## On multi-marginal optimal transport

## Guillaume Carlier ${ }^{\text {a }}$.

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[^0]Yann Brenier and (applied) transport



Aim of this talk is to review a few results on some multi-marginal problems i.e. problems of the form:

$$
\begin{equation*}
\inf _{\gamma \in \Pi\left(\mu_{1}, \cdots, \mu_{N}\right)} \int_{X_{1} \times \cdots \times X_{N}} c\left(x_{1}, \cdots, x_{N}\right) \mathrm{d} \gamma\left(x_{1}, \cdots, x_{N}\right), \tag{1}
\end{equation*}
$$

where $\Pi\left(\mu_{1}, \cdots, \mu_{N}\right)$ is the set of probability measures on $X_{1} \times \cdots \times X_{N}$ having $\mu_{1}, \cdots, \mu_{N}$ as marginals. Much less is known than in the two-marginals case (e.g. Monge solution for twisted costs, Brenier, McCann, Gangbo theory, regularity...).

Important motivation: Brenier's (CPAM, 1999) relaxation of Arnold's interpretation of incompressible Euler as a geodesic problem on the group of measure preserving diffeomorphisms.

$$
\begin{equation*}
\partial_{t} u+\nabla \cdot(u \otimes u)+\nabla p=0, \nabla \cdot u=0, t \in(0, T), x \in \mathbf{T}^{\mathbf{d}} \tag{2}
\end{equation*}
$$

The two-endpoints problem asks that the flow $X$ of $u$ at the final time $T$ is a prescribed measure-preserving map $h$. At least formally (2) is the Euler-Lagrange equation for the minimization of

$$
\int_{0}^{T} \int_{\mathbf{T}^{\mathbf{d}}}|\dot{X}(t, x)|^{2} \mathrm{~d} x \mathrm{~d} t
$$

subject to $X_{0}=\mathrm{id}, X_{T}=h$ and of course that $X_{t}$ is measure-preserving for every $t$.

No minimizer in general (Shnirelman). Yann's relaxation (in a nutshell):

$$
\begin{equation*}
\inf _{Q \in \Gamma(h)} I(Q):=\int_{\Omega} E(\omega) \mathrm{d} Q(\omega) \tag{3}
\end{equation*}
$$

where $E(\omega)=\int_{0}^{T}|\dot{\omega}(t)|^{2} \mathrm{~d} t$ and $\Gamma(h)$ is the set of probability measures on $\Omega=C\left([0, T], \mathbf{T}^{\mathbf{d}}\right)$ such that

$$
e_{t \#} Q=\mathcal{L}, t \in[0, T],\left(e_{0}, e_{T}\right)_{\#} Q=(\mathrm{id}, h)_{\#} \mathcal{L}
$$

where $e_{t}$ is the evaluation map a time $t$ and $\mathcal{L}$ is Lebesgue's measure on $\mathbf{T}^{\mathbf{d}}$.

It is an infinitely many-marginals limit case $N \rightarrow \infty$ of (1),

$$
\inf _{\gamma \in \Pi(\mathcal{L}, \cdots, \mathcal{L})} \int_{\left(\mathbf{T}^{\mathrm{d}}\right)^{\mathbf{N}}} C_{N}\left(x_{1}, \cdots, x_{N}\right) \mathrm{d} \gamma\left(x_{1}, \cdots, x_{n}\right)
$$

with

$$
C_{N}\left(x_{1}, \cdots, x_{N}\right)=N \sum_{k=1}^{N-1}\left|x_{k+1}-x_{k}\right|^{2}+N\left|x_{N}-h\left(x_{1}\right)\right|^{2}
$$

Without the last term: quadratic multi-marginal OT by
Gangbo-Świȩch. (1996) (I'll come back to this in relation with Wasserstein barycenters).

