

# “Exact” semi-discrete approaches to moment measures, affine spheres, gradient flows and variational MFG

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Maud, two weeks old today

- 1 Moment measures
  - Optimal transport formulation for moment measures
  - Optimization among convex functions
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- 2 Variant:  $q$ -moment measures
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# Moment Measures

**Definition** A probability measure  $\mu \in \mathcal{P}(\mathbb{R}^d)$  is said to be the moment measure of a convex function  $\psi : \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$  if  $\mu = (\nabla\psi)_\#(e^{-\psi} dx)$ .

**Applications** Kähler geometry (given a convex function  $\psi$  one can construct a Kähler manifold  $X_\psi$  whose Ricci tensor is half of the metric tensor iff the moment measure of  $\psi$  is uniform on a convex set), Stein kernels (writing  $\mu$  as a moment measure of  $\psi$  allows useful change-of-variables)...

**Natural questions** given  $\mu$ , can we find  $\psi$ ? is it unique? which measures  $\mu$  are moment measures of suitable functions  $\psi$ ? to which class of convex function should we restrict?

Note that if  $\psi$  is nice and the log-concave density  $e^{-\psi}$  is integrable, then  $\mu$  is *non-degenerate* ( $\text{spt } \mu$  is full-dimensional), and  $m_1(\mu) := \int |y| d\mu(y) < \infty$ ; moreover,  $\int y d\mu(y) = \int \nabla\psi(x) e^{-\psi(x)} dx = - \int \nabla(e^{-\psi}) = 0$ .

D. CORDERO-ERAUSQUIN, B. KLARTAG, *Moment Measures*, *J. Funct. An.* 2015

R. BERMAN, B. BERNDTSSON, *Real Monge-Ampere equations and Kähler-Ricci solitons on toric log Fano varieties*, *Ann. Fac. Sci. Toulouse*, 2013

S. K. DONALDSON, *Kähler geometry on toric manifolds, and some other manifolds with large symmetry*, 2008.

M. FATHI, *Stein kernels and moment maps*, *Ann. Prob.*, to appear

# An optimal transport interpretation

Cordero-Erausquin and Klartag proposed a variational formulation to find  $\psi$  given  $\mu$ . This can also be done using optimal transport.

We look for a log-concave density  $\rho$  such that the Brenier map  $\nabla\psi$  from  $\rho$  to  $\mu$  satisfies  $\psi + \log\rho = 0$ . This is an optimality condition for

$$\min_{\rho} \mathcal{E}(\rho) + \mathcal{T}(\rho, \mu)$$

where  $\mathcal{E}(\rho) = \int \rho \log \rho \, dx$  and  $\mathcal{T}$  is the *maximal correlation* transport cost

$$\begin{aligned} \mathcal{T}(\rho, \mu) &= \max \{ \mathbb{E}[X \cdot Y] : X \sim \rho, Y \sim \mu \} \\ &= \max \left\{ \int x \cdot y \, d\gamma(x, y) : \gamma \text{ transp. plan from } \rho \text{ to } \mu \right\} \\ &= \min \left\{ \int \psi \, d\rho + \int \psi^* \, d\mu : \psi \text{ convex} \right\} \end{aligned}$$

F. SANTAMBROGIO, Dealing with moment measures via entropy and optimal transport, *J. Funct. An.* 2016

# Bounded and unbounded domains, continuity of $\psi$

Fix a convex compact set  $\Omega \subset \mathbb{R}^d$ , and solve  $\min_{\rho \in \mathcal{P}(\Omega)} \mathcal{E}(\rho) + \mathcal{T}(\rho, \mu)$ .  
A solution exists, and  $\mu$  is a moment measure... with no condition on  $\mu$ !

Yet, we have  $\rho > 0$  on  $\Omega$ , and  $\psi$  is bounded on  $\Omega$ ,  $\psi = +\infty$  on  $\mathbb{R}^d \setminus \Omega$ .  
The discontinuity of  $\psi$  is the issue (note that if  $\text{spt} \mu$  is compact then  $\psi$  is expected to be Lipschitz).

**Definition**  $\psi$  is said to be *essentially continuous* if for  $\mathcal{H}^{d-1}$ -a.e. point  $x \in \partial\{\psi < +\infty\}$  we have  $\lim_{x' \rightarrow x} \psi(x') = +\infty$ .

**Result** if  $\rho$  solves  $\min_{\rho \in \mathcal{P}_1(\mathbb{R}^d)} \mathcal{E}(\rho) + \mathcal{T}(\rho, \mu)$  then  $\rho = e^{-\psi}$ ,  $\nabla \psi$  is the Brenier map from  $\rho$  to  $\mu$ , and  $\psi$  is essentially continuous (i.e.  $\rho \rightarrow 0$  a.e. on the boundary of  $\text{spt} \rho$ ).

