

Lectures on optimal transport

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1 Roadmap

- L1. Discrete optimal transport
- L2. Inverse optimal transport
- L3. Optimal transport and quantile methods

2 Optimal transport in the discrete case

Central planner's solution

Workers characteristics $x \in X$

n_x workers of type x

Firms characteristics $y \in Y$

m_y firms of type y

$$\sum_x n_x = \sum_y m_y$$

A matching π_{xy} is the mass of workers of type x matched with firms of type y

Constraints:

$$\sum_y \pi_{xy} = n_x$$

$$\sum_x \pi_{xy} = m_y$$

Let Φ_{xy} be the productivity (in dollar terms) of a worker of type x matched with a firm of type y .

Central planner's problem:

$$\max_{\pi \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy}$$

s.t.

$$\sum_y \pi_{xy} = n_x$$

$$\sum_x \pi_{xy} = m_y$$

$$\max_{\pi \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy} + \min_{u_x, v_y} \sum_x u_x \left(n_x - \sum_y \pi_{xy} \right) + \sum_y v_y \left(m_y - \sum_x \pi_{xy} \right)$$

$$\max_{\pi \geq 0} \min_{u_x, v_y} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y) + \sum_x u_x n_x + \sum_y v_y m_y$$

$$\min_{u_x, v_y} \max_{\pi \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y) + \sum_x u_x n_x + \sum_y v_y m_y$$

$$\min_{u_x, v_y} \sum_x u_x n_x + \sum_y v_y m_y + \max_{\pi \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y)$$

This becomes

$$\min_{u_x, v_y} \sum_x u_x n_x + \sum_y v_y m_y + \max_{\pi \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y)$$

hence we arrive at the **dual to the central planner's problem**

$$\begin{aligned} \min_{u_x, v_y} & \sum_x u_x n_x + \sum_y v_y m_y \\ \text{s.t. } & u_x + v_y \geq \Phi_{xy} \end{aligned}$$

Complementary slackness

$$\pi_{xy} > 0 \implies u_x + v_y = \Phi_{xy}$$

The dual problem can be interpreted as the equilibrium in the wage market.

Indeed, consider the dual

$$\begin{aligned} \min_{u_x, v_y} & \sum_x u_x n_x + \sum_y v_y m_y \\ \text{s.t. } & u_x + v_y \geq \Phi_{xy} \end{aligned}$$

Rewrite the constraint into

$$v_y \geq \max_x \{\Phi_{xy} - u_x\}$$

Claim: the dual can rewrite as

$$\begin{aligned} \min_{u_x, v_y} & \sum_x u_x n_x + \sum_y v_y m_y \\ \text{s.t. } & v_y = \max_x \{\Phi_{xy} - u_x\} \end{aligned}$$

Equation

$$v_y = \max_x \{\Phi_{xy} - u_x\}$$

interprets as profit maximization by the firm.

2.1 Becker's theory of marriage

Becker's model of heterosexual marriage market

$x \in X$ man's characteristics in number n_x

$y \in Y$ woman's characteristics in number m_y

Assume that if x matches with y then

- x enjoys utility α_{xy}
- y enjoys utility γ_{xy}

Becker assumed **fully transferable utility**: if x gives up a quantity τ of utility to y , then after transfers

x gets $\alpha_{xy} - \tau$

y gets $\gamma_{xy} + \tau$

Note: we could get $\gamma_{xy} + f(\tau)$ but this would not be optimal transport. This is called matching with imperfectly transferable utility.

The limit without any possible transfers is called non-transferable utility model, this is Gale-Shapley's model.

Back to Becker's model

No matter the transfer, x and y if they match get joint surplus $\Phi_{xy} = \alpha_{xy} + \gamma_{xy}$.

2.2 Actual model of transportation

Koopmans-Beckmann model.

$x \in X$ the locations of plants. Production (of a commodity) by plant x is n_x per day.

$y \in Y$ the locations of cities. Consumption of the same commodity by city y is m_y per day.

Total production = total consumption

(unit) Transportation cost from plant x to city y is c_{xy} per unit of mass.

Tolstoi's problem (1920).