## Outline

(1) Matching for teams
(2) Wasserstein barycenters
(3) Limit behavior
(4) Numerics

## Matching for teams

Matching for teams Joint with I. Ekeland. Market for houses, quality $z \in Z$. For one house $z$ to be available, need for one buyer and a team of producers (mason, plumber, electrician). We shall denote by the index $i \in\{1, \cdots, I\}$ the different populations (buyers, plumbers, electricians, masons...), the agents in each population are hetererogeneous, they are characterized by a certain type which affects their (quality dependent) cost function.

More precisely for each $i$, we are given a compact metric space of types $X_{i}$ and a cost function $c_{i} \in C\left(X_{i} \times Z, \mathbf{R}\right)$ with the interpretation that $c_{i}\left(x_{i}, z\right)$ is the cost for an agent of population $i$ with type $x_{i}$ to work in a team that produces good $z$. The distribution of type $x_{i}$ in population $i$ is known and given by some Borel probability measure $\mu_{i} \in \mathcal{P}\left(X_{i}\right)$. We look for an equilibrium i.e. a system of transfers (paid by the buyer to the producers) which clears the markets: everybody is in a team and the supply and demands for houses coincides.

A system of transfers is a collection of continuous functions $\varphi_{1}, \ldots \varphi_{I}: Z \rightarrow \mathbf{R}$ where $\varphi_{i}(z)$ is the amount paid to $i$ by the other members of the team for producing $z$. An obvious equilibrium requirement is that teams are self-financed i.e.

$$
\begin{equation*}
\sum_{i=1}^{I} \varphi_{i}(z)=0, \forall z \in Z \tag{4}
\end{equation*}
$$

Given transfers $\varphi_{1}, \ldots \varphi_{I}$, an agent from population $i$ with type $x_{i} \in X_{i}$, gets a net minimal cost given by $c_{i}$-transform of $\varphi_{i}$ :

$$
\begin{equation*}
\varphi_{i}^{c_{i}}\left(x_{i}\right):=\min _{z \in Z}\left\{c_{i}\left(x_{i}, z\right)-\varphi_{i}(z)\right\} \tag{5}
\end{equation*}
$$

Agents are rational: they choose cost miniminizing qualities i.e. a $z \in Z$ such that

$$
\begin{equation*}
\varphi_{i}^{c_{i}}\left(x_{i}\right)+\varphi_{i}(z)=c_{i}\left(x_{i}, z\right) \tag{6}
\end{equation*}
$$

The last unknown is a collection of plans $\gamma_{i} \in \mathcal{P}\left(X_{i} \times Z\right)$ such that $\gamma_{i}\left(A_{i} \times A\right)$ represents the probability that an agent in population $i$ has a type in $A_{i}$ and belongs to a team that produces a quality in $A$. At equilibrium the first marginal of $\gamma_{i}$ should be $\mu_{i}$ (this is equilibrium on the $i$-th labor market) and the second marginal of $\gamma_{i}$ should not depend on $i$ (this is equilibrium on the quality good market), this common marginal represents the equilibrium quality line.

Equilibrium: transfer system $\left(\varphi_{1}, \ldots \varphi_{I}\right) \in C(Z, \mathbf{R})^{I}$, probability measures $\gamma_{i} \in \mathcal{P}\left(X_{i} \times Z\right)$ and a probability measure $\nu \in \mathcal{P}(Z)$ such that

- teams are self-financed i.e. (4) holds,
- $\gamma_{i} \in \Pi\left(\mu_{i}, \nu\right)$ for $i=1, \ldots, I$ (equilibrium on the labor markets and on the good market),
- (6) holds on the support of $\gamma_{i}$ for $i=1, \ldots, I$ (i.e. agents choose cost minimizing qualities).

