

The concentration of measure phenomenon

M. Ledoux

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first historical observations

E. Borel 1914

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(geometric) law of large numbers

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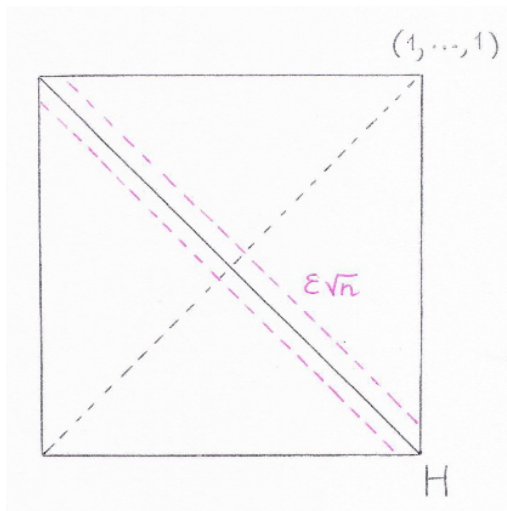
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high dimensional effect

real birth of measure concentration

new proof by **V. Milman 1970**

Dvoretzky's theorem on spherical sections of convex bodies

real birth of measure concentration

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for all $\varepsilon > 0$, there exists $\delta(\varepsilon) > 0$

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$$K \cap F$$

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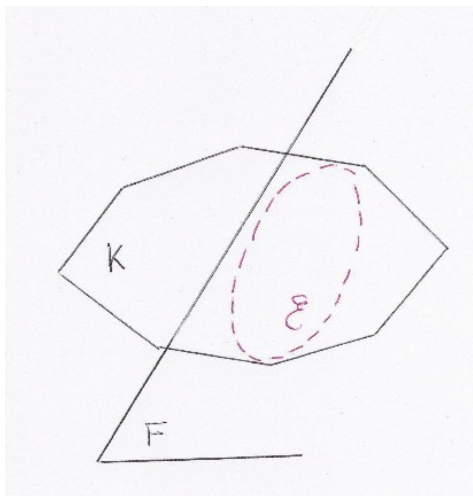
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concentration of spherical measures in high dimension

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asymptotic geometric analysis

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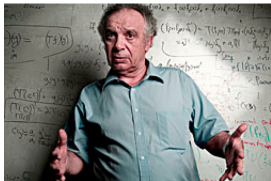
asymptotic geometric analysis

“The concentration of measure phenomenon, ubiquitous in probability theory and statistical mechanics, was brought to geometry (starting from Banach spaces) by Vitali Milman, following the earlier work by Paul Lévy”

(M. Gromov 1999)

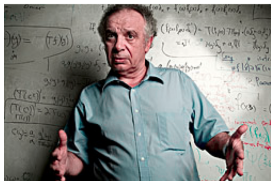
“The idea of concentration of measure, which was discovered by Vitali Milman, is arguably one of the great ideas of analysis in our times”

(M. Talagrand 1996)



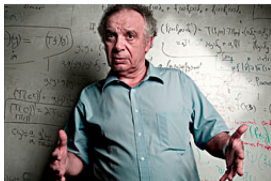
Vitali Milman

David Milman (Krein-Milman's theorem)



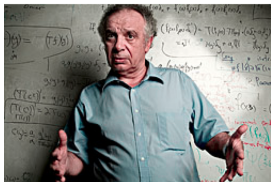
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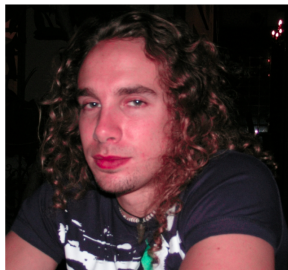


Vitali Milman, Pierre Milman

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main tool : **Lévy's inequality**

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origin : **isoperimetric inequalities**

isoperimetric inequalities

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Queen Dido



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extremal sets are geodesic balls