# Bounds on $\mathcal{E}$ and $\mathcal{T}$ , existence

Using  $t \log t + e^{s-1} \geq st$  we get

$$\mathcal{E}(\rho) \geq \int \rho(x)h(x) dx - \int e^{h(x)-1} dx$$

for any function  $h$  such that  $e^{h-1} \in L^1(\mathbb{R}^d)$  and  $h \in L^1(\rho)$ . Using  $h = -\sqrt{|x|}$  we get

$$\mathcal{E}(\rho) \geq - \int \rho(x) \sqrt{|x|} dx - \int e^{-\sqrt{|x|}-1} dx \geq -C - \sqrt{m_1(\rho)}.$$

For  $\mathcal{T}$ , if we suppose that  $\mu$  is centered ( $\int y d\mu(y) = 0$ ) and non-degenerate, then there exists  $c > 0$  such that

$$\mathcal{T}(\rho, \mu) \geq cm_1(\rho) \quad \text{for all } \rho \text{ with } \int x d\rho(x) = 0.$$

Minimizing sequences  $(\rho_n)_n$  can be supposed to be also centered if  $\mu$  is. Then we can apply the above bounds, get tightness for minimizing sequences, and prove existence of a minimizer.

# Geodesic convexity, uniqueness and characterization

Is the optimal  $\rho$  unique? is the condition “ $\rho = e^{-\psi}$ , with  $\mu$  moment measure of  $\psi$ ” equivalent to being optimal?

This requires some convexity, but  $\rho \mapsto \mathcal{T}(\rho, \mu)$  is concave!

Informally (we are not supposing  $\rho, \mu \in \mathcal{P}_2(\mathbb{R}^d)$ ) we have

$$\mathcal{T}(\rho, \mu) = \int \frac{1}{2}|x|^2 d\rho(x) + \int \frac{1}{2}|y|^2 d\mu(y) - \frac{1}{2}W_2^2(\rho, \mu),$$

and we know that  $\rho \mapsto \int \frac{1}{2}|x|^2 d\rho(x)$  is 1-geodesically convex in  $W_2$ , while  $\rho \mapsto \frac{1}{2}W_2^2(\rho, \mu)$  is 1-geodesically concave.

And  $\mathcal{E}$  is geodesically convex thanks to McCann's condition.

We can then prove

**Uniqueness and characterization** If  $\mu$  is centered and not supported on a hyperplane, the solution of  $\min_{\rho \in \mathcal{P}_1(\mathbb{R}^d)} \mathcal{E}(\rho) + \mathcal{T}(\rho, \mu)$  exists and is unique up to translations. Moreover, being a solution of this optimization problem is equivalent to being of the form  $\rho = e^{-\psi}$ , with  $\mu$  moment measure of  $\psi$ .

R. J. McCann, A convexity principle for interacting gases, *Adv. Math.* 1997



# Optimization among convex functions

We are looking at a min-min problem

$$\min \left\{ \mathcal{E}(\rho) + \int \psi(x)\rho(x) dx + \int \psi^*(y) d\mu(y) : \rho \in \mathcal{P}_1(\mathbb{R}^d), \psi \text{ convex} \right\}.$$

If we consider  $\psi$  as a secondary variable, for every  $\rho$  we take  $\min_{\psi}$ , we obtain  $\mathcal{T}(\rho, \mu)$ . If instead we first compute  $\min_{\rho}$ , we have to compute

$$\inf \left\{ \int \rho(x) \log \rho(x) dx + \int \psi(x)\rho(x) dx : \rho \geq 0, \int \rho(x) dx = 1 \right\}.$$

Setting  $c = \int e^{-\psi(x)} dx$ , the above inf equals  $-\log c$ . Hence we need to solve

$$\min \left\{ \int \psi^* d\mu - \log \left( \int e^{-\psi} dx \right) : \psi \text{ convex} \right\}.$$

The variational approach by Cordero-Erausquin and Klartag considers the same problem in terms of  $u = \psi^*$ : the first term becomes linear and the second, magically, convex (thanks to Prékopa-Leindler inequality).

