

# 1 Solution to the exercise

Exercise. Consider a setting where there are  $n_x$  workers of type  $x$  and  $m_y$  firms of type  $y$ . If a worker of type  $x \in \mathcal{X}$  is matched to a firm of type  $y \in \mathcal{Y}$  with a gross wage  $w_{xy}$ , then the worker and the firm respectively get utility

$$\alpha_{xy} + (1 - \tau) w_{xy} \text{ and } \gamma_{xy} - w_{xy}$$

where  $\tau \in (0, 1)$  is a linear tax rate,  $\alpha_{xy} \leq 0$  is the job amenity, and  $\gamma_{xy} \geq 0$  is the economic output productivity. Unmatched workers and firms get zero payoff.

(i) Show that the equilibrium matching  $\mu_{xy}^\tau$  is the optimal matching associated to surplus  $\Phi_{xy}^\tau = \alpha_{xy} + (1 - \tau) \gamma_{xy}$ .

(ii) How is the Walrasian vector of wages  $w_{xy}$  determined based on the dual program?

(iii) Assume there are three types of workers and four types of firms, there is a mass one of each type of worker and of each type of firm, and

$$\alpha = \begin{pmatrix} -16 & -4 & -8 & -20 \\ -12 & -8 & -4 & -4 \\ -4 & -8 & -8 & -16 \end{pmatrix} \text{ and } \gamma = \begin{pmatrix} 4 & 8 & 4 & 2 \\ 4 & 3 & 6 & 6 \\ 9 & 4 & 8 & 2 \end{pmatrix}$$

Let

$$A = \sum_{xy} \mu_{xy}^\tau \alpha_{xy} \text{ and } \Gamma = \sum_{xy} \mu_{xy}^\tau \gamma_{xy}$$

Using Gurobi, fill out the following table

$\tau$	.00	0.25	0.50	0.75
$A$				
$\Gamma$				

and comment.

## 1.1 Solution

Question (i)

Consider an equilibrium matching  $(\mu_{xy}, w_{xy})$

(1) Population constraints.

$$\sum_y \mu_{xy} \leq n_x$$

$$\sum_x \mu_{xy} \leq m_y$$

(2)

for each  $x$ ,

$$\mu_{xy} > 0 \implies \begin{cases} y \in \arg \max_{y'} \{ \alpha_{xy'} + (1 - \tau) w_{xy'}, 0 \} \\ x \in \arg \max_{x'} \{ \gamma_{x'y} - w_{x'y}, 0 \} \end{cases}$$

Introduce

$$\begin{aligned} u_x &= \max_{y'} \{ \alpha_{xy'} + (1 - \tau) w_{xy'}, 0 \} \\ v_y &= \max_{x'} \{ \gamma_{x'y} - w_{x'y}, 0 \} \end{aligned}$$

and rewrite the conditions as

$$\mu_{xy} > 0 \implies \begin{cases} \alpha_{xy} + (1 - \tau) w_{xy} = u_x \\ \gamma_{xy} - w_{xy} = v_y \end{cases}$$

which implies

$$\mu_{xy} > 0 \implies \begin{cases} \alpha_{xy} + (1 - \tau) w_{xy} = u_x \\ \gamma_{xy} (1 - \tau) - w_{xy} (1 - \tau) = v_y (1 - \tau) \end{cases}$$

that is

$$\mu_{xy} > 0 \implies \alpha_{xy} + (1 - \tau) \gamma_{xy} = u_x + (1 - \tau) v_y$$

However in general

$$\begin{aligned} u_x + (1 - \tau) v_y &\geq \alpha_{xy} + (1 - \tau) w_{xy} \\ &\quad + (1 - \tau) \gamma_{xy} - (1 - \tau) w_{xy} \end{aligned}$$

thus

$$u_x + (1 - \tau) v_y \geq \alpha_{xy} + (1 - \tau) \gamma_{xy}$$

Let's recap:

Define  $\tilde{v}_y = (1 - \tau) v_y$

We have:

(1)

$$\sum_y \mu_{xy} \leq n_x$$

$$\sum_x \mu_{xy} \leq m_y$$

$$(2) \ u_x + \tilde{v}_y \geq \Phi_{xy}^\tau$$

$$u_x \geq 0$$

$$\tilde{v}_y \geq 0$$

(3)

if  $\mu_{xy} > 0$  then  $u_x + \tilde{v}_y = \Phi_{xy}^\tau$

if  $n_x > \sum_y \mu_{xy}$  then  $u_x = 0$

if  $m_y > \sum_x \mu_{xy}$  then  $\tilde{v}_y = 0$

These are the CS conditions associated with

$$\begin{aligned} \max_{\mu \geq 0} \quad & \sum_{xy} \mu_{xy} \Phi_{xy}^\tau \\ s.t. \quad & \sum_y \mu_{xy} \leq n_x \\ & \sum_x \mu_{xy} \leq m_y \end{aligned}$$

which has dual

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

(ii) Assume  $(u, \tilde{v})$  is a solution to the dual problem above. How can we recover  $w_{xy}$  based on  $u$  and  $\tilde{v}$ ?