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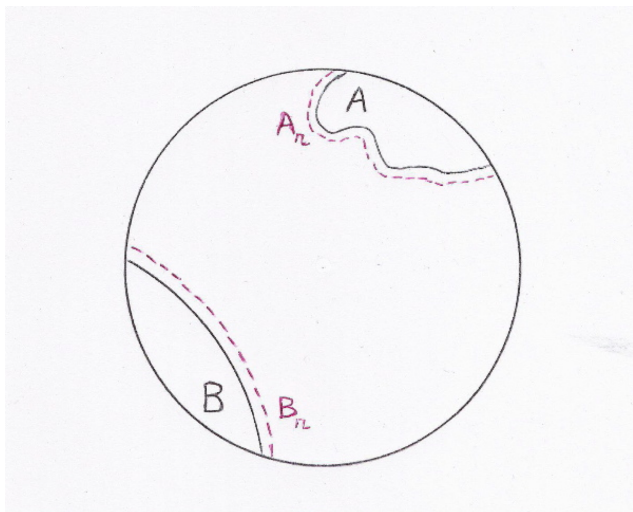
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infinitesimal form

$$r \rightarrow 0 \quad \text{vol}(\partial A) \geq \text{vol}(\partial B)$$

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normalized volume $\mu(\cdot) = \frac{\text{vol}(\cdot)}{\text{vol}(\mathbb{S}^n)}$

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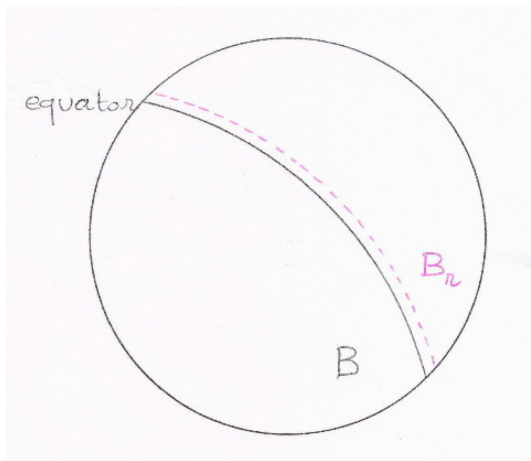
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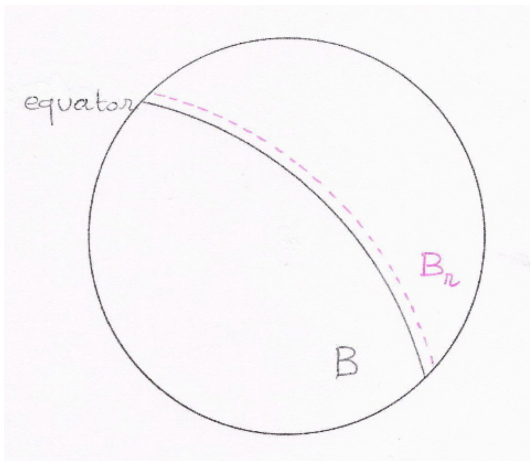
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another example : **Gaussian concentration**

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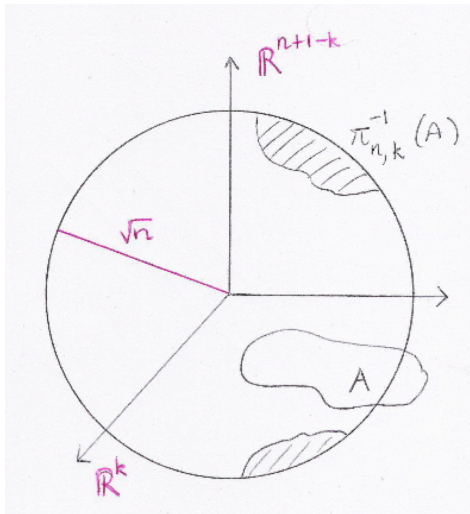
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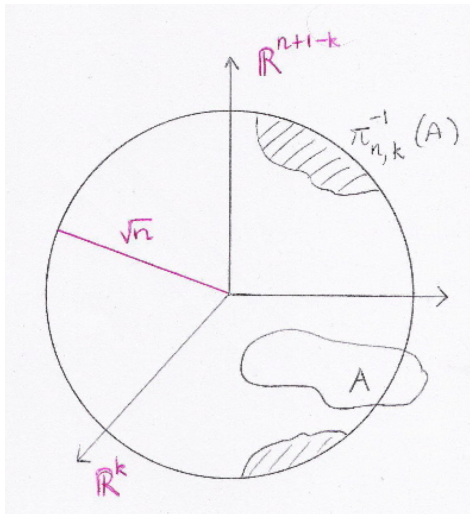
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Gaussian isoperimetric inequality (in \mathbb{R}^k)

