

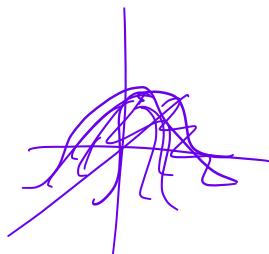
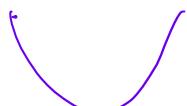
LECTURE 2

- I. Borell's thm \Rightarrow BRUNN-MINKOWSKI inequality
- Lebesgue measure μ has density $f(x) = 1$
- f is log-concave $1 = e^{-0}$ convex function
- \Rightarrow Lebesgue measure satisfies BM.

* Gaussian measure $d\gamma = e^{-\frac{|x|^2}{2}} \cdot (2\pi)^{-\frac{n}{2}} dx$

$$f(x) = e^{-\frac{|x|^2}{2}} \cdot c_n = e^{-V}$$

$$V(x) = \frac{|x|^2}{2} + \tilde{c}_n - \text{convex function}$$



$$\gamma(\lambda K + (1-\lambda)L) \geq \gamma(K)^\lambda \gamma(L)^{1-\lambda}$$

- info about normal distribution

Theorem (PREKOPA-LEINDLER)

$$\left[\begin{array}{l} \lambda \in [0, 1], \quad f, g, h : \mathbb{R}^n \rightarrow \mathbb{R} \quad \text{s.t. } \int e^{-f}, \int e^{-g}, \int e^{-h} \\ \text{(measurable)} \quad \text{all exist} \\ \text{s.t. } \forall x, y \in \mathbb{R}^n \quad \boxed{h(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)g(y)} \\ \text{THEN} \quad \boxed{\int e^{-h} \geq (\int e^{-f})^\lambda \cdot (\int e^{-g})^{1-\lambda}} \end{array} \right]$$

Derivation of Bozell's theorem (and thus Brunn-Minkowski)
 from Prekopa-Leindler inequality

$d\mu = \varphi(x) dx$ — measure with density φ

φ is log-concave

K, L - Bozell
measurable

$$e^{-h(x)} = \varphi(x) \cdot \mathbb{1}_{\lambda K + (1-\lambda)L}(x)$$

$$e^{-f(x)} = \varphi(x) \cdot \mathbb{1}_K(x)$$

$$e^{-g(x)} = \varphi(x) \cdot \mathbb{1}_L(x)$$

$$\text{here: } h(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)g(y) \quad (\text{rel})$$

due to log-concavity of φ

Prekopa's condition is satisfied \Rightarrow

$$\int e^{-h} \geq \left(\int e^{-f} \right)^\lambda \left(\int e^{-g} \right)^{1-\lambda}$$

$$\int_{\lambda K + (1-\lambda)L} \varphi \geq \left(\int_K \varphi \right)^\lambda \left(\int_L \varphi \right)^{1-\lambda}$$

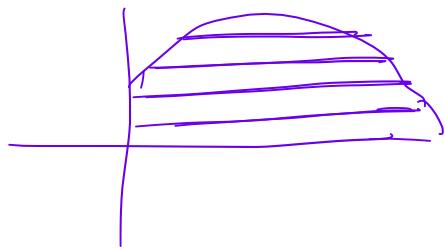
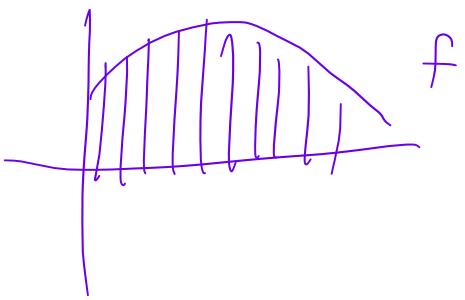
$$\mu(\lambda K + (1-\lambda)L) \geq \mu(K)^\lambda \cdot \mu(L)^{1-\lambda} \quad \square$$

