# 'MATH+ECON+CODE' MASTERCLASS ON MATCHING MODELS, OPTIMAL TRANSPORT AND APPLICATIONS

Alfred Galichon (New York University)

Wednesday: "Optimal transport II" Block 7. Continuous multivariate matching

### LEARNING OBJECTIVES: BLOCK 7

- ► Existence of potentials in the quadratic case
- ► Knott-Smith criterion and Brenier's and McCann's theorems
- ► Some examples

### REFERENCES FOR BLOCK 7

- ► [OTME], Ch. 6
- ► [TOT] Villani (2003). *Topics in Optimal Transportation*. AMS. Ch. 1 and 2.

# Section 1

**THEORY** 

#### Introduction

As a consequence of the previous lecture, we have seen that if P is a continuous distribution over  $\mathbb{R}^d$  (distribution of the inhabitants' locations), and if  $Q = \sum_{k=1}^M q_k \delta_{y_k}$  is a discrete distribution over  $\mathbb{R}^d$  (distribution of the fountains' locations), then there exists a mapping T such that T#P=Q, that is

$$Y = T(X)$$

where:

- ▶  $X \sim P$  and  $Y \sim Q$ , and T(x) is the location of the fountain assigned to the inhabitant at x.
- ▶  $T(x) = \nabla u(x)$ , where u is a convex function which is given by  $u(x) = \max_{k} \{x^{\mathsf{T}} y_k v_k\}$ .
- Note the connection with Becker's model: when the dimension d = 1, T is piecewise constant and nondecreasing (positive assortative matching).
- ▶ In this lecture, we shall generalize these results to the case when *Q* is a general distribution (not necessarily discrete). *P* will have a density, and the support of *P* and *Q* will be assumed to be convex.

### Introduction (continued)

lacktriangle Assume that  $\mathcal X$  and  $\mathcal Y$  are convex subsets of  $\mathbb R^d$ , and that

$$\Phi(x, y) = x^{\mathsf{T}}y.$$

and P and Q are two probability distributions on  $\mathcal{X}$  and  $\mathcal{Y}$ .

► The Monge-Kantorovich theorem provides assumptions under which the value of the primal problem

$$\mathcal{W} = \sup_{\pi \in \mathcal{M}(P,Q)} \mathbb{E}_{\pi} \left[ X^{\mathsf{T}} Y \right] \tag{1}$$

coincides with the value of the dual

$$W = \inf_{u(x)+v(y)>x^{\mathsf{T}}v} \mathbb{E}_{P}\left[u\left(X\right)\right] + \mathbb{E}_{Q}\left[v\left(Y\right)\right]. \tag{2}$$

Note, however, that the M-K theorem requires  $\Phi$  to be bounded by above, which is not the case of  $\Phi(x,y)=x^{\mathsf{T}}y$  unless we assume P and Q have bounded support. We could alternatively work with  $\Phi(x,y)=-|x-y|^2/2$ , in which case we should assume that P and Q have finite second moment and replace u(x) by  $u(x)+|x|^2/2$ , and v by a similar quantity. We shall assume away these concerns for now.

#### **EXISTENCE OF POTENTIALS**

The following result ensures that u and v exist as soon as P and Q have finite second moments.

### **THEOREM**

If P and Q have finite second moments, then there exists a pair (u, v) solution to the dual Monge-Kantorovich problem

$$\inf_{u(x)+v(y)\geq x^{\intercal}y}\mathbb{E}_{P}\left[u\left(X\right)\right]+\mathbb{E}_{Q}\left[v\left(Y\right)\right].$$

See theorem 2.9 in [TOT].

#### **CONVEXITY OF THE POTENTIALS**

Assume that a dual minimizer (u, v) exists; if needed, redefine u and v so that they take value  $+\infty$  outside of the support of P and Q, assumed to be convex. As argued, u and v are then related by

$$v(y) = \max_{x \in \mathbb{R}^d} \left\{ x^\mathsf{T} y - u(x) \right\} \tag{3}$$

$$u(x) = \max_{y \in \mathbb{R}^d} \left\{ x^{\mathsf{T}} y - v(y) \right\} \tag{4}$$

hence we see immediately that if (u, v) is a solution to the dual problem, then u and v are convex functions. Further, the expression of v as a function of u is the same as the expression of u as a function of v.

