

Classical Non-Linear Methods: Introduction to M-Estimation

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Plan for Classical Non-Linear Methods

Lecture 4: M-estimation, Intro, Non-linear LS (W.12)

Lecture 5: Asymptotic properties of M-estimators (W.12)

Lecture 6: M-estimator inference, Variance estimation (W.12)

Lecture 7: Maximum likelihood estimation (W.13)

Outline

Introduction

Non-Linear Regression

Identification
Estimation

Introduction

Non-Linear Estimation Chapters

W. Chapters 12–13: Abstract and technical.

- ▶ I'll try to limit technicalities.

But generality can be useful! Unified framework.

- ▶ **Ex:** OLS, Non-linear LS, MLE, Least absolute deviations...

There will be no exam questions in Ch. 12–13 *specifically*.

But important—and required—background knowledge.

Big Picture: Steps in Econometric Analysis

1. **Identification:** Given distribution of observables, can we recover parameters? If so, how?
2. **Estimation:** Given finite sample of observations, how to construct parameter estimates?
3. **Inference:** Confidence intervals, prediction intervals, hypothesis testing, etc.

Steps in Econometrics Analysis

- ▶ **Identification:** As if sample infinitely large.
- ▶ **Estimation:** Finite sample. Which formula(e)/algorithm?
- ▶ **Inference:** Builds on (asymptotic) distribution theory.

Steps highly interdependent.

- ▶ Identification method may suggest estimator.
- ▶ Inference method hinges on estimation method.

Non-Linear Regression

Non-Linear Regression Model

y : scalar outcome variable.

\mathbf{x} : K -vector of explanatory variables.

Parametric model for $E[y | \mathbf{x}]$:

$$\mathcal{M} := \{\mathbf{x} \mapsto m(\mathbf{x}, \boldsymbol{\theta}) ; \boldsymbol{\theta} \in \Theta\}$$

- ▶ $m(\mathbf{x}, \boldsymbol{\theta})$: Candidate for $E[y | \mathbf{x}]$.
- ▶ $\Theta \subseteq \mathbb{R}^P$ parameter space. (P fixed!)

Mean model correctly specified if fctn $E[y | \mathbf{x}] \in \mathcal{M}$, i.e.

for some $\boldsymbol{\theta}_o \in \Theta$, $E[y | \mathbf{x}] = m(\mathbf{x}, \boldsymbol{\theta}_o)$ for all \mathbf{x} .

$\boldsymbol{\theta}_o$ often called “true value of theta.”

Examples of Functional Form

Ex 1. If y unrestricted, may take

$$m(\mathbf{x}, \boldsymbol{\theta}) = \mathbf{x}\boldsymbol{\theta}. \quad (\text{linear (mean) regression})$$

Ex 2. If $y \geq 0$, may take

$$m(\mathbf{x}, \boldsymbol{\theta}) = \exp(\mathbf{x}\boldsymbol{\theta}). \quad (\text{exponential regression})$$

Ex 3. If $y \in [0, 1]$, may take

$$m(\mathbf{x}, \boldsymbol{\theta}) = \frac{1}{1 + \exp(-\mathbf{x}\boldsymbol{\theta})}. \quad (\text{logistic regression})$$

Here: $K = P$. But $K \gtrless P$ allowed.

Error Formulation

- ▶ Assume correct specification (NLS.1).

- ▶ Defining $u := y - m(\mathbf{x}, \boldsymbol{\theta}_o)$, may write

$$y = m(\mathbf{x}, \boldsymbol{\theta}_o) + u, \quad E[u | \mathbf{x}] = 0.$$

- ▶ $E[u | \mathbf{x}] = 0$ a consequence of correct specification.
- ▶ Error formulation here only useful for abbreviations.

Discussion

$E[u | \mathbf{x}] = 0$ does *not* imply u and \mathbf{x} independent.

... only cond'l *mean* independence.

May have $\text{var}(u | \mathbf{x})$ nonconstant (in \mathbf{x}).

- ▶ If $y \geq 0$, must have $u \geq -m(\mathbf{x}, \theta_o) \dots$

Dealing with *semiparametric* model for $D(y|\mathbf{x})$.

- ▶ Parametric model for mean $E[y | \mathbf{x}]$.
- ▶ Other characteristics (var, skewness, etc.) unrestricted.

Identification

Identification

We'll show: θ_o solves population problem (PP)

$$\min_{\theta \in \Theta} E \left[|y - m(\mathbf{x}, \theta)|^2 \right]. \quad (\text{PP})$$

- ▶ Function $m(\cdot, \cdot)$ + parameter space Θ known quantities.
- ▶ Hence, **IF** given $D(y, \mathbf{x})$, PP problem known.
- ▶ θ_o identified if PP solution *unique*.

