

The square negative correlation property on ℓ_p^n balls

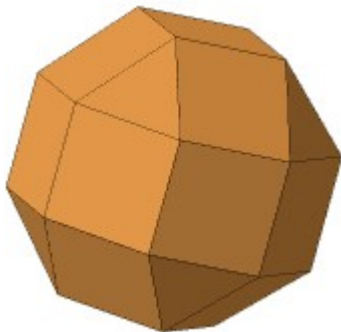
David Alonso Gutiérrez
Joint work with Julio Bernués

Universidad de Zaragoza

7th of September, 2018

Convex bodies

- $K \subset \mathbb{R}^n$ is called a convex body if it is convex, compact and has non-empty interior.



Isotropic bodies

A convex body $K \subseteq \mathbb{R}^n$ is isotropic if it has volume 1 and

- $\int_K x dx = 0$ (centered at 0)
- $\int_K \langle x, \theta \rangle^2 dx = L_K^2 \quad \forall \theta \in S^{n-1}$.

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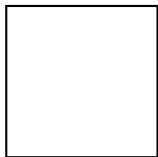
Given K we consider a random vector X uniformly distributed in K and, for every $\theta \in S^{n-1}$, the real random variable $\langle X, \theta \rangle$ with density $f_\theta(t) = |K \cap (\theta^\perp + t\theta)|$.

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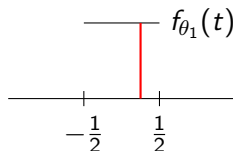
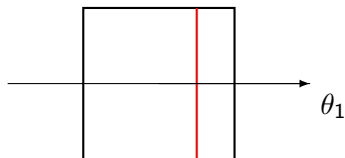


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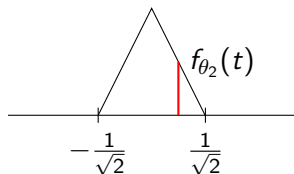
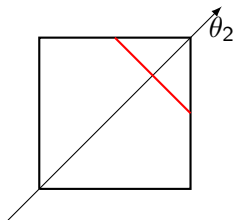


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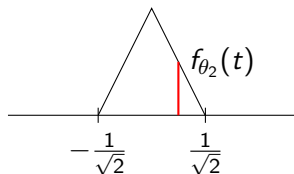
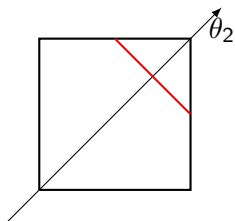


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K is isotropic if all the $\langle X, \theta \rangle$ are centered and have the same variance.

Isotropic bodies

- $L_K \geq L_{B_2^n} = \frac{\Gamma(1+\frac{n}{2})^{\frac{1}{n}}}{\pi\sqrt{n+2}}$

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- True for 1-unconditional bodies, polytopes with number of vertices proportional to the dimension, zonoids, unit balls of finite dimensional Schätten classes...

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- $G \sim \mathcal{N}(0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{t \in \mathbb{R}} \left| \mathbb{P} \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} > t \right) - \mathbb{P}(G > t) \right| = 0$$

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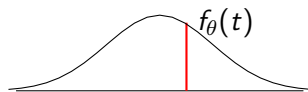
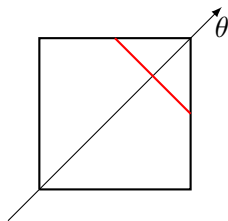
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Let X be a random vector uniformly distributed on $L_K^{-1}K$ with K isotropic. For how many directions $\theta \in S^{n-1}$ can we say

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Sudakov (1978), Diaconis-Freedman (1984), von Weizsäcker (1997), Antilla-Ball-Perissinaki (2003).

