

B-property for the cross-polytope on subspaces

Tomasz Tkocz

Mathematics Department
Carnegie Mellon University

based on joint work with

Piotr Nayar

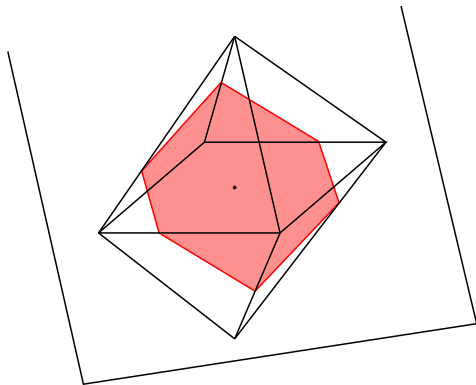
2 July 2019

Main result

Theorem. Let H be a subspace of \mathbb{R}^n . Then the function

$$F_H(t_1, \dots, t_n) = \text{vol}_H (\text{diag}(e^{t_1}, \dots, e^{t_n}) B_1^n \cap H)$$

is log-concave on \mathbb{R}^n .



Motivation 1

Theorem. $F_H(t) = \text{vol}_H(\text{diag}(e^{t_1}, \dots, e^{t_n})B_1^n \cap H)$ is log-concave.

Strong B-property: $t \mapsto \mu(\text{diag}(e^{t_1}, \dots, e^{t_n})K)$ is log-concave.

E.g.

★ $\frac{d\mu(x)}{dx} = \prod e^{-|x_i|^2}$, K convex, symmetric (C-EFM'04)

★ $\frac{d\mu(x)}{dx} = \prod e^{-|x_i|^{p_i}}$, $p_i \in (0, 1]$, K convex, symmetric

★ $\frac{d\mu(x)}{dx} = e^{-(\sum |x_i|^2)^{p/2}}$, $p \in (0, 1]$, K convex, symmetric (ENT'18)

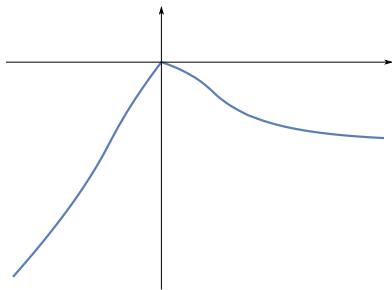
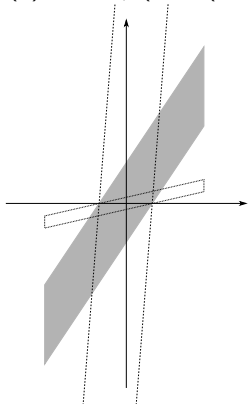
★ $\mu = \text{vol}_H$, $K = B_1^n$

Strong B-property – log-concave negative examples

★ μ = centred Gaussian measure, K = box (C-ER'18)

★ μ = uniform on a parallelogram K ,

$f(t) = \log \mu(\text{diag}(1, e^t)K)$ is not concave



Motivation 2

Conjecture (BLYZ'12). For every $n \geq 1$, every symmetric convex bodies K, L in \mathbb{R}^n and $\lambda \in [0, 1]$,

$$\text{vol}_n(K^\lambda L^{1-\lambda}) \geq \text{vol}_n(K)^\lambda \text{vol}_n(L)^{1-\lambda}.$$

$K^\lambda L^{1-\lambda}$ = *geometric mean* (defined via support functions)

Fix $n \geq 1$. This conjecture is equivalent to (S'15'16)

Conjecture'. For every $N \geq n$, every n -dim subspace H of \mathbb{R}^N ,

$$F_H(t_1, \dots, t_N) = \text{vol}_H \left(\text{diag}(e^{t_1}, \dots, e^{t_N}) B_\infty^N \cap H \right)$$

is log-concave on \mathbb{R}^N .

Proof

Theorem. $F_H(t) = \text{vol}_H(\text{diag}(e^{t_1}, \dots, e^{t_n})B_1^n \cap H)$ is log-concave.

Key Lemma.

$$F_H(t) = c \cdot \exp\left(\sum t_j\right) \mathbb{E} \left[\frac{1}{\sqrt{\det\left(\sum e^{2t_j} Y_j v_j v_j^\top\right)}} \right],$$

Y_j are i.i.d. $\text{Exp}(1)$, v_j are vectors given by H .

To finish, is $\mathbb{E} \left[\frac{1}{\sqrt{\det\left(\sum e^{2t_j} Y_j v_j v_j^\top\right)}} \right]$ log-concave?

Proof

$$\begin{aligned} \mathbb{E} \left[\frac{1}{\sqrt{\det \left(\sum e^{2t_j} Y_j v_j v_j^\top \right)}} \right] & \text{ is log-concave?} \\ &= \int_{(0, \infty)^n} \frac{1}{\sqrt{\det \left(\sum e^{2t_j} y_j v_j v_j^\top \right)}} e^{-\sum y_j} dy \\ &\stackrel{y_j = e^{s_j}}{=} \int_{\mathbb{R}^n} \frac{1}{\sqrt{\det \left(\sum e^{2t_j + s_j} v_j v_j^\top \right)}} e^{-\sum e^{s_j}} e^{\sum s_j} ds \end{aligned}$$

By Prékopa-Leindler, enough to show that the integrand is log-concave.