Identification

$\pm m(\mathbf{x}, \boldsymbol{\theta}_o)$ and expanding square,

$$\begin{aligned}|y - m(\mathbf{x}, \boldsymbol{\theta})|^2 &= |[y - m(\mathbf{x}, \boldsymbol{\theta}_o)] - [m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)]|^2 \\&= |y - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2 + |m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2 \\&\quad - 2u[m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)].\end{aligned}$$

Taking expectations,

$$\begin{aligned}\mathrm{E} \left[|y - m(\mathbf{x}, \boldsymbol{\theta})|^2 \right] &= \mathrm{E} \left[|y - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2 \right] \\&\quad + \mathrm{E} \left[|m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2 \right].\end{aligned}$$

Identification

Have shown

$$\begin{aligned} \mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta})|^2\right] &= \mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right] \\ &\quad + \mathrm{E}\left[|m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right]. \end{aligned}$$

It follows that

$$\mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta})|^2\right] \geq \mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right] \text{ for all } \boldsymbol{\theta} \in \Theta.$$

$\Rightarrow \boldsymbol{\theta}_o$ solves PP.

Q: When unique?

Identification Condition

Have shown

$$\begin{aligned} \mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta})|^2\right] &= \mathrm{E}\left[|y - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right] \\ &\quad + \mathrm{E}\left[|m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right]. \end{aligned}$$

$\boldsymbol{\theta}_o$ uniquely solves PP if and only if

$$\mathrm{E}\left[|m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2\right] > 0 \text{ for all } \boldsymbol{\theta} \in \Theta \setminus \{\boldsymbol{\theta}_o\}.$$

Q: When will identification fail?

Identification Failure: Linear Case

Ex: Linear regression, $m(\mathbf{x}, \boldsymbol{\theta}) = \mathbf{x}\boldsymbol{\theta}$ with $\Theta = \mathbb{R}^K$.

Here

$$\begin{aligned} \mathrm{E} \left[|m(\mathbf{x}, \boldsymbol{\theta}) - m(\mathbf{x}, \boldsymbol{\theta}_o)|^2 \right] &= \mathrm{E} \left[|\mathbf{x}(\boldsymbol{\theta} - \boldsymbol{\theta}_o)|^2 \right] \\ &= (\boldsymbol{\theta} - \boldsymbol{\theta}_o)' \mathrm{E} [\mathbf{x}'\mathbf{x}] (\boldsymbol{\theta} - \boldsymbol{\theta}_o). \end{aligned}$$

- ▶ > 0 if $\mathrm{E} [\mathbf{x}'\mathbf{x}]$ positive definite.
- ▶ Just usual (population) rank condition (OLS.2).

If not full rank...

Identification Failure: Non-linear example

Ex: Nonlinear regression with $\Theta = \mathbb{R}^4$ and

$$m(\mathbf{x}, \boldsymbol{\theta}) = \theta_1 + \theta_2 x_2 + \theta_3 x_3^{\theta_4}.$$

- ▶ Suppose $\theta_{o,3} = 0$. (Truth linear.)
- ▶ At $\boldsymbol{\theta}$ with $\theta_3 = 0$ ($= \theta_{o,3}$)...
- ▶ ... criterion function *independent of* θ_4 .
- ▶ For this $\boldsymbol{\theta}_o$, identification fails.
- ▶ Example of poorly identified model.

Estimation

Estimation

θ_o solves PP,

$$\theta_o \in \operatorname{argmin}_{\theta \in \Theta} E \left[|y - m(\mathbf{x}, \theta)|^2 \right].$$

Analogy principle suggests,

$$\hat{\theta} \in \operatorname{argmin}_{\theta \in \Theta} \frac{1}{N} \sum_{i=1}^N [y_i - m(\mathbf{x}_i, \theta)]^2.$$

Non-linear least squares (NLS) estimator.

For now, assume existence (but not uniqueness) of solution.

Consistency?

Q: Does NLS consistently estimate θ_o ?

It turns out answer is “yes,” provided (roughly)

1. θ_o is identified,
2. Criterion function convergence

$$\frac{1}{N} \sum_{i=1}^N [y_i - m(\mathbf{x}_i, \boldsymbol{\theta})]^2 \xrightarrow{\text{“}\rightarrow\text{”}} E[|y - m(\mathbf{x}, \boldsymbol{\theta})|^2]$$

is suitable strong (functional!) sense.

Next: More detail in general setting.