

## 4. Allocation Maps with General Cost Functions

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**Introduction:** In the theory of allocations one is interested to transfer a domain  $\Omega_1$  into a domain  $\Omega_2$  (one can think on sending  $k$  points  $X_1, \dots, X_k$  in a one to one fashion to  $k$  points  $Y_1, Y_k$ ), minimizing certain cost function  $C(X, Y)$ . (See for instance Rachev ([R]). For  $C(X, Y) = \frac{1}{2}|X - Y|^2$ , this problem has interest in several fields, and a complete existence theory was given by Brenier ([B]) and a regularity theory was developed by the author ([C1], [C2]).

Here we redo Brenier's theory for general strictly convex cost function  $C(X - Y)$ .

In a conversation R. McCann told us that he had obtained similar results in collaboration with W. Gangbo.

In all of this, note  $f$  and  $g$  will be two bounded functions with compact support  $\Omega_1$  and  $\Omega_2$  respectively, and the compatibility condition

$$\int_{\Omega_1} f(X) dX = \int_{\Omega_2} g(Y) dY.$$

We will consider a cost function  $C(X - Y)$ , smooth (say  $C^{1,\alpha}$ ) and strictly convex.

In particular the map (for fixed  $Y_0$ )

$$X \longrightarrow \nabla_X C(X - Y)$$

is continuous with a continuous inverse.

We are interested to find, among all transformations  $Y(X)$  that carry the density  $f$  onto the density  $g$  (i.e., for every continuous function  $h$ ,

$$\int h(Y)g(Y)dY = \int h(Y(X))f(X)dX$$

the one that minimizes the allocation cost

$$\int C(X - Y(X))f(X)dX.$$

We will do that through a heuristically standard dual problem, following the ideas of Brenier ([B]) in the case of  $C(X - Y) = |X - Y|^2$  providing the necessary details to complete this program. The dual problem is the following:

**Problem 1:** Among all pairs of continuous functions  $\varphi(X), \psi(Y)$  defined in  $\Omega_1, \Omega_2$ , and satisfying

$$\varphi(X) + \psi(Y) \geq -C(X - Y)$$

minimize

$$\int \varphi(X)f(X)dX + \int \psi(Y)g(Y)dY.$$

We will show that this problem has a solution, that the map

$$Y = X + (\nabla C)^{-1}(\nabla \varphi(X))$$

is well defined and "nice" and that it solves the allocation problem. Of particular interest

is the case

$$C(X - Y) = |X - Y|^p \quad (1 < p < \infty)$$

and  $p = 1 + \epsilon$ , since, for  $\epsilon$  going to zero, this provides a "smooth" approximation to the solution of the Monge mass transfer problem.

We start with the following simple

**Theorem 1.**

(a) Problem 1 has a minimizing pair  $\varphi_0, \psi_0$ .

(b)  $\varphi_0, \psi_0$  are  $C$ -convex, i.e.,

$$\begin{aligned} \varphi_0(X) &= \sup_X -C(X - Y) - \psi_0(Y) \\ \psi_0(Y) &= \sup_X -C(X - Y) - \varphi_0(X). \end{aligned}$$

In particular  $\varphi_0, \psi_0$  are Lipschitz and "C<sup>1</sup> by below" (i.e., have a uniformly C<sup>1</sup> function supporting them by below).

**Proof.** Given a pair  $\varphi, \psi$ , of admissible functions, its energy can be improved by replacing  $\varphi$  by

$$\varphi^* = \sup_Y [-C(X - Y) - \psi(Y)]$$

and vice versa.

Therefore we may restrict ourselves to  $C$ -convex pairs  $\varphi, \psi$ .

Such pairs must be normalized because if  $\varphi, \psi$  are admissible, then for any constant  $\lambda, \varphi + \lambda, \psi - \lambda$  are admissible and with the same energy.

Thus, we may impose that  $\varphi(X_0) = 0$ .

