# **Numerical Optimization**

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Spring 2025

# Example: Generalized Method of Moments (GMM)

- Sample size *n*. Moment conditions

$$\hat{m}(\theta) \equiv \frac{1}{n} \sum_{i=1}^{n} m_i(\theta) = 0 \tag{1}$$

- GMM estimator:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \hat{m}(\theta)' \hat{W} \hat{m}(\theta) \tag{2}$$

- Example:
  - Linear IV:  $m_i(\theta) = z_i(y_i x_i'\theta)$
  - Logistic IV:  $m_i(\theta) = z_i \left( y_i \frac{1}{1 + \exp\left[-x_i'\theta\right]} \right)$

# Example: Generalized Method of Moments (GMM)

- Asymptotic:

$$\sqrt{n}\left(\hat{\theta}-\theta_{0}\right)\rightarrow_{d}N\left(0,V\right)$$
 (3)

where 
$$V = (G'WG)^{-1} G'WV_mWG (G'WG)^{-1}$$
,  $G = G(\theta_0) = \nabla_{\theta'} m(\theta_0)$  and  $V_m = Var[m(\theta_0)]$ 

- Estimate *V*:
  - $\hat{G} = \frac{1}{n} \sum_{i=1}^{n} \nabla_{\theta'} m_i \left( \hat{\theta} \right)$
  - $\hat{V}_{m} = \frac{1}{n} \sum_{i=1}^{n} m_{i} \left(\hat{\theta}\right) m_{i} \left(\hat{\theta}\right)' \left[\frac{1}{n} \sum_{i=1}^{n} m_{i} \left(\hat{\theta}\right)\right] \left[\frac{1}{n} \sum_{i=1}^{n} m_{i} \left(\hat{\theta}\right)\right]'$
- Optimal *W*:
  - If  $W=V_m^{-1}$ , then  $V=\left[G'V_m^{-1}G\right]^{-1}$

#### Newton-Raphson Method

- One-dimension unconstrained optimization:  $\min_{x} f(x)$ 
  - The second-order Taylor expansion around initial guess  $x_0$ :  $f(x_0 + t) = f(x_0) + f'(x_0) t + \frac{1}{2}f''(x_0) t^2$
  - FOC:  $f'(x_0) + f''(x_0) t = 0 \Rightarrow t = -\frac{f'(x_0)}{f''(x_0)}$
  - Iteration:  $x_k = x_{k-1} \frac{f'(x_{k-1})}{f''(x_{k-1})}$  for k = 1, 2, ...
- Higher dimensions:

$$\mathbf{x}^{(k)} = \mathbf{x}^{(k-1)} - \underbrace{\left[\nabla_{\mathbf{x}^2}^2 f\left(\mathbf{x}^{(k-1)}\right)\right]^{-1}}_{\text{Hessian}} \underbrace{\nabla_{\mathbf{x}} f\left(\mathbf{x}^{(k-1)}\right)}_{\text{Jacobian}}$$
(4)

# Broyden-Fletcher-Goldfarb-Shano (BFGS) Method

- Approximate the inverse of the Hessian matrix: initial guess  $B_0 = \mathbf{I}$
- Let  $\mathbf{h} = \mathbf{x}^{(1)} \mathbf{x}^{(0)}$  and  $\mathbf{y} = \nabla_{\mathbf{x}} f\left(\mathbf{x}^{(1)}\right) \nabla_{\mathbf{x}} f\left(\mathbf{x}^{(0)}\right)$ . By the definition of the Hessian matrix, we want to obtain  $B_1$  such that  $B_1\mathbf{y} = \mathbf{h}$
- Update  $B_1=B_0-rac{B_0{f y}y'B_0}{{f y}'B_0{f y}}+rac{{f h}{f h}'}{{f y}'{f h}}.$  It is straightforward to verify that  $B_1{f y}={f h}$
- Update  $\mathbf{x}^{(k)} = \mathbf{x}^{(k-1)} B_{k-1} f\left(\mathbf{x}^{(k-1)}\right)$  for  $k=1,2,\ldots$

# Newton and Quasi-Newton Methods: Example

- Solve  $\min_{x_1, x_2} f(x_1, x_2) = -\log(1 2x_1 x_2) \log x_1 \log x_2$
- Jacobian matrix:

$$J(x) = \begin{bmatrix} \frac{2}{1 - 2x_1 - x_2} - \frac{1}{x_1} \\ \frac{1}{1 - 2x_1 - x_2} - \frac{1}{x_2} \end{bmatrix}$$
 (5)