# Semi-discrete approach to the JKO scheme

In the JKO scheme for gradient flows in  $W_2$  we solve problems of the form

$$\min_{\rho} \frac{1}{2} W_2^2(\rho, \mu) + \mathcal{F}(\rho),$$

where  $\mathcal{F}(\rho) = \int f(\rho(x)) dx$ . This can be formulated as

$$\min_{u \text{ convex}} : \nabla u \in \Omega \quad \frac{1}{2} \int_{\Omega} |\nabla u(x) - x|^2 d\mu(x) + \mathcal{F}((\nabla u)_{\#} \mu).$$

Suppose that  $\mu = \sum_j a_j \delta_{x_j}$  is discrete and look for a convex function on its support  $S := \{x_j\}_j$ . Require that its *subdifferential*

$$\partial u(x) := \{p \in \mathbb{R}^d : u(x) + p \cdot (y - x) \leq u(y) \text{ for all } y \in S\}$$

is non-empty. Any element of  $\partial u(x)$  can play the role of  $\nabla u(x)$ , but, how to define  $F$ ? Spreading the mass  $a_j$  uniformly on  $\partial u(x_j)$  one obtains a functional (convex if  $f$  satisfies McCann's condition)

$$u \mapsto \sum_j f\left(\frac{a_j}{|\partial u(x_j) \cap \Omega|}\right) |\partial u(x_j) \cap \Omega|,$$

which depends on the areas of the subdifferential cells.

J.-D. BENAMOU, G. CARLIER, Q. MÉRIGOT, É. OUDET Discretization of functionals involving the Monge-Ampère operator, *Num. Math.*, 2016.

# Voronoi and Laguerre cells, and semi-discrete OT

Given some points  $(x_j)_j$ , their Voronoi cells  $V_j$  are defined by

$$V_j := \left\{ x \in \Omega : \frac{1}{2}|x - x_j|^2 \leq \frac{1}{2}|x - x_{j'}|^2 \text{ for all } j' \right\}.$$

These cells  $V_j$  are convex polyhedra. In optimal transport a variant of these cells is useful: given values  $\phi_j$ , we look for the *Laguerre cells*

$$W_j := \left\{ x \in \Omega : \frac{1}{2}|x - x_j|^2 - \phi_j \leq \frac{1}{2}|x - x_{j'}|^2 - \phi_{j'} \text{ for all } j' \right\}.$$

Note that the Laguerre cells corresponding to  $\phi_j := -u(x_j) + \frac{1}{2}|x_j|^2$  are nothing but the subdifferentials of  $u$ .

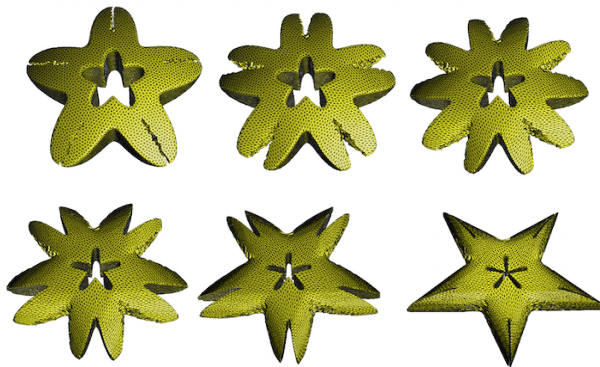
If  $\rho$  is a density on  $\Omega$  and  $\mu = \sum_j a_j \delta_{x_j}$ , then finding an optimal transport from  $\rho$  to  $\mu$  is equivalent to finding  $\phi_j$  such that  $\rho(W_j) = a_j$  for every  $j$ .

This amounts to solving the dual Kantorovich problem in terms of the finite-dimensional variable  $\phi$ :

$$\max_{\phi} \sum_j a_j \phi_j + \int_{\Omega} \phi^c d\rho := \sum_j \left( a_j \phi_j + \int_{W_j} \left( \frac{1}{2}|x - x_j|^2 - \phi_j \right) d\rho(x) \right).$$

# Algorithmic geometry and semi-discrete numerics for OT

Algorithmic geometry is now able to deal with Laguerre cells of many ( $10^9$ ) points in 2D and 3D, compute their measures, and differentiate this in terms of the values of  $\psi_j$ .



$W_2$  geodesic between two different stars in 3D, computed via semi-discrete optimal transport ( $10^6$  Dirac masses to a  $10^6$  simplex triangulation).

