

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

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Day 5, January 19 2018: "Empirical matching models"

Block 15. Rank constrained models

- ▶ affinity matrix
- ▶ index models
- ▶ rank-constraint models

- ▶ Becker (1973). A Theory of Marriage: Part I. *JPE*.
- ▶ [COQ] Chiappori, Oreffice and Quintana-Domeque (2012). “Fatter Attraction: Anthropometric and Socioeconomic Matching on the Marriage Market,” *Journal of Political Economy*.

- Chiappori, Oreffice and Quintana-Domeque [COQ] assume individuals match on a scalar “index of attractiveness” subsuming BMI, salary, education. Then the surplus function is

$$\Phi(x, y) = \left(\sum_k \zeta_k x_k \right) \left(\sum_l \nu_l y_l \right)$$

$\zeta_k / \zeta_{k'}$ and $\nu_l / \nu_{l'}$ are marginal rates of substitution: how much richer do men/women need to be in order to compensate an increase in Body Mass Index?

- This problem can be solved by looking for the vectors of weights ζ and ν such that the rank correlation of $\zeta^T x$ and $\nu^T y$ is maximal.

- ▶ [COQ] look at the characteristics of married couples, in particular body mass index, wages, and education.
- ▶ According to [COQ] (*Journal of Political Economy*, 2012): “Men may compensate 1.3 additional units of BMI with a 1%-increase in wages, while women may compensate two BMI units with one year of education.”

► Recall

$$\mathcal{W}(A) = \max_{\pi \in \mathcal{M}(P, Q)} \int x' A y d\pi(x, y) - \sigma \int \pi(x, y) d\pi(x, y).$$

and note that

$$\frac{\partial \mathcal{W}(A)}{\partial A_{ij}} = C_{ij}^A$$

- We are therefore looking for the estimator \hat{A} of the true A such that $\partial \mathcal{W}(A) / \partial A_{ij} = \hat{C}_{ij}$.
- Thus we shall estimate A by \hat{A} the solution of

$$\min_A \left\{ \mathcal{W}(A) - \sum_{ij} A_{ij} \hat{C}_{ij} \right\}$$

which is a nice and smooth convex minimization problem.

- Several proposal to estimate ζ and ν :

1. Becker (1973): use Hotelling's canonical correlation analysis

$$\max_{\zeta, \nu} \mathbb{E} [\zeta^T X Y^T \nu],$$

which is unbiased if (X, Y) is Gaussian. Can be biased outside that case, cf. Dupuy-Galichon (AES, 2015).

2. Chiappori, Oreffice and Quintana-Domeque (JPE 2013): when Y is 1-dimensional, regress Y on X .
3. Terviö (AER 2007): maximize Spearman's rank correlation

$$\max_{\zeta, \nu} \mathbb{E} [F_{\zeta^T X} (\zeta^T X) F_{\nu^T Y} (\nu^T Y)],$$

where $F_{\zeta^T X}$ and $F_{\nu^T Y}$ are the cdfs of $\zeta^T X$ and $\nu^T Y$ respectively.

4. In the spirit of Han (JE 1987), maximize

$$\sum_{ij} (1 \{ \zeta^T X_i > \zeta^T X_j \} 1 \{ \nu^T Y_i > \nu^T Y_j \} + 1 \{ \zeta^T X_i < \zeta^T X_j \} 1 \{ \nu^T Y_i < \nu^T Y_j \})$$

5. Dupuy-Galichon-Sun (2017): perform rank-constrained estimation of $\Phi(x, y) = x' A y$ using nuclear norm regularization.

- Recall that any $d \times d$ matrix A has a singular value decomposition

$$A = U\Lambda V^T$$

where U and V are orthogonal matrices, and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_d)$ is diagonal with positive entries ordered in descending order, i.e.

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d \geq 0.$$

- Note:
 - Λ are the eigenvalues of AA^T , and also of $A^T A$.
 - If A is symmetric positive, then Λ are the eigenvalues of A
 - The rank of A is the number of nonzero entries of λ .
- The nuclear norm of A , denoted $|A|_*$, is simply the L1 norm of λ , that is

$$|A|_* = \sum_{i=1}^d \lambda_i.$$

- Controlling for nuclear norm is a good proxy for controlling for rank.
- Further, the nuclear norm is convex.

- The nuclear norm can be expressed as

$$|A|_* = \max_{U, V \in O_d} \text{Tr}(U^T A V)$$

from which its gradient may be inferred (from the envelope theorem).

- In general, one can use the nuclear norm for problems of the type

$$\min_A W(A) + \gamma |A|_*$$

which will drive low-rank solutions.

Section 1

CODING

- We apply this technique to the personality trait dataset.