

# An Introduction to Monge Ampère Equation

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# 1 Introduction

**Theorem 1.1** (Brenier). *Given two probability measures  $\mu, \nu$  in  $\mathbb{R}^n$  with finite second moments and absolutely continuous w.r.t. Lebesgue measure*

$$\mu, \nu \ll dx$$

*By Brenier, there exists  $T(x)$  defined  $\mu$ -a.e. s.t.*

$$\int_{\mathbb{R}^n} \eta(T(x)) d\mu(x) = \int_{\mathbb{R}^n} \eta(y) d\nu(y) \quad \forall \eta \in C_c^0(\mathbb{R}^n)$$

*and there is a convex function  $u(x)$  s.t.*

$$T(x) = \nabla u(x) \quad \forall \mu - a.e.$$

**Remark 1.1.** *Suppose we knew that*

$$\mu = f dx \quad \nu = g dy$$

*and suppose that  $T(x) \in C^1$ . If*

$$\begin{aligned} D &:= \{f > 0\} \\ D^* &:= \{g > 0\} \end{aligned}$$

*and  $D, D^*$  bounded, with  $f, g$  continuous in  $D$  and  $D^*$ . Then one may apply the change of variables formula so that*

$$\int_{\mathbb{R}^n} \eta(T(x)) f(x) dx = \int_{\mathbb{R}^n} \eta(T(x)) g(T(x)) \det(DT(x)) dx \quad \forall \eta \in C_c^0(\mathbb{R}^n)$$

*This shows from continuity that*

$$g(T(x)) \det(DT(x)) = f(x) \quad \forall x \in D$$

*Notice when  $T(x) \in D^*$  for  $x \in D$ . Using*

$$T = \nabla u$$

*one has*

$$\begin{aligned} \det(D^2 u(x)) &= \frac{f(x)}{g(\nabla u(x))} \quad \forall x \in D \\ \nabla u(D) &= D^* \quad \text{Geometric Neumann boundary condition} \end{aligned}$$

*Understanding regularity of optimal transport maps gets to understanding regularity of Monge Ampere equations. In the case for  $\nu$  with density 1,  $g(\nabla(u))$  goes away. Now taking*

$$g \equiv 1 \quad \text{in } D^*$$

*one obtain*

$$\begin{aligned} \det(D^2 u(x)) &= \frac{f(x)}{g(\nabla u(x))} \quad \forall x \in D \\ \nabla u(D) &= D^* \quad u \text{ convex in } D \end{aligned}$$

*One has 2nd Boundary Value Problem (1st order Dirichlet BVP) with*

$$u|_{\partial D} \quad \text{prescribed}$$

*Comparing with*

$$\begin{aligned} \Delta u &= f \\ u &= h \quad \partial D \end{aligned}$$

*one has regularity estimates if*

$$f \in L^p \implies u \in W^{2,p}$$

*If moreover  $u$  is convex and  $\lambda_k(u) \geq 0$ , with  $\sum_{i=1}^n \lambda_i \leq C$  then  $|\lambda_i| \leq C$ . But meanwhile, even in  $n = 2$ , for*

$$\lambda_1 \cdot \lambda_2 \leq C$$

*even if  $\lambda_1 \geq 0$  and  $\lambda_2 \geq 0$ , one has no guarantee that*

$$\lambda_1 \leq C \quad \text{or} \quad \lambda_2 \leq C$$

**Remark 1.2** (Pogorelov). *There exists  $u$  convex solving in a weak sense*

$$\det(D^2u) = 1 \quad \text{in } \mathbb{R}^3$$

*and  $u \notin C^2$ . Between  $C^0$  and  $C^2$ , all the fight happens.*

## 2 Alexandrov's Perspective: Subdifferential and Convex Function

Now the goal is, for a convex

$$u : D \rightarrow \mathbb{R}$$

we want to construct a Monge-Ampère measure  $\mathcal{M}_u$ , which is a Borel measure s.t.