Q. MÉRIÇOT, A multiscale approach to optimal transport, *Comput. Graph. Forum*, 2011.

B. LÉVY A numerical algorithm for  $L^2$  semi-discrete optimal transport in 3D, *M2AN*, 2015.

# A better semi-discrete approach for moment measures

The natural counterpart of the BCMO scheme to solve the moment measure optimization problem would be discretize  $\mu$  as  $\sum_j a_j \delta_{x_j}$  and minimize

$$(u, P) \mapsto \sum_j x_j P_j + a_j \log \left( \frac{a_j}{|\partial u(x_j) \cap \Omega|} \right), \quad P_j \in \partial u(x_j).$$

**Main difficulty:** we need to use  $\Omega = \mathbb{R}^d$ , and the method does not work. Instead, it is possible to solve

$$\min \int u \, d\mu - \log \left( \int e^{-u^*} \, dx \right) := \sum_j a_j u_j - \log \left( \sum_j \int_{\partial u(x_j)} e^{-x \cdot x_j + u_j} \, dx \right)$$

Let us set  $F(u) = \sum_j \int_{\partial u(x_j)} e^{-x \cdot x_j + u_j} \, dx$  and  $G = -\log F$ .

We will solve by convex optimization methods  $\min \langle a, u \rangle + G(u)$ , or, equivalently,  $\min \langle a, u \rangle : F(u) = 1$ , via **Newton's method**.

# Derivatives and Hessian

We can compute the derivatives of  $F$  and  $G$ .

$$\partial_j F = \int_{\partial u(x_j)} e^{-u^*} dx; \quad \text{for } i \neq j \quad \partial_{ij} F = \int_{\Gamma_{ij}} e^{-u^*} \frac{1}{|x_i - x_j|} d\mathcal{H}^{d-1},$$

where  $\Gamma_{ij} = \partial u(x_j) \cap \partial u(x_i)$  (note  $i \sim j$  if  $\Gamma_{ij} \neq \emptyset$ ), and

$$\partial_{jj} F = \int_{\partial u(x_j)} e^{-u^*} dx - \sum_{i: i \sim j, i \neq j} \int_{\Gamma_{ij}} e^{-u^*} \frac{1}{|x_i - x_j|} d\mathcal{H}^{d-1}.$$

Set  $\lambda_j := \int_{\partial u(x_j)} e^{-u^*} dx$  and  $\gamma_{ij} := \int_{\Gamma_{ij}} e^{-u^*} \frac{1}{|x_i - x_j|} d\mathcal{H}^{d-1}$ . Note  $F = \sum_i \lambda_i$ .

$$\partial_{ij} G = -\frac{\partial_{ij} F}{F} + \frac{\partial_i F \partial_j F}{F^2}.$$

Take  $v \in \mathbb{R}^N$  and compute (tedious computations + manipulations)

$$\sum_{ij} (\partial_{ij} G) v_i v_j = \frac{1}{F} \sum_{ij: i \sim j} \gamma_{ij} |v_i - v_j|^2 - \frac{1}{F} \sum_j \lambda_j |v_j - \bar{v}|^2,$$

where  $\bar{v} = \sum_i \lambda_i v_i / F$ .

# Discrete Brascamp-Lieb inequality

For the convergence of the Newton method, we would like uniform convexity of  $G$ , at least in the orthogonal space to the trivial invariance direction (where  $u_j$  is an affine function of  $x_j$ ).

**Brascamp-Lieb inequality:** for  $\psi$  convex and  $\int v e^{-\psi} = 0$ , we have

$$\int |v|^2 e^{-\psi} \leq \int (D^2\psi)^{-1}(\nabla v, \nabla v) e^{-\psi}$$

with equality if and only if  $v = \hat{w} \cdot \nabla\psi$  for a fixed  $\hat{w}$ .

**Discrete counterpart:** take  $v = v_j$  on  $\partial u(x_j)$  and  $\psi = u^*$ , and suppose  $\sum_j \lambda_j v_j = 0$ . Then

$$\sum_j \lambda_j |v_j|^2 \leq \sum_{ij:i \sim j} \int_{\Gamma_{ij}} e^{-\psi} \frac{1}{|x_i - x_j|} |v_i - v_j|^2 = \sum_{ij:i \sim j} \gamma_{ij} |v_i - v_j|^2,$$

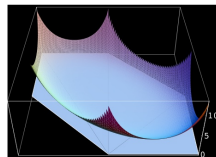
with equality in the same case, i.e. when  $v_j$  is a linear function of  $u_j$ . Applied to  $v - \bar{v}$ , this gives the desired lower bound on  $D^2G$ .

H. J. BRASCAMP, E. H. LIEB, On extensions of the Brunn-Minkowski and Prékopa-Leindler theorems, including inequalities for log concave functions, and with an application to the diffusion equation, *J. Funct. Anal.*, 1976.

Work in progress with B. Klartag and Q. Mérigot

# Numerics for moment measures

Few numerical studies exist for moment measures, in particular when  $\mu$  is the uniform measure on a hexagon or a regular polygon in 2D (including work by Donaldson and other geometers).



