Maximum Simulated Likelihood

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What is Maximum (Non-Simulated) Likelihood?

- $(X_1 \sim P_1, \dots, X_N \sim P_N)$ is a collection of random vectors
    - Not necessarily independent and not necessarily identically distributed
- Each P_i depends on some common parameter vector $\theta \in \Theta$
- For convenience, assume that $(X_1 \sim P_1, \dots, X_N \sim P_N)$ are independent
- The **likelihood function** of θ is the joint distribution of $(X_1, \dots, X_N)$ under θ and evaluated at $\boldsymbol{x}$:

$$L(\theta|\boldsymbol{x}) = f\left(\boldsymbol{x}|\theta\right) = \prod_{i=1}^{N} P_i\left(x_i; \theta\right)$$

- The **log-likelihood function** of θ is

$$LL(\theta|\boldsymbol{x}) = \log f\left(\boldsymbol{x}|\theta\right) = \sum_{i=1}^{N} \log P_i\left(x_i; \theta\right)$$

What is Maximum (Non-Simulated) Likelihood?

- Then a **maximum likelihood estimator** of θ is

$$\widehat{\theta}_{ML} \in \arg\max_{\widetilde{\theta}} L\left(\widetilde{\theta}|\boldsymbol{x}\right) \iff \widehat{\theta}_{ML} \in \arg\max_{\widetilde{\theta}} LL\left(\widetilde{\theta}|\boldsymbol{x}\right)$$

- What if there is **no closed form** for $\{P_i(\cdot;\theta)\}_{i=1}^{N}$?

- Those masses/densities could be approximated with simulation...

What is Maximum Simulated Likelihood?

- The **simulated likelihood function** of θ is a simulated approximation to the joint distribution of $(X_1, \ldots, X_N)$ under θ and evaluated at $\boldsymbol{x}$:

$$SL(\theta|\boldsymbol{x}) = \check{f}\left(\boldsymbol{x}|\theta\right) = \prod_{i=1}^{N} \check{P}_i\left(x_i;\theta\right)$$

  where $\check{P}_i$ is a simulated approximation to P_i

- The **simulated log-likelihood function** of θ is

$$SLL(\theta|\boldsymbol{x}) = \log \check{f}\left(\boldsymbol{x}|\theta\right) = \sum_{i=1}^{N} \log \check{P}_i\left(x_i;\theta\right)$$

- Then a **maximum simulated likelihood estimator** of θ is

$$\widehat{\theta}_{MSL} \in \arg\max_{\widetilde{\theta}} SL\left(\widetilde{\theta}|\boldsymbol{x}\right) \iff \widehat{\theta}_{MSL} \in \arg\max_{\widetilde{\theta}} SLL\left(\widetilde{\theta}|\boldsymbol{x}\right)$$

A Simple Example: Mixed Logit

- Consider the indirect utility function with **random coefficients**:

$$V_{ij} = X_{ij}'\beta_i + \varepsilon_{ij} \quad \text{with} \quad \beta_i \sim f(\beta;\theta)$$

- $\varepsilon_{ij} \overset{\text{iid}}{\sim}$ T1EV, so individual choice probabilities (conditional on β_i) are

$$P(X_{ij})\,|\beta_i = \frac{e^{X_{ij}'\beta_i}}{\sum_{k=0}^{J} e^{X_{ik}'\beta_i}}$$

- β_i is random, so let us integrate it out:

$$P(X_{ij};\theta) = \int \frac{e^{X_{ij}'\beta_i}}{\sum_{k=0}^{J} e^{X_{ik}'\beta_i}} f(\beta_i;\theta)\, d\beta_i$$

A Simple Example: Mixed Logit

- Oh no! That integral may **not** have a **closed form**!
- But wait, if we assumed $f(\beta;\theta)$, we could **simulate** it...
  1. Draw β^r from $f(\beta;\theta)$
  2. Compute $P(X_{ij})|\beta^r$
  3. Repeat (1) and (2) R times, with $R \gg 0$
  4. Compute the simple average of $\{P(X_{ij})|\beta^r\}_{r=1}^{R}$
- A **simulated approximation** to the individual choice probability is

$$\check{P}(X_{ij};\theta) = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{X_{ij}'\beta^r}}{\sum_{k=0}^{J} e^{X_{ik}'\beta^r}}$$

A Simple Example: Mixed Logit

- Almost done...
- Now we can compute the **simulated log likelihood**:

$$SLL(\theta|\boldsymbol{x}) = \sum_{i=1}^{N} \sum_{j=0}^{J} D_{ij} \log \check{P}\left(X_{ij};\theta\right)$$

where $D_{ij} = 1$ if individual i chose good j, and 0 otherwise

- A **maximum simulated likelihood estimator** of θ is

$$\widehat{\theta}_{MSL} \in \arg\max_{\widetilde{\theta}} SLL\left(\widetilde{\theta}|\boldsymbol{x}\right)$$