$$\mathcal{M}_u(E) = \int_E (\det(D^2u)) dx \quad \forall u \in C^2$$

**Definition 2.1** (Subdifferential, Convexity). *From now on  $D \subset \mathbb{R}^n$  open bounded, and*

$$u : \overline{D} \rightarrow \mathbb{R}$$

*is continuous. Given  $x \in D$ , define the subdifferential of  $u$  at  $x$  as the set-valued map*

$$\partial u(x) := \{p \in \mathbb{R}^n \mid u(y) \geq u(x) + p \cdot (y - x) \quad \forall y \in D\}$$

*This is defined w.r.t.  $D$ . But of course this could be an empty set. The function*

$$u : D \rightarrow \mathbb{R}$$

*is convex in  $D$  if*

$$\partial u(x) \neq \emptyset \quad \forall x \in D$$

*When the set  $D$  is not convex, the definition could be different from the classical definition of convexity. Our definition says any point in  $D$  have at least one supporting hyperplane.*

**Example 2.1.** *For  $u(x) = |x|$  with  $n \geq 1$*

$$\partial u(0) = \overline{B_1(0)}$$

**Example 2.2.** *If  $u$  is convex, and differentiable at  $x_0 \in D$ , then the subdifferential of  $u$  at  $x_0$*

$$\partial u(x_0) = \{\nabla u(x_0)\}$$

**Remark 2.1.**

$$(u(x) - u(x_0) - \nabla u(x_0) \cdot (x - x_0))$$

**Proposition 2.1.** *Now for  $u$  convex in  $D$*

1. *For any  $x, y \in D$  s.t.*

$$(1-t)x + ty \in D \quad \forall t \in [0, 1]$$

*then*

$$u((1-t)x + ty) \leq (1-t)u(x) + tu(y)$$

2. *If  $u$  is  $C^1$  in  $D$ , then the monotone map*

$$(\nabla u(x) - \nabla u(y), x - y) \geq 0$$

*for any  $x, y$  as in (i).*

3. *If  $u \in C^2$  near  $x$ , then*

$$D^2u(x) \geq 0$$

*Proof.* For any fixed  $z \in D$  s.t.  $z \in [x, y]$ , then

$$u(x) \geq u(z) + \nabla u(z) \cdot (x - z)$$

$$u(y) \geq u(z) + \nabla u(z) \cdot (y - z)$$

$$\varepsilon u(x) \geq \varepsilon u(z) + \varepsilon \nabla u(z) \cdot (x - z)$$

$$(1 - \varepsilon)u(y) \geq (1 - \varepsilon)u(z) + (1 - \varepsilon)\nabla u(z) \cdot (y - z)$$

$$\varepsilon u(x) + (1 - \varepsilon)u(y) \geq u(z) + \nabla u(z) \cdot (\varepsilon x + (1 - \varepsilon)y - z) \quad \text{adding up}$$

now choosing  $z = \varepsilon x + (1 - \varepsilon)y$  so the latter cancels we obtain (i). From (i), given  $x$  and  $h \in \mathbb{R}^n$  small,

$$u(x + he) + u(x - he) \geq 2u(x)$$

Move to the Left we have the second derivative choose the direction  $e \in \mathbb{S}^{n-1}$ . □

**Remark 2.2.** Now any convex function away from the domain  $D$  is Lipschitz. In dimension 1 with  $I = [a, b]$

$$\partial u(x) \subset \left[-\frac{\text{osc} u}{\varepsilon}, \frac{\text{osc} u}{\varepsilon}\right]$$

where  $\varepsilon = d(x, \partial I) = \max\{|x - a|, |x - b|\}$ . Equivalently, if

$$K(y) := u(x) + \frac{\text{osc} u}{\varepsilon} |y - x|$$

then

$$u(y) \leq K(y)$$

We need to use the fact that if  $u \leq v$  in  $D$  at  $x_0$ , then

$$\partial u(x_0) \subset \partial v(x_0)$$

**Lemma 2.1.** If  $u$  is convex in  $D$ , and there exists a ball  $B_{R+\varepsilon}(x_0) \subset D$ . Then we get

$$\sup_{x, y \in B_R(x_0), x \neq y} \frac{|u(x) - u(y)|}{|x - y|} \leq \frac{\text{osc} u}{\varepsilon}$$