Shown under a concentration hypothesis:

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Klartag (2007):

$$\mathbb{P} \left(\left| \frac{|X|}{\sqrt{n}} - 1 \right| \geq \frac{c}{n^\kappa} \right) \leq Ce^{-n^\kappa}$$

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- $\text{Var}|X|^2 \leq Cn^{\frac{1}{2}}L_K^2 \mathbb{E}|X|^2$. (Lee-Vempala, 2016)
- True for uniformly distributed random vectors on B_p^n (Antilla-Ball-Perissinaki, 2003), Orlicz balls (Wojtaszczyk, 2007), unconditional bodies (Klartag, 2012)

The square negative correlation property

Definition

A centered log-concave random vector $X \in \mathbb{R}^n$ satisfies the square negative correlation property with respect to the orthonormal basis $\{\eta_i\}_{i=1}^n$ if for every $i \neq j$

$$\mathbb{E}\langle X, \eta_i \rangle^2 \langle X, \eta_j \rangle^2 - \mathbb{E}\langle X, \eta_i \rangle^2 \mathbb{E}\langle X, \eta_j \rangle^2 \leq 0$$

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- X uniformly distributed on $P_{\theta^\perp} B_\infty^n$, any $\{\eta_i\}_{i=1}^n$. A., Bastero (2013).

The square negative correlation property

- X uniformly distributed on K isotropic, $\{\eta_i\}_{i=1}^n$

$$\begin{aligned}\text{Var}|X|^2 &= \sum_{i=1}^n (\mathbb{E}\langle X, \eta_i \rangle^4 - (\mathbb{E}\langle X, \eta_i \rangle^2)^2) \\ &+ \sum_{i \neq j} (\mathbb{E}\langle X, \eta_i \rangle^2 \langle X, \eta_j \rangle^2 - \mathbb{E}\langle X, \eta_i \rangle^2 \mathbb{E}\langle X, \eta_j \rangle^2)\end{aligned}$$

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$$\text{Var}|X|^2 \leq \sum_{i=1}^n (\mathbb{E}\langle X, \eta_i \rangle^4 - (\mathbb{E}\langle X, \eta_i \rangle^2)^2)$$

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$$\begin{aligned}\text{Var}|X|^2 &\leq \sum_{i=1}^n (\mathbb{E}\langle X, \eta_i \rangle^4 - (\mathbb{E}\langle X, \eta_i \rangle^2)^2) \\ &\leq C \sum_{i=1}^n (\mathbb{E}\langle X, \eta_i \rangle^2)^2\end{aligned}$$

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Proposition (A., Bernués (2018))

Let X be a random vector uniformly distributed on a 1-symmetric convex body, $\xi_1 = \frac{e_1 + e_2}{\sqrt{2}}$, $\xi_2 = \frac{e_1 - e_2}{\sqrt{2}}$, and $f : S^{n-1} \times S^{n-1} \rightarrow \mathbb{R}$

$$f(\eta_1, \eta_2) = \mathbb{E}\langle X, \eta_1 \rangle^2 \langle X, \eta_2 \rangle^2 - \mathbb{E}\langle X, \eta_1 \rangle^2 \mathbb{E}\langle X, \eta_2 \rangle^2.$$

Then, if $\langle \eta_1, \eta_2 \rangle = 0$

$$f(\eta_1, \eta_2) = f(e_1, e_2) + 2(f(\xi_1, \xi_2) - f(e_1, e_2)) \sum_{i=1}^n \eta_1(i)^2 \eta_2(i)^2.$$

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$$F(x) = \frac{\Gamma(5x)\Gamma(x)}{\Gamma(3x)^2}.$$

- F is strictly increasing in $(0, 1]$ and $F\left(\frac{1}{2}\right) = 3.$

The square negative correlation property on B_p^n

Theorem (A., Bernués (2018))

Let X be a random vector uniformly distributed on B_p^n , $\xi_1 = \frac{e_1 + e_2}{\sqrt{2}}$,
 $\xi_2 = \frac{e_1 - e_2}{\sqrt{2}}$. If $\langle \eta_1, \eta_2 \rangle = 0$

$$\begin{aligned} f(\xi_1, \xi_2) &\leq f(\eta_1, \eta_2) \leq f(e_1, e_2) && \text{if } p \geq 2 \\ f(e_1, e_2) &\leq f(\eta_1, \eta_2) \leq f(\xi_1, \xi_2) && \text{if } p \leq 2 \end{aligned}$$

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- $f(e_1, e_2) = \frac{\Gamma\left(1 + \frac{n}{p}\right) \Gamma\left(\frac{3}{p}\right)^2}{\Gamma\left(1 + \frac{n+4}{p}\right) \Gamma\left(\frac{1}{p}\right)^2} \left(1 - \frac{\Gamma\left(1 + \frac{n}{p}\right) \Gamma\left(1 + \frac{n+4}{p}\right)}{\Gamma\left(1 + \frac{n+2}{p}\right)^2}\right)$

