

### 3.7 Lecture 19 (14/Nov): cont. Bourgain embedding

#### 3.7.1 cont. Bourgain embedding: $L_1$

We use this notation for open balls:

$$B_r(x) = \{z : d(x, z) < r\}$$

and for closed balls,  $\bar{B}_r(x) = \{z : d(x, z) \leq r\}$ .

Recall that we are now analyzing the embedding for any single pair of points  $x, y$ .

Let  $\rho_0 = 0$  and, for  $t > 0$  define

$$\rho_t = \sup\{r : |B_r(x)| < 2^t \text{ or } |B_r(y)| < 2^t\} \quad (3.17)$$

up to  $\hat{t} = \max\{t : \text{RHS} < d(x, y)/2\}$ .

It is possible to have  $\hat{t} = 0$  (for instance if no other points are near  $x$  and  $y$ ).

Observe that for the *closed* balls  $\bar{B}$  we have that for all  $t \leq \hat{t}$ ,  $|\bar{B}_{\rho_t}(x)| \geq 2^t$  and  $|\bar{B}_{\rho_t}(y)| \geq 2^t$ . This means in particular that (due to the radius cap at  $d(x, y)/2$ , which means that  $y$  is excluded from these balls around  $x$  and vice versa),  $\hat{t} < s$ .

Set  $\rho_{\hat{t}+1} = d(x, y)/2$ , which means that it still holds for  $t = \hat{t} + 1$  that  $|B_{\rho_t}(x)| < 2^t$  or  $|B_{\rho_t}(y)| < 2^t$ , although (in contrast to  $t \leq \hat{t}$ ),  $\rho_{\hat{t}+1}$  is not the largest radius for which this holds.

Note  $\hat{t} + 1 \geq 1$ . Also,  $\rho_{\hat{t}+1} > \rho_{\hat{t}}$  (because the latter was defined to be less than  $d(x, y)/2$ ). But for  $t \leq \hat{t}$  it is possible to have  $\rho_t = \rho_{t-1}$ .

$\hat{t} + 1$  will be the number of scales used in the analysis of the lower bound for the pair  $x, y$ . I.e., we use the sets  $T_{ij}$  for  $0 \leq t \leq \hat{t} + 1$ . Any contribution from higher- $t$  (smaller expected cardinality) sets is “bonus.”

Consider any  $1 \leq t \leq \hat{t} + 1$ .

**Lemma 61** *With positive probability (specifically at least  $(1 - 1/\sqrt{e})/4$ ),  $|\tau_{t1}(x) - \tau_{t1}(y)| > \rho_t - \rho_{t-1}$ .*

**Proof:** Suppose wlog that  $|B_{\rho_t}(x)| < 2^t$ . By Eqn (3.17) (with  $t - 1$ ),  $|\bar{B}_{\rho_{t-1}}(y)| \geq 2^{t-1}$  (and the same for  $x$  but we don't need that). If

$$T_{t1} \cap B_{\rho_t}(x) = \emptyset \quad (3.18)$$

and

$$T_{t1} \cap \bar{B}_{\rho_{t-1}}(y) \neq \emptyset \quad (3.19)$$

then

$$\|\tau_{t1}(x) - \tau_{t1}(y)\| > \rho_t - \rho_{t-1}.$$

We wish to show that this conjunction happens with constant probability. (See Fig. 3.9.)

The two events (3.18), (3.19) are independent because  $T_{t1}$  is generated by independent sampling, and because, due to the radius cap at  $d(x, y)/2$  (and because  $\rho_t < \rho_{t+1}$ ),  $B_{\rho_t}(x) \cap \bar{B}_{\rho_{t-1}}(y) = \emptyset$ .

First, the  $x$ -ball event (3.18):

$$\begin{aligned} \Pr(T_{t1} \cap B_{\rho_t}(x) = \emptyset) &= (1 - 2^{-t})^{|B_{\rho_t}(x)|} \\ &\geq (1 - 2^{-t})^{2^t} \\ &= (1 - 2^{-t})^{2^t} \\ &\geq 1/4 \quad \text{for } t \geq 1 \end{aligned}$$

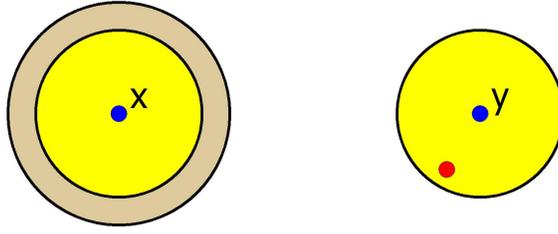


Figure 3.9: Balls  $B_{\rho_{t-1}}(x), B_{\rho_t}(x), B_{\rho_{t-1}}(y)$  depicted. Events 3.18 and 3.19 have occurred, because no point has been selected for  $T_{t1}$  in the larger-radius ( $\rho_t$ ) region around  $x$ , while some point (marked in red) has been selected for  $T_{t1}$  in the smaller-radius ( $\rho_{t-1}$ ) region around  $y$ .

(For large  $t$  this is actually about  $1/e$ .)