The techniques coming from semi-discrete OT make this challenge almost trivial: we discretize  $\mu$  as an atomic measure, keeping it centered, and non-supported on a hyperplane. Then we apply a damped Newton algorithm to the minimization of  $G$ .

Convergence along Newton iterations are guaranteed by uniform convexity and we can consider that the solution is “exact”. Convergence as the discretization of  $\mu$  becomes finer can be proven by  $\Gamma$ -convergence.

C. DORAN, M. HEADRICK, C. P. HERZOG, J. KANTOR, T. WISEMAN Numerical Kaehler-Einstein metric on the third del Pezzo, *Comm. Math. Phys.* 2008.

R. S. BUNCH, S. K. DONALDSON Numerical approximations to extremal metrics on toric surfaces, *Handbook Geom. An.*, 2008.

J. KITAGAWA, Q. MÉRIGOT, B. THIBERT Convergence of a Newton algorithm for semi-discrete optimal transport *JEMS*, to appear.



# $q$ -moment measures and transport variational formulation

**Variante** Given  $q > 0$ , a probability measure  $\mu \in \mathcal{P}(\mathbb{R}^d)$  is said to be the  $q$ -moment measure of a convex function  $\psi : \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$  if we have  $\mu = (\nabla\psi)_{\#} \left( \frac{1}{\psi(x)^{d+q}} dx \right)$ .

The condition  $q > 0$  guarantees integrability of  $\psi^{-(d+q)}$ . We consider now

$$\min_{\rho} \mathcal{E}_{\alpha}(\rho) + \mathcal{T}(\rho, \mu)$$

where  $\mathcal{E}_{\alpha}(\rho) = - \int \frac{1}{\alpha} (\rho^{ac})^{\alpha} dx$ ,  $\alpha = 1 - \frac{1}{d+q} \in (0, 1)$ , and  $\rho^{ac}$  is the density of the absolutely continuous part of  $\rho$ .

$\mathcal{E}_{\alpha}$  is known to be l.s.c. for the weak- $*$  convergence as soon as  $\alpha \in (0, 1)$ . It is geodesically convex for  $\alpha > 1 - 1/d$  (i.e.  $q > 0$ ). For lower bounds use

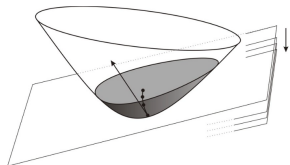
$$-\frac{1}{\alpha} t^{\alpha} + \left( \frac{1}{\alpha} - 1 \right) (s_{-})^{-\frac{\alpha}{1-\alpha}} \geq ts.$$

This provides  $E_{\alpha}(\rho) \geq -C - Cm_1(\rho)^{\delta}$  but  $\delta > d/(d+q-1)$  and we need  $q > 1$  for tightness and existence.

**Result** If  $q > 1$  and  $\mu$  is centered and non-degenerate there exists unique (up to translations) an optimal  $\rho$ , which is a.c. and bounded from above, and is of the form  $\rho = \psi^{-(d+q)}$ , where  $\nabla\psi$  is the Brenier map from  $\rho$  to  $\mu$ .

# Connections with affine spheres

**Affine normals** Given a smooth strictly convex body  $\Omega$  and  $x_0 \in \partial\Omega$ , take  $\Pi_0$  the tangent plane to  $\partial\Omega$  at  $x_0$ ,  $(\Pi_t)_t$  a family of parallel planes to  $\Pi_0$ ,  $\Omega_t := \Omega \cap \Pi_t$  and  $z(t)$  the barycenter of  $\Omega_t$ . The tangent direction at  $t = 0$  to the curve  $t \mapsto z(t)$  is called affine normal to  $\Omega$  at  $x_0$ .



**Affine spheres** An affine sphere is a convex body where the affine normal vectors at each point of the boundary point towards a same common point. If  $\partial\Omega$  is parameterized as a graph of a function, being an affine sphere is a 3rd order PDE on this function.

**PDE characterization** Take a convex function  $\psi > 0$  on  $\mathbb{R}^d$  and define  $n : \mathbb{R}_+ \times \mathbb{R}^d$  via  $n(1, x) = \psi(x)$  and then extended by 1-homogeneity. Take the set  $B := \{n \leq 1\}$  and let  $K$  be the intersection  $\partial B \cap (\{0\} \times \mathbb{R}^d)$ . Then  $B$  is an affine hemisphere centered at the origin if and only if  $\psi$  solves  $\psi^{d+2} \det(D^2\psi) = c$ , i.e. if the 2-moment measure of  $\psi$  is the uniform measure on the convex set  $K^\circ$ .

