

**Lemma 15.1.** Let  $\xi, \nu$  - random variables. Assume that

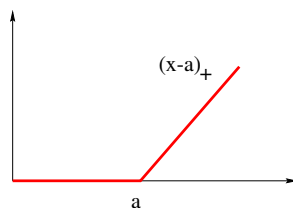
$$\mathbb{P}(\nu \geq t) \leq \Gamma e^{-\gamma t}$$

where  $\Gamma \geq 1$ ,  $t \geq 0$ , and  $\gamma > 0$ . Furthermore, for all  $a > 0$  assume that

$$\mathbb{E}\phi(\xi) \leq \mathbb{E}\phi(\nu)$$

where  $\phi(x) = (x - a)_+$ . Then

$$\mathbb{P}(\xi \geq t) \leq \Gamma \cdot e \cdot e^{-\gamma t}.$$



*Proof.* Since  $\phi(x) = (x - a)_+$ , we have  $\phi(\xi) \geq \phi(t)$  whenever  $\xi \geq t$ .

$$\begin{aligned} \mathbb{P}(\xi \geq t) &\leq \mathbb{P}(\phi(\xi) \geq \phi(t)) \\ &\leq \frac{\mathbb{E}\phi(\xi)}{\phi(t)} \leq \frac{\mathbb{E}\phi(\nu)}{\phi(t)} = \frac{\mathbb{E}(\nu - a)_+}{(t - a)_+} \end{aligned}$$

Furthermore,

$$\begin{aligned} \mathbb{E}(\nu - a)_+ &= \mathbb{E} \int_0^{(\nu - a)_+} 1 dx \\ &= \mathbb{E} \int_0^\infty I(x \leq (\nu - a)_+) dx \\ &= \int_0^\infty \mathbb{E} I(x \leq (\nu - a)_+) dx \\ &= \int_0^\infty \mathbb{P}((\nu - a)_+ \geq x) dx \\ &= \int_0^\infty \mathbb{P}(\nu \geq a + x) dx \\ &\leq \int_0^\infty \Gamma e^{-\gamma a - \gamma x} dx = \frac{\Gamma e^{-\gamma a}}{\gamma}. \end{aligned}$$

Hence,

$$\mathbb{P}(\xi \geq t) \leq \frac{\Gamma e^{-\gamma a}}{\gamma(t - a)_+} = \frac{\Gamma \cdot e \cdot e^{-\gamma t}}{1} = \Gamma \cdot e \cdot e^{-\gamma t}$$

where we chose optimal  $a = t - \frac{1}{\gamma}$  to minimize  $\frac{\Gamma e^{-\gamma a}}{\gamma}$ .

□

**Lemma 15.2.** Let  $x = (x_1, \dots, x_n)$ ,  $x' = (x'_1, \dots, x'_n)$ . If for functions  $\varphi_1(x, x')$ ,  $\varphi_2(x, x')$ ,  $\varphi_3(x, x')$

$$\mathbb{P}\left(\varphi_1(x, x') \geq \varphi_2(x, x') + \sqrt{\varphi_3(x, x') \cdot t}\right) \leq \Gamma e^{-\gamma t}$$

then

$$\mathbb{P}\left(\mathbb{E}_{x'} \varphi_1(x, x') \geq \mathbb{E}_{x'} \varphi_2(x, x') + \sqrt{\mathbb{E}_{x'} \varphi_3(x, x') \cdot t}\right) \leq \Gamma \cdot e \cdot e^{-\gamma t}.$$

(i.e. if the inequality holds, then it holds with averaging over one of the copies)

*Proof.* First, note that  $\sqrt{ab} = \inf_{\delta > 0} (\delta a + \frac{b}{4\delta})$  with  $\delta_* = \sqrt{\frac{b}{4a}}$  achieving the infima. Hence,

$$\begin{aligned} \{\varphi_1 \geq \varphi_2 + \sqrt{\varphi_3 t}\} &= \{\exists \delta > 0, \varphi_1 \geq \varphi_2 + \delta \varphi_3 + \frac{t}{4\delta}\} \\ &= \{\exists \delta > 0, (\varphi_1 - \varphi_2 - \delta \varphi_3)4\delta \geq t\} \\ &= \underbrace{\{\sup_{\delta > 0} (\varphi_1 - \varphi_2 - \delta \varphi_3)4\delta \geq t\}}_{\nu} \end{aligned}$$

and similarly

$$\{\mathbb{E}_{x'} \varphi_1 \geq \mathbb{E}_{x'} \varphi_2 + \sqrt{\mathbb{E}_{x'} \varphi_3 t}\} = \underbrace{\{\sup_{\delta > 0} (\mathbb{E}_{x'} \varphi_1 - \mathbb{E}_{x'} \varphi_2 - \delta \mathbb{E}_{x'} \varphi_3)4\delta \geq t\}}_{\xi}.$$

By assumption,  $\mathbb{P}(\nu \geq t) \leq \Gamma e^{-\gamma t}$ . We want to prove  $\mathbb{P}(\xi \geq t) \leq \Gamma \cdot e \cdot e^{-\gamma t}$ . By the previous lemma, we only need to check whether  $\mathbb{E}\phi(\xi) \leq \mathbb{E}\phi(\nu)$ .

