

# An extension of a Bourgain–Lindenstrauss–Milman inequality

Omer Friedland, Sasha Sodin

Tel Aviv University

June 28, 2007

# 1) Definitions

Let  $(E, \|\cdot\|)$  be a normed space, and let  $v_1, \dots, v_n \in E \setminus \{0\}$ .

Define a norm  $\|\cdot\|$  on  $\mathbb{R}^n$ :

$$\|\cdot\| = \mathbb{E} \left\| \sum_{i=1}^n \varepsilon_i x_i v_i \right\|, \quad (1)$$

where the expectation is over the choice of  $n$  independent random signs  $\varepsilon_1, \dots, \varepsilon_n$ .

# 1) Definitions

Let  $(E, \|\cdot\|)$  be a normed space, and let  $v_1, \dots, v_n \in E \setminus \{0\}$ .

Define a norm  $|||\cdot|||$  on  $\mathbb{R}^n$ :

$$|||x||| = \mathbb{E} \left\| \sum_{i=1}^n \varepsilon_i x_i v_i \right\|, \quad (1)$$

where the expectation is over the choice of  $n$  independent random signs  $\varepsilon_1, \dots, \varepsilon_n$ .

## Remark

This is an *unconditional* norm; that is,

$$|||(x_1, x_2, \dots, x_n)||| = |||(|x_1|, |x_2|, \dots, |x_n|)|||.$$

## 2) Motivation

We ask whether it is possible to average  $O(n)$  of the terms, rather than the  $2^n$  terms in (1) ?

In order to obtain a norm that is isomorphic to  $||| \cdot |||$  and is in particular (isomorphically) unconditional.

### 3) Theorem (Sodin & F.)

Let  $N = (1 + \delta)n$ ,  $\delta > 0$ , and let

$$\{\varepsilon_{ij} \mid 1 \leq i \leq n, 1 \leq j \leq N\}$$

be a collection of independent random signs. Then

$$\mathbb{P} \left\{ \forall x \in \mathbb{R}^n \quad c\delta^2 \|x\| \leq \frac{1}{N} \sum_{j=1}^N \left\| \sum_{i=1}^n \varepsilon_{ij} x_i v_i \right\| \leq C \|x\| \right\} \geq 1 - e^{-c'\delta n},$$

where  $c', c, C > 0$  are universal constants.

## 4) Some remarks

- ▶ This theorem extends a result due to Bourgain, Lindenstrauss and Milman, who considered the case of large  $\delta \geq C > 1$ .

## 4) Some remarks

- ▶ This theorem extends a result due to Bourgain, Lindenstrauss and Milman, who considered the case of large  $\delta \geq C > 1$ .
- ▶ Their argument yields the upper bound for the full range of  $\delta$ , so the innovation is in the lower bound for small  $\delta > 0$ .

## 4) Some remarks

- ▶ This theorem extends a result due to Bourgain, Lindenstrauss and Milman, who considered the case of large  $\delta \geq C > 1$ .
- ▶ Their argument yields the upper bound for the full range of  $\delta$ , so the innovation is in the lower bound for small  $\delta > 0$ .
- ▶ With the stated dependence on  $\delta$ , the corresponding result for the scalar case, i.e.  $\dim E = 1$ , was proved by Rudelson, improving previous bounds on  $c(\delta)$  by Kashin,  
Johnson - Schechtman,  
Litvak - Pajor - Rudelson - Tomczak-Jaegermann - Vershynin  
and Artstein-Avidan - Friedland - Milman - Sodin.



## 4) Some remarks

- ▶ This theorem extends a result due to Bourgain, Lindenstrauss and Milman, who considered the case of large  $\delta \geq C > 1$ .
- ▶ Their argument yields the upper bound for the full range of  $\delta$ , so the innovation is in the lower bound for small  $\delta > 0$ .
- ▶ With the stated dependence on  $\delta$ , the corresponding result for the scalar case, i.e.  $\dim E = 1$ , was proved by Rudelson, improving previous bounds on  $c(\delta)$  by Kashin, Johnson - Schechtman, Litvak - Pajor - Rudelson - Tomczak-Jaegermann - Vershynin and Artstein-Avidan - Friedland - Milman - Sodin.
- ▶ This scalar case is one of the two main ingredients of our proof, the second one being Talagrand's concentration inequality.

