

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

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Thursday: "Multinomial choice"

Block 12. Dynamic discrete choice

- ▶ Finite-horizon Rust's model
- ▶ identification and estimation
- ▶ normalization issues

- ▶ Rust (1987): “Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher. *Econometrica*.
- ▶ Aguirregabiria and Mira (2007): “Sequential estimation of dynamic discrete games.” *Econometrica*.
- ▶ Pesendorfer and Schmidt-Dengler (2008): “Asymptotic least squares estimators for dynamic games.” *Review of Economic Studies*.
- ▶ Arcidiacono and Miller (2011): “Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity.” *Econometrica*.
- ▶ Chiong, Galichon and Shum (2016). Duality in discrete choice models. *Quantitative economics*.

# Section 1

## THEORY

- Recall the dynamic programming model seen in block 3. The setting is the same: there are  $n_x$  units (buses) in state  $x$  at the initial period ( $t = 1$ ); at each period, one must choose for each unit some alternative  $y \in \mathcal{Y}$ ; the probability of transiting to state  $x'$  at period  $t + 1$  conditional on being in state  $x$  and choosing alternative  $y$  at time  $t$  is  $P_{x'|xy}^t$ .
- The difference with the setting seen in block 3 is that, following Rust, the utility associated with choosing  $y$  in state  $x$  at  $t$  is no longer deterministic, but includes an additional random term  $\varepsilon_y \sim \mathbf{P}_{xt}$ , so it is

$$u_{xy}^t + \varepsilon_y.$$

The stochastic structure is such that  $x_t, (x_t, \varepsilon), (x_t, y_t)$  is a Markov chain – which rules out persistent shocks, i.e. there cannot be correlation between  $\varepsilon_t$  and  $\varepsilon_{t+1}$  conditional on  $(x_{t+1}, y_{t+1})$ .

- As a result of the random utility term, Bellman's equation becomes

$$\begin{aligned} U_x^t &= \mathbb{E}_{\mathbf{P}_{xt}} \left[ \max_{y \in \mathcal{Y}} \left\{ u_{xy}^t + \sum_{x'} U_{x'}^{t+1} P_{x'|xy} + \varepsilon_y \right\} \right] \\ &= G_{xt}(u_x^t + \sum_{x'} U_{x'}^{t+1} P_{x'|x}). \end{aligned}$$

- Set  $W_{xt}(U) = G_{x(t-1)}(u_x^{t-1} + \sum_{x'} U_{x'}^t P_{x'|x})$  for  $1 < t < T$ , the equation becomes

$$U_x^{t-1} = W_{xt}(U).$$

- Note that

$$\frac{\partial W_{xt}(U)}{\partial U_{x'}} = \sum_y P_{x'|xy} \sigma_{x(t-1),y}$$

is the conditional probability of a transition to  $x'$  given being at  $x$  at time  $t-1$ , denoted  $\mu_{x'|x}^{t-t}$ .

- In the logit case, one has

$$U_x^t = \log \sum_{y \in \mathcal{Y}} \exp \left( u_{xy}^t + \sum_{x'} U_{x'}^{t+1} P_{x'|xy} \right)$$

- Setting  $V_x^t = \exp(U_x^t)$  and  $v_{xy}^t = \exp(u_{xy}^t)$ , this becomes an algebraic expression

$$V_x^t = \sum_{y \in \mathcal{Y}} v_{xy}^t \prod_{x' \in \mathcal{X}} (V_{x'}^t)^{P_{x'|xy}}.$$

- The dual problem can be expressed as:

$$\begin{aligned} \min_{U_x^t, x \in \mathcal{X}} \sum n_x U_x^1 \\ \text{s.t. } U_x^{t-1} = W_{xt}(U^t) \quad 1 < t \leq T \\ U_x^T = G_{xT}(u_x^T) \end{aligned} \tag{1}$$

- In the logit case, with  $V_x^t = \exp(U_x^t)$  and  $v_{xy}^t = \exp(v_{xy}^t)$ , one has

$$\begin{aligned} \min_{U_x^t, t \in T, x \in \mathcal{X}} \sum_{x \in \mathcal{X}} n_x \log V_x^1 \\ \text{s.t. } V_x^t = \sum_{y \in \mathcal{Y}} v_{xy}^t \prod_{x' \in \mathcal{X}} (V_{x'}^t)^{P_{x'|xy}}, \quad t < T \\ V_x^T = \sum_{y \in \mathcal{Y}} v_{xy}^T. \end{aligned}$$



- Set  $n_x^t$  the Lagrange multipliers associated with the constraints. First order conditions in the dual problem yield

$$n_x = n_x^1$$
$$n_x^t = \sum_{x'} \frac{\partial W_{x(t-1)}}{\partial U_{x'}^{t-1}} n_{x'}^{t-1}, 1 < t \leq T$$

- The second line are Kolmogorov-forward equations (forward propagation of mass)

$$\sum_{x'} \mu_{x'|x}^{t-t} n_{x'}^{t-1} = n_x^t.$$

- Let  $W_t(U^t; n^{t-1}) = \sum_x n_x^{t-1} W_{xt}(U_x^t)$ , and let  $W_t^*(n^t; n^{t-1})$  be its Legendre transform with respect its first variable.
- **Theorem:** the value of the primal problem is

$$\max_{n^t} \left\{ \sum_{x \in \mathcal{X}} n_x^T G_{xt}(u_{x.}^T) - \sum_{\substack{x \in \mathcal{X} \\ 1 \leq t \leq T}} W_t^*(n^t; n^{t-1}) \right\}$$

s.t.  $n_x^1 = n_x$

- Start from the dual

$$\begin{aligned} \min_{U_x^t} \quad & \sum_{x \in \mathcal{X}} n_x U_x^1 \\ \text{s.t.} \quad & U_x^{t-1} = W_{xt}(U^t) \quad 1 < t \leq T \\ & U_x^T = G_{xT}(u_{x.}^T) \end{aligned} \tag{2}$$