B. KLARTAG Affine hemispheres of elliptic type, *Algebra i Analiz*, 2017

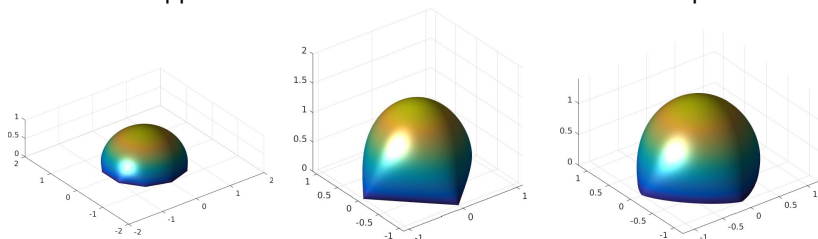
# Semidiscrete optimization and numerical results

With the same discretization, we now need now to solve

$$\min \langle a, u \rangle - \frac{1}{d+q-1} \int \frac{1}{(u^*)^{d+q-1}} : \int \frac{1}{(u^*)^{d+q}} = 1.$$

The estimates for the uniform convexity are now based on a discrete version of the *dimensional Brascamp-Lieb* inequality.

The Newton approach is also efficient and allows for fast computations.



Few affine hemispheres in  $\mathbb{R}^3$  based on different convex sets in  $\mathbb{R}^2$ .

V. H. NGUYEN Dimensional variance inequalities of Brascamp-Lieb type and a local approach to dimensional Prékopa's theorem. *J. Funct. An.* 2014

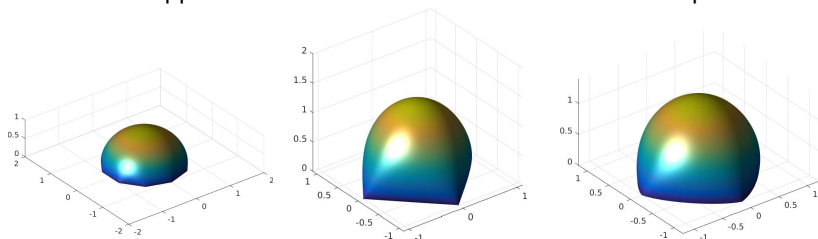
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# Moreau-Yosida regularization of internal energies


**Definition** On a Hilbert space  $X$ , given  $H : X \rightarrow \mathbb{R} \cup \{+\infty\}$ , its Moreau-Yosida regularization  $H_\varepsilon$  is defined as  $H_\varepsilon(x) := \inf_y \frac{|x-y|^2}{2\varepsilon} + H(y)$ . It is always semi-concave, and convex if  $H$  is convex. If  $H$  is l.s.c., we have  $H_\varepsilon \rightarrow H$  as  $\varepsilon \rightarrow 0$ , with  $\Gamma$ -convergence.

In the Wasserstein space, we could take  $\mathcal{F} : \mathcal{P}(\Omega) \rightarrow \mathbb{R} \cup \{+\infty\}$  and define

$$\mathcal{F}_\varepsilon(\mu) := \min_\rho \frac{W_2^2(\mu, \rho)}{2\varepsilon} + \mathcal{F}(\rho).$$

Suppose  $\mu = \sum_j a_j \delta_{x_j}$  and  $\mathcal{F}(\rho) = \int f(\rho(x)) dx$ . Using the transport cost  $c(x, y) = |x - y|^2/2$ , the dual of the above optimization problem is

$$\max_\phi \int \frac{\phi}{2\varepsilon} d\mu - \int f^* \left( -\frac{\phi^c(x)}{2\varepsilon} \right) dx.$$

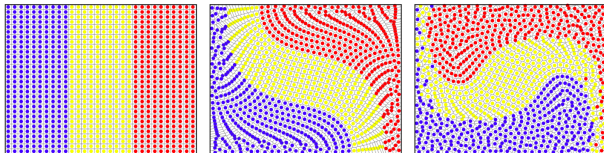
Setting  $\frac{|x|^2}{2} - \phi(x) = u(x)$  and  $\frac{|y|^2}{2} - \phi^c(y) = u^*(y)$ , the above problem is very similar to the previous ones (only,  $\phi^c$  is not affine on each cell, but quadratic). Algorithmic geometry can easily find the optimal  $\rho$  given  $\mu$ , and differentiate  $\mathcal{F}_\varepsilon$  in terms of the positions and masses of the atoms of  $\mu$ . 