Variational characterization of equilibria

$$
\begin{equation*}
\inf _{\nu \in \mathcal{P}(Z)} J(\nu):=\sum_{i=1}^{I} W_{c_{i}}\left(\mu_{i}, \nu\right) \tag{7}
\end{equation*}
$$

and its dual (concave maximization) formulation

$$
\begin{equation*}
\sup \left\{\sum_{i=1}^{I} \int_{X_{i}} \varphi_{i}^{c_{i}}\left(x_{i}\right) \mu_{i}\left(d x_{i}\right): \sum_{i=1}^{I} \varphi_{i}=0\right\} \tag{8}
\end{equation*}
$$

Theorem $1\left(\varphi_{i}, \gamma_{i}, \nu\right)$ is an equilibrium if and only if:

- $\nu$ solves (7),
- the transfers $\left(\varphi_{1}, \ldots \varphi_{I}\right)$ solve (8),
- for $i=1, \ldots, I, \gamma_{i}$ solves the Monge-Kantorovich problem $W_{c_{i}}\left(\mu_{i}, \nu\right)$.


## Wasserstein barycenters

Given $\left(\mu_{1}, \ldots, \mu_{I}\right) \in \mathcal{P}_{2}\left(\mathbf{R}^{d}\right)$ and weights $\lambda_{i}>0$ summing to 1 , consider:

$$
\begin{equation*}
\inf _{\nu \in \mathcal{P}_{2}\left(\mathbf{R}^{d}\right)} J(\nu):=\sum_{i=1}^{I} \lambda_{i} W_{2}^{2}\left(\mu_{i}, \nu\right) \tag{9}
\end{equation*}
$$

Existence is obvious. Special case of Fréchet mean. Special case of the matching for teams problem (quadratic costs).
Extensions to Riemannian manifolds Kim, Pass.

Uniqueness holds as soon as one of the $\mu_{i}$ 's does not give mass to small sets (in this case $\nu \mapsto W_{2}^{2}\left(\mu_{i}, \nu\right)$ is strictly convex).

Proposition 1 Assume that there is an index $i \in\{1, \ldots I\}$ such that $\mu_{i}$ vanishes on small sets. Then (10) admits a unique solution $\bar{\nu}$.

As soon as one of the $\mu_{i}$ 's vanishes on small sets, this therefore enables one to define unambiguously the barycenter $\left(\operatorname{bar}\left(\mu_{i}, \lambda_{i}\right)_{i=1, \ldots, I}\right)$ of the $\mu_{i}$ 's with weights $\lambda_{i}$. It is known that Fréchet means are unique on nonpositively curved metric spaces (Sturm) BUT the Wasserstein space is not nonpositively curved! Here, it is standard convexity which matters.

Characterization by duality. Dual of (9):

$$
\begin{equation*}
\sup \left\{F\left(f_{1}, \ldots, f_{I}\right)=\sum_{i=1}^{I} \int_{\mathbf{R}^{d}} S_{\lambda_{i}} f_{i} d \mu_{i}: \sum_{i=1}^{I} f_{i}=0,\right\} \tag{10}
\end{equation*}
$$

where

$$
S_{\lambda} f(x):=\inf _{y \in \mathbf{R}^{d}}\left\{\frac{\lambda}{2}|x-y|^{2}-f(y)\right\}, \quad \forall x \in \mathbf{R}^{d}, \lambda>0
$$

Both the infimum in (9) and the supremum in (10) are attained and values coincide.

Let $\left(f_{1}, \ldots, f_{I}\right)$ be a solution of (10) and define the convex potentials:

$$
\begin{equation*}
\lambda_{i} \phi_{i}(x):=\frac{\lambda_{i}}{2}|x|^{2}-S_{\lambda_{i}} f_{i}(x), \tag{11}
\end{equation*}
$$

by duality, if $\bar{\nu}$ solves (9) and $\gamma_{i}$ is an optimal transport plan between $\mu_{i}$ and $\bar{\nu}$ then:

- the support of $\gamma_{i}$ is included in $\partial \phi_{i}$,
- $\sum_{i} \phi_{i}^{*}(y) \leq \frac{1}{2}|y|^{2}$ for all $y \in \mathbf{R}^{d}$ with an equality on the support of $\bar{\nu}$.

