

1 Monge-Kantorovich duality in the discrete case

$$\begin{aligned} \max_{\pi_{xy} \geq 0} \quad & \sum_{xy} \pi_{xy} \Phi_{xy} \\ & \sum_y \pi_{xy} = p_x \quad [u_x] \\ & \sum_x \pi_{xy} = q_y \quad [v_y] \end{aligned}$$

$$\begin{aligned} \max_{\pi_{xy} \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy} + \sum_x \min_{u_x} u_x \left(p_x - \sum_y \pi_{xy} \right) + \sum_y \min_{v_y} v_y \left(q_y - \sum_x \pi_{xy} \right) \\ \max_{\pi_{xy} \geq 0} \min_{u_x, v_y} \sum_{xy} \pi_{xy} \Phi_{xy} + \sum_x u_x p_x + \sum_y v_y q_y - \sum_{xy} \pi_{xy} (u_x + v_y) \\ \min_{u_x, v_y} \sum_x u_x p_x + \sum_y v_y q_y + \max_{\pi_{xy} \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y) \end{aligned}$$

thus

$$\begin{aligned} \min_{u_x, v_y} \quad & \sum_x u_x p_x + \sum_y v_y q_y \\ s.t. \quad & u_x + v_y \geq \Phi_{xy} \end{aligned}$$

1.1 Kantorovich duality

Primal

$$\begin{aligned} \max_{\pi_{xy} \geq 0} \quad & \sum_{xy} \pi_{xy} \Phi_{xy} \\ & \sum_y \pi_{xy} = p_x \quad [u_x] \\ & \sum_x \pi_{xy} = q_y \quad [v_y] \end{aligned}$$

Dual

$$\begin{aligned} \min_{u_x, v_y} \quad & \sum_x u_x p_x + \sum_y v_y q_y \\ s.t. \quad & u_x + v_y \geq \Phi_{xy} \quad [\pi_{xy} \geq 0] \end{aligned}$$

By complementary slackness, $\pi_{xy} > 0 \implies u_x + v_y = \Phi_{xy}$.

Interpretation: u_x =equilibrium wage of worker x v_y =equilibrium profit of firm y .

$$u_x + v_y \geq \Phi_{xy}.$$

Claim: If (u, v) is a solution to the dual problem, then

$$v_y = \max_{x \in \mathcal{X}} \{\Phi_{xy} - u_x\} \text{ and } u_x = \max_{y \in \mathcal{Y}} \{\Phi_{xy} - v_y\}.$$

Economic interpretation: u_x and v_y are the worker's and firm's indirect utilities.

2 One-dimensional case

Consider the case $\mathcal{X} = \mathcal{Y} = \mathbb{R}$

and $\Phi(x, y) = xy$

Monge-Kantorovich duality: primal

$$\begin{aligned} \max_{(X, Y)} \quad & E[XY] \\ \text{s.t. } X & \sim P, Y \sim Q \end{aligned}$$

and the dual

$$\begin{aligned} \min_{u, v} \quad & \int u(x) dP(x) + \int v(y) dQ(y) \\ \text{s.t.} \quad & u(x) + v(y) \geq xy \end{aligned}$$

If u and v (solutions to the dual) exist then

$$v(y) = \max_{x \in \mathbb{R}} \{xy - u(x)\} \text{ and } u(x) = \max_{y \in \mathbb{R}} \{xy - v(y)\}.$$

by first order conditions if $x \in \arg \max_{x \in \mathbb{R}} \{xy - u(x)\}$, then

$$u'(x) = y.$$

Assume P and Q is absolutely continuous with respect Lebesgue.

Theorem: the solution to the primal problem

$$\begin{aligned} \max_{(X, Y)} \quad & E[XY] \\ \text{s.t. } X & \sim P, Y \sim Q \end{aligned}$$

is such that $T(\cdot)$ is increasing and continuous, and such that $T\#P = Q$.