*Proof.* Define cone

$$K(y) := u(x) + \frac{\text{osc} u}{\varepsilon} |y - x| \quad \forall y \in B_R(x_0)$$

By the remark in  $n = 1$ , we have

$$u(y) \leq K(y) \quad \forall y \in B_R$$

Now we have

$$u(y) \leq u(x) + \frac{\text{osc} u}{\varepsilon} |y - x|$$

by Rearranging

$$\frac{|u(y) - u(x)|}{|x - y|} \leq \frac{\text{osc} u}{\varepsilon}$$

□

**Theorem 2.1** (Rademacher's).

$$\nabla u(x) \quad \text{exists a.e. } x \in D$$

and

$$|\nabla u(x)| \leq \frac{\text{osc} u}{d(x, \partial D)} \quad \text{a.e. } x \in D$$

**Corollary 2.1.** For any  $x \in D$

$$\partial u(x) \subset \overline{B_{\frac{\text{osc} u}{d(x, \partial D)}}(0)}$$

Now we have

$$\partial u(x) = \begin{cases} \{\nabla u(x)\} & \text{a.e. } x \\ \text{remains to discover} & \end{cases}$$

### 3 Alexandrov Solution and Monge-Ampère measure

Next we proceed to define

$$\partial u(E) := \bigcup_{x \in E} \partial u(x)$$

then we define the Monge-Ampère measure as

$$\mathcal{M}_u(E) := |\partial u(E)|$$

Now ‘ $\mathcal{M}_u = \mu$ ’ is to say  $\det(D^2u) = \mu$ .

**Definition 3.1** (Monge-Ampère measure). *Given a Borel measure  $\nu$  in  $\mathbb{R}^n$ , and  $u : D \rightarrow \mathbb{R}$  convex, finite at every point (hence continuous), with  $D \subset \mathbb{R}^n$  open and bounded, we define the Monge-Ampère measure associated to  $\nu$  as*

$$\mathcal{M}_u^\nu(E) := \nu(\partial u(E)) \quad \forall E \in \mathcal{B}$$

where

$$\partial u(E) := \bigcup_{x \in E} \partial u(x)$$

In particular if  $\nu$  is the Lebesgue measure, we denote

$$\mathcal{M}_u(E)$$

as the Monge-Ampère measure of  $u$ .

**Definition 3.2** (Alexandrov Solution). *Given  $D$  and*

$$h : \partial D \rightarrow \mathbb{R}$$

continuous, and

$$f : D \rightarrow \mathbb{R}$$

where  $f \in L^1(D)$ . We say

$$u : \overline{D} \rightarrow \mathbb{R}$$

is an Alexandrov Solution of

$$\det(D^2u(x)) = f(x)$$

if  $u$  is convex, continuous in  $\overline{D}$  and

$$\mathcal{M}_u(E) = \int_E f(x) dx \quad \forall E \in \mathcal{B} \quad E \Subset D$$

In particular, one studies the Dirichlet problem: find  $u$  convex solving

$$\begin{aligned} \det(D^2u) &= f & D \\ u &= h & \partial D \end{aligned}$$

**Remark 3.1.** *Suppose  $u$  is an Alexandrov Solution of the Dirichlet problem, i.e.*

$$\mathcal{M}_u(E) = \int_E f(x) dx$$

If  $u$  is  $C^2(D)$  and

$$\det(D^2u) > 0$$

Then  $u$  solves

$$\det(D^2u(x)) = f(x) \quad \text{Lebesgue a.e. } x \in D$$

*Proof.* Change of Variables. □

**Remark 3.2.** *Conversely, if*

$$u : D \rightarrow \mathbb{R}$$

*is convex,  $C^2(D)$  and for  $f \in L^1(D)$*

$$\det(D^2 u(x)) = f(x) \quad \text{Lebesgue a.e. } x \in D$$

*Then*

$$\mathcal{M}_u(E) = \int_E f(x) dx$$

**Theorem 3.1** (Existence of Alexandrov Solution). *If  $D$  is a strictly convex domain, bounded, and*

$$h : \partial D \rightarrow \mathbb{R}$$

*is continuous, and  $\mu$  is a probability measure in  $D$ . Then there exists a unique Alexandrov Solution  $\mathcal{M}_u = \mu$  to*

