A)$$

Proof of Talagrand's convex distance inequality

Shall show a weaker version:

$$\mathbb{P}(X^n \in A) \mathbb{P}(d_T(X^n, A) > t) \leq e^{-t^2/10}$$

Lemma: Denoting $g(x) = d_T(x, A)$.

* $g(x)$ is $(4, 0)$ -weakly-self bounding with $g(x) - g_i(x^{(i)}) \leq 1$.

Then, using the left-tail bound for weakly-self bounding functions

$$\begin{aligned} \mathbb{P}(d_T(X, A)^2 \leq \mathbb{E}[d_T(X, A)^2] - t) \\ \leq \exp\left(-\frac{t^2}{2 \cdot 4 \cdot \mathbb{E}[d_T(X, A)^2]}\right). \end{aligned}$$

In particular,

$$\mathbb{P}(A) = \mathbb{P}(d_T(X, A)^2 \leq 0) \leq \exp\left(-\frac{\mathbb{E}[d_T(X, A)^2]}{8}\right).$$

Also,

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$$\log \mathbb{E} e^{\lambda(d_T(x,A)^2 - \mathbb{E}[d_T(x,A)^2])} \leq \frac{2\mathbb{E}[d_T(x,A)^2]\lambda^2}{(1-2\lambda)}.$$

choosing $\lambda = \frac{1}{10}$,

$$\mathbb{E} \left[\exp \left(\frac{d_T(x,A)^2}{10} \right) \right] \leq \exp \left(\frac{\mathbb{E}[d_T(x,A)^2]}{8} \right)$$

$$\begin{aligned} \text{Thus, } \mathbb{P}(d_T(x,A) > t) &\leq e^{-t^2/10} \cdot \mathbb{E} \left[\exp \left(\frac{d_T(x,A)^2}{10} \right) \right] \\ &\leq e^{-t^2/10} \cdot \exp \left(\frac{\mathbb{E}[d_T^2(x,A)]}{8} \right) \end{aligned}$$

which gives

$$\mathbb{P}(A) \mathbb{P}(d_T(x,A) > t) \leq e^{-t^2/10}.$$

Proof of Lemma

Alternative form of d_T

$$\begin{aligned} d_T(x,A) &= \sup_{C: \|C\|_2 \leq 1} \inf_{y \in A} \sum_{i=1}^n C_i \mathbb{1}_{\{x_i \neq y_i\}} \\ &= \sup_{C: \|C\|_2 \leq 1} \inf_{y \in M(A)} \sum_{i=1}^n C_i \nu(x_i \neq y_i) \end{aligned}$$

(by Sion's
minimax
Theorem)

$$= \inf_{y \in M(A)} \sup_{C: \|C\|_2 \leq 1} \sum_{i=1}^n C_i \nu(x_i \neq y_i)$$

(by CS)

$$= \inf_{y \in M(A)} \sqrt{\sum_{i=1}^n \nu(x_i \neq y_i)^2}$$

$$\text{Let } g_i(x^{(i)}) = \inf_{x'_i \in \mathcal{X}} g(x^{(i-1)}, x'_i, x^{(i+1)}).$$

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$$* \boxed{g(x) - g_i(x^{(i)}) \leq 1}$$

$$\begin{aligned} \text{Let } g_i(x^{(i)}) &= g(x^{(i)}, \tilde{x}_i, x_{-i}^n) \\ &= \sum_{j \neq i} \tilde{v}(x_j \neq y_j)^2 + \tilde{v}(\tilde{x}_i \neq y_i) \end{aligned}$$

$$\text{Then, } g(x) \leq \sum_{j=1}^n \tilde{v}(x_j \neq y_j)^2$$

$$\begin{aligned} \Rightarrow g(x) - g_i(x^{(i)}) &\leq \tilde{v}(\tilde{x}_i \neq y_i) - \tilde{v}(x_i \neq y_i) \\ &\leq 1. \end{aligned}$$

$$* \boxed{\sum_{i=1}^n (g(x) - g_i(x^{(i)}))^2 \leq 4g(x)}$$

It suffices to show:

$$\boxed{\begin{aligned} &\exists c \text{ s.t. } \|c\|_2 \leq 1 \text{ and} \\ &(\sqrt{g(x)} - \sqrt{g_i(x^{(i)})})^2 \leq c_i^2, \quad 1 \leq i \leq n \end{aligned}} \quad (\#)$$

Then,

$$\begin{aligned} \sum_{i=1}^n (g(x) - g_i(x^{(i)}))^2 &\leq \sum_{i=1}^n c_i^2 \cdot 4g(x) \\ &\leq 4g(x). \end{aligned}$$

It remains to show (#). Let $\tilde{c}$ achieve $\sqrt{g(x)}$, i.e.,

$$\sqrt{g(x)} = \inf_{v \in \mathcal{M}(A)} \sum_{i=1}^n \tilde{c}_i v(x_i \neq y_i).$$

Further, noting that

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$$\begin{aligned}\sqrt{g_i(x^{(i)})} &\geq \inf_{y \in M(A)} \sum_{j \neq i} \tilde{c}_j v(x_j \neq y_j) + \tilde{c}_i v(\tilde{x}_i \neq y_i) \\ &= \sum_{j \neq i} \tilde{c}_j \tilde{v}(x_j \neq y_j) + \tilde{c}_i \tilde{v}(\tilde{x}_i \neq y_i).\end{aligned}$$

$$\begin{aligned}\text{Thus, } \sqrt{g(x)} - \sqrt{g_i(x^{(i)})} &\leq \tilde{c}_i [\tilde{v}(x_i \neq y_i) - \tilde{v}(\tilde{x}_i \neq y_i)] \\ &\leq \tilde{c}_i,\end{aligned}$$

and since $g(x) \geq g_i(x^{(i)})$,

$$\left(\sqrt{g(x)} - \sqrt{g_i(x^{(i)})}\right)^2 \leq \tilde{c}_i^2.$$

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F Examples

Ex1 Longest increasing subsequence

$f(x)$ = length of the longest increasing subsequence of x .

* f satisfies BDP with $(1, 1, \dots, 1)$

$$\Rightarrow P(|f(x) - \mathbb{E}f(x)| > t) \leq 2 \cdot e^{-2t^2/n}.$$

* $f(x)/\sqrt{n}$ is Lipschitz in d_T .

$$\Rightarrow P(f(x) > \mathbb{E}f(x) + t) \leq 2 \cdot e^{-t^2/4n}.$$

Proof. Let $g(x)$ denote the indices corresponding to the LIS of x . Then, $f(x) = |g(x)|$ and so,

$$f(y) \geq \sum_{i=1}^n \mathbb{1}_{\{i \in g(x), x_i = y_i\}}$$

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$$= f(x) - \sum_{i=1}^n \mathbb{1}_{\{i \in g(x), x_i \neq y_i\}}$$

$$\Rightarrow f(x) - f(y) \leq \sum_{i=1}^n \mathbb{1}_{\{i \in g(x)\}} \cdot \mathbb{1}_{\{x_i \neq y_i\}}$$

(It is possible to improve the tail bound to

$$\mathbb{P}(f(x) > Mf(x) + t) \leq \exp\left(-\frac{t^2}{4(Mf + t)}\right)$$

Fact: $Mf(x) = O(\sqrt{n})$ for $X_1, \dots, X_n$ iid unif $\{0,1\}$.)