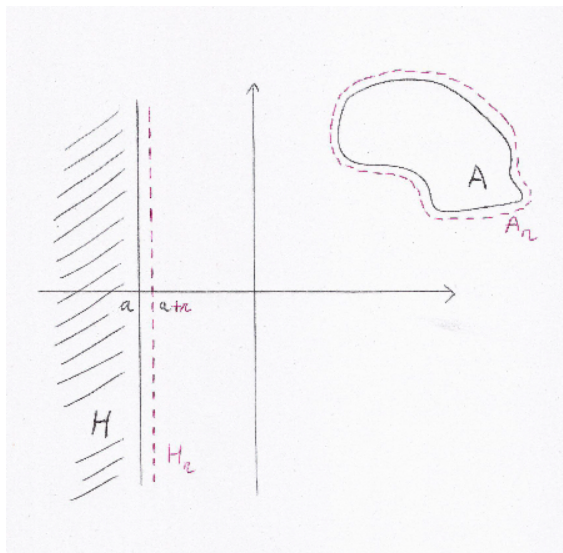
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(balls with centers at infinity)



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C. Borell, V. Sudakov - B. Tsirelson 1974

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extension to Wiener space

framework for measure concentration

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equivalent formulation on functions (Lévy's inequality)

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illustration

simple (functional) proof of Gaussian concentration $\alpha_\gamma(r) \leq e^{-r^2/2}$

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$$(1 - \varepsilon)|p_i - p_j| \leq |\pi(p_i) - \pi(p_j)| \leq (1 + \varepsilon)|p_i - p_j|$$

π **quasi-isometry**

find π at random

$$\mathbb{R}^{nk} \ni X = (X_{ij})_{1 \leq i \leq k, 1 \leq j \leq n}, \quad u \in \mathbb{R}^n$$

$$F(X) = |Xu|, \quad |u|\text{-Lipschitz}$$

$$\int_{\mathbb{R}^{nk}} F d\gamma \sim \sqrt{k} |u|$$

$$\gamma(|Xu - \sqrt{k}|u|| \geq r|u|) \leq 2e^{-r^2/2}$$

$$r = \varepsilon\sqrt{k}, \quad \ell \text{ points } u_1, \dots, u_\ell \quad (u = p_i - p_j)$$

$$\gamma\left(\bigcup_{i=1}^{\ell} \left\{ \frac{|Xu_i|}{\sqrt{k}} \notin [(1-\varepsilon)|u_i|, (1+\varepsilon)|u_i|] \right\}\right) \leq 2\ell e^{-\varepsilon^2 k/2} < 1$$

$$k \sim \frac{1}{\varepsilon^2} \log \ell, \quad \ell \sim N^2$$

further concentration examples

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discrete cube

$$X = \{0, 1\}^n$$

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B. Maurey 1979

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same **on any** product space

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$$\mu = \mu_1 \otimes \cdots \otimes \mu_n$$

principle of proof

$$n = 1$$

$$F \text{ } L\text{-Lipschitz, } \int_{X_1} F d\mu_1 = 0$$

Jensen

$$\int_{X_1} e^F d\mu_1 \leq \int_{X_1 \times X_1} e^{F(x)-F(y)} d\mu_1(x)d\mu_1(y)$$

$$|F(x) - F(y)| \leq L d(x, y) = L \mathbf{1}_{x \neq y}$$

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induction over n

symmetric group : martingale arguments

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induction over the dimension n

application

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same as for Gaussian

illustration

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empirical processes

X_1, \dots, X_n independent identically distributed in (S, \mathcal{S})

\mathcal{F} collection of functions $f : S \rightarrow [0, 1]$

$$Z = \sup_{f \in \mathcal{F}} \sum_{i=1}^n f(X_i)$$

Z Lipschitz and convex

concentration inequalities on

$$\mathbb{P}\left(|Z - \mathbb{E}(Z)| \geq r\right), \quad r > 0$$

oriented last passage percolation

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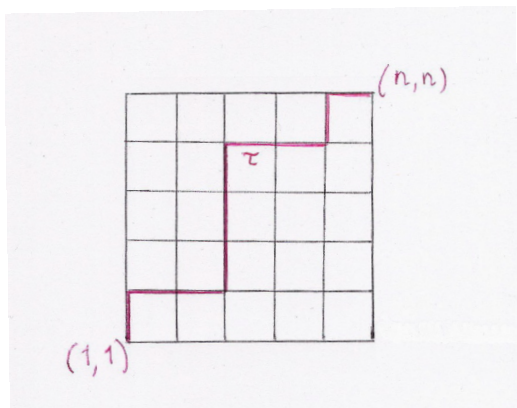
τ up/right paths from $(1, 1)$ to (n, n)

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new challenges of measure concentration