$$\begin{aligned} \xi &= \sup_{\delta > 0} \mathbb{E}_{x'} (\varphi_1 - \varphi_2 - \delta \varphi_3)4\delta \\ &\leq \mathbb{E}_{x'} \sup_{\delta > 0} (\varphi_1 - \varphi_2 - \delta \varphi_3)4\delta \\ &= \mathbb{E}_{x'} \nu \end{aligned}$$

Thus,

$$\phi(\xi) \leq \phi(\mathbb{E}_{x'} \nu) \leq \mathbb{E}_{x'} \phi(\nu)$$

by Jensen's inequality ( $\phi$  is convex). Hence,

$$\mathbb{E}\phi(\xi) \leq \mathbb{E}\mathbb{E}_{x'} \phi(\nu) = \mathbb{E}\phi(\nu).$$

□

We will now use Lemma 15.2. Let  $\mathcal{F} = \{f : \mathcal{X} \mapsto [c, c + 1]\}$ . Let  $x_1, \dots, x_n, x'_1, \dots, x'_n$  be i.i.d. random variables. Define

$$F = \{(f(x_1) - f(x'_1), \dots, f(x_n) - f(x'_n)) : f \in \mathcal{F}\} \subseteq [-1, 1]^n.$$

Define

$$d(f, g) = \left( \frac{1}{n} \sum_{i=1}^n ((f(x_i) - f(x'_i)) - (g(x_i) - g(x'_i)))^2 \right)^{1/2}.$$

In Lecture 14, we proved

$$\begin{aligned} \mathbb{P}_\varepsilon \left( \forall f \in \mathcal{F}, \frac{1}{n} \sum_{i=1}^n \varepsilon_i (f(x_i) - f(x'_i)) \leq \frac{2^{9/2}}{\sqrt{n}} \int_0^{d(0, f)} \log^{1/2} \mathcal{D}(\mathcal{F}, \varepsilon, d) d\varepsilon \right. \\ \left. + 2^{7/2} d(0, f) \sqrt{\frac{t}{n}} \right) \geq 1 - e^{-t}. \end{aligned}$$

Complement of the above is

$$\mathbb{P}_\varepsilon \left( \exists f \in \mathcal{F}, \frac{1}{n} \sum_{i=1}^n \varepsilon_i (f(x_i) - f(x'_i)) \geq \frac{2^{9/2}}{\sqrt{n}} \int_0^{d(0, f)} \log^{1/2} \mathcal{D}(\mathcal{F}, \varepsilon, d) d\varepsilon + 2^{7/2} d(0, f) \sqrt{\frac{t}{n}} \right) \leq e^{-t}.$$

Taking expectation with respect to  $x, x'$ , we get

$$\mathbb{P} \left( \exists f \in \mathcal{F}, \frac{1}{n} \sum_{i=1}^n \varepsilon_i (f(x_i) - f(x'_i)) \geq \frac{2^{9/2}}{\sqrt{n}} \int_0^{d(0, f)} \log^{1/2} \mathcal{D}(\mathcal{F}, \varepsilon, d) d\varepsilon + 2^{7/2} d(0, f) \sqrt{\frac{t}{n}} \right) \leq e^{-t}.$$

Hence (see below)

$$\mathbb{P} \left( \exists f \in \mathcal{F}, \frac{1}{n} \sum_{i=1}^n (f(x_i) - f(x'_i)) \geq \frac{2^{9/2}}{\sqrt{n}} \int_0^{d(0, f)} \log^{1/2} \mathcal{D}(\mathcal{F}, \varepsilon, d) d\varepsilon + 2^{7/2} d(0, f) \sqrt{\frac{t}{n}} \right) \leq e^{-t}.$$

To see why the above step holds, notice that  $d(f, g)$  is invariant under permutations  $x_i \leftrightarrow x'_i$ . We can remove  $\varepsilon_i$  since  $x$  and  $x'$  are i.i.d and we can switch  $x_i$  and  $x'_i$ . To the right of " $\geq$ " sign, only distance  $d(f, g)$  depends on  $x, x'$ , but it's invariant to the permutations.

By Lemma 15.2 (minus technical detail " $\exists f$ "),

$$\begin{aligned} \mathbb{P} \left( \exists f \in \mathcal{F}, \mathbb{E}_{x'} \frac{1}{n} \sum_{i=1}^n (f(x_i) - f(x'_i)) \geq \mathbb{E}_{x'} \frac{2^{9/2}}{\sqrt{n}} \int_0^{d(0, f)} \log^{1/2} \mathcal{D}(\mathcal{F}, \varepsilon, d) d\varepsilon \right. \\ \left. + 2^{7/2} \sqrt{\frac{\mathbb{E}_{x'} d(0, f)^2 t}{n}} \right) \leq e \cdot e^{-t}, \end{aligned}$$

where

$$\mathbb{E}_{x'} \frac{1}{n} \sum_{i=1}^n (f(x_i) - f(x'_i)) = \frac{1}{n} \sum_{i=1}^n f(x_i) - \mathbb{E}f$$

and

$$\mathbb{E}_{x'} d(0, f)^2 = \mathbb{E}_{x'} \frac{1}{n} \sum_{i=1}^n (f(x_i) - f(x'_i))^2.$$

The Dudley integral above will be bounded by something non-random in the later lectures.