Proof of the Prekopa-Leindler inequality

By induction in dimension

Recall the "layer-cake formula" $f \geq 0$

$$\int_{\mathbb{R}^n} f(x) d\mu = \int_0^\infty \mu(\{x \in \mathbb{R}^n : f(x) > s\}) ds$$



$$F(x) = e^{-f(x)} \geq 0$$

$$G(y) = e^{-g(y)} \geq 0$$

$$H(z) = e^{-h(z)} \geq 0$$

$$h(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)g(y)$$

$$H(\lambda x + (1-\lambda)y) \geq F(x)^{\lambda} G(y)^{1-\lambda}$$

we want

$$\int H \geq (\int F)^{\lambda} (\int G)^{1-\lambda}$$

Step 1 dimension = 1

$$\int_{\mathbb{R}} H = \int_0^\infty |\{t \in \mathbb{R} : H(t) > s\}| ds \quad \textcircled{E}$$

$$\{H > s\} \geq \lambda \{F > s\} + (1-\lambda) \{G > s\}$$

↑ 1-dim Monotonic sum

$$\textcircled{E} \quad \int_0^\infty (\lambda |\{F > s\}| + (1-\lambda) |\{G > s\}|) ds$$

$$= \lambda \int_0^\infty |\{F > s\}| ds + (1-\lambda) \int_0^\infty |\{G > s\}| ds$$

logical exercise

$$= \lambda \int_{\mathbb{R}} F + (1-\lambda) \int_{\mathbb{R}} G \geq (\int_{\mathbb{R}} F)^{\lambda} \cdot (\int_{\mathbb{R}} G)^{1-\lambda}$$

layer-cake

$$\lambda a + (1-\lambda)b \geq a^{\lambda} b^{1-\lambda}$$

Base of induction - verified

Step 2 Induction

Suppose the P-L thm is verified in \mathbb{R}^{n-1} .

$$H_n(x_n) = \int_{\mathbb{R}^{n-1}} H(x_1, \dots, x_n) dx_1 \dots dx_{n-1}$$

$$x = (x_1, \dots, x_n) = (\bar{x}, x_n)$$

Same way F_n, G_n .

We have $H(\lambda(\bar{x}, x_n) + (1-\lambda)(\bar{y}, y_n)) \geq F((\bar{x}, x_n))^{\lambda} \cdot G((\bar{y}, y_n))^{1-\lambda}$

by the assumption or P-L

Induction hypothesis: on \mathbb{R}^{n-1} P-L holds

$$\int_{\mathbb{R}^{n-1}} H(x_1, \dots, x_n) dx_1 \dots dx_{n-1} \geq \left(\int_{\mathbb{R}^{n-1}} F \right)^{\lambda} \left(\int_{\mathbb{R}^{n-1}} G \right)^{1-\lambda} \quad \text{i.e.}$$

$$H_n(\lambda x_n + (1-\lambda)y_n) \geq F_n(x_n)^{\lambda} G_n(y_n)^{1-\lambda}$$

(1-dim funeronal funerons)

By step 1 $\int H_n \geq \left(\int F_n \right)^{\lambda} \left(\int G_n \right)^{1-\lambda}$

i.e. $H_n \geq (F_n)^{\lambda} / (G_n)^{1-\lambda}$

JH = $\langle \cdot, \cdot \rangle(\beta^*)$

Thus the Brunn-Minkowski inequality is also proven! So is the isoperimetric inequality!

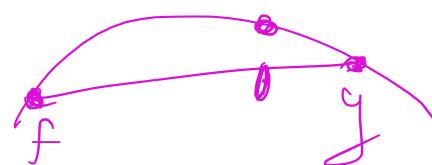
Remark Prekopa-Leindler inequality is a member of a larger family, Boell-Brascamp-Lieb inequality
check notes

(IV) Main idea: From concavity principles
to isoperimetry via linearizations.

In general, suppose \mathcal{F} is a functional

$$\forall f, g \quad \mathcal{F}((1-t)f + tg) \geq (1-t)\mathcal{F}(f) + t\mathcal{F}(g)$$

$$t \in [0, 1] \quad (\text{i.e. } \mathcal{F} \text{ is concave})$$



Define

$$\mathcal{L}(t) = \mathcal{F}((1-t)f + tg) - \underbrace{(1-t)\mathcal{F}(f) + t\mathcal{F}(g)}$$

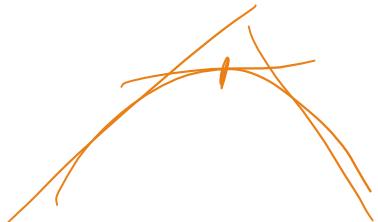
- $\mathcal{L}(t) \geq 0$ on $t \in [0, 1]$

- $\mathcal{L}(0) = 0$



① If $\mathcal{L}'(0)$ makes sense then

$$\boxed{\mathcal{L}'(0) \geq 0}$$



F - convex and twice differentiable

$$F'' \leq 0$$

$$F(x) = -x^2$$

$$F'' = -2$$

②

$$\boxed{\mathcal{L}''(0) \leq 0}$$

$$\uparrow \frac{d^2}{dt^2} F$$

Concavity principles give new inequalities!