The square negative correlation property on B_p^n

Theorem (A., Bernués (2018))

Let X be a random vector uniformly distributed on B_p^n , $\xi_1 = \frac{e_1 + e_2}{\sqrt{2}}$, $\xi_2 = \frac{e_1 - e_2}{\sqrt{2}}$. If $\langle \eta_1, \eta_2 \rangle = 0$

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The square negative correlation property on B_p^n

- $$f(\xi_1, \xi_2) = \frac{\Gamma\left(1 + \frac{n}{p}\right) \Gamma\left(\frac{3}{p}\right)^2 \left(F\left(\frac{1}{p}\right) - 1 - 2 \frac{\Gamma\left(1 + \frac{n}{p}\right) \Gamma\left(1 + \frac{n+4}{p}\right)}{\Gamma\left(1 + \frac{n+2}{p}\right)^2} \right)}{2 \Gamma\left(1 + \frac{n+4}{p}\right) \Gamma\left(\frac{1}{p}\right)^2}$$

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The square negative correlation property on B_p^n

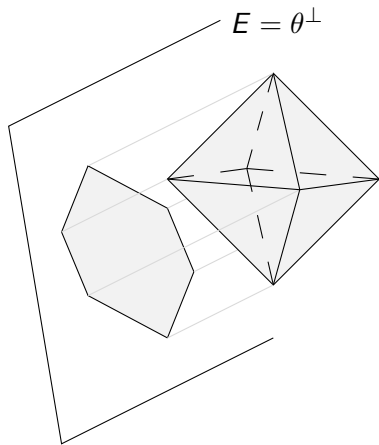
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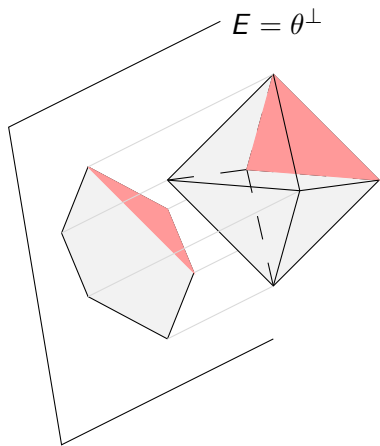
Cauchy's formula

$P_{\theta^\perp} K$



Cauchy's formula

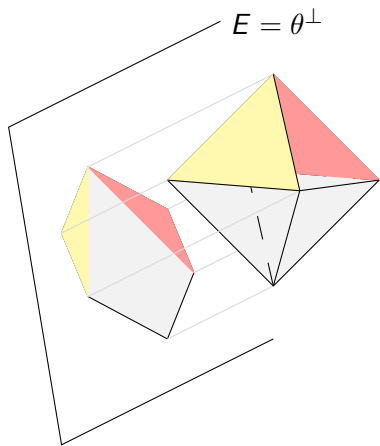
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$$\int_{P_E K} f(x) dx =$$

Cauchy's formula

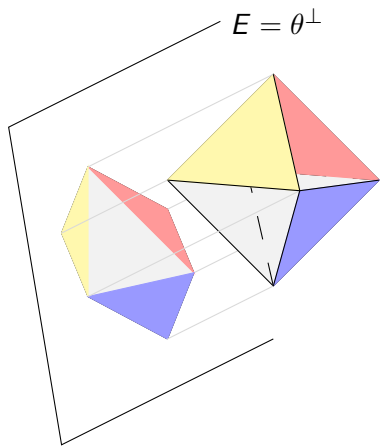
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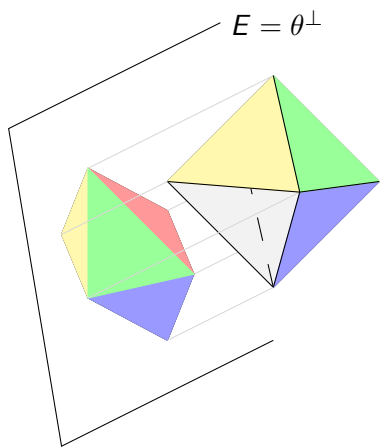
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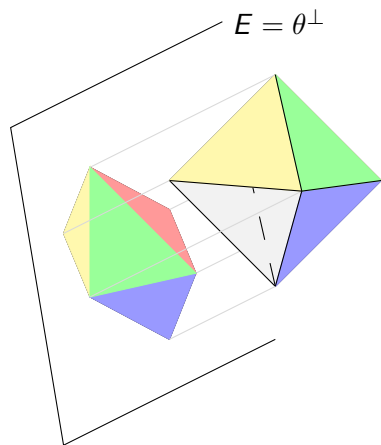
$$P_{\theta^\perp} K = \bigcup_{F \in \mathcal{F}_{n-1}(K) : \langle \nu(F), \theta \rangle \geq 0} P_E F$$