This bounds  $\psi$  by below by

$$\psi(Y) \geq -C(X_0 - Y)$$

and  $\varphi$  by above and below by  $\text{diam}(\Omega_1) \cdot [\sup_{Y \in \Omega_2} \|C(X, Y)\|_{L^p}]$ . Further, if  $M$  is large  $\varphi$  and  $\bar{\psi} = M$  form an admissible pair, as long as

$$M \geq 2 \sup_{X, Y \in \Omega_1, \Omega_2} |C(X - Y)|$$

Thus  $\varphi, \min(\psi, M)$  are a new admissible pair.

We can restrict therefore our minimization to a family of uniformly bounded uniformly Lipschitz pairs  $\varphi, \psi$ , and thus we can extract a minimizing sequence  $\varphi_k, \psi_k$  that converges uniformly to a minimizer  $\varphi_0, \psi_0$ .

We now study the uniqueness and differentiability properties of  $\varphi_0, \psi_0$ .

For that purpose we will assign to every  $X_0$  in  $\Omega_1$  the set of "images"

$$K(X_0) = \{Y \in \bar{\Omega}_2 : \varphi(Y_0) + \psi(Y) = -C(X_0, Y)\}.$$

If  $Y \in K(X_0)$ ,  $-\psi(Y) - C(X, Y)$  supports (is tangent by below)  $\varphi(X)$  at  $X_0$ . Thus heuristically

$$\nabla_X \varphi(X_0) = -\nabla C(X_0 - Y).$$

Since  $\nabla C$  is a bicontinuous invertible map with inverse  $\nabla C^*(P)$  ( $P \in R^n$ ) we should recuperate  $Y$  as  $Y = (\nabla C^*)(\nabla \varphi(X_0) + X_0)$ . That is, always heuristically,

$$K(X_0) = \nabla C^*(\nabla \varphi(X_0)) + X_0.$$

Before the next theorem, a few elementary remarks about  $\varphi(X)$  and  $\psi(Y)$ .

We say that a function  $w$  is  $C^{1,\alpha}$  convex if

$$w(X) = \sup_{\lambda \in \Lambda} g_\lambda(X),$$

with  $g_\lambda(X)$  in  $C^{1,\alpha}$ , uniformly in  $\lambda$ .

**Lemma 1.** Let  $w$  be  $C^{1,\alpha}$  convex, then

(a) at every point  $X_0$ ,  $w(X)$  is asymptotic to the convex cone

$$\Gamma_{X_0} = \sup_{\substack{g_\lambda(X) \\ g_\lambda(X) = w(Y_0)}} (\nabla g_\lambda(X_0, X - Y_0) + w(X_0)).$$

More precisely

$$\Gamma_{X_0}(X) - C|X - X_0|^{1+\alpha} \leq w(X) \leq \Gamma_{X_0}(X) + o(|X - X_0|).$$

(b) If, say,  $0$  is a supporting gradient to  $\Gamma_{X_0}$  at  $X_0$ , (i.e.,  $0 = \nabla g_{\lambda_1}(X_0)$ ), and  $Z = \nabla g_{\lambda_2}(X_1)$  is a supporting gradient at  $X_1$ , then

$$\langle Z, X_1 - X_0 \rangle \geq -|X_1 - X_0|^{1+\alpha}.$$

(c) A point of Lebesgue differentiability for  $\nabla w$  is a point of continuity.

(d) The sets of points that have more than one supporting  $g$  are a set of measure zero.

**Proof.** (a) is clear.

(b) follows from the fact that:

$$\langle Z, X_1 - X_0 \rangle \geq w(X_1) - w(X_0) \geq$$

$$\Gamma_{X_0}(X_1) - w(X_0) \geq -C|X_1 - X_0|^{1+\alpha},$$

since  $0$  is a supporting gradient.

(c) If  $X_0$  is not a point of continuity it has two supporting  $g'_s$ , with gradients (say)  $0$  and  $te_1$ .