#### **COMPLEMENTARY SLACKNESS**

We want to relate the solutions to the primal and dual problems. Recall that in the finite-dimensional case, where the primal and the dual problems are related by a complementary slackness condition. In the present case, let  $(X,Y)\sim\pi$  be a solution to the primal problem, and  $(u,u^*)$  be a solution to the dual problem. Then almost surely X and Y are willing to match, which, by the previous discussion, implies that

$$u(X) + u^*(Y) = X^{\mathsf{T}}Y, \tag{5}$$

that is, the support of  $\pi$  is included in the set  $\{(x,y):u(x)+u^*(y)=x^{\mathsf{T}}y\}$ . This condition appears as the correct generalization of the complementary slackness condition in the finite-dimensional case. Without surprise, taking the expectation with respect to  $\pi$  of equality (5) yields the equality between the value of the dual problem on the left-hand side, and the value of the primal problem on the right-hand side.

### COMPLEMENTARY SLACKNESS (CTD)

The following statement provides a generalization of the complementary slackness condition in finite dimension.

### THEOREM (KNOTT-SMITH)

Let  $\pi \in \mathcal{M}(P,Q)$  and u be a convex function. Then  $\pi$  and  $(u,u^*)$  are respective solutions to the primal and the dual Monge-Kantorovich problems if and only if

$$u(x) + u^*(y) = x^{\mathsf{T}}y \text{ holds for } \pi\text{-almost all } (x, y).$$
 (6)

### PROOF.

Assume that (6) holds. Then, note that  $(u,u^*)$  satisfies the constraints of the dual; further, taking expectation with respect to  $\pi$  yields  $\mathbb{E}_P\left[u\left(X\right)\right]+\mathbb{E}_Q\left[v\left(Y\right)\right]=\mathbb{E}_\pi\left[X^\intercal Y\right]$ , which implies that  $\pi$  is an optimal primal solution and  $(u,u^*)$  is an optimal dual solution. Conversely, assume that  $\pi$  is an optimal primal solution and  $(u,u^*)$  is an optimal dual solution. Then  $\mathbb{E}_\pi\left[u\left(X\right)+u^*\left(Y\right)-X^\intercal Y\right]=0$ ; but  $(x,y)\to u\left(x\right)+u^*\left(y\right)-x^\intercal y$  is nonnegative, thus (6) holds.

## THEOREM (BRENIER)

Assume that P and Q have finite second moments, and P has a density. Then the solution  $(X,Y) \sim \pi \in \mathcal{M}(P,Q)$  to the primal problem is represented by

$$Y = \nabla u(X)$$

where  $(u, u^*)$  is a solution to the dual problem. Such u is unique up to a constant.

Intuition of the proof: if u is differentiable, then y is matched with x that maximizes  $\{x^{\mathsf{T}}y - u(x)\}$  over  $x \in \mathbb{R}^d$ . By first order conditions, such x satisfy  $\nabla u(x) = y$ . It turns out, however, that differentiability is not a serious concern (at least, almost never).

### **DIFFERENTIABILITY OF CONVEX FUNCTIONS**

While we evoked the case when the Kantorovich potentials u and v are differentiable, there is no a-priori guarantee that they are so. However, an important result in Analysis called Rademacher's theorem implies that the set of non-differentiable points of a convex function is of zero Lebesgue measure, and hence can be ignored for practical purposes as soon as P is continuous. Thus the Monge map solution, T(x), can be defined as  $T(x) = \nabla u(x)$  wherever the latter quantity exists, and T(x) can be defined arbitrarily elsewhere, without affecting the distributional properties of T(X).