$$\begin{aligned} \det(D^2 u) &= \mu & D \\ u &= h & \partial D \end{aligned}$$

**Theorem 3.2** (Convergence). *Consider an infinite sequence*

$$u_n : D \rightarrow \mathbb{R}$$

*of finite convex functions converging locally uniformly to*

$$u : D \rightarrow \mathbb{R}$$

*Then the measures*

$$\mathcal{M}_{u_n} \rightharpoonup \mathcal{M}_u$$

*i.e.*

$$\lim_{n \rightarrow \infty} \int_D \phi(x) \mathcal{M}_{u_n}(dx) = \int_D \phi(x) \mathcal{M}_u(dx) \quad \forall \phi \in C_c^0(D)$$

**Remark 3.3** (On the limitations of the Alexandrov Solution). *Not every solution to optimal transport is an alexandrov solution. Consider in  $\mathbb{R}^2$ , the measure*

$$\mu := \mathbb{1}_{B_1} dx$$

*with*

$$\nu := \mathbb{1}_{D^*} dx$$

*where*

$$D^* = (B_1 \cap (\{x_1 < 0\} - (1, 0))) \cup (B_1 \cap (\{x_1 > 0\} + (1, 0)))$$

*Brenier's Theorem produces an Optimal Transport map which  $\mu$ -a.e. satisfies*

$$T(x) = \nabla u(x)$$

*for a convex function  $u$ . And the Monge-Ampère Equation holds in the sense that*

$$\int \eta(T(x)) \mu(dx) = \int \eta(y) \nu(dy)$$

*Notice for*

$$u(x) = \frac{1}{2}|x|^2 \quad \forall x \in \mathbb{R}^2$$

*one has  $\nabla u(x) = x$ . In this case  $u$  is given by*

$$u(x) = \frac{1}{2}(x_1^2 + x_2^2) + |x_1|$$

*now  $\mu$ -a.e.*

$$\nabla u(x) = \begin{cases} x - e_1 \\ x + e_1 \end{cases}$$

Claim :  $u$  is not an Alexandrov Solution of

$$\det(D^2u) = 1 \quad D$$

Why? Since

$$\partial u(x) = \begin{cases} x - e_1 & \{x_1 < 0\} \\ x + [-1, 1]e_1 & x_1 = 0 \\ x + e_1 & \{x_1 > 0\} \end{cases}$$

As a result, in  $B_1$ , given set

$$E = \{(0, x_2) \mid |x_2| \leq 1\}$$

then

$$|\partial u(E)| > 0$$

The whole region

$$\partial u(E) = [-1, 1]^2$$

is filling everything inside. The support of  $\nu$  isn't a convex set. Alexandrov is too strong a solution that depends on the PDE. It is too sensitive. This was later fixed by Caffarelli.

### 3.1 Tools from Subdifferential

One has properties of  $\partial u(x)$ .

**Lemma 3.1** (Lower Semi-continuity). *If  $x_k \rightarrow x_* \in D$ , then*

$$\limsup_{k \rightarrow \infty} \partial u(x_k) \subset \partial u(x_*)$$

*Proof.* Suppose  $p_k \in \mathbb{R}^n$  is sequence of points such that there exists  $n_k \rightarrow \infty$  s.t.

$$p_k \in \partial u(x_{n_k})$$

i.e.,

$$u(x) \geq u(x_{n_k}) + p_k \cdot (x - x_{n_k}) \quad \forall x \in D$$

Then we claim the sequence  $\{p_k\}$  is bounded. This is implied by that

$$\partial u(x) \subset \overline{B_{\frac{\text{osc } u}{d(x, \partial D)}}(0)}$$

Hence WLOG  $p_k \rightarrow p_\infty$ . Then for any  $x \in D$

$$\begin{aligned} u(x) &\geq \lim_{k \rightarrow \infty} \{u(x_{n_k}) + p_k \cdot (x - x_{n_k})\} \\ u(x) &\geq u(x_*) + p_\infty \cdot (x - x_*) \quad \forall x \end{aligned}$$