These duality conditions lead to the following characterization
Proposition 2 Assume that $\mu_{i}$ vanishes on small sets for every $i=1, . ., p$, then the following conditions are equivalent:

1. $\bar{\nu}=\left(\operatorname{bar}\left(\mu_{i}, \lambda_{i}\right)_{i=1, \ldots, I}\right)$,
2. There exist convex potentials $\phi_{i}$ such that $\nabla \phi_{i}$ is Brenier's map transporting $\mu_{i}$ to $\bar{\nu}$, and a constant $C$ such that

$$
\begin{equation*}
\sum_{i=1}^{p} \lambda_{i} \phi_{i}^{*}(y) \leq C+\frac{|y|^{2}}{2}, \forall y \in \mathbf{R}^{d} \text {, with equality } \bar{\nu} \text {-a.e. } \tag{12}
\end{equation*}
$$

The optimality conditions for the barycenter $\bar{\nu}$, at least formally take the form of an obstacle-like system of Monge-Ampère equations. Set $\psi_{i}=\phi_{i}^{*}$, so $\mu_{i}=\nabla \psi_{i \#} \bar{\nu}$, therefore

$$
\begin{equation*}
\bar{\nu}=\mu_{i}\left(\nabla \psi_{i}\right) \operatorname{det}\left(D^{2} \psi_{i}\right), i=1, \ldots, I \tag{13}
\end{equation*}
$$

which is supplemented with

$$
\begin{equation*}
\sum_{i=1}^{I} \lambda_{i} \psi_{i}(y) \leq \frac{|y|^{2}}{2} \tag{14}
\end{equation*}
$$

with equality on the support of $\bar{\nu}$, yielding in particular (formally)

$$
\sum_{i=1}^{I} \lambda_{i} \nabla \psi_{i}=\text { id } \bar{\nu} \text {-a.e.. }
$$

There is another characterization of the barycenter in terms of a multi-marginal quadratic optimal transport problem which was solved by Gangbo-Świȩch. Adopting this viewpoint one finds the following structure for the barycenter:

$$
\bar{\nu}=\left(\lambda_{1} \mathrm{id}+\sum_{i=2}^{I} \lambda_{i} \nabla u_{i}^{*} \circ \nabla u_{1}\right)_{\#} \mu_{1}
$$

where each $u_{i}$ is strongly convex $\left(D^{2} u_{i} \geq \lambda_{i} \mathrm{id}\right)$ and such that $\nabla u_{i}^{*} \circ \nabla u_{1}$ transports $\mu_{1}$ to $\mu_{i}$.

With M. Agueh, we observed that this gives integral estimates for barycenters. Indeed, take $F:[0, \infty) \rightarrow \mathbf{R}, F(0)=0$ continuous, satisfying McCann's condition $(0, \infty) \ni t \mapsto t^{d} F\left(t^{-d}\right)$ is convex and nonincreasing, then

Proposition 3 The internal energy $E(\rho)=\int_{\mathbf{R}^{d}} F(\rho(x)) d x$ is convex along barycenters i.e.

$$
E\left(\operatorname{bar}\left(\mu_{i}, \lambda_{i}\right)_{i=1, \ldots, I}\right) \leq \sum_{i=1} \lambda_{i} E\left(\mu_{i}\right)
$$

Proof. Write $\left.\bar{\nu}:=\operatorname{bar}\left(\mu_{i}, \lambda_{i}\right)_{i=1, \ldots, I}\right)=\left(\sum_{i=1}^{I} \nabla u_{i}^{*}\right)_{\#} \nu_{1}$ with $\nu_{1}:=\nabla u_{1 \#} \mu_{1}$, so $T_{i}:=\nabla u_{i}^{*}$ transports $\nu_{1}$ to $\mu_{i}$ and $T:=\sum_{i=1}^{I} \lambda_{i} T_{i}$ transports $\nu_{1}$ to $\bar{\nu}$, so

$$
E(\nu)=\int_{\mathbf{R}^{d}} F\left(\frac{\nu_{1}}{\operatorname{det} D T}\right) \operatorname{det} D T
$$

and $\operatorname{det} D T^{1 / d} \geq \sum_{i=1}^{N} \lambda_{i} \operatorname{det}\left(D T_{i}\right)^{1 / d}$; one gets the result by McCann's condition.