Define π_{xy} the mass of commodity which will route from x to y . The optimal shipping plan is given by

$$\min_{\pi \geq 0} \sum_{xy} \pi_{xy} c_{xy}$$

s.t.

$$\sum_y \pi_{xy} = n_x$$

$$\sum_x \pi_{xy} = m_y$$

The dual of this problem is

$$\max_{p_x, p_y} \sum_y m_y p_y - \sum_x n_x p_x$$

$$p_y - p_x \leq c_{xy}$$

$\sum_y m_y p_y = \sum_x n_x p_x + \sum_{xy} \pi_{xy} c_{xy}$: total price at destination = total price at origin + total shipping cost

The constraint in the dual

$$p_y \leq c_{xy} + p_x$$

says that there is no pair xy such that

$$p_y > c_{xy} + p_x$$

this is a no-arbitrage conditions.

$$\Phi(x, y) = x^\top A y = \sum_{kl} A_{kl} x^k y^l$$

Most LP solvers compute

$$\max_{z \geq 0} c^\top z$$

$$\text{s.t. } Mz = d$$

$$\max_{\pi \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy}$$

s.t.

$$\begin{aligned}\sum_y \pi_{xy} &= n_x \\ \sum_x \pi_{xy} &= m_y\end{aligned}$$

$$\text{vec}(\pi)$$

$$\begin{aligned}I_X \pi 1_Y &= n \\ 1_X^\top \pi I_Y &= m^\top\end{aligned}$$

Get $\text{vec}(\pi 1_Y) = (\dots) \text{vec}(\pi)$ and $\text{vec}(1_X^\top \pi) = (\dots) \text{vec}(\pi)$

We have

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

This gives

$$\begin{aligned}\text{vec}(I_X \pi 1_Y) &= n \\ \text{vec}(1_X^\top \pi I_Y) &= m\end{aligned}$$

therefore

$$\begin{aligned}(I_X \otimes 1_Y^\top) \text{vec}(\pi) &= n \\ (1_X^\top \otimes I_Y) \text{vec}(\pi) &= m\end{aligned}$$

The OT problem can be computed as

$$\max_{\pi \geq 0} \text{vec}(\pi)^\top \text{vec}(\Phi)$$

s.t.

$$\begin{aligned}(I_X \otimes 1_Y^\top) \text{vec}(\pi) &= n \\ (1_X^\top \otimes I_Y) \text{vec}(\pi) &= m\end{aligned}$$

3 Entropic regularization

$$\max_{\pi \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy} - \sigma \sum_{xy} \pi_{xy} \ln \pi_{xy}$$

s.t.

$$\begin{aligned}\sum_y \pi_{xy} &= n_x \quad [u_x] \\ \sum_x \pi_{xy} &= m_y \quad [v_y]\end{aligned}$$

$$\begin{aligned}& \max_{\pi \geq 0} \sum_{xy} \pi_{xy} \Phi_{xy} - \sigma \sum_{xy} \pi_{xy} \ln \pi_{xy} + \min_{u_x, v_y} \sum_x u_x \left(n_x - \sum_y \pi_{xy} \right) + \\ & \sum_y v_y \left(m_y - \sum_x \pi_{xy} \right) \\ & \max_{\pi \geq 0} \min_{u_x, v_y} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y - \sigma \log \pi_{xy}) + \sum_x u_x n_x + \sum_y v_y m_y \\ & \min_{u_x, v_y} \max_{\pi \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y - \sigma \log \pi_{xy}) + \sum_x u_x n_x + \sum_y v_y m_y \\ & \min_{u_x, v_y} \sum_x u_x n_x + \sum_y v_y m_y + \max_{\pi \geq 0} \sum_{xy} \pi_{xy} (\Phi_{xy} - u_x - v_y - \sigma \log \pi_{xy})\end{aligned}$$

FOC in the inner problem

$$(\Phi_{xy} - u_x - v_y - \sigma \log \pi_{xy}) - \sigma = 0$$

thus

$$\pi_{xy} = \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right)$$

and the value of the inner problem is $\sigma \sum_{xy} \pi_{xy} = \sigma \sum_{xy} \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right)$.