Hence

$$p_\infty \in \partial u(x_*)$$

□

**Corollary 3.1.** *If*

$$u : D \rightarrow \mathbb{R}$$

*is convex and  $x_0 \in D$  is such that*

$$\partial u(x_0) = \{p_0\}$$

*Then  $u$  is  $C^1$  at  $x_0$  and*

$$\nabla u(x_0) = p_0$$



*Proof.* Let's restate the corollary. For  $e \in \mathbb{R}^n$ , we want to show

$$\frac{u(x + he) - u(x)}{h} \xrightarrow{h \rightarrow 0} e \cdot p_0$$

this limit exists. On one hand, by assumption

$$\begin{aligned} u(x_0 + he) &\geq u(x_0) + hp_0 \cdot e \\ \frac{u(x_0 + he) - u(x_0)}{h} &\geq e \cdot p_0 \quad \forall e \in \mathbb{R}^n \quad \forall |h| \text{ small} \end{aligned}$$

To check the limit exists, it suffices to check for any discrete sequence  $h_n \rightarrow 0$ . Given a sequence  $\{h_n\}_n$  s.t.  $\lim_{n \rightarrow \infty} h_n = 0$ . Choose for each  $n$  an element of the subdifferential

$$p_n \in \partial u(x_0 + h_n e)$$

Then

$$u(x_0) \geq u(x_0 + h_n e) + (x_0 - (x_0 + h_n e)) \cdot p_n$$

Bounding from above can also be achieved by touching from below!

$$\begin{aligned} u(x_0) &\geq u(x_0 + h_n e) - h_n e \cdot p_n \\ e \cdot p_n &\geq \frac{u(x_0 + h_n e) - u(x_0)}{h_n} \\ e \cdot p_n &\geq \frac{u(x_0 + h_n e) - u(x_0)}{h_n} \geq e \cdot p_0 \end{aligned}$$

But since

$$\partial u(x_0) = \{p_0\}$$

the only possible limiting point is  $p_0$ . WLOG the sequence  $\{p_n\}$  is Cauchy up to a subsequence (using subdifferential is bounded away from the boundary), then

$$p_n \rightarrow p_0$$

This shows that

$$\limsup_{n \rightarrow \infty} e \cdot p_n = e \cdot p_0$$

By lower-semicontinuity Lemma 3.1, the two-sided inequality yields

$$\lim_{h_n \rightarrow 0} \frac{u(x_0 + h_n e) - u(x_0)}{h_n} = e \cdot p_0$$

□

## 3.2 $\mathcal{M}_u$ is Borel measure

Next, we aim to show

**Theorem 3.3.**  $\mathcal{M}_u$  is indeed a Borel measure. Moreover it is finite on compact sets.

Let's begin with some lemma.

**Lemma 3.2** (Subdifferential preserves Compactness). *If  $E \subset D$  is compact, then  $\partial u(E)$  is also compact.*

*Proof.* Since  $E$  is compact,  $\text{dist}(E, \partial D)$  is positive. Thus there exists  $M > 0$  s.t.

$$\partial u(E) \subset B_M(0)$$

as in Corollary 2.1. Consider

$$\{p_n\} \subset \partial u(E)$$

Then  $\{p_n\} \subset B_M(0)$ . Then by compactness of  $\overline{B_M(0)}$  there exists a subsequence  $\{p'_n\}$  and  $p_\infty$  s.t.

$$p'_n \rightarrow p_\infty$$

For each  $n$  pick  $x_n \in E$  s.t.

$$p'_n \in \partial u(x_n)$$

Now  $\{x_n\} \subset E$  and again by compactness, there is a subsequence  $\{p''_n\}$  and  $\{x'_n\}$  and  $x_\infty$  s.t.

$$\begin{aligned} x_\infty &\in E \\ p''_n &\in \partial u(x'_n) \\ x'_n &\rightarrow x_\infty \end{aligned}$$