In particular for $F(t)=t^{p}, p \in(1,+\infty)$ this gives $L^{p}$ bounds:

$$
\int_{\mathbf{R}^{d}} \bar{\nu}(x)^{p} \mathrm{~d} x \leq \sum_{i=1}^{N} \lambda_{i}\left\|\mu_{i}\right\|_{L^{p}}^{p}
$$

as well as the limiting cases: $\mu_{i} \in L^{1} \Rightarrow \bar{\nu} \in L^{1}$,
and as for the $L^{\infty}$ case:
Theorem 2 Let $\left(\mu_{1}, \ldots, \mu_{I}\right)$ be probability measures with finite second moments and let $\left(\lambda_{1}, \ldots, \lambda_{I}\right)$ be positive reals that sum to 1. If $\mu_{1} \in L^{\infty}$, then $\bar{\nu}:=\operatorname{bar}\left(\left(\mu_{i}, \lambda_{i}\right)\right) \in L^{\infty}$ and more precisely:

$$
\begin{equation*}
\|\bar{\nu}\|_{L^{\infty}} \leq \frac{1}{\lambda_{1}^{d}}\left\|\mu_{1}\right\|_{L^{\infty}} \tag{15}
\end{equation*}
$$

It is not kown if there is more regularity? Like $\mu_{i} \in C^{k, \alpha} \Rightarrow \bar{\nu} \in C^{k, \alpha}$ (in the periodic case say)? Also is $\bar{\nu}$ Lipschitz in the weights?

## Examples

- $I=2$ the barycenter of $\left(\mu_{0},(1-t)\right)$ and $\left(\mu_{1}, t\right)$ is McCann's (or Wasserstein geodesic) interpolant:

$$
\nu_{t}:=((1-t) \mathrm{id}+t \nabla \phi)_{\#} \mu_{0}=\left(t \mathrm{id}+(1-t) \nabla \phi^{*}\right)_{\#} \mu_{1}
$$

where $\nabla \phi$ is the Brenier's map between $\mu_{0}$ and $\mu_{1}$.

- $d=1$, in dimension one $\operatorname{bar}\left(\mu_{i}, \lambda_{i}\right)_{i}$ is simply obtained as the image of $\mu_{1}$ by the linearly interpolated transport map $\sum_{i} \lambda_{i} T_{i}^{1}$ where $T_{i}^{1}$ is the monotone transport from $\mu_{1}$ to $\mu_{i}$.
- Gaussian case $\mu_{i}$ is a gaussian measure with mean 0 and covariance matrix $S_{i}, \bar{\nu}=\mathcal{N}(0, \bar{S})$ where $\bar{S}$ is the unique positive definite root of the matrix equation

$$
\begin{equation*}
\sum_{i=1}^{p} \lambda_{i}\left(S^{1 / 2} S_{i} S^{1 / 2}\right)^{1 / 2}=S \tag{16}
\end{equation*}
$$

## Limit behavior

Given a well-behaved $m \in \mathcal{P}\left(\mathcal{P}_{2}\left(\mathbf{R}^{d}\right)\right)$ (for instance supported on regular measures supported on some ball), Bigot and Klein have considered the barycenter of $m, \bar{\nu}=\operatorname{bar}(m)$ as the minimizer of

$$
\nu \mapsto \int_{\mathcal{P}_{2}\left(\mathbf{R}^{d}\right)} W_{2}^{2}(\mu, \nu) \mathrm{d} m(\mu)
$$

Assume now that for some (large $N$ ) we are given an i.i.d. sample $\hat{\mu}_{1}, \cdots, \hat{\mu}_{N}$ drawn according to $m$ and define (the random measure)

$$
\hat{\nu}_{N}:=\operatorname{bar}\left(\left(\hat{\mu}_{1}, \cdots, \hat{\mu}_{N}, \frac{1}{N}\right)\right) .
$$

From what we saw before, mild conditions on $m$ ensure that $\bar{\nu}$ and $\hat{\nu}_{N}$ have densities.