# Incompressible Euler equation

Euler equations for incompressible fluids  $\partial_t v + (v \cdot \nabla)v = \nabla p, \nabla \cdot v = 0$  are known to represent geodesics among measure-preserving diffeomorphism. In the Brenier's variational interpretation, they can be obtained via

$$\min \int_C K(\omega) dQ(\omega) : (e_t)_\# Q = dx, (e_0, e_1)_\# Q = \bar{\gamma} \in \mathcal{P}(\Omega \times \Omega),$$

where  $C$  is the space of curves  $\omega : [0, 1] \rightarrow \Omega$  and  $K(\omega) := \int |\omega'(t)|^2 / 2 dt$ . The condition  $(e_t)_\# Q = dx$  can be replaced, as a variational approximation, by adding  $\mathcal{F}_\varepsilon((e_t)_\# Q)$  where  $\mathcal{F}(\rho) = 0$  if  $\rho = dx, +\infty$  if not.



Y. BRENIER The least action principle and the related concept of generalized flows for incompressible perfect fluids, *J. Amer. Math. Soc.* 1989.

Q. MÉRIGOT, J.-M. MIREBEAU Minimal geodesics along volume preserving maps, through semi-discrete optimal transport *SINUM* 2016.

T. GALLOÛET, Q. MÉRIGOT A Lagrangian scheme à la Brenier for the incompressible Euler equations *Foundation of Computational Mathematics*, to appear

# Variational MFG with local congestion costs - 1

In a population of agents everybody chooses its own trajectory, solving

$$\min \int_0^T \left( \frac{|x'(t)|^2}{2} + g(\rho_t(x(t))) \right) dt + \Psi(x(T)),$$

with given initial point  $x(0)$ ; suppose that  $g$  is increasing, i.e. agents try to avoid overcrowded regions. Yet,  $\rho$  depends on their overall choices, and hence we look for a Nash equilibrium. If  $\varphi$  is their value function we have

$$\begin{cases} -\partial_t \varphi + \frac{|\nabla \varphi|^2}{2} = g(\rho), \\ \partial_t \rho - \nabla \cdot (\rho \nabla \varphi) = 0, \\ \varphi(T, x) = \Psi(x), \quad \rho(0, x) = \rho_0(x). \end{cases}$$

J.-M. LASRY, P.-L. LIONS, *Jeux à champ moyen. (I & II) C. R. Math. Acad. Sci. Paris*, 2006, *Mean-Field Games, Japan. J. Math.* 2007.

M. HUANG, R.P. MALHAMÉ, P.E. CAINES, Large population stochastic dynamic games: closed-loop McKean-Vlasov systems and the Nash certainty equivalence principle, *Comm. Info. Syst.* 2006

P.-L. LIONS, courses at Collège de France, 2006/12, videos available on the web

P. CARDALIAGUET, lecture notes, [www.ceremade.dauphine.fr/~cardalia/](http://www.ceremade.dauphine.fr/~cardalia/)

# Variational MFG with local congestion costs - 2

It happens that an equilibrium can be found by minimizing the (global) energy

$$\mathcal{A}(\rho, v) := \int_0^T \int_{\Omega} \left( \frac{1}{2} \rho_t |v_t|^2 + f(\rho_t) \right) + \int_{\Omega} \Psi \rho_T$$

where  $f' = g$  under the constraint  $\partial_t \rho + \nabla \cdot (\rho v) = 0$ .

This can also be written in Lagrangian terms as

$$\min \left\{ \int_C K dQ + \int_0^T \mathcal{F}((e_t)_{\#} Q) + \int_{\Omega} \Psi d(e_T)_{\#} Q, Q \in \mathcal{P}(C), (e_0)_{\#} Q = \rho_0 \right\}.$$

or, for curves valued in the Wasserstein space, as

$$\min \left\{ \int_0^T \left( \frac{1}{2} |\rho'(t)|^2 + \mathcal{F}(\rho(t)) \right) dt + \int_{\Omega} \Psi d\rho_T : \rho(0) = \rho_0 \right\}.$$

P. CARDALIAGUET, P.J. GRABER. Mean field games systems of first order. *ESAIM: COCV*, 2015.

J.-D. BENAMOU, G. CARLIER Augmented Lagrangian methods for transport optimization, Mean-Field Games and degenerate PDEs, *JOTA*, 2015.

J.-D. BENAMOU, G. CARLIER, F. SANTAMBROGIO, Variational Mean Field Games, *Active Particles I*, 2016





# Lagrangian approximation of variational MFG

We can consider atomic measures on  $C$ , i.e.  $Q = \sum_j a_j \delta_{\omega_j}$  where, for simplicity,  $a_j = 1/N$  (but different choices could model *major players*).