We have

$$\begin{aligned} u_x &= \max_{y'} \{ \alpha_{xy'} + (1 - \tau) w_{xy'}, 0 \} \\ \tilde{v}_y &= (1 - \tau) v_y = \max_{x'} \{ (1 - \tau) \gamma_{x'y} - (1 - \tau) w_{x'y}, 0 \} \end{aligned}$$

thus

$$\begin{aligned} u_x &\geq \alpha_{xy} + (1 - \tau) w_{xy} \\ \tilde{v}_y &\geq (1 - \tau) \gamma_{xy} - (1 - \tau) w_{xy} \end{aligned}$$

that is  $(1 - \tau) w_{xy} \geq (1 - \tau) \gamma_{xy} - \tilde{v}_y$ , hence

$$\frac{u_x - \alpha_{xy}}{1 - \tau} \geq w_{xy} \geq \gamma_{xy} - \frac{\tilde{v}_y}{(1 - \tau)}$$

Claim: if  $w_{xy}$  satisfies these inequalities, then it is a vector of equilibrium wages.

Indeed, if  $\mu_{xy} > 0$  then  $u_x + \tilde{v}_y = \alpha_{xy} + (1 - \tau) \gamma_{xy}$ , which implies

$$\frac{u_x - \alpha_{xy}}{1 - \tau} = \gamma_{xy} - \frac{\tilde{v}_y}{(1 - \tau)}$$

## 2 Continuous optimal transport

Recall discrete case

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

which has dual

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

Let's assume  $\sum_x n_x = \sum_y m_y = 1$ . In that case  $\mu_{xy}$  satisfies

$$\sum_{xy} \mu_{xy} = 1$$

Thus  $\mu_{xy}$  can be interpreted as a probability on  $\mathcal{X} \times \mathcal{Y}$ . If  $(X, Y)$  is a random pair with probability  $\mu$ , then the constraints on  $\mu$  imply that

$$\begin{aligned} \Pr(X = x) &= \sum_{x'y'} \mu_{x'y'} 1\{x' = x\} = \sum_{y'} \mu_{xy'} = n_x \\ \Pr(Y = y) &= m_y \end{aligned}$$

Therefore we can rewrite the problem as

$$\begin{aligned} \max_{(X,Y) \sim \mu} & E[\Phi_{XY}] \\ & X \sim n \\ & Y \sim m \end{aligned}$$

and the dual problem as

$$\begin{aligned} \min_{u,v} & E_n[u_X] + E_m[v_Y] \\ \text{s.t.} & u_x + v_y \geq \Phi_{xy} \end{aligned}$$

In the sequel,  $\mathcal{X}$  and  $\mathcal{Y}$  will be  $R^n$  and  $\Phi_{xy} = x^\top y$ .

Let's assume  $u(x)$  and  $v(y)$  are solutions to the dual. We have

$$v(y) = u^*(y) \text{ and } u(x) = v^*(x),$$

where

$$\begin{aligned} u^*(y) &= \max_x \{x^\top y - u(x)\} \\ v^*(x) &= \max_y \{x^\top y - v(y)\} \end{aligned}$$

We have that  $u^*$  and  $v^*$  are convex.

Do we always have  $u^{**}(x) = u(x)$ . NO if  $u$  is not convex.  
YES if  $u$  is convex.

In the finite case, the support of  $\mu$  is the set of  $xy$  such that  $\mu_{xy} > 0$ .

Complementary slackness

$$(x, y) \in \text{Supp}(\mu) \implies x \in \arg \max_{x'} \{x'^\top y - u(x')\}$$

this implies optimality conditions

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

This means that if  $(X, Y) \sim \mu$  is an optimal solution and if  $(u, v)$  is an optimal dual solution, then

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

This leads us to the Brenier theorem.

If  $n$  has a density wrt Lebesgue and finite second moments then for any  $m$  with finite second moments there is a convex function  $u$ , such that there is a  $X \sim n$  and  $Y \sim m$  and

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

(Extended by Gangbo and McCann)

In dimension 1, what does this mean?

In dimension 1, gradient of convex function = derivative of a convex function = nondecreasing function.

Assume  $n = U([0, 1])$ , and assume  $m$  is a distribution on the real line with cdf  $F_m$ . My statement means that for  $X \sim U([0, 1])$  there is a  $Y \sim F_m$  and

$$Y = T(X)$$

where  $T$  is nondecreasing. In this case,  $T(x) = F_m^{-1}(x)$ .

In deed,  $\Pr(F_m^{-1}(X) \leq y) = \Pr(X \leq F_m(y)) = F_m(y)$ .