Bigot and Klein derived from the usual law of large numbers a LLN for Wasserstein barycenters, namely that

$$
W_{2}^{2}\left(\hat{\nu}_{N}, \bar{\nu}\right) \rightarrow 0 \text { a.s. }
$$

in other words the $L^{2}(\bar{\nu})$ random map $\hat{T}_{N}$ that transports optimally the true barycenter $\bar{\nu}$ to its empirical counterpart $\hat{\nu}_{N}$ converges to the identity map a.s.. It is tempting to go one step further through some sort of CLT, which is the validity of

$$
\hat{h}_{N}:=\sqrt{N}\left(\hat{T}_{N}-\mathrm{id}\right)
$$

converging in law to some gaussian on $\mathcal{N}(0, \Sigma)$ for a certain trace class, positive self adjoint $\Sigma$ on $L^{2}\left(\bar{\nu}, \mathbf{R}^{d}\right)$.

This seems difficult to establish in general but with M. Agueh, we could prove validity in some cases

Proposition 4 The Wasserstein CLT holds in the following cases:

- $m$ is a Benoulli between two $\mathcal{P}_{2}\left(\mathbf{R}^{d}\right)$ measures, one of which vanishes on small sets,
- $d=1$ and $m$ is concentrated on a bounded (for $W_{2}$ ) set of nonatomic measures,
- $m=\sum_{i=1}^{I} \lambda_{i} \delta_{\mu_{i}}$ for nondegenerate gaussian $\mu_{i}$ 's.


## Numerics

By now, there are fast solvers for entropic-regularized approximation of multi-marginals OT following the seminal work of Cuturi, Benamou et al., Nenna. Take the matching for teams example:

$$
\inf _{\gamma:=\left(\gamma_{1}, \cdots, \gamma_{I}\right) \in C_{1} \cap C_{2}}\left\{\sum_{i=1}^{I} F(\gamma):=\int_{X_{i} \times Z} c_{i}(x, z) \mathrm{d} \gamma_{i}\left(x_{i}, z\right)\right\}
$$

where

$$
C_{1}:=\left\{\left(\gamma_{1}, \cdots, \gamma_{I}\right): \pi_{X_{i} \#} \gamma_{i}=\mu_{i}, \forall i\right\}
$$

and

$$
C_{2}:=\left\{\left(\gamma_{1}, \cdots, \gamma_{I}\right): \exists \nu \in \mathcal{P}(Z) \pi_{Z \#} \gamma_{i}=\nu, \forall i\right\}
$$

Entropic regularization, $\varepsilon>0$

$$
\inf _{\gamma \in C_{1} \cap C_{2}} F(\gamma)+\varepsilon \sum_{i=1}^{I} \int_{X_{i} \times Z} \gamma_{i}\left(x_{i}, z\right) \ln \left(\gamma_{i}\left(x_{i}, z\right)\right) \mathrm{d} x_{i} \mathrm{~d} z
$$

which is the same as

$$
\inf _{\gamma \in C_{1} \times C_{2}} \sum_{i=1}^{N} \mathrm{KL}\left(\gamma_{i} \mid \theta_{i}\right)
$$

where $\theta_{i}:=e^{-c_{i} / \varepsilon}$ and

$$
\mathrm{KL}\left(\gamma_{i} \mid \theta_{i}\right):=\int_{X_{\times} Z} \gamma_{i}\left(x_{i}, z\right) \ln \left(\frac{\gamma_{i}\left(x_{i}, z\right)}{\theta_{i}\left(x_{i}, z\right)}\right) \mathrm{d} x_{i} \mathrm{~d} z
$$