- Hessian matrix:

$$H(x) = \begin{bmatrix} \frac{4}{(1-2x_1-x_2)^2} + \frac{1}{x_1^2} & \frac{2}{(1-2x_1-x_2)^2} \\ \frac{2}{(1-2x_1-x_2)^2} & \frac{1}{(1-2x_1-x_2)^2} + \frac{1}{x_2^2} \end{bmatrix}$$
 (6)

# Example: Optimal Tariffs in the Armington Model

- Mathematical programming with equilibrium constraints (MPEC): for some country  $n^*$ 

$$\max_{\left(\widehat{1+t_{in^*}};\hat{w}_{i},\hat{X}_{i},\hat{P}_{i}\right)_{i=1}^{N}} \hat{U}_{n^*} \equiv \frac{\hat{X}_{n^*}}{\hat{P}_{n^*}}$$
s.t.
$$\hat{w}_{i}w_{i}L_{i} = \sum_{n=1}^{N} \frac{1}{1+t'_{in}} \hat{\lambda}_{in}\hat{X}_{n}\lambda_{in}X_{n}, \quad \hat{\lambda}_{in} = \frac{(\hat{w}_{i}\hat{\kappa}_{in})^{1-\sigma}}{\sum_{k=1}^{N} \lambda_{kn} (\hat{w}_{k}\hat{\kappa}_{kn})^{1-\sigma}}, \quad \hat{\kappa}_{in} = \widehat{1+t_{in}}$$

$$\hat{X}_{n}X_{n} = \hat{w}_{n}w_{n}L_{n} + \sum_{i=1}^{N} \frac{t'_{in}}{1+t'_{in}} \hat{\lambda}_{in}\hat{X}_{n}\lambda_{in}X_{n}$$

$$\hat{P}_{i} = \left[\sum_{k=1}^{N} \lambda_{ki} (\hat{w}_{k}\hat{\kappa}_{ki})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$
(7)

#### Constrained Optimization

- General form of MPEC: policies s; equilibrium outcomes x

$$\max_{\mathbf{s},\mathbf{x}} O(\mathbf{x}, \mathbf{s})$$
s.t.  $F(\mathbf{x}, \mathbf{s}) = 0$  (8)

- General form of constrained optimization:

$$\min_{\mathbf{x}} O(\mathbf{x})$$
s.t.
$$F_{i}(\mathbf{x}) = 0, \quad i = 1, ..., I$$

$$G_{j}(\mathbf{x}) \leq 0, \quad j = 1, ..., J$$
(9)

#### Constrained Optimization

- Lagrange function:

$$\mathcal{L}(\mathbf{x}, \mu, \lambda) \equiv O(\mathbf{x}) + \mu' F(\mathbf{x}) + \lambda' G(\mathbf{x})$$
(10)

- Karush-Kuhn-Tucker (KKT) conditions:

- FOC: 
$$\nabla_{\mathbf{x}} \mathcal{L}\left(\mathbf{x}^*, \mu^*, \lambda^*\right) \equiv \nabla_{\mathbf{x}} O\left(\mathbf{x}^*\right) + \sum_{i=1}^{J} \mu_i^* \nabla_{\mathbf{x}} F_i\left(\mathbf{x}^*\right) + \sum_{j=1}^{J} \lambda_j^* \nabla_{\mathbf{x}} G_j\left(\mathbf{x}^*\right) = 0$$

- 
$$F_i(\mathbf{x}^*) = 0, \quad i = 1, ..., I$$

- 
$$\lambda_{j}^{*} \geq 0$$
 and  $\lambda_{j}^{*} G_{j}(\mathbf{x}^{*}) = 0$ 

- In practice: Constrained ⇒ Unconstrained
  - Interior point (Barrier) methods: Barrier function
  - Active set methods: KKT

## Constrained Optimization: Example

- Problem:

$$\min_{x_1 \ge 0, x_2 \ge 0} 2x_1^2 - 12x_1 + 3x_2^2 - 18x_2 + 45$$
s.t.
$$3x_1 + x_2 \le 12$$

$$x_1 + x_2 \le 6$$
(11)

