

Bounds for expectations of k -maxima of log-concave vectors

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Aim: X – random vector. Find upper and lower estimates of

$$\mathbb{E} k\text{-}\max_i |X_i| \quad \text{and} \quad \mathbb{E} \max_{|I|=k} \sum_{i \in I} |X_i| = \mathbb{E} \sum_{l=1}^k l\text{-}\max_i |X_i|$$

by the same quantity (up to universal constants).

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To estimate

$$\mathbb{E} \max_{|I|=k} \sum_{i \in I} |X_i|$$

we will need the parameter

$$t(k, X) := \inf \left\{ t > 0 : \frac{1}{t} \sum_{i=1}^n \mathbb{E} |X_i| \mathbf{1}_{\{|X_i| \geq t\}} \leq k \right\}.$$

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For $t > t(k, X)$,

$$\begin{aligned} \max_{|I|=k} \sum_{i \in I} |X_i| &\leq \max_{|I|=k} \sum_{i \in I} |X_i| \mathbf{1}_{\{|X_i| < t\}} + \max_{|I|=k} \sum_{i \in I} |X_i| \mathbf{1}_{\{|X_i| \geq t\}} \\ &\leq tk + \sum_{i=1}^n |X_i| \mathbf{1}_{\{|X_i| \geq t\}} \leq 2tk, \end{aligned}$$

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Question: For which random vectors X ,

$$\max_{|I|=k} \sum_{i \in I} |X_i| \geq ckt(k, X)?$$

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Let X satisfy

$$\mathbb{P}(|X_i| \geq s, |X_j| \geq t) \leq \alpha \mathbb{P}(|X_i| \geq s) \mathbb{P}(|X_j| \geq t) \quad (1)$$

for all $i \neq j$ and all $s, t > 0$. ($\alpha \geq 1$)

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Note that random vectors with independent coordinates satisfy (1).

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Theorem (Latała-St. '19)

Then there exists a constant $c(\alpha) > 0$ which depends only on α such that for any $1 \leq k \leq n$,

$$c(\alpha)kt(k, X) \leq \mathbb{E} \max_{|I|=k} \sum_{i \in I} |X_i| \leq 2kt(k, X).$$

We may take $c(\alpha) = (288(5 + 4\alpha)(1 + 2\alpha))^{-1}$.

Definition

We say that a random vector X in \mathbb{R}^n is log-concave if for any compact subsets A, B of \mathbb{R}^n and any $\lambda \in (0, 1)$ we have

$$\mathbb{P}(X \in A)^\lambda \mathbb{P}(X \in B)^{1-\lambda} \leq \mathbb{P}(X \in \lambda A + (1 - \lambda)B).$$

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Theorem (Latała-St. '19)

Let X be a **log-concave** random vector with **uncorrelated coordinates** (i.e. $\text{Cov}(X_i, X_j) = 0$ for $i \neq j$). Then for any $1 \leq k \leq n$,

$$ckt(k, X) \leq \mathbb{E} \max_{|I|=k} \sum_{i \in I} |X_i| \leq 2kt(k, X).$$

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Example 1. Let $X = (\varepsilon_1 g, \varepsilon_2 g, \dots, \varepsilon_n g)$, where $\varepsilon_1, \dots, \varepsilon_n, g$ are independent, $\mathbb{P}(\varepsilon_i = \pm 1) = 1/2$ and g has the normal $\mathcal{N}(0, 1)$ distribution.

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We introduce a parameter which is more sensitive for rescaling a single coordinate.

$$t^*(p, X) := \inf \left\{ t > 0 : \sum_{i=1}^n \mathbb{P}(|X_i| \geq t) \leq p \right\} \quad \text{for } 0 < p < n.$$

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Theorem (Latała-St. '19)

Let X be a mean zero **log-concave** n -dimensional random vector with **uncorrelated coordinates** and $1 \leq k \leq n$. Then

$$\mathbb{E} k\text{-max}_{i \leq n} |X_i| \geq \frac{1}{2} \text{Med} \left(k\text{-max}_{i \leq n} |X_i| \right) \geq ct^* \left(k - \frac{1}{2}, X \right).$$

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The proof uses a lower bound for sums of k biggest $|X_i|$.

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The proof uses a lower bound for sums of k biggest $|X_i|$. Although the parameter t^* is more adequate than t to estimate $\mathbb{E} k\text{-max}_{i \leq n} |X_i|$, not only the lower bound, but also the upper bound is non-trivial. The upper bound turns out to be even more challenging (for us):

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$$\mathbb{P} \left(k\text{-max}_{i \leq n} |X_i| \geq Ct^* \left(k - \frac{1}{2}, X \right) \right) \leq 1 - c \quad (2)$$

and

$$\mathbb{E} k\text{-max}_{i \leq n} |X_i| \leq Ct^* \left(k - \frac{1}{2} k^{5/6}, X \right). \quad (3)$$

Moreover, if X is additionally **unconditional** then

$$\mathbb{E} k\text{-max}_{i \leq n} |X_i| \leq Ct^* \left(k - \frac{1}{2}, X \right).$$

The unconditionality assumption plays a crucial role in the proof of the next lemma, which allows to derive (3) from (2).

Lemma

Let X be an unconditional log-concave n -dimensional random vector. Then for any $1 \leq k \leq n$,

$$\mathbb{P} \left(k\text{-max}_{i \leq n} |X_i| \geq ut \right) \leq \mathbb{P} \left(k\text{-max}_{i \leq n} |X_i| \geq t \right)^u \quad \text{for } u > 1, t > 0.$$

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Question: Is it true that for log-concave uncorrelated vectors X we have

$$\mathbb{P} \left(k\text{-max}_{i \leq n} |X_i| \geq ut \right) \leq \mathbf{C} \mathbb{P} \left(k\text{-max}_{i \leq n} |X_i| \geq t \right)^{\mathbf{C}u} \quad \text{for } u > 1, t > 0?$$

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$$c \frac{k}{n} \leq \mathbb{E}k\text{-min}_{i \leq n} |X_i| = \mathbb{E}(n - k + 1)\text{-max}_{i \leq n} |X_i| \leq C \left(\frac{k}{n} + n^{-1/6} \right).$$

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