Yesterday, we saw the case when  $n$  is continuous and  $m$  is discrete. In that case,  $u$  is convex and piecewise affine, that is

$$u(x) = \max_j \{x^\top y_j - p_j\}$$

We have that

$$\nabla u(x) = y_j \text{ where } \{j\} = \arg \max_j \{x^\top y_j - p_j\}.$$

### 3 Network flow problems

Consider a directed network.

Nodes (=cities)  $z \in Z$

A city can be a producer, a consumer or a transit point.

For each  $z$ ,  $q_z$  = net consumption of silk at node  $z$ .

(=consumption - production)

$q_z > 0$  means  $z$  is a consumer

$q_z < 0$  means  $z$  is a producer

$q_z = 0$  means  $z$  is a transit point.

$$\sum_{z: q_z < 0} (-q_z) = \sum_{z: q_z > 0} q_z$$

$\sum_{z \in Z} q_z = 0$  means that overall production = overall consumption.

Arcs. The set of arcs is a subset  $A$  of  $Z \times Z$ .

if  $xy \in A$ , then  $x$  is the origin of  $xy$  and  $y$  is the destination.

Paths. A path from  $x$  to  $y$  is a series of nodes  $x_0 = x, x_1, \dots, x_T = y$  where  $x_t x_{t+1} \in A$ .

Assumption (connectedness) – there is a path from any producer to any consumer.

Define a flow as a vector  $(\mu_{xy}) \in \mathbb{R}_+^A$ .

Conditions on  $\mu$  to be a feasible flow.

$\mu_{xy} \geq 0$  for all  $xy \in A$

Consider a node  $z \in Z$

$$\sum_{x: xz \in A} \mu_{xz} - \sum_{y: zy \in A} \mu_{zy} = q_z$$

A flow  $\mu$  that satisfies such equation is called a feasible flow.

Central planner's problem.

Let's assume  $c_a$  is the cost of shipping one unit of the commodity through arc  $a$ . The central planner's problem is

$$\begin{aligned} \min_{\mu_{xy} \geq 0} \quad & \sum_{xy \in A} \mu_{xy} c_{xy} \\ \text{s.t.} \quad & \sum_{x: xz \in A} \mu_{xz} - \sum_{y: zy \in A} \mu_{zy} = q_z \quad [p_z]. \end{aligned}$$

$$\begin{aligned} \min_{\mu_{xy} \geq 0} \quad & \sum_{xy \in A} \mu_{xy} c_{xy} + \sum_z p_z \left( q_z - \sum_{x: xz \in A} \mu_{xz} + \sum_{y: zy \in A} \mu_{zy} \right) \\ \min_{\mu_{xy} \geq 0} \quad & \sum_{xy \in A} \mu_{xy} c_{xy} + \sum_z p_z q_z - \sum_{xz \in A} \mu_{xz} p_z + \sum_{zy \in A} \mu_{zy} p_z \\ \min_{\mu_{xy} \geq 0} \max_{p_z} \quad & \sum_{xy \in A} \mu_{xy} c_{xy} + \sum_z p_z q_z - \sum_{xy \in A} \mu_{xy} p_y + \sum_{xy \in A} \mu_{xy} p_x \\ \max_{p_z} \quad & \sum_z p_z q_z + \min_{\mu_{xy} \geq 0} \sum_{xy \in A} \mu_{xy} (c_{xy} - p_y + p_x) \end{aligned}$$

that is

$$\begin{aligned} \max_{p_z} \quad & \sum_z p_z q_z \\ \text{s.t.} \quad & p_y - p_x \leq c_{xy} \end{aligned}$$

$$\mu_{xy} > 0 \implies p_y - p_x = c_{xy}$$

Interpretation of  $p_z$ : price of one unit of the commodity at  $z$ .

$p_y - p_x - c_{xy} \leq 0$  is a no-arbitrage condition.

$\mu_{xy} > 0 \implies p_y - p_x = c_{xy}$  means that traders trade only if there is nonnegative profit.

Cheapest path. Recall that a path from  $x$  to  $y$  is a series of nodes  $x_0 = x, x_1, \dots, x_T = y$  where  $x_t x_{t+1} \in A$ .

The cost of a path  $x_0 x_1 \dots x_T$  is  $c_{x_0 x_1} + c_{x_1 x_2} + \dots + c_{x_{T-1} x_T}$ .

The cheapest path from  $x$  to  $y$  is the path that achieves minimum cost.

**Exercise.** Consider the problem of the cheapest path from any point  $x$  to a destination  $y^*$ .

Let  $P_x^t$  be the cost of going from  $x$  to  $y^*$  in at most  $t$  steps if it is possible, and  $P_x^t = +\infty$  otherwise.

- 1) What is  $P_x^1$
- 2) Show that  $P_x^{t+1}$  and  $P_x^t$  are related by a Bellman equation.
- 3) Deduce an algorithm to determine the cheapest path from any point  $x$  to a destination  $y^*$ .