Let us split  $X - X_0 = \lambda e_1 + \mu e_2$  ( $e_2 \perp e_1$ ). If  $X$  stays in the cone

$$\lambda \leq -M|\mu|,$$

from (b) we get

$$-\lambda(z_1 \pm \frac{\lambda}{M}z_2) \geq -C\lambda^{1+\alpha}$$

or

$$z_1 \leq \frac{1}{M}|z_2| + C\lambda^\alpha.$$

On the other hand, if  $X$  stays in the cone  $\lambda \geq M|\mu|$  we get

$$z_1 - t \geq \frac{1}{M}|z_2| - C\lambda^\alpha.$$

For  $M$  large,  $\lambda$  small, depending on  $t$  and  $\sup \nabla g_\lambda$ , these sets stay away from each other and  $X_0$  cannot be a point of Lebesgue differentiability for  $\nabla w$ . (d) follows from (c).

**Corollary.**  $K(X_0)$  is single valued and continuous almost everywhere in  $X$ .

We are now ready to prove the change of variable formula.

**Theorem.** Let  $h$  be a continuous function in the support of  $g$ . Then

$$\int h(Y)g(Y)dY = \int h(K(X))f(X)dX.$$

**Proof.** We consider, in the optimization problem the perturbation

$$\begin{aligned} \psi_\epsilon(Y) &= \psi(Y) + \epsilon h(Y) \\ \varphi_\epsilon(X) &= \sup_Y -C(X - Y) - \psi(Y) - \psi(Y) - \epsilon h(Y). \end{aligned}$$

The energy variation should thus be positive

$$\begin{aligned} 0 \leq \delta E_\epsilon &= \epsilon \int h(Y)g(Y)dY + \\ &+ \int (\varphi_\epsilon(X) - \varphi(X))f(X)dX. \end{aligned}$$

Notice that by definition  $|\varphi_\epsilon(X) - \varphi(X)| \leq \epsilon \sup_Y |h(Y)|$ .

Therefore we divide by  $\epsilon$  and we get

$$0 \leq \int h(Y)g(Y)dY + \int \frac{[\varphi_\epsilon(X) - \varphi(X)]f(X)dX}{\epsilon}.$$

The second term consists of uniformly bounded functions of which will be enough to compute the a.e. limit to obtain the limiting integrand.

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For that we just consider the points  $X$  of continuity for  $K(X)$ .

We notice that

$$-\epsilon h(K(X)) \leq \varphi_\epsilon(X) - \varphi(X) \leq -\epsilon h(Y_\epsilon)$$

for  $Y_\epsilon$  the point that realizes the value of  $\varphi_\epsilon$ . But if a subsequence  $Y_\epsilon$  converges to a  $Y_0$  different to  $(K(X))$  in the limit we will have a second supporting function  $-C(X - Y_0) - \psi(Y_0)$  for  $\varphi$  at  $X$ , a contradiction. Thus the a.e. limit of  $\frac{\varphi_\epsilon(X) - \varphi(X)}{\epsilon}$  is  $h(K(X))$ .

To complete this presentation, we show that the map  $Y(X)$  minimizes the allocation integral.

**Theorem.** Among all measurable maps  $Y(X)$  that satisfy the change of variable formula,  $K(X)$  is the unique minimizer of the cost function

$$\int C(Y(X) - X) f(X)dX.$$

In particular, the pair  $\varphi, \psi$  is unique.

**Proof.** We write  $I = \int \psi(Y)g(Y)dY$  using both changes of coordinates:

$$\begin{aligned} 0 &= \int [\psi(Y(X)) - \psi(K(X))]f(X)dX \\ &\geq \int [-C(Y(X) - X) - \varphi(X)] \\ &\quad - [-C(K(X) - X) - \varphi(X)]f(X)dX. \end{aligned}$$

(since for one we have inequality and the other equality) with equality in the integrals if and only if we have that  $Y(X) \in K(X)$  a.e., that is  $Y(X) = K(X)$ , a.e.

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