Is $(s, t) \mapsto \det \left(\sum e^{2t_j + s_j} v_j v_j^\top \right)$ log-convex?

Proof

Is $(s, t) \mapsto \det \left(\sum e^{2t_j + s_j} v_j v_j^\top \right)$ log-convex?

Fact. For $k \times k$ PSD matrices A_1, \dots, A_n ,

$$\det \left(\sum x_j A_j \right) = \sum_{j=(j_1, \dots, j_k)} \underbrace{D(A_{j_1}, \dots, A_{j_k})}_{\geq 0} x_{j_1} \dots x_{j_k}.$$

Fact. For $a_j \geq 0$,

$$t \mapsto \sum a_j e^{t_j}$$

is log-convex.

Proof. Hölder: $\sum a_j e^{\lambda t_j + (1-\lambda) u_j} \leq (\sum a_j e^{t_j})^\lambda (\sum a_j e^{u_j})^{1-\lambda}$.

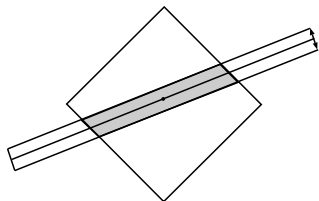
Proof of key lemma

Key lemma. $\text{vol}_H(B_1^n \cap H) = c \cdot \mathbb{E} \left[\frac{1}{\sqrt{\det(\sum Y_j v_j v_j^T)}} \right].$

$$H = \text{span}(u_1, \dots, u_k)^\perp = \{x \in \mathbb{R}^n, \forall j \leq k \langle x, u_j \rangle = 0\}$$

$$H(\varepsilon) = \{x \in \mathbb{R}^n, \forall j \leq k |\langle x, u_j \rangle| \leq \varepsilon/2\}$$

$$\begin{aligned} \text{vol}_H(B_1^n \cap H) &= c \cdot \lim_{\varepsilon \rightarrow 0} \varepsilon^{-k} \int_{H(\varepsilon)} e^{-\sum |x_i|} dx \\ &= c' \cdot \lim_{\varepsilon \rightarrow 0} \varepsilon^{-k} \mathbb{P}(X \in H(\varepsilon)) \end{aligned}$$



$$X = (X_1, \dots, X_n) \text{ i.i.d. } \text{SymExp}(1)$$

Key fact. $X_i \stackrel{d}{=} \sqrt{2Y_i}G_i, Y_i \sim \text{Exp}(1), G_i \sim N(0, 1)$

$$\langle X, v \rangle = \sum X_i v_i = \sum G_i \sqrt{2Y_i} v_i = \langle G, \tilde{v} \rangle, \tilde{v}_i = \sqrt{2Y_i} v_i$$

Proof of key lemma

$$\text{vol}_H(B_1^n \cap H) = c' \cdot \lim_{\varepsilon \rightarrow 0} \varepsilon^{-k} \mathbb{P}(X \in H(\varepsilon))$$

Key fact. $X_i \stackrel{d}{=} \sqrt{2Y_i}G_i$, $Y_i \sim \text{Exp}(1)$, $G_i \sim N(0, 1)$

$$\langle X, v \rangle = \sum X_i v_i = \sum G_i \sqrt{2Y_i} v_i = \langle G, \tilde{v} \rangle, \quad \tilde{v}_i = \sqrt{2Y_i} v_i$$

$$\begin{aligned} \mathbb{P}(X \in H(\varepsilon)) &= \mathbb{P}(\forall j \ |\langle X, u_j \rangle| \leq \varepsilon/2) \\ &= \mathbb{P}(\forall j \ |\langle G, \tilde{u}_j \rangle| \leq \varepsilon/2) \\ &= \mathbb{E}_Y \mathbb{P}_G(\text{Proj}_{\tilde{U}} G \in \varepsilon K), \end{aligned}$$

$$\tilde{U} = \text{span}\{\tilde{u}_j\}, \quad K = \{x \in \tilde{U}, \forall j \leq k \ |\langle x, \tilde{u}_j \rangle| \leq 1/2\}$$

Proof of key lemma

$$\begin{aligned}\text{vol}_H(B_1^n \cap H) &= c' \cdot \lim_{\varepsilon \rightarrow 0} \varepsilon^{-k} \mathbb{E}_Y \mathbb{P}_G(\text{Proj}_{\tilde{U}} G \in \varepsilon K) \\ &= c'' \cdot \lim_{\varepsilon \rightarrow 0} \varepsilon^{-k} \mathbb{E}_Y [\varepsilon^k \text{vol}(K) + o(\varepsilon^k)] \\ &= c'' \cdot \mathbb{E}_Y [\text{vol}(K)] \\ &= c''' \cdot \mathbb{E}_Y \left[\frac{1}{\sqrt{\det(\sum Y_j v_j v_j^\top)}} \right],\end{aligned}$$

where

$$\begin{bmatrix} \text{---} & u_1 & \text{---} \\ & \vdots & \\ \text{---} & u_k & \text{---} \end{bmatrix} = \begin{bmatrix} | & & | \\ v_1 & \cdots & v_n \\ | & & | \end{bmatrix} \cdot \quad \square$$

Thanks!