## 5) Theorem (Talagrand)

Let  $w_1, \dots, w_n \in E$  be vectors in a normed space  $(E, \|\cdot\|)$ , and let  $\varepsilon_1, \dots, \varepsilon_n$  be independent random signs. Then for any  $t > 0$

$$\mathbb{P} \left\{ \left| \left\| \sum_{i=1}^n \varepsilon_i w_i \right\| - \mathbb{E} \left\| \sum_{i=1}^n \varepsilon_i w_i \right\| \right| \geq t \right\} \leq C_1 e^{-c_1 t^2 / \sigma^2},$$

where  $c_1, C_1 > 0$  are universal constants, and

$$\sigma^2 = \sigma^2(w_1, \dots, w_n) = \sup \left\{ \sum_{i=1}^n \varphi(w_i)^2 \mid \varphi \in E^*, \|\varphi\|^* \leq 1 \right\}.$$

## 6) Proof

Let us denote  $|||x|||_N = \frac{1}{N} \sum_{j=1}^N \left\| \sum_{i=1}^n \varepsilon_{ij} x_i v_i \right\|$ .

This is a random norm depending on the choice of  $\varepsilon_{ij}$ .

Let  $S_{|||\cdot|||}^{n-1} = \{x \in \mathbb{R}^n : |||x||| = 1\}$  be the unit sphere of  $(\mathbb{R}^n, |||\cdot|||)$ ;

## 6) Proof

Let us denote  $|||x|||_N = \frac{1}{N} \sum_{j=1}^N \left\| \sum_{i=1}^n \varepsilon_{ij} x_i v_i \right\|$ .

This is a random norm depending on the choice of  $\varepsilon_{ij}$ .

Let  $S_{|||\cdot|||}^{n-1} = \{x \in \mathbb{R}^n : |||x||| = 1\}$  be the unit sphere of  $(\mathbb{R}^n, |||\cdot|||)$ ;

We estimate the following probability

$$\mathbb{P} \left\{ \forall x \in S_{|||\cdot|||}^{n-1} \quad c\delta^2 \leq |||x|||_N \leq C \right\} \geq$$

## 7) Proof

$$\begin{aligned} & \mathbb{P} \left\{ \forall x \in S_{\|\cdot\|}^{n-1} \quad c\delta^2 \leq \|x\|_N \leq C \right\} \\ & \geq 1 - \mathbb{P} \left\{ \exists x \in S_{\|\cdot\|}^{n-1}, \|x\|_N > C \right\} \\ & \quad - \mathbb{P} \left\{ \left( \forall y \in S_{\|\cdot\|}^{n-1}, \|y\|_N \leq C \right) \wedge \left( \exists x \in S_{\|\cdot\|}^{n-1}, \|x\|_N < c\delta^2 \right) \right\} . \end{aligned}$$

## 7) Proof

$$\begin{aligned} & \mathbb{P} \left\{ \forall x \in S_{\|\cdot\|}^{n-1} \quad c\delta^2 \leq \|x\|_N \leq C \right\} \\ & \geq 1 - \mathbb{P} \left\{ \exists x \in S_{\|\cdot\|}^{n-1}, \|x\|_N > C \right\} \\ & \quad - \mathbb{P} \left\{ \left( \forall y \in S_{\|\cdot\|}^{n-1}, \|y\|_N \leq C \right) \wedge \left( \exists x \in S_{\|\cdot\|}^{n-1}, \|x\|_N < c\delta^2 \right) \right\}. \end{aligned}$$

### Remark

As we mentioned, the needed estimate for the upper bound follows from the argument in BLM.