## Mutual Optimization: Nash Equilibria

- 1. Initial guess  $(t'_{in})^{(0)}$  for all i, n
- 2. For each n, solve for the welfare-maximizing  $(t'_{in})$ , given  $(t'_{i,-n})^{(0)}$ :  $(t'_{in})^{(1)}$
- 3. Iterate until  $(t'_{ip})^{(k)} = (t'_{ip})^{(k-1)}$

### Example: Nash Tariffs between the U.S. and China

#### For some country k:

$$\max_{\substack{(t'_{ik})_{i\neq k}: (\hat{w}_{i}, \hat{X}_{i}, \hat{P}_{i})_{i=1}^{N}}} \hat{U}_{k} \equiv \frac{\hat{X}_{k}}{\hat{P}_{k}}$$
s.t.
$$\hat{P}_{n} = \left[ \sum_{i=1}^{N} \lambda_{in} (\hat{w}_{i} \hat{\kappa}_{in})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

$$\hat{w}_{i} w_{i} L_{i} = \sum_{n=1}^{N} \frac{1}{1 + t'_{in}} \hat{\lambda}_{in} \hat{X}_{n} \lambda_{in} X_{n}, \quad \hat{\lambda}_{in} = \frac{(\hat{w}_{i} \hat{\kappa}_{in})^{1-\sigma}}{\sum_{i'=1}^{N} \lambda_{i'} n (\hat{w}_{i'} \hat{\kappa}_{i'})^{1-\sigma}}, \quad \hat{\kappa}_{in} = \widehat{1 + t_{in}}$$

$$\hat{X}_{n} X_{n} = \hat{w}_{n} w_{n} L_{n} + \sum_{i=1}^{N} \frac{t'_{in}}{1 + t'_{in}} \hat{\lambda}_{in} \hat{X}_{n} \lambda_{in} X_{n}$$
(12)

# Nested Fixed Point (NFXP)

- MPEC:

$$\max_{\mathbf{s},\mathbf{x}} O(\mathbf{x}, \mathbf{s})$$

$$\mathbf{s.t.} F(\mathbf{x}, \mathbf{s}) = 0$$
(13)

- NFXP
  - $F(\mathbf{x}, \mathbf{s}) = 0 \Rightarrow \mathbf{x} = H(\mathbf{s})$  (inner loop)
  - $\max_{s} O(H(s), s)$  (outer loop)
- FOC: for  $\mathbf{x}^* = H(\mathbf{s}^*)$ 
  - $\nabla_{\mathbf{x}} O(\mathbf{x}^*, \mathbf{s}^*) \nabla_{\mathbf{s}} H(\mathbf{s}^*) + \nabla_{\mathbf{s}} O(\mathbf{x}^*, \mathbf{s}^*) = 0$
  - $\nabla_{\mathbf{s}} H(\mathbf{s}^*)$ : Implicit Differentiation

$$\nabla_{\mathbf{s}} H(\mathbf{s}^*) = -\left[\nabla_{\mathbf{x}} F(\mathbf{x}^*, \mathbf{s}^*)\right]^{-1} \nabla_{\mathbf{s}} F(\mathbf{x}^*, \mathbf{s}^*)$$
(14)

## Example: Optimal Spatial Transfers

- N regions. Total labor  $\bar{L}$ , freely mobile
- Each region produces a distinctive variety. Representative consumer in region n has a CES utility:

$$U_n = B_n \left[ \sum_{i=1}^N C_{in}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1$$
 (15)

where amenity  $B_n \equiv \bar{B}_n L_n^{-\beta}$  and  $L_n$  is the labor in region n

- Each variety is produced using labor under perfect competition. Unit cost:

$$c_i = \frac{w_i}{A_i}, \quad A_i = \bar{A}_i L_i^{\alpha} \tag{16}$$

- Iceberg trade cost  $\tau_{in} \geq 1$ . Price index in region n:

$$P_n^{1-\sigma} = \sum_{i=1}^{N} \left(\frac{w_i \tau_{in}}{A_i}\right)^{1-\sigma} \tag{17}$$