The outer problem becomes

$$\min_{u_x, v_y} F(u, v) := \sum_x u_x n_x + \sum_y v_y m_y + \sigma \sum_{xy} \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right)$$

Foc yield

$$\begin{aligned} \text{wrt } u_x: n_x &= \sum_y \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right) \\ \text{wrt } v_y: m_y &= \sum_x \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right) \end{aligned}$$

(Blockwise) Coordinate descent.

Given v_y 's compute u_x by $\min_{u_x} F(u, v)$

$$n_x = \sum_y \exp\left(\frac{\Phi_{xy} - u_x - v_y - \sigma}{\sigma}\right)$$

yields

$$\exp(u_x/\sigma) = \sum_y \exp\left(\frac{\Phi_{xy} - v_y - \sigma}{\sigma}\right) / n_x$$

similarly Given u_x 's compute v_y by $\min_{v_y} F(u, v)$

yields

$$\exp(v_y/\sigma) = \sum_x \exp\left(\frac{\Phi_{xy} - u_x - \sigma}{\sigma}\right) / m_y$$

Sinkhorn's algorithm / Iterated Proportional Fitting Procedure

<https://arxiv.org/abs/1609.06349>

Write $A_x = \exp(-u_x/\sigma)$ and $B_y = \exp(-v_y/\sigma)$

and $K_{xy} = \exp\left(\frac{\Phi_{xy} - \sigma}{\sigma}\right)$, we have

$$A_x = n_x / \sum_y K_{xy} B_y$$

similarly Given u_x 's compute v_y by $\min_{v_y} F(u, v)$

yields

$$B_y = m_y / \sum_x K_{xy} A_x$$

When σ is small

$$u_x = \sigma \log\left(\sum_y \exp\left(\frac{\Phi_{xy} - v_y - \sigma}{\sigma}\right)\right) - \sigma \log n_x$$

log-sum-exp trick

When computing numerically

$$\sigma \log \sum_y \exp\left(\frac{z_y}{\sigma}\right)$$

you should

$$m = \max_y \{z_y\}$$

and use the fact that for any c

$$\sigma \log \sum_y \exp\left(\frac{z_y - c}{\sigma}\right) + c = \sigma \log \sum_y \exp\left(\frac{z_y}{\sigma}\right)$$

use this with $c = m$ and get

$$\sigma \log \sum_y \exp\left(\frac{z_y}{\sigma}\right) = \sigma \log \sum_y \exp\left(\frac{z_y - m}{\sigma}\right) + m$$

4 Inverse optimal transport

Go back to the labor market, but this time introducing unmatched agents

Consider primal problem

$$\begin{aligned} \max_{\pi \geq 0} \quad & \sum_{xy} \pi_{xy} \Phi_{xy} \\ \text{s.t.} \quad & \\ & \sum_y \pi_{xy} \leq n_x \\ & \sum_x \pi_{xy} \leq m_y \end{aligned}$$

which has dual

$$\begin{aligned} \min_{u_x \geq 0, v_y \geq 0} \quad & \sum_x n_x u_x + \sum_y m_y v_y \\ \text{s.t.} \quad & \\ & u_x + v_y \geq \Phi_{xy} \end{aligned}$$

Introduce unobserved heterogeneity.

Now we assume that n_x and m_y are very large.

Individual worker $i \in I$ has type $x_i \in X$

Individual firm $j \in J$ has type $y_j \in Y$

Assume that the joint output generated by i and j together is

$\Phi_{ij} = \Phi_{x_i y_j} + \varepsilon_{i y_j} + \eta_{x_i j}$. (Separability assumption).