Yet  $(e_t)_\# Q = \sum_j a_j \delta_{\omega_j(t)}$  is atomic and  $\mathcal{F} = +\infty$ .

**Idea:** replacing  $\mathcal{F}$  with  $\mathcal{F}_\varepsilon$  the problem is perfectly posed on atomic measures, and  $\Gamma$ -converges (non-trivial details) to the problem with  $\mathcal{F}$ .

The corresponding optimization problem is non-convex, but provides Lagrangian trajectories for a MFG with an approximate congestion cost.

Computations are easy for  $f(s) = s \log s$  (i.e.  $g(s) = \log s$ ), where densities are Gaussians on each cells, and for the particular case  $f(s) = 0$  for  $s \in [0, 1]$ ,  $= +\infty$  if not (density-constrained MFG: here densities are uniform on cells, and vanish outside, as in partial transport problems).

P. CARDALIAGUET, A. MÉSZÁROS, F. SANTAMBROGIO, First order Mean Field Games with density constraints: Pressure equals Price, *SIAM J. Contr. Opt.*, 2016

Work in progress with Q. Mérigot and C. Sarrazin; Master and PhD thesis of C. Sarrazin.

# Lagrangian approximation of gradient flows with diffusion

The same idea (replacing  $\mathcal{F}$  with  $\mathcal{F}_\varepsilon$ ) can be used in gradient flows

$$\partial_t \rho - \nabla \cdot \left( \rho \nabla \left( \frac{\delta \mathcal{F}}{\delta \rho} \right) \right) - \nabla \cdot (\rho \nabla V) = 0,$$

in particular for local functionals  $\mathcal{F}(\rho) = \int f(\rho(x)) dx$  which give rise to diffusion and would not be well-defined on atomic measures (note that we added a potential energy  $\int V d\rho$ ).

For instance, the Fokker-Planck equation  $\partial_t \rho - \Delta \rho - \nabla \cdot (\rho \nabla V)$  uses  $\mathcal{F} = \mathcal{E}$  and lets Gaussian appear in the Moreau-Yosida regularization.

The idea is looking for  $\mu(t) = \sum_j a_j \delta_{\omega_j(t)}$ , with

$$\omega_j'(t) = -\nabla V(\omega_j(t)) - \nabla_j \mathcal{F}_\varepsilon(\mu(t)).$$

Convergence proofs cannot only be based on  $\Gamma$ -convergence and are not trivial (or require extra assumptions), as usual when dealing with gradient flows (a control on the slope is needed).

E. SANDIER, S. SERFATY *Gamma-convergence of gradient flows with applications to Ginzburg-Landau*, *Comm. PDE*, 2004

# Numerical approximation of crowd motion

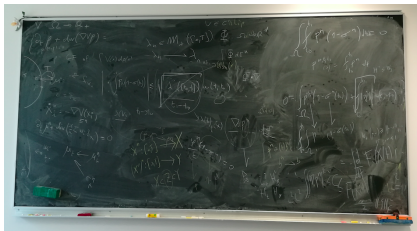
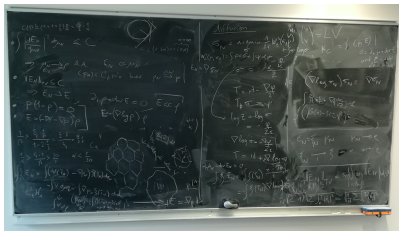
Using  $\mathcal{F}(\rho) = 0$  if  $\rho \leq 1$ ,  $+\infty$  otherwise we obtain a crowd motion model of gradient-flow type.

$$\begin{cases} \partial_t \rho - \nabla \cdot (\rho(\nabla V + \nabla p)) \\ \rho \geq 0, \rho \leq 1, \rho(1 - \rho) = 0. \end{cases}$$

The Moreau-Yosida computation for the constraint part consists in partial transport. The gradient  $\nabla_j \mathcal{F}_\varepsilon$  w.r.t. to the positions of the atoms equals  $\frac{x_j - \beta_j}{\varepsilon}$ , where  $\beta_j$  is the barycenter of the cell corresponding to  $x_j$ .

B. MAURY, A. ROUDNEFF-CHUPIN AND F. SANTAMBROGIO, A macroscopic crowd motion model of gradient flow type, *Math. Mod. Meth. Appl. Sci.*, 2010

Work in progress with Q. Mériçot and F. Stra



*The End*

Thanks for your attention

Few images have been stolen from various sources on the internet. I thank their authors.