# **Example: Optimal Spatial Transfers**

- Wage tax/subsidy+Welfare equalization:

$$U = U_n = B_n \frac{(1 + s_n) w_n}{P_n} \tag{18}$$

- Labor allocation and welfare:

$$\frac{L_n}{\bar{L}} = \frac{\left[\bar{B}_n \frac{(1+s_n)w_n}{P_n}\right]^{\frac{1}{\beta}}}{\sum_{k=1}^{N} \left[\bar{B}_k \frac{(1+s_k)w_k}{P_k}\right]^{\frac{1}{\beta}}} \quad U = \left[\sum_{k=1}^{N} \left[\bar{B}_k \frac{(1+s_k)w_k}{P_k}\right]^{\frac{1}{\beta}}\right]^{\beta} \tag{19}$$

- Governmental budget balance:

$$\sum_{n=1}^{N} s_n w_n L_n = 0 \tag{20}$$

# Example: Optimal Spatial Transfers

- Optimal spatial transfers:  $(s_n^*)$ 

$$\max_{(s_{n}:w_{n},P_{n},L_{n})_{n=1}^{N}} U = \left[ \sum_{k=1}^{N} \left[ \bar{B}_{k} \frac{(1+s_{k}) w_{k}}{P_{k}} \right]^{\frac{1}{\beta}} \right]^{\beta}$$
s.t.
$$w_{i}L_{i} = \sum_{n=1}^{N} \lambda_{in} (1+s_{n}) w_{n}L_{n}, \quad \lambda_{in} \equiv \frac{X_{in}}{X_{n}} = \frac{\left(\frac{w_{i}\tau_{in}}{\bar{A}_{i}L_{i}^{\alpha}}\right)^{1-\sigma}}{\sum_{k=1}^{N} \left(\frac{w_{k}\tau_{kn}}{\bar{A}_{k}L_{k}^{\alpha}}\right)^{1-\sigma}}$$

$$\frac{L_{n}}{\bar{L}} = \frac{\left[\bar{B}_{n} \frac{(1+s_{n})w_{n}}{P_{n}}\right]^{\frac{1}{\beta}}}{\sum_{k=1}^{N} \left[\bar{B}_{k} \frac{(1+s_{k})w_{k}}{P_{k}}\right]^{\frac{1}{\beta}}}, \quad P_{n}^{1-\sigma} = \sum_{i=1}^{N} \left(\frac{w_{i}\tau_{in}}{\bar{A}_{i}L_{i}^{\alpha}}\right)^{1-\sigma}$$

$$\sum_{n=1}^{N} s_{n}w_{n}L_{n} = 0$$
(21)

## Multiple Equilibria and Global Optimization

- When  $\alpha > \beta$ , there could be multiple equilibria
- Local optima under multiple equilibria: how to find the globally optimal spatial transfers?
  - In general, a very difficult problem
  - Simulated annealing: a probabilistic technique for approximating the global optimum of a given function

## Simulated Annealing

- Annealing:
  - Heating a metal to a high temperature, allowing its atoms to move freely within the structure
  - As the metal is slowly cooled, the atoms gradually settle into a low-energy crystalline configuration
- Optimization:  $min_x f(x)$ 
  - 1. Initial guess x<sub>0</sub>
  - 2. Given a constant  $c_0 > 0$ 
    - 2.1 Generate  $x_1$  from the neighborhood of  $x_0$  (perturbation techniques)
    - 2.2 If  $f(\mathbf{x}_1) < f(\mathbf{x}_0)$ ,  $\mathbf{x}_1$  becomes the current solution
    - 2.3 If  $f(\mathbf{x}_1) \geq f(\mathbf{x}_0)$ ,  $\mathbf{x}_1$  becomes the current solution with probability  $\exp\left[\frac{f(\mathbf{x}_0) f(\mathbf{x}_1)}{c_0}\right]$
  - 3. Decrease  $c_0$  based on a pre-specified rule: e.g.  $c_1 = 0.85 * c_0$
  - 4. Iterate until  $c_k \simeq 0$

# Simulated Annealing

- Example:  $f(x) = \sin(x) + \sin(\frac{10}{3}x)$  for  $x \in [-\pi, \pi]$ 
  - The global minima is  $x \simeq -2.30$  with  $f(x) \simeq -1.73$
  - Starting from x = 0, search the global minima using simulated annealing

## Summary

- Unconstrained optimization
- Constrained optimization: MPEC
- Globally optimal: simulated annealing