The dual is

$$\begin{aligned} \min \quad & \sum_{i \in I} u_i + \sum_{j \in J} v_j \\ \text{s.t.} \quad & \\ & u_i + v_j \geq \Phi_{ij} := \Phi_{x_i y_j} + \varepsilon_{i y_j} + \eta_{x_i j} \\ & u_i \geq \varepsilon_{i0} \\ & v_j \geq \eta_{0j} \end{aligned}$$

Take a look at the constraint

$$u_i + v_j \geq \Phi_{x_i y_j} + \varepsilon_{i y_j} + \eta_{x_i j}$$

rewrtie this as

$$u_i - \varepsilon_{i y} + v_j - \eta_{x j} \geq \Phi_{xy} \text{ for all } i : x_i = x \text{ and for all } j : y_j = y$$

$$\min_{i: x_i = x} \{u_i - \varepsilon_{i y}\} + \min_{j: y_j = y} \{v_j - \eta_{x j}\} \geq \Phi_{xy}$$

define $U_{xy} = \min_{i: x_i = x} \{u_i - \varepsilon_{i y}\}$ and $V_{xy} = \min_{j: y_j = y} \{v_j - \eta_{x j}\}$, in which case the constraints become

$$U_{xy} + V_{xy} \geq \Phi_{xy}$$

We have $U_{xy} = \min_{i: x_i = x} \{u_i - \varepsilon_{i y}\}$, therefore $u_i \geq \max_y \{U_{xy} + \varepsilon_{i y}, \varepsilon_{i0}\}$ and similarly $v_j \geq \max_x \{V_{xy} + \eta_{x j}, \eta_{0j}\}$

The micro problem rewrites

$$\begin{aligned} \min \quad & \sum_{i \in I} u_i + \sum_{j \in J} v_j \\ \text{s.t.} \quad & \\ & U_{xy} + V_{xy} \geq \Phi_{xy} \\ & u_i \geq \max_y \{U_{xy} + \varepsilon_{i y}, \varepsilon_{i0}\} \\ & v_j \geq \max_x \{V_{xy} + \eta_{x j}, \eta_{0j}\} \end{aligned}$$

and in fact

$$\begin{aligned} & \min \sum_{i \in I} u_i + \sum_{j \in J} v_j \\ & \text{s.t.} \\ & U_{xy} + V_{xy} \geq \Phi_{xy} \\ & u_i = \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} \\ & v_j = \max_x \{V_{xy} + \eta_{xj}, \eta_{0j}\} \end{aligned}$$

which can rewrite

$$\begin{aligned} & \min \sum_{i \in I} \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} + \sum_{j \in J} \max_x \{V_{xy} + \eta_{xj}, \eta_{0j}\} \\ & \text{s.t.} \\ & U_{xy} + V_{xy} \geq \Phi_{xy} \end{aligned}$$

that is

$$\begin{aligned} & \min \sum_x n_x \sum_{i: x_i=x} \frac{1}{n_x} \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} + \sum_y m_y \sum_{j: y_j=y} \frac{1}{m_y} \max_x \{V_{xy} + \eta_{xj}, \eta_{0j}\} \\ & \text{s.t.} \\ & U_{xy} + V_{xy} \geq \Phi_{xy} \end{aligned}$$

We shall assume a statistical behaviour of ε_{iy} and η_{xj} 's. Assume that $(\varepsilon_{iy})_y$ is distributed according to P

and that $(\eta_{xj})_x$ is distributed according to Q .

By the law of large numbers the above expression converges to

$$\begin{aligned} & \min_{U,V} \sum_x n_x E_P [\max_y \{U_{xy} + \varepsilon_y, \varepsilon_0\}] + \sum_y m_y E_Q [\max_x \{V_{xy} + \eta_x, \eta_0\}] \\ & \text{s.t.} \\ & U_{xy} + V_{xy} \geq \Phi_{xy} \end{aligned}$$

Define $G_x(U) = E_P [\max_y \{U_{xy} + \varepsilon_y, \varepsilon_0\}]$ and $H_y(V) = E_Q [\max_x \{V_{xy} + \eta_x, \eta_0\}]$ and $G(U) = \sum_x n_x G_x(U)$ and $H(V) = \sum_y m_y H_y(V)$ the problem becomes

$$\begin{aligned} & \min_{U,V} G(U) + H(V) \\ & \text{s.t.} \\ & U_{xy} + V_{xy} = \Phi_{xy} \end{aligned}$$

$$\min_U G(U) + H(\Phi - U)$$

FOC

$$\frac{\partial G(U)}{\partial U_{xy}} = \frac{\partial H}{\partial V_{xy}} (\Phi - U)$$

$$\begin{aligned} \frac{\partial G(U)}{\partial U_{xy}} &= n_x \frac{\partial G_x(U)}{\partial U_{xy}} = n_x \Pr(y \in \arg \max \{U_{xy} + \varepsilon_y, \varepsilon_0\}) \\ \frac{\partial H(V)}{\partial V_{xy}} &= m_y \Pr(x \in \arg \max \{V_{xy} + \eta_x, \eta_0\}) \end{aligned}$$