$$\int_{P_E K} f(x) dx = \sum_{\substack{F \in \mathcal{F}_{n-1}(K) \\ \langle \nu(F), \theta \rangle \geq 0}} \int_{P_E F} f(x) dx$$

Cauchy's formula

$$P_{\theta^\perp} K = \bigcup_{F \in \mathcal{F}_{n-1}(K): \langle \nu(F), \theta \rangle \geq 0} P_E F \quad P_E K = \bigcup_{F \in \mathcal{F}_{n-1}(K): \langle \nu(F), \theta \rangle \leq 0} P_E F$$



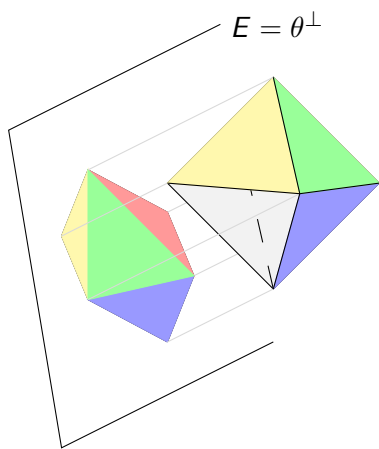
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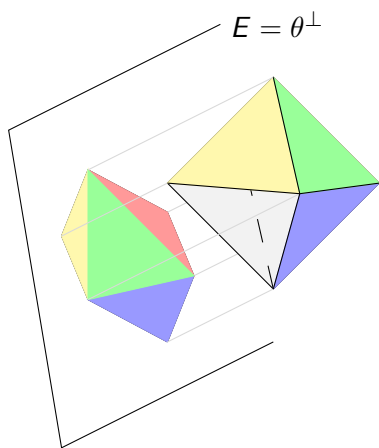
$$\int_{P_E K} f(x) dx = \frac{1}{2} \sum_{F \in \mathcal{F}_{n-1}(K)} \int_{P_E F} f(x) dx$$



Cauchy's formula

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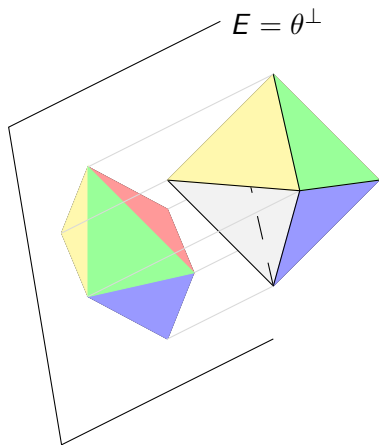


$$\begin{aligned} \int_{P_E K} f(x) dx &= \frac{1}{2} \sum_{F \in \mathcal{F}_{n-1}(K)} \int_{P_E F} f(x) dx \\ &= \frac{1}{2} \sum_{F \in \mathcal{F}_{n-1}(K)} \int_F f(P_E y) |\langle \nu(F), \theta \rangle| dy \end{aligned}$$

Cauchy's formula

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$$= \frac{1}{2} \int_{\partial K} f(P_E y) |\langle \nu(y), \theta \rangle| d\sigma_K(y)$$

$d\sigma_K$ Hausdorff measure on ∂K

- By Cauchy's formula, if X is uniformly distributed on $P_{\theta^\perp}(B_p^n)$

$$\mathbb{E}f(X) = \frac{\int_{\partial B_p^n} f(P_{\theta^\perp}(x)) \frac{|\langle \nabla \|\cdot\|_p(x), \theta \rangle|}{\|\nabla \|\cdot\|_p(x)\|} d\sigma_p^n(x)}{\int_{\partial B_p^n} \frac{|\langle \nabla \|\cdot\|_p(x), \theta \rangle|}{\|\nabla \|\cdot\|_p(x)\|} d\sigma_p^n(x)}.$$