But then by Lower Semi-continuity 3.1 we get

$$p_\infty \in \partial u(x_\infty)$$

More precisely, for every  $n$  and for every  $x \in D$  we have

$$u(x) \geq u(x'_n) + p''_n \cdot (x - x'_n)$$

Since

$$\begin{aligned} \lim_{n \rightarrow \infty} u(x'_n) &= u(x_\infty) \\ \lim_{n \rightarrow \infty} p''_n &= p_\infty \\ \lim_{n \rightarrow \infty} x'_n &= x_\infty \end{aligned}$$

Thus

$$\begin{aligned} u(x) &\geq u(x_\infty) + p_\infty \cdot (x - x_\infty) \\ p_\infty &\in \partial u(x_\infty) \end{aligned}$$

Thus  $p_\infty \in E$  and so  $\partial u(E)$  is compact. □

In the following we need to understand how big is the set s.t.

$$\{p \mid \text{there exists } x_1, x_2 \in D \text{ s.t. } x_1 \neq x_2 \text{ and } p \in \partial u(x_1) \cap \partial u(x_2)\} \quad (1)$$

It is surprising that this is Lebesgue measure 0! Hence it is measurable. We want to show this set corresponds to non-differentiability of the function and conclude by Rademacher 2.1.

**Definition 3.3** (Legendre-Transform). *Given  $u : D \rightarrow \mathbb{R}$   $u \in C(\overline{D})$  convex, we define*

$$u^*(y) := \sup_{x \in D} \{x \cdot y - u(x)\}$$

*Note  $u^*$  may not be finite for certain values of  $y$ .*

**Remark 3.4.** *If  $y \in \partial u(D)$ , then  $u^*(y)$  is finite and*

$$u^*(y) := \sup_{x \in D} \{x \cdot y - u(x)\} = \max_{x \in D} \{x \cdot y - u(x)\}$$

**Remark 3.5** (Duality).  $x_0 \in \partial u^*(y_0)$  implies  $y_0 \in \partial u(x_0)$ . Now by Rademacher's 2.1,  $\partial u^*(y)$  is a singleton for all  $y$  outside a set of Lebesgue measure zero.

**Corollary 3.2** (The set has measure zero). *The set (1) has Lebesgue measure zero.*

Now let's go!

**Lemma 3.3.** *The set*

$$S := \{E \subset D \mid \partial u(E) \text{ is Lebesgue measurable}\}$$

*is a  $\sigma$ -algebra containing  $\mathcal{B}(D)$ .*

*Proof.* We already know

$$E \subset S$$

if  $E$  is compact. Now we need to show  $S$  is a  $\sigma$ -algebra. Consider an infinite sequence

$$\{E_n\} \subset S$$

Then want to see

$$\partial u\left(\bigcup_n E_n\right) = \bigcup_n \partial u(E_n) \quad \text{is measurable}$$

But the set on the RHS is the countable union of Lebesgue-measurable sets, thus it is measurable and thus its union  $\bigcup_n E_n$  is also in  $S$ . Our previous argument implies that  $D \in S$ . What's left is if  $E \in S$ , we want to show  $D \setminus E \in S$ . But this is

$$\partial u(D \setminus E) = (\partial u(D) \setminus \partial u(E)) \cup (\partial u(D \setminus E) \cap \partial u(E))$$

But the right-most set  $\partial u(D \setminus E) \cap \partial u(E) \subset (1)$  hence it has Lebesgue measure zero. Now we check the part  $\partial u(D) \setminus \partial u(E)$  is measurable. But due to  $E, D \in S$ , indeed it is measurable, hence  $D \setminus E \in S$ .  $\square$

*Proof of Theorem 3.3.* We show  $\mathcal{M}_u$  is a measure in  $S$  and finite on compact sets. We show the  $\sigma$ -additivity. Consider countable family of sets  $\{E_n\} \subset S$  pairwise disjoint. Set

$$F_m := \partial u(E_m)$$

All we need to show is that

$$\left| \bigcup_m F_m \right| = \sum_m |F_m|$$

We only need to know  $F_m$  is pairwise disjoint. Notice that by Corollary 3.2

$$|F_m \cap F_n| = 0$$

if  $m \neq n$ . So let's write

$$\bigcup_m F_m = F_1 \cup (F_2 \setminus F_1) \cup (F_3 \setminus (F_1 \cup F_2)) \cup \dots \cup (F_m \setminus (F_1 \cup \dots \cup F_{m-1}))$$

as a disjoint union. So

$$\left| \bigcup_m F_m \right| = \sum_m |F_m \setminus (F_1 \cup \dots \cup F_{m-1})|$$