Dual problem:

Start from the penalized problem

$$\begin{aligned} & \min_{U,V} G(U) + H(V) + \max_{\pi \geq 0} \sum \pi_{xy} (\Phi_{xy} - U_{xy} - V_{xy}) \\ & \max_{\pi \geq 0} \sum \pi_{xy} \Phi_{xy} + \min_{U,V} \{G(U) + H(V) - \sum \pi_{xy} (U_{xy} + V_{xy})\} \\ & \max_{\pi \geq 0} \sum \pi_{xy} \Phi_{xy} - \max_U \{\sum \pi_{xy} U_{xy} - G(U)\} - \max_V \{\sum \pi_{xy} V_{xy} - H(V)\} \end{aligned}$$

Define the convex conjugates / Legendre-Fenchel transforms of G and H as

$$G^*(\pi) = \max_U \left\{ \sum \pi_{xy} U_{xy} - G(U) \right\}$$

$$H^*(\pi) = \max_V \left\{ \sum \pi_{xy} V_{xy} - H(V) \right\}$$

and the problem becomes

$$\max_{\pi_{xy} \geq 0} \left\{ \sum \pi_{xy} \Phi_{xy} - G^*(\pi) - H^*(\pi) \right\}$$

FOC yield

$$\Phi_{xy} = \frac{\partial G^*(\pi)}{\partial \pi_{xy}} + \frac{\partial H^*(\pi)}{\partial \pi_{xy}}$$

When P (the distribution of $(\varepsilon_{iy})_y$) is the Gumbel distribution (extreme-value type 1 – distribution with cdf $\exp(-\exp(-z))$)

https://en.wikipedia.org/wiki/Gumbel_distribution

then $G_x(U) = \log(1 + \sum_y \exp U_{xy})$, and therefore $G(U) = \sum_x n_x \log(1 + \sum_y \exp U_{xy})$.

We have

$$G_x^*(\pi) = \sum_{y \in Y} \frac{\pi_{xy}}{n_x} \log \frac{\pi_{xy}}{n_x} + \frac{\pi_{x0}}{n_x} \log \frac{\pi_{x0}}{n_x} \text{ where } \pi_{x0} = n_x - \sum_y \pi_{xy}$$

Therefore the primal problem in this case rewrites

$$\max_{\pi_{xy} \geq 0} \left\{ \sum \pi_{xy} \Phi_{xy} - \sum_x n_x \sum_{y \in Y} \frac{\pi_{xy}}{n_x} \log \frac{\pi_{xy}}{n_x} - \pi_{x0} \log \frac{\pi_{x0}}{n_x} - \sum_y m_y \sum_{x \in X} \frac{\pi_{xy}}{m_y} \log \frac{\pi_{xy}}{m_y} - \pi_{0y} \log \frac{\pi_{0y}}{m_y} \right\}$$

which yields

$$\max_{\pi_{xy} \geq 0} \left\{ \sum \pi_{xy} \Phi_{xy} - \sum_{xy} \pi_{xy} \log \frac{\pi_{xy}^2}{n_x m_y} - \pi_{x0} \log \frac{\pi_{x0}}{n_x} - \pi_{0y} \log \frac{\pi_{0y}}{m_y} \right\}$$

First order conditions wrt π_{xy} :

$$\Phi_{xy} = 2 + 2 \log \pi_{xy} - \log(n_x m_y) - (1 + \log \pi_{x0} - \log n_x) - (1 + \log \pi_{0y} - \log m_y).$$

This is Choo and Siow's formula (Journal of Political Economy, 2006)

$$\Phi_{xy} = \log \frac{\pi_{xy}^2}{\pi_{x0} \pi_{0y}}.$$