### McCann's theorem

The previous result allows to provide a representation of a large class of probability distributions Q over  $\mathbb{R}^d$  as the probability distribution of  $\nabla u(X)$ , for X with a fixed distribution P. There is however a limitation, in the sense that it requires that Q has finite second moments, which is needed to interpret u as entering the solution to the dual problem. Fortunately, McCann's theorem addresses this issue:

## THEOREM (McCann)

Assume that P and Q are probability distributions such that P has a density. Then there is a unique (up to a constant) function u such that

$$Y = \nabla u(X)$$

holds almost surely with  $X \sim P$  and  $Y \sim Q$ .

# Section 2

# APPLICATIONS AND EXAMPLES

#### **MATCHING AFFINITY**

▶ Brenier-McCann's theorem allows us to describe a model of the heterosexual marriage market where *P* and *Q* are continuous distributions that stand for the distributions of the men and the women's characteristics, and the surplus function is

$$\Phi\left(x,y\right) = x^{\mathsf{T}}Ay$$

i.e.  $\Phi\left(x,y\right) = \sum_{1 \leq k,l \leq d} A_{kl} x_k y_l$ , that is  $A_{kl}$  stand for the "affinity" between characteristics  $x_k$  of the man and  $y_l$  of the woman. Recall this model is equivalent to  $\Phi\left(x,y\right) = \sum_{1 \leq k,l \leq d} A_{kl} \left|x_k - y_l\right|^2 / 2$ .

### EXERCISE

Assume A is invertible. Show that the optimal matching can be given by y = T(x) where  $T = A^{-1}\nabla u(x)$ , where u is a convex function. Characterize u as the solution of a minimization problem.

#### A 2-DIMENSIONAL MODEL OF AFFINITY MATCHING

▶ Consider the a particular case of the previous model when d=2 and A is diagonal, i.e.  $A=diag\ (\lambda_1,\lambda_2)$ . Then  $\Phi^\lambda\ (x,y)=\lambda_1x_1y_1+\lambda_2x_2y_2$ . Assume  $x_1$  and  $y_1$  are interpreted as the man and woman's income, and  $x_2$  and  $y_2$  are interpreted as the man and woman's education.

### EXERCISE

Consider  $C = \{(\textit{Cov}(X_1, Y_1), \textit{Cov}(X_2, Y_2)), \pi \in \mathcal{M}(P, Q)\}.$ 

- (a) Show that C is a convex set.
- (b) Show that  $(0,0) \in \mathcal{C}$  and interpret this point.
- (c) Show that the boundary points of  $\mathcal C$  are the solution to an optimal transport problem with some surplus  $\Phi^\lambda$ .
- (d) What can be said of  $\max \{C_1 : (C_1, C_2) \in C\}$  and  $\max \{C_2 : (C_1, C_2) \in C\}$ ?
- (e) Characterize the solution to the optimal transport problem with surplus  $\Phi^{\lambda}$  when  $\lambda = (1, \varepsilon)$ , for  $\varepsilon \to 0$ .

### THE GAUSSIAN CASE

▶ When  $P = \mathcal{N}(0, \Sigma_X)$  and  $Q = \mathcal{N}(0, \Sigma_Y)$  and  $\Phi(x, y) = x^T A y$ , and  $\Sigma_X$ ,  $\Sigma_Y$  and A are invertible, one can get a solution in closed form.

### **EXERCISE**

(a) Consider first the case when  $\Sigma_X = I_d$  and  $A = I_d$ . Then show that the optimal transport map is given by

$$T(x) = \sum_{v}^{1/2} x$$
.

(b) Using the result in (a), show that when  $A=I_d$ , but with general  $\Sigma_X$  and  $\Sigma_Y$ , the solution is obtained by

$$T(x) = \Sigma_X^{-1/2} \left( \Sigma_X^{1/2} \Sigma_Y \Sigma_X^{1/2} \right)^{1/2} \Sigma_X^{-1/2} x.$$

(c) Using the result in (b), show that when A,  $\Sigma_X$  and  $\Sigma_Y$  are general invertible matrices, the solution is obtained by

$$T(x) = A^{-1} \Sigma_X^{-1/2} \left( \Sigma_X^{1/2} A^{\mathsf{T}} \Sigma_Y A \Sigma_X^{1/2} \right)^{1/2} \Sigma_X^{-1/2} x.$$