

*Measure concentration, functional inequalities,  
and curvature of metric measure spaces*

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between analysis, geometry and probability theory

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theory of optimal transportation

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using a concentration property  
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# spherical concentration



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

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$$\mu(A_r) \approx 1$$

application by V. Milman

$m$  (normalized) Haar measure on  $\mathcal{O}_{n+1}$

$$m(\{T \in \mathcal{O}_{n+1}; Tx \in A\}) = \mu(A), \quad x \in \mathbb{R}^{n+1}, A \subset \mathbb{S}^n$$

$\|\cdot\|$  gauge of  $K$

show that for  $\dim(E) \geq \delta(\varepsilon) \log n$

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**variety of examples and tools**

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Gauss space : curvature 1 dimension  $\infty$

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infinite dimensional analysis

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(PDE and calculus of variations viewpoint)

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$u = \chi_A, v = \chi_B$ , multiplicative form of Brunn-Minkowski

$$\text{vol}_n(\theta A + (1 - \theta)B) \geq \text{vol}_n(A)^\theta \text{vol}_n(B)^{1-\theta}$$



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$$dx \rightarrow d\gamma(x) = e^{-|x|^2/2} \frac{dx}{(2\pi)^{n/2}}$$

if  $w(\theta x + (1-\theta)y) \geq e^{-\theta(1-\theta)|x-y|^2/2} u(x)^\theta v(y)^{1-\theta}$ ,  $x, y \in \mathbb{R}^n$

then 
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relative entropy

M. Talagrand 1996

concentration via the transportation cost inequality (K. Marton)

$$A, B \subset \mathbb{R}^n, \quad d(A, B) \geq r > 0$$

$$\gamma_A = \gamma(\cdot | A), \quad \gamma_B = \gamma(\cdot | B)$$

$$W_2(\gamma_A, \gamma_B) \leq \left( \log \frac{1}{\gamma(A)} \right)^{1/2} + \left( \log \frac{1}{\gamma(B)} \right)^{1/2}$$

$$\frac{r}{\sqrt{2}} \leq W_2(\gamma_A, \gamma_B) \leq \left( \log \frac{1}{\gamma(A)} \right)^{1/2} + \left( \log \frac{1}{\gamma(B)} \right)^{1/2}$$

$$\gamma(A) \geq 1/2, \quad B = \text{complement of } A_r$$

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A. Stam 1959, L. Gross 1975

concentration via the logarithmic Sobolev inequality (I. Herbst)

$$F : \mathbb{R}^n \rightarrow \mathbb{R} \quad \text{1-Lipschitz,} \quad \int F d\gamma = 0$$

$$f = e^{\lambda F} / \int e^{\lambda F} d\gamma, \quad \lambda \in \mathbb{R}$$

differential inequality on  $\int e^{\lambda F} d\gamma$

$$\int e^{\lambda F} d\gamma \leq e^{\lambda^2/2}, \quad \lambda \in \mathbb{R}$$

$$\gamma(\{F < r\}) \geq 1 - e^{-r^2/2}, \quad r > 0$$

Brunn-Minkowski inequality

logarithmic Sobolev inequality

transportation cost inequality



# hierarchy

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**dimension free measure concentration**

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**parametrisation methods**

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equivalent to a curvature condition

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(manifold case R. McCann 1995)

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non-smooth analysis, PDE methods

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- ◇ main result : stability of the definition by Gromov-Hausdorff limit



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connecting  $\mu_0, \mu_1, \mu_\theta = T_\theta(\mu_0)$

definition of curvature : postulate that entropy is  $c$ -convex along  $T_\theta$

$$H(\mu_\theta | \mu) \leq (1 - \theta)H(\mu_0 | \mu) + \theta H(\mu_1 | \mu) - c\theta(1 - \theta)W_2(\mu_0, \mu_1)^2$$

- ◇ generalizes Ricci curvature in manifolds
- ◇ allows for geometric and functional inequalities
- ◇ main result : stability of the definition by Gromov-Hausdorff limit

J. Lott - C. Villani, K.-Th. Sturm 2006