Claim: in this case,

part (1) $T(x) = F_Q^{-1}(F_P(x))$.

Indeed, $T(X) \sim Q$ when $X \sim P$ implies

$$P(T(X) \leq y) = F_Q(y)$$

thus

$$\begin{aligned}\Pr(X \leq T^{-1}(y)) &= F_Q(y) \\ F_P(T^{-1}(y)) &= F_Q(y) \\ T^{-1}(y) &= F_P^{-1} \circ F_Q \\ T &= F_Q^{-1} \circ F_P.\end{aligned}$$

part (2) a solution (u, v) to the dual problem is given using

$$u(x) = \int_0^x F_Q^{-1}(F_P(z)) dz$$

and $v(y) = \max_x \{xy - u(x)\}$.

Particular case: when $P = \mathcal{U}([0, 1])$, $F_P(x) = x$ on $[0, 1]$, and

$$T(x) = F_Q^{-1}(x)$$

is the quantile map of Q and also

$$u'(x) = F_Q^{-1}(x).$$

This could have given us a definition of quantile!

3 Multivariate case and a notion of multivariate quantiles

Now assume that $\mathcal{X} = \mathcal{Y} = \mathbb{R}^d$ and $\Phi(x, y) = x^\top y$.

Assume that we are in the conditions that give existence of dual solutions (u, v) (e.g. compactness of support of P and Q).

Then we have

$$v(y) = \max_{x \in \mathbb{R}^d} \{x^\top y - u(x)\} \text{ and } u(x) = \max_{y \in \mathbb{R}^d} \{x^\top y - v(y)\}.$$

Note that $u(x)$ and $v(y)$ are convex functions.

If x is matched to y , we get by FOC

$$\frac{\partial u(x)}{\partial x_i} = y_i$$

hence

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

Hence, we are looking for a convex function $u : \mathbb{R}^d \rightarrow \mathbb{R}$ such that if $X \sim P$, then

$$\nabla u(X) \sim Q.$$

Because $\nabla u(x)$ is the gradient of a convex function

$$(\nabla u(x) - \nabla u(x'))^\top (x - x') \geq 0$$

Let's see what this problem is in dimension 1. In dimension 1, $\nabla u(x) = u'(x)$. The derivative of a convex function is a nondecreasing function, call it $T(x)$. Thus, in dimension 1, this problem consists of looking for a nondecreasing function T such that

$$T(X) \sim Q$$

which is $T(x) = F_Q^{-1} \circ F_P(x)$.

4 Day 2

4.1 Computation of discrete OT problems as LP problems

$$\begin{aligned} \max_{\pi_{xy} \geq 0} \quad & \sum_{xy} \pi_{xy} \Phi_{xy} \\ & \sum_y \pi_{xy} = p_x \quad [u_x] \\ & \sum_x \pi_{xy} = q_y \quad [v_y] \end{aligned}$$

$\text{vec}(\Pi)$ using the Fortran convention $\Pi_{11}, \Pi_{21}, \Pi_{31}$ -stack the columns

$$\begin{aligned} \max_{\pi_{xy} \geq 0} \quad & \sum_{xy} \pi_{xy} \Phi_{xy} \\ & \Pi 1_Y = p \\ & \Pi^\top 1_X = q \end{aligned}$$

One has

$$\text{vec}(BXA^\top) = (A \otimes B) \text{vec}(X)$$

thus

$$\begin{aligned} \text{vec}(I_X \Pi 1_Y) &= p \\ (1_Y^\top \otimes I_X) \text{vec}(\Pi) &= p \end{aligned}$$

similarly

$$\begin{aligned} \text{vec}(1_X^\top \Pi I_Y) &= \text{vec}(q^\top) = q \\ (I_Y \otimes 1_X^\top) \text{vec}(\Pi) &= q \end{aligned}$$