But notice

$$F_m = (F_m \setminus (F_1 \cup \dots \cup F_{m-1})) \cup (F_m \cap (F_1 \cup \dots \cup F_{m-1}))$$

where the latter set has measure zero by Corollary 3.2. So

$$|F_m| = |F_m \setminus (F_1 \cup \dots \cup F_{m-1})|$$

$\square$

## 4 The Brenier Perspective

We do the delicate part of the theory first. We start with the Dual of the Kantorovich Problem.

**Definition 4.1** (Dual of the Kantorovich Problem). *The problem is: Given data*

1. two  $\mu, \nu$  measures in  $\mathbb{R}^n$  compactly supported,
2. and  $D \Subset \text{supp}(\mu)$
3.  $D^* \Subset \text{supp}(\nu)$

We want to maximize over pairs of function  $(\phi, \psi)$  the quantity

$$\int \phi(x) \mu(dx) + \int \psi(y) \nu(dy)$$

subject to the condition

$$\phi \in L^1(\mu) \quad \psi \in L^1(\nu) \quad \phi(x) + \psi(y) \leq \frac{1}{2}|x - y|^2$$

The Maximum to this problem is equal to the minimum to the original problem.

**Theorem 4.1.** *There is a solution  $(\phi_0, \psi_0)$  to Dual of Kantorovich Problem 4.1, which are pairs of convex function and Legendre duals of each other, i.e.,*

$$\begin{aligned} \phi_0(x) &= \inf_{y \in D^*} \left\{ \frac{1}{2}|x - y|^2 - \psi_0(y) \right\} \\ \psi_0(y) &= \inf_{x \in D} \left\{ \frac{1}{2}|x - y|^2 - \phi_0(x) \right\} \end{aligned}$$

and (recall  $\mu \ll dx$ ) for any  $\eta \in C_c^\infty$ , we have the ‘Brenier Condition’

$$\int \eta(y) \nu(dy) = \int \eta(y(x)) \mu(dx) \quad \text{where } y(x) := \nabla_x \left( \frac{1}{2}|x|^2 - \phi_0(x) \right) \text{ is convex} \quad (2)$$

**Remark 4.1.** (2) is the weak formulation of the Euler-Lagrange Equation of the Dual problem.

*Proof of ‘Brenier Condition’ (2).* Take  $\phi_0, \psi_0$  optimal. Take any  $\eta \in C_c^\infty$  and we define

$$\psi_s(y) := \psi_0(y) + s\eta(y)$$

We pick

$$\phi_s(x) := \inf_y \left\{ \frac{1}{2}|x - y|^2 - \psi_s(y) \right\}$$

One may check  $\phi_s$  and  $\psi_s$  is an admissible pair for our problem. Indeed

$$\phi_s(x) := \inf_y \left\{ \frac{1}{2}|x - y|^2 - \psi_s(y) \right\} \leq \frac{1}{2}|x - y|^2 - \psi_s(y) \quad \forall y$$

One should also check that

$$s \mapsto \Theta(s) := \int \phi_s(x) \mu(dx) + \int \psi_s(y) \nu(dy)$$

has a global maximum at  $s = 0$ . The next thing we do is take a derivative.