- Write the saddlepoint formulation

$$\min_{U^t} \max_{n^t} \left\{ \begin{aligned} & \sum_{x \in \mathcal{X}} n_x U_x^1 - \sum_{x, 1 \leq t \leq T} n_x^t U_x^t \\ & + \sum_{x, 1 < t \leq T} n_x^{t-1} W_{xt}(U^t) \\ & + \sum_x n_x^T G_{xT}(u_{x.}^T) \end{aligned} \right\}$$

- Saddlepoint rewrites

$$\max_{n^t} \min_{U^t} \left\{ \sum_x n_x^T G_{xt}(u_x^T) + \sum_x (n_x - n_x^1) U_x^1 \right. \\ \left. + \sum_{1 < t \leq T} n_x^{t-1} W_{xt}(U_x^t) - n_x^t U_x^t \right\}$$

- Recall that  $W_t(U^t; n^{t-1}) = \sum_x n_x^{t-1} W_{xt}(U_x^t)$ , and  $W_t^*(n^t; n^{t-1})$  be its Legendre transform with respect its first variable, one has

$$\max_{n_x^t, t \geq 1} \left\{ \sum_{t < T} n_x^T G_{xt}(u_x^T) - \sum_{1 < t \leq T} W_t^*(n^t; n^{t-1}) \right\} \\ \text{s.t. } n_x^1 = n_x$$

QED.

► Recall

$$\begin{aligned} \max_{n_x^t, t \geq 1} & \left\{ \sum_{t < T} n_x^T G_{xt}(u_x^T) - \sum_{1 < t \leq T} W_t^* \left( n^t; n^{t-1} \right) \right\} \\ \text{s.t. } & n_x^1 = n_x \end{aligned}$$

► For  $1 \leq t < T$ , one has

$$\frac{\partial W_t^*}{\partial n_x^t} \left( n^t; n^{t-1} \right) + \frac{\partial W_{t+1}^*}{\partial n_x^t} \left( n^{t+1}; n^t \right) = 0,$$

and note that

$$\frac{\partial W_t^*}{\partial n_x^t} = U_x^t \text{ and } \frac{\partial W_{t+1}^*}{\partial n_x^t} \left( n^{t+1}; n^t \right) = -W_{xt+1}(U^{t+1})$$

hence the first order condition recovers the Bellman equation.

- One has

$$W_t(U; n^{t-1}) = \sum_x n_x^{t-1} \log \sum_{y \in \mathcal{Y}} \exp \left( u_{xy}^{t-1} + \sum_{x'} U_{x'}^t P_{x'|xy} \right)$$

and thus

$$\begin{aligned} & W_t(n^t; n^{t-1}) \\ &= \max_U \left\{ \sum_x n_x^t U_x - \sum_x n_x^{t-1} \log \sum_{y \in \mathcal{Y}} \exp \left( u_{xy}^{t-1} + \sum_{x'} U_{x'}^t P_{x'|xy} \right) \right\} \end{aligned}$$

- Sadly, no closed-form formula.

- Rust studies the infinite-horizon version of the problem, in which case  $u_{xy}^t$  does not depend on  $t$ , and, if  $\beta > 0$  is a discount factor, then the intertemporal utility is given by the set of equations

$$U_x = W_x(\beta U),$$

where  $W_x(\beta U) = \mathbb{E} \left[ \max_y \left\{ u_{xy} + \sum_{x'} \beta U_{x'} P_{x'|xy} + \varepsilon_y \right\} \right]$ .

- It's possible to show that  $(U_x) \rightarrow (W_x(\beta U))$  is a contraction mapping, so the above equation has a unique solution.

► Let

$$w_{xy} = u_{xy} + \sum_{x'} \beta U_{x'} P_{x'|xy}$$

We have

$$\begin{cases} w_{xy} = \ln \pi_{y|x} + a_x \\ U_x = \log \sum_y \exp w_{xy} \end{cases}$$



- If we choose the normalization  $u_{x0} = 0$ , we have

$$w_{x0} = \sum_{x'} \beta U_{x'} P_{x'|x0}$$

and

$$w_{xy} - w_{x0} = \ln \frac{\pi_{y|x}}{\pi_{0|x}}$$

- Hence

$$U_x = w_{x0} - \log \pi_{0|x}$$

- Thus

$$U_x = \sum_{x'} \beta U_{x'} P_{x'|x0} - \log \pi_{0|x} \quad (3)$$

- Let  $L$  be the column vector whose general term is  $(\log \pi_{y|0})_{x \in \mathcal{X}}$ , let  $U$  be the column vector whose general term is  $(U_x)_{x \in \mathcal{X}}$ , and let  $\Pi$  be the  $|\mathcal{X}| \times |\mathcal{X}|$  matrix whose general term is

$$\Pi_{xx'} = Pr(x_{t+1} = x' | x_t = x, y = 0).$$

Equation (3), rewritten in matrix notation, is

$$L = (\beta \Pi - I) U$$

- It is possible to show that for  $\beta < 1$ , matrix  $I - \beta \Pi^0$  is invertible. Thus Equation (3) becomes

$$U = (\beta \Pi - I)^{-1} L. \tag{4}$$

- Therefore  $U_x$  is identified from data.

- It follows that all the remaining quantities are also identified by

$$w_{x0} = U_x + \log \pi_{0|x}$$

$$w_{xy} = w_{x0} + \log \frac{\pi_{y|x}}{\pi_{0|x}}$$

$$u_{xy} = w_{xy} - \beta \mathbb{E}[U_{x'} | x, y]$$