## 8) Lower Bound

Denote  $\sigma^2(x) = \sigma^2(x_1 v_1, \dots, x_n v_n)$  for  $x = (x_1, \dots, x_n) \in \mathbb{R}^n$ ,

and we recall that

$$\sigma^2(x_1 v_1, \dots, x_n v_n) = \sup \left\{ \sum_{i=1}^n \varphi(x_i v_i)^2 \mid \varphi \in E^*, \|\varphi\|^* \leq 1 \right\} .$$

## 8) Lower Bound

Denote  $\sigma^2(x) = \sigma^2(x_1 v_1, \dots, x_n v_n)$  for  $x = (x_1, \dots, x_n) \in \mathbb{R}^n$ ,

and we recall that

$$\sigma^2(x_1 v_1, \dots, x_n v_n) = \sup \left\{ \sum_{i=1}^n \varphi(x_i v_i)^2 \mid \varphi \in E^*, \|\varphi\|^* \leq 1 \right\} .$$

We estimate the last term

$$\mathbb{P} \left\{ \left( \forall y \in S_{\|\cdot\|_N}^{n-1}, \|\|y\|\|_N \leq C \right) \wedge \left( \exists x \in S_{\|\cdot\|_N}^{n-1}, \|\|x\|\|_N < c\delta^2 \right) \right\} .$$



## 9) Lower Bound

We decompose the sphere  $S_{||\cdot||}^{n-1} = U \cup V$ ,

$$U = \left\{ x \in S_{||\cdot||}^{n-1} \mid \sigma(x) \geq \sigma_0 \right\} ,$$

$$V = \left\{ x \in S_{||\cdot||}^{n-1} \mid \sigma(x) < \sigma_0 \right\} ,$$

where  $\sigma_0$  is a universal constant that we choose later.

10)  $x \in U$

Recall Rudelson's estimate for the scalar case, i.e.  $\dim E = 1$ :

Let  $N = (1 + \delta)n$ ,  $0 < \delta < 1$ , and let

$$\{\varepsilon_{ij} \mid 1 \leq i \leq n, 1 \leq j \leq N\}$$

be a collection of independent random signs. Then, with high probability, for any  $y \in \mathbb{R}^n$

$$\frac{1}{N} \sum_{j=1}^N \left| \sum_{i=1}^n \varepsilon_{ij} y_i \right| \geq c_4 \delta^2 |y| ,$$

where  $c_4 > 0$  a universal constant, and  $|\cdot|$  is the standard Euclidean norm.

11)  $x \in U$

Therefore, for any  $x \in \mathbb{R}^n$  and for any  $\varphi \in E^*$  with  $\|\varphi\|^* \leq 1$ , we have

$$\begin{aligned} \|x\|_N &\geq \frac{1}{N} \sum_{j=1}^N \left| \varphi \left( \sum_{i=1}^n \varepsilon_{ij} x_i v_i \right) \right| = \frac{1}{N} \sum_{j=1}^N \left| \sum_{i=1}^n \varepsilon_{ij} \varphi(x_i v_i) \right| \\ &\geq c_4 \delta^2 \sqrt{\sum_{i=1}^n \varphi(x_i v_i)^2}. \end{aligned} \tag{2}$$

## 12) $x \in U$

Recall that  $U = \left\{ x \in S_{\|\cdot\|}^{n-1} \mid \sigma(x) \geq \sigma_0 \right\}$ .

Inequality (2) holds for every  $\varphi \in E^*$  with  $\|\varphi\|^* \leq 1$ , and hence we get

$$\begin{aligned} \|x\|_N &\geq c_4 \delta^2 \sqrt{\sup \left\{ \sum_{i=1}^n \varphi(x_i v_i)^2 \mid \varphi \in E^*, \|\varphi\|^* \leq 1 \right\}} \\ &= c_4 \delta^2 \sigma(x) \\ &\geq c_4 \delta^2 \sigma_0 . \end{aligned}$$

13)  $x \in V$

Now, let us consider the other case where

$$x \in V = \left\{ x \in S_{||\cdot||}^{n-1} \mid \sigma(x) < \sigma_0 \right\}.$$

### 13) $x \in V$

Now, let us consider the other case where

$$x \in V = \left\{ x \in S_{\|\cdot\|}^{n-1} \mid \sigma(x) < \sigma_0 \right\}.$$

Let  $\mathcal{N}_\theta \subset V$  be a  $\theta$ -net for  $V$ , it is known that  $|\mathcal{N}_\theta| \leq (3/\theta)^n$ .

Note that for any  $y \in \mathcal{N}_\theta$  we have  $\sigma(y) < \sigma_0$ .