**Lemma 4.1.**  $\Theta(s)$  is differentiable at  $s = 0$  and

$$\Theta'(0) = \int -\eta(y(x)) \mu(dx) + \int \eta(y) \nu(dy) \quad (3)$$

*Proof.* Look at

$$\frac{\Theta(s) - \Theta(0)}{s} = \int \frac{\phi_s(x) - \phi_0(x)}{s} \mu(dx) + \int \eta(y) \nu(dy)$$

Now the map  $y(x)$  is going to be important. The goal is to find

$$\lim_{s \rightarrow 0} \frac{\phi_s(x) - \phi_0(x)}{s} \quad \mu\text{-a.e. } x$$

Notice

$$\begin{aligned} \phi_s(x) &= \inf_y \left\{ \frac{1}{2} |x - y|^2 - \psi(y) - s\eta(y) \right\} \\ &\leq \inf_y \left\{ \frac{1}{2} |x - y|^2 - \psi(y) \right\} + s \|\eta\|_\infty \\ \phi_s(x) &\geq \inf_y \left\{ \frac{1}{2} |x - y|^2 - \psi(y) \right\} - s \|\eta\|_\infty \\ \left| \frac{\phi_s(x) - \phi_0(x)}{s} \right| &\leq \|\eta\|_\infty \end{aligned}$$

Now one may apply DCT. If  $\phi_0$  is differentiable at a point  $x_0$ , then this means that the function

$$y \mapsto \frac{1}{2} |x_0 - y|^2 - \psi(y)$$

can only have one minimum in  $\overline{D^*}$ . Indeed if  $y_0$  achieves the minimum, then  $\nabla \phi(x_0) = x_0 - y$  there is only one choice. This defines for a.e.  $x$  the function (due to unique correspondence of  $y$  for each  $x$ )

$$y(x) = x - \nabla \phi(x)$$

i.e., in the domain of  $y(x)$ , we have

$$y(x) = \operatorname{argmin}_y \left\{ \frac{1}{2} |x - y|^2 - \psi_0(y) \right\}$$

Then we take  $x$  where  $\phi_0$  is differentiable. We consider any sequence  $s_n \rightarrow 0$  as  $n \rightarrow \infty$ . Then for each  $n$  we choose  $y_n$  s.t.

$$y_n \in \operatorname{argmin}_y \left\{ \frac{1}{2} |x - y|^2 - \psi_{s_n}(y) \right\}$$

Then we write

$$\phi_{s_n}(x) - \phi_0(x) = \left( \frac{1}{2} |x - y_n|^2 - \psi_0(y_n) \right) - s_n \eta(y_n) - \left( \frac{1}{2} |x - y_0|^2 - \psi_0(y_0) \right)$$

We make an observation: Since

$$y \mapsto |x - y|^2 - \psi_0(y)$$

has a unique minimum at  $y_0$ , and it is differentiable since

$$x \in \operatorname{Domain}(\nabla \phi)$$

One can take

$$\left( \frac{1}{2} |x - y_n|^2 - \psi_0(y_n) \right) - \left( \frac{1}{2} |x - y_0|^2 - \psi_0(y_0) \right) = o(|y_n - y_0|)$$

Later we'll see  $o(|y_n - y_0|) \leq o(s_n)$ . Then

$$\frac{1}{s_n} (\phi_{s_n}(x) - \phi_0(x)) = o(|y_n - y_0|) - \eta(y_n)$$

An exercise is to check that

$$y_n \rightarrow \operatorname{argmin}_y \left\{ \frac{1}{2} |x - y|^2 - \psi(y) \right\} = \{y(x_0)\}$$

Then we have proved that for a.e.  $x \in D$

$$\lim_{s \rightarrow 0} \frac{\phi_s(x) - \phi_0(x)}{s} = -\eta(y(x))$$

And finally by Dominated Convergence we have (3)

$$\Theta'(0) = \int -\eta(y(x))\mu(dx) + \int \eta(y)\nu(dy)$$

□

And since  $\Theta'(0) = 0$  we get that

$$\int \eta(x - \nabla \phi_0(x))\mu(dx) = \int \eta(y)\nu(dy) \quad \forall \eta \in C_c^\infty$$

□

Some suggested readings:

1. Proof of Rockefeller's Theorem
2. Displacement convexity/interpolation

$$\mu_0, \mu_1 \quad y(x) = \text{Brenier Map}$$

and

$$\mu_t := ((1-t)x + ty(x))_{\#} \mu_0$$

3. The Wasserstein metric.
4. The JKO Scheme.