Random vectors on hyperplane projections of B_p^n

- By Cauchy's formula, if X is uniformly distributed on $P_{\theta^\perp}(B_p^n)$

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- Since $d\sigma_p^n(x) = n|B_p^n| \|\nabla \|\cdot\|_p(x)\| d\mu_p^n(x)$ (Naor, Romik, 2003)

$$\mathbb{E}f(X) = \frac{\int_{\partial B_p^n} f(P_{\theta^\perp}(x)) |\langle \nabla \|\cdot\|_p(x), \theta \rangle| d\mu_p^n(x)}{\int_{\partial B_p^n} |\langle \nabla \|\cdot\|_p(x), \theta \rangle| d\mu_p^n(x)}.$$

Probabilistic representation of $d\mu_p^n$ (Schechtman-Zinn (1990))

Let g_1, \dots, g_n be independent copies of a random variable with density

$$\frac{e^{-|t|^p}}{2\Gamma\left(1 + \frac{1}{p}\right)}$$

and

$$S = \left(\sum_{i=1}^n |g_i|^p \right)^{\frac{1}{p}}.$$

Then

- The random vector $\frac{g}{S} = \left(\frac{g_1}{S}, \dots, \frac{g_n}{S}\right)$ and the random variable S are independent.
- $\frac{g}{S}$ is distributed on ∂B_p^n according to $d\mu_p^n$.

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If X is uniformly distributed on $P_{\theta^\perp}(B_p^n)$

$$\mathbb{E}f(X) = \frac{\mathbb{E}f\left(P_H\left(\frac{\mathbf{g}}{S}\right)\right)\phi}{\mathbb{E}\phi}, \quad \phi = \left| \sum_{i=1}^n \frac{|g_i|^{p-1}}{S^{p-1}} \operatorname{sgn}(g_i)\theta_i \right|$$

The square negative correlation property on hyperplane projections of B_p^n

$\theta_0 = \left(\frac{1}{\sqrt{n}}, \dots, \frac{1}{\sqrt{n}} \right)$, $P_{\theta_0^\perp}(B_p^n)$ is isotropic.

Theorem (A., Bernués, 2018)

Let X be a random vector uniformly distributed on $P_{\theta_0^\perp}(B_p^n)$,
 $\xi_1 = \frac{e_1 - e_2 + e_3 - e_4}{2}$, $\xi_2 = \frac{e_1 - e_2 - e_3 + e_4}{2}$, $\bar{\xi}_1 = \frac{e_1 - e_2}{\sqrt{2}}$, $\bar{\xi}_2 = \frac{e_3 - e_4}{\sqrt{2}}$ and
 $f : S_{\theta_0^\perp} \times S_{\theta_0^\perp} \rightarrow \mathbb{R}$

$$f(\eta_1, \eta_2) = \mathbb{E}\langle X, \eta_1 \rangle^2 \langle X, \eta_2 \rangle^2 - \mathbb{E}\langle X, \eta_1 \rangle^2 \mathbb{E}\langle X, \eta_2 \rangle^2.$$

If $p \geq 2$ there exists $n_0(p)$ such that if $n \geq n_0$ and $\langle \eta_1, \eta_2 \rangle = 0$

$$f(\xi_1, \xi_2) \leq f(\eta_1, \eta_2) \leq f(\bar{\xi}_1, \bar{\xi}_2).$$

If $1 \leq p \leq 2$ there exists $n_1(p)$ such that if $n \geq n_1$ and $\langle \eta_1, \eta_2 \rangle = 0$

$$f(\bar{\xi}_1, \bar{\xi}_2) \leq f(\eta_1, \eta_2) \leq f(\xi_1, \xi_2).$$

The square negative correlation property on hyperplane projections of B_p^n

Corollary (A., Bernués, 2018)

Let X be a random vector uniformly distributed on $P_{\theta_0^\perp}(B_p^n)$. There exists $n_0(p)$ such that for all $n \geq n_0$ X satisfies the SNCP with respect to every orthonormal basis in θ_0^\perp .