Therefore by Talagrand's inequality

$$\mathbb{P} \left\{ \left\| \sum_{i=1}^n \varepsilon_i y_i v_i \right\| < 1/2 \right\} \leq C_1 \exp\left(-\frac{c_1}{4\sigma_0^2}\right).$$

14)  $x \in V$

And hence we get that

$$\begin{aligned} & \mathbb{P} \left\{ \frac{1}{N} \sum_{j=1}^N \left\| \sum_{i=1}^n \varepsilon_{ij} y_i v_i \right\| < \frac{1}{4} \right\} \\ &= \mathbb{P} \left\{ \sum_{j=1}^N \left\| \sum_{i=1}^n \varepsilon_{ij} y_i v_i \right\| < \frac{1}{2} \cdot \frac{N}{2} \right\} \leq 2^N \left\{ C_1 \exp \left( -\frac{c_1}{4\sigma_0^2} \right) \right\}^{N/2}. \end{aligned}$$

15)  $x \in V$

Now, we choose  $0 < \theta < \frac{1}{8C}$  and  $\sigma_0 > 0$  such that the following inequality holds (where  $C > 0$  comes from the upper bound):

$$2^N \left\{ C_1 \exp\left(-\frac{c_1}{4\sigma_0^2}\right) \right\}^{N/2} \cdot |\mathcal{N}_\theta| \leq 2^{-N}$$



## 15) $x \in V$

Now, we choose  $0 < \theta < \frac{1}{8C}$  and  $\sigma_0 > 0$  such that the following inequality holds (where  $C > 0$  comes from the upper bound):

$$2^N \left\{ C_1 \exp\left(-\frac{c_1}{4\sigma_0^2}\right) \right\}^{N/2} \cdot |\mathcal{N}_\theta| \leq 2^{-N}$$

Then with high probability we have for any  $y \in \mathcal{N}_\theta$  that  $\|y\|_N \geq 1/4$ .

## 15) $x \in V$

Now, we choose  $0 < \theta < \frac{1}{8C}$  and  $\sigma_0 > 0$  such that the following inequality holds (where  $C > 0$  comes from the upper bound):

$$2^N \left\{ C_1 \exp\left(-\frac{c_1}{4\sigma_0^2}\right) \right\}^{N/2} \cdot |\mathcal{N}_\theta| \leq 2^{-N}$$

Then with high probability we have for any  $y \in \mathcal{N}_\theta$  that  $\|y\|_N \geq 1/4$ .

Using the upper bound, we infer:

$$\begin{aligned} \|x\|_N &\geq \|y\|_N - \|x - y\|_N \\ &\geq 1/4 - C/8C = 1/4 - 1/8 = 1/8, \quad x \in V, \end{aligned}$$

which concludes the proof. □

## 16) Definitions

Let  $(E, \|\cdot\|)$  be a normed space, and let  $v_1, \dots, v_n \in E \setminus \{0\}$ .

Define a norm  $|||\cdot|||$  on  $\mathbb{R}^n$ :

$$|||x||| = \int_{\mathbb{R}^n} \left\| \sum_{i=1}^n a_i x_i v_i \right\| d\mu(a),$$

where  $a_i$  is the  $i^{\text{th}}$  coordinate of a vector  $a$  and  $\mu$  is a log-concave probability measure  $\mu$  on  $\mathbb{R}^n$ .

## 17) Theorem

Let  $N = (1 + \delta)n$ ,  $\delta > 0$ , and let

$$\{a(1), \dots, a(N) \in \mathbb{R}^n\}$$

be a set of  $N$  independent random vectors, distributed with respect to a log-concave probability measure  $\mu$  on  $\mathbb{R}^n$ .

## 17) Theorem

Let  $N = (1 + \delta)n$ ,  $\delta > 0$ , and let

$$\{a(1), \dots, a(N) \in \mathbb{R}^n\}$$

be a set of  $N$  independent random vectors, distributed with respect to a log-concave probability measure  $\mu$  on  $\mathbb{R}^n$ .

Then with high probability for any  $x \in \mathbb{R}^n$

$$c(\delta) \|x\| \leq \frac{1}{N} \sum_{j=1}^N \left\| \sum_{i=1}^n a(j)_i x_i v_i \right\| \leq C \|x\|,$$

where  $c(\delta) > 0$  is a constant depending only on  $\delta$ .