Second, the  $y$ -ball event (3.19):

$$\begin{aligned} \Pr(T_{t1} \cap \bar{B}_{\rho_{t-1}}(y) \neq \emptyset) &= 1 - (1 - 2^{-t})^{|B_{\rho_{t-1}}(y)|} \\ &\geq 1 - (1 - 2^{-t})^{2^{t-1}} \end{aligned}$$

and recalling  $1 + x \leq e^x$  for all real  $x$ ,

$$\geq 1 - e^{-1/2}$$

Consequently,  $|\tau_{t1}(x) - \tau_{t1}(y)| > \rho_t - \rho_{t-1}$  with probability at least  $(1 - 1/\sqrt{e})/4$ .  $\square$

Now, let  $G_{x,y,t}$  be the “good” event that at least  $(1 - 1/\sqrt{e})/8$  of the coordinates at level  $t$ , namely  $\{\tau_{tj}\}_{j=1}^{s'}$ , have

$$|\tau_{tj}(x) - \tau_{tj}(y)| > \rho_t - \rho_{t-1}.$$

If the good event occurs for all  $t$ , then for all  $x, y$ ,

$$\|\tau(x) - \tau(y)\|_1 \geq \frac{1}{s} \frac{(1 - 1/\sqrt{e})}{8} \frac{d(x, y)}{2}.$$

Here the first factor is from the normalization, the second from the definition of good events, and the third from the cap on the  $\rho_t$ 's.

We can upper bound the probability that a good event  $G_{x,y,t}$  fails to happen using Chernoff:

$$\Pr(\neg G_{x,y,t}) \leq e^{-\Omega(s')}.$$

Now taking a union bound over all  $x, y, t$ ,

$$\Pr(\cup_{x,y,t} \neg G_t) \leq e^{-\Omega(s')} n^2 \lg n < 1/2$$

for a suitable  $s' \in \Theta(\log n)$ .

To be specific we can use the following version of the Chernoff bound (see problem set 4):

**Lemma 62** Let  $F_1, \dots, F_{s'}$  be independent Bernoulli rvs, each with expectation  $\geq \mu$ .  $\Pr(\sum F_i < (1 - \varepsilon)\mu s') \leq e^{-\varepsilon^2 \mu s' / 2}$ .

which permits us (plugging in  $\varepsilon = 1/2$ ) to take  $s' = \frac{32\sqrt{e}}{\sqrt{e-1}} \log(n^2 \lg n)$ .  $\square$

*Exercise:* Form a Fréchet embedding  $X \rightarrow \mathbb{R}^n$  by using as  $T_i$ 's all singleton sets. Argue that this is an isometry of  $X$  into  $(\mathbb{R}^n, L_\infty)$ . Consequently  $L_\infty$  is *universal* for finite metrics. (This, I believe, was Fréchet's original result [38].)

### 3.7.2 Embedding into any $L_p$ , $p \geq 1$

As a matter of fact the above embedding method has distortion just as good into  $L_p$ , for any  $p \geq 1$ . Start by expanding:

$$\|\tau(x) - \tau(y)\|_p = \left( \frac{1}{ss'} \sum_{ij} (\tau_{ij}(x) - \tau_{ij}(y))^p \right)^{1/p} \quad (3.20)$$

We begin with the upper bound, which is unexciting:

$$\begin{aligned} (3.20) &\leq \left( \frac{1}{ss'} \sum_{ij} (d(x, y))^p \right)^{1/p} \\ &= d(x, y). \end{aligned}$$

For the lower bound, we use the power-means inequality. Note that (3.20) is a  $p$ 'th mean of the quantities  $(\tau_{ij}(x) - \tau_{ij}(y))$ , ranging over  $i, j$ . So from Lemma 15,

$$(3.20) \geq \frac{1}{ss'} \sum_{ij} |\tau_{ij}(x) - \tau_{ij}(y)| = \|\tau(x) - \tau(y)\|_1$$

so for any  $\tau$  and any  $p > 1$ , the  $L_p$  distortion of  $\tau$  is no more than its  $L_1$  distortion. This demonstrates the generalization of Theorem (60) with  $L_p^{O(\log^2 n)}$  ( $p \geq 1$ ) replacing  $L_1^{O(\log^2 n)}$ .

### 3.7.3 Aside: Hölder's inequality

Although we already proved the power means inequality directly in Lemma 15, it is worth seeing how it fits into a framework of inequalities. The power means inequality is a comparison between two integrals over a measure space that is also a probability space (i.e., the total measure of the space is 1). Power means follows immediately from an important inequality that holds for *any* measure space (and indeed generalizes the Cauchy-Schwarz inequality), Hölder's inequality:

**Lemma 63 (Hölder)** *For norms with respect to any fixed measure space, and for  $1/p + 1/q = 1$  ( $p$  and  $q$  are "conjugate exponents"),  $\|f\|_p \cdot \|g\|_q \geq \|fg\|_1$ .*

To see the power means inequality, note that over a probability space,  $\|f\|_p$  is simply a  $p$ 'th mean. Now plug in the function  $g = 1$  and Hölder gives you power means.