therefore, calling $\pi = \text{vec}(\Pi)$

$$\begin{aligned} & \max_{\pi \geq 0} \pi^\top \text{vec}(\Phi) \\ \text{s.t.} \quad & (1_{\mathcal{Y}}^\top \otimes I_{\mathcal{X}}) \pi = p \\ & (I_{\mathcal{Y}} \otimes 1_{\mathcal{X}}^\top) \pi = q \end{aligned}$$

thus the constraint matrix

$$A = \begin{pmatrix} 1_{\mathcal{Y}}^\top \otimes I_{\mathcal{X}} \\ I_{\mathcal{Y}} \otimes 1_{\mathcal{X}}^\top \end{pmatrix}$$

4.2 Quantile regression with shape constraints

$$V(\tau) = 1 \{Y \geq X^\top \beta(\tau)\}$$

Natural shape restriction

$$\tau \in [0, 1] \rightarrow x^\top \beta(\tau) \text{ is increasing}$$

this implies that

$$\tau \rightarrow V(\tau) = 1 \{Y \geq X^\top \beta(\tau)\} \text{ is weakly decreasing a.s.}$$

We have transformed the problem into

$$\begin{aligned} & \max_{\pi \geq 0} \quad U^\top \pi Y \\ \text{s.t.} \quad & \pi X = \mu \bar{x} \\ & \pi^\top 1_T = p \end{aligned}$$

The objective function

$$\sum_{tj} \pi_{tj} U_t Y_j = E_\pi [UY]$$

the constraints

$$\sum_j \pi_{tj} X_{jk} = \mu_t \bar{x}_k$$

Let's assume 1 is included in the regressors, i.e. $X_{j1} = 1$. In this case

$$\sum_j \pi_{tj} = \mu_t$$

Finally

$$\sum_j \pi_{tj} X_{jk} = \mu_t \bar{x}_k, \quad k \geq 2$$

rewrites as

$$\frac{\sum_j \pi_{tj} X_{jk}}{\sum_j \pi_{tj}} = \bar{x}_k, k \geq 2$$

that is

$$E_\pi [X_k | U] = \bar{x}_k$$

therefore, we are led

$$\begin{aligned} \max_{\pi(u, (x, y)) \geq 0} \quad & E_\pi [UY] \\ \text{s.t.} \quad & U \sim \mu \\ & (X, Y) \sim P \\ & E [X^k | U] = E [X^k], k \geq 2 \end{aligned}$$

The last constraint $E [X^k | U] = E [X^k]$ means that X should be mean-independent from U .

Let's see a version of the problem with full independence

$$\begin{aligned} \max_{\pi(u, (x, y)) \geq 0} \quad & E_\pi [UY] \\ \text{s.t.} \quad & U \sim \mu \\ & (X, Y) \sim P \\ & X \text{ and } U \text{ independent} \end{aligned}$$

write

$$E_\pi [UY] = E [E [UY | X]]$$

this is maximized by taking for each x the optimal coupling between $U \sim \mathcal{U}([0, 1])$ and $P_{Y|X=x}$. This is given to us by $Y = Q_{Y|X}(U|x)$. Thus the solution to the problem with full independence is given to us by

$$Y = Q_{Y|X}(U|X)$$

and hence

$$U = F_{Y|X}(Y|X).$$

Back to mean-independence, write the dual of the above primal problem

$$\begin{aligned} \max_{\pi(u, (x, y)) \geq 0} \quad & E_\pi [UY] \\ \text{s.t.} \quad & U \sim \mu \\ & (X, Y) \sim P \\ & E [X^k | U] = E [X^k], k \geq 2 \end{aligned}$$

the dual to this problem is

$$\begin{aligned} \min_{\varphi(u), \psi(x, y), b^k(u)} \quad & E [\varphi(U)] + E [\psi(X, Y)] + E [\bar{x}^\top b(U)] \\ \text{s.t.} \quad & \varphi(u) + \psi(x, y) + x^\top b(u) \geq x^\top y \end{aligned}$$