Example $\log |tK + (1-t)L| \geq t \log |K| + (1-t) \log |L|$

$$F = \log |K|$$

$$\mathcal{L}(t) = \log |tK + (1-t)L| - t \log |K| - (1-t) \log |L|$$

$$\boxed{\mathcal{L}'(0) \geq 0}$$

$$K = B_2^n$$

This amounts to isoperimetric inequality

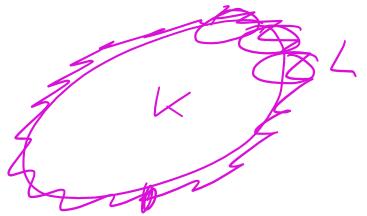
In general, Minkowski's first inequality:

K, L convex bodies

$$V_1(K, L) = \liminf_{\varepsilon \rightarrow 0} \frac{|K + \varepsilon L \setminus K|}{\varepsilon} \cdot \frac{1}{n}$$

"anisotropic perimeter"

$$V_1(K, L) \geq |K|^{\frac{n-1}{n}} \cdot |L|^{\frac{1}{n}}$$



(III) How to understand the P-L inequality as a concavity principle?

$$h(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)g(y) \quad (\star)$$

$$\Rightarrow \int e^{-h} \geq \left(\int e^{-f} \right)^{\lambda} \cdot \left(\int e^{-g} \right)^{1-\lambda}$$

Suppose f, g are log-concave

What is the optimal λ to satisfy (\star) ?

Def "Inf-convolution" $t \in [0, 1]$

$\Delta = -ft$

$$f \square_t g(z) = \inf_{\substack{(1-t)x+ty=z \\ \text{function} \\ \text{that interpolates} \\ \text{between } f \text{ and } g}} (1-t)f(x) + tg(y)$$

for $t \in [0, 1]$

- $f \square_t g((1-t)x+ty) \geq (1-t)f(x) + tg(y)$

- $f \square_t g$ is smallest possible to satisfy it

D / . $\int e^{-f \square_t g} = \left(\int e^{-f} \right)^{1-t} \left(\int e^{-g} \right)^t$

$$F-L \cdot \int e^{-\Delta} \geq (f e^{\frac{1}{2}}) (f e^{\frac{1}{2}})$$

$$f \square_0 g = f$$

$$f \square_1 g = g$$

Want to find a transform T s.t.

$$T((1-t)f + tg) = f \square_t g ?$$

Example

$$f(x) = \prod_K^\infty(x) = \begin{cases} 0 & \text{if } x \in K \\ \infty & \text{if } x \notin K \end{cases}$$

\equiv ∞

K -convex set



$$\prod_K^\infty D_L \prod_L^\infty = \inf_{x,y: \frac{x+y}{2} \in K} \left(\frac{\prod_K^\infty(x) + \prod_L^\infty(y)}{2} \right)$$

$$\Rightarrow \prod_{\frac{K+L}{2}}^\infty$$

Def (support function of a convex body K)

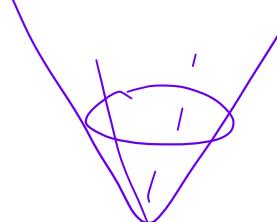
$$h_K(x) = \sup_{y \in K} \langle x, y \rangle \stackrel{\uparrow}{=} \|x\|_{K^0}$$

IF K is symmetric

f convex function

h_K convex function

$$h_{K+L} = h_K + h_L$$



i.e. we want $T \Pi_K^\infty = h_K$?

IV

Legendre Transform

Def $f: \mathbb{R}^n \rightarrow \mathbb{R}$ function

$$f^*(x) := \sup_{y \in \mathbb{R}^n} (\langle x, y \rangle - f(y))$$

Claim $(f \square_t g)^* = (1-t)f^* + tg^*$

Reformulation of the Prekopa-Leindler Inequality

$$\int e^{-(1-t)f + tg)^*} \geq (\int e^{-f^*})^t (\int e^{-g^*})^{1-t}$$

i.e. $\log \int e^{-f^*}$ is concave !!!

Remark Hölder's inequality $\log \int e^{-f}$ is convex