Bregman iterative projections (aka IPFP, Sinkhorn...) start from $\gamma_{0}=\theta$ and KL alternately project onto $C_{1}$ and $C_{2}$. The projection onto $C_{1}$ is close form, the projection onto $C_{2}$ a well, $\gamma:=\operatorname{proj}_{K L}^{C_{2}}(\bar{\gamma})$ is indeed given by

$$
\gamma_{i}\left(x_{i}, z\right)=\bar{\gamma}_{i}\left(x_{i}, z\right) a_{i}(z)
$$

where

$$
a_{i}(z):=\frac{\left(\bar{\nu}_{1}(z) \times \cdots \times \bar{\nu}_{I}(z)\right)^{\frac{1}{I}}}{\bar{\nu}_{i}(z)}
$$

and

$$
\bar{\nu}_{i}(z):=\int_{X_{i}} \bar{\gamma}_{i}\left(x_{i}, z\right) \mathrm{d} x_{i} .
$$

Convergence is well undertsood (Contraction for the Hilbert projective metric etc...).

Old idea (goes back too Schrödinger), related to several streams of research:

- probability in statistics (Csisczar, Dykstra, Léonard, Föllmer, Rüschendorf...),
- optimization (Bregman, Bauschke, Lewis, Cominetti, San-Martin...).

OT framework: Galichon, Salanié (economics) and Cuturi (machine learning, link with Sinkhorn). Easily adapts to multi-marginals, partial transport, barycenters.... cf. Benamou, C., Cuturi, Nenna and Peyré.

An application of entropic regularization to $W_{2}$ barycenters:


An application to Euler in 1d (see the beautiful simulations of L. Nenna in higher dimensions):


## On repulsive costs

So far, I have only addressed easy cases where the structure of the cost is mainly attractive, there are many other relevant cases which are far from being fully understood and where the cost is rather repulsive. The most challenging example is the Coulomb cost which arises in density functional theory:

$$
\begin{equation*}
\inf _{\gamma \in \Pi(\rho, \cdots, \rho)} \int_{\left(\mathbf{R}^{d}\right)^{N}} \sum_{i<j} \frac{1}{\left|x_{i}-x_{j}\right|} \mathrm{d} \gamma\left(x_{1}, \cdots, x_{N}\right) \tag{17}
\end{equation*}
$$

$N$ electrons, $\rho$ : single-electron density. Received a lot of attention in recent years (Friesecke, Cotar, Pass, Klüppelberg, Buttazzo, De Pascale, Gori-Giorgi, Colombo, Di Marino, Nenna...). Symmetric problem (Ghoussoub-Moameni, Ghoussoub-Maurey). Determinant cost (C.-Nazaret).

A striking example due to S. Di Marino, L. Nenna and A. Gerolin (2015), take $N=3, X_{1}=X_{2}=X_{3}=[0,1]$, $\mu_{1}=\mu_{2}=\mu_{3}=\mu$ is the Lebesgue measure on $[0,1]$ and $c\left(x_{1}, x_{2}, x_{3}\right)=\left(x_{1}+x_{2}+x_{3}\right)^{2}$ (repulsive harmonic case) then there exists an optimal plan of the form $(\mathrm{id}, T, T \circ T)_{\#} \mu$ with $T \circ T \circ T=\mathrm{id}$ and $T$ is fractal (nowhere smooth). This is also a challenge for numerics.

## Happy birthday Yann!! C'est gééénial (the other Benamou-Brenier formula).



To conclude: on repulsive costs $/ 3$


[^0]:    ${ }^{\text {a }}$ CEREMADE, Université Paris Dauphine and MOKAPLAN, Inria-Paris