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- Consider a dynamic program with **finite horizon**, $t \in \{0, \ldots, T\}$
- In each period, agents choose **one of K possible alternatives**
- Alternatives are mutually exclusive, so **decisions** are

$$d_k(t) = \begin{cases} 0 & \text{if } k \text{ is not chosen at time } t \\ 1 & \text{if } k \text{ is chosen at time } t \end{cases}$$

- A **current period reward** is associated with choice k at time t, $R_k(t)$
- The **state space** at time t is $S(t)$

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

The **value function** depends on both state space and time horizon:

$$V\left(S(t), t\right) = \max\left\{V_1\left(S(t), t\right), \dots, V_K\left(S(t), t\right)\right\}$$

where each **choice value function** obeys the Bellman equation

$$V_k\left(S(t), t\right) = \begin{cases} R_k(S(t), t) + \delta\mathbb{E}\left[V\left(S(t+1), t+1\right) | S(t), d_k(t) = 1\right] & \text{if } t < T \\ R_k(S(t), t) & \text{if } t = T \end{cases}$$

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- Labor supply is discrete: **zero (0), part-time (1), full-time (2)**
- Per-period reward functions are given by

$$R_0(S(t), t) = \gamma + \varepsilon_{0t}$$
$$R_1(S(t), t) = w_1(x_t) + \varepsilon_{1t}$$
$$R_2(S(t), t) = w_2(x_t) + \varepsilon_{2t}$$

where γ is a constant and $\boldsymbol{w}$ are wage offers

- The **state space** is

$$S(t) = \{x_t, \varepsilon_{0t}, \varepsilon_{1t}, \varepsilon_{2t}\}$$

where x_t denotes experience and $\boldsymbol{\varepsilon}_t$ are shocks to the value of non-market time or labor productivity shocks

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- The **state space evolves** according to

$$x_{t+1} = x_t + 0.5 \times d_1(t) + 1 \times d_2(t)$$
$$f\left(\varepsilon_{t+1} | S(t), d_k(t)\right) = f\left(\varepsilon_{t+1} | x_t, d_k(t)\right)$$

- Working:
  - part time increases the experience stock by 0.5
  - full time increases the experience stock by 1
- We also assume shocks are **serially independent**
  - Issues become even more clear if you relax this assumption

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- Recall that the value function is

$$V\left(S(t),t\right) = \max\left\{V_0\left(S(t),t\right), V_1\left(S(t),t\right), V_2\left(S(t),t\right)\right\}$$

- Then, at time $t-1$ and **for all choices $\boldsymbol{k}$**, agents must compute the **expected maximum** of the choice-specific value functions

$$\mathbb{E}\left[\max\left\{V_0\left(S(t),t\right), V_1\left(S(t),t\right), V_2\left(S(t),t\right)\right\} | S(t-1), d_k(t-1)\right]$$

where $\mathbb{E}\left[\cdot\right]$ is a **three-variate multiple integral** with respect to the joint distribution of ε

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- Solve the model by **backward recursion**
- At time T there is no future, so choice is based on per-period reward
- At time $T-1$, the expected maximum must be computed for all k possible choices and all possible realizations of x_{T-1}
- When you reach time 0, you need to have computed **all possible** choice-specific value functions (*paths* of possible state realizations)!
- This becomes even worse if the ε shocks are not serially independent
- How to **avoid computing** all of these three-variate multiple integrals with no closed form?

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- Before finding out, one step back...
- **Why are we doing this?**
- Our goal is NOT to solve the model per se, but solve the model in order to **estimate structural parameters**, for instance δ and γ
- In practice, we have **a panel** with **observed labor supply choices**
- If someone with 9 years of experience worked part time in $t = 2007$

$$\mathbb{P}\left(d_1(t) = 1, w_{1t} | x_t = 9\right) = \mathbb{P}\left(w_{1t}, V_1(S(t), t) \geq V_0(S(t), t), V_1(S(t), t) \geq V_2(S(t), t)\right)$$

- This is **one term** in the likelihood function!

MSL and Dynamic Discrete Choice: Keane & Wolpin (1994)

- **If** we could compute integrals, we would multiply those $\mathbb{P}(\cdot)$ across i and over t, and obtain the maximum likelihood estimator

- But since we cannot, Keane and Wolpin (1994) proposes a method based on **simulation**
  1. Take a draw r from the joint distribution of $\boldsymbol{\varepsilon} \equiv (\varepsilon_0, \varepsilon_1, \varepsilon_2)$
  2. Calculate $V_0^r(S(t), t)$, $V_1^r(S(t), t)$, $V_2^r(S(t), t)$
  3. Pick the maximum among $V_0^r(S(t), t)$, $V_1^r(S(t), t)$, $V_2^r(S(t), t)$
  4. Repeat (1)–(3) R times, with $R \gg 0$
  5. Compute the simple average of R maximum choice-specific values
  6. Perform (1)–(5) in each t and for every possible $S(t)$

The End

Thank you!