

Advanced Time Series

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Overview of today's exercise

- Programming rules in GAUSS
- Writing the log-likelihood function AR(1) - Theory
- Using CML in GAUSS
- Estimating the parameters of an AR(1) process
- Writing the log-likelihood function MA(1) - Theory
- Estimating the parameters of a MA(1) process

Programming rules in GAUSS I

- ALWAYS start simple!!! Start with the simple calculations! Next enrich your program step by step!
- Start in a procedure ALWAYS from the inside and then go outside!
- CHECK frequently the results of your programming! (check them in the output window.)
- ALWAYS start with small n !

Programming rules in GAUSS II

- Comment your program!!!
- Use useful and sensible names for your variables and programs!
- Create your own program collection!

Likelihood function AR(1) for 1st and 2nd observation

$$Y_t = c + \phi Y_{t-1} + \varepsilon_t$$

$$\varepsilon_t = iidN(0, \sigma^2)$$

density of first observation

$$Y_1 \sim N(c/(1 - \phi), \sigma^2/(1 - \phi^2))$$

$$f_{Y_1}(y_1; c, \phi, \sigma^2) = \frac{1}{\sqrt{2\pi} \sqrt{\sigma^2/(1 - \phi^2)}} \exp \left[\frac{-\{y_1 - [c/(1 - \phi)]\}^2}{2\sigma^2/(1 - \phi^2)} \right]$$

density of second observation

$$Y_2 = c + \phi Y_1 + \varepsilon_2$$

$$(Y_2 | Y_1 = y_1) \sim N((c + \phi y_1), \sigma^2)$$

$$f_{Y_2 | Y_1}(y_2 | y_1; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(y_2 - c - \phi y_1)^2}{2\sigma^2} \right]$$

$$\varepsilon_2 = y_2 - c - \phi y_1$$

$$f_{Y_2 | Y_1}(y_2 | y_1; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_2)^2}{2\sigma^2} \right]$$

joint density of first and second observation

$$f_{Y_2, Y_1}(y_2, y_1; \boldsymbol{\theta}) = f_{Y_1}(y_1; \boldsymbol{\theta}) \cdot f_{Y_2 | Y_1}(y_2 | y_1; \boldsymbol{\theta})$$

Writing the joint likelihood function AR(1)

$$f_{Y_T, Y_{T-1}, \dots, Y_1}(y_T, y_{T-1}, \dots, y_1; \boldsymbol{\theta}) = f_{Y_1}(y_1; \boldsymbol{\theta}) \cdot \prod_{t=2}^T f_{Y_t|Y_{t-1}}(y_t|y_{t-1}; \boldsymbol{\theta})$$

$$f_{Y_t|Y_{t-1}}(y_t|y_{t-1}; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(y_t - c - \phi y_{t-1})^2}{2\sigma^2} \right]$$

$$f_{Y_t|Y_{t-1}}(y_t|y_{t-1}; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_t)^2}{2\sigma^2} \right]$$

Taking logs yields

$$\mathcal{L}(\boldsymbol{\theta}) = \log f_{Y_1}(y_1; \boldsymbol{\theta}) + \sum_{t=2}^T \log f_{Y_t|Y_{t-1}}(y_t|y_{t-1}; \boldsymbol{\theta})$$

Writing the log-likelihood function AR(1)

$$\begin{aligned}
 \mathcal{L}(\boldsymbol{\theta}) &= \log f_{Y_1}(y_1; \boldsymbol{\theta}) \rightarrow \text{deterministic} \\
 &+ \log f_{Y_2|Y_1}(y_2|y_1; \boldsymbol{\theta}) \rightarrow \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_2)^2}{2\sigma^2} \right] \right) \\
 &\dots \\
 &+ \log f_{Y_T|Y_{T-1}}(y_T|y_{T-1}; \boldsymbol{\theta}) \rightarrow \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_T)^2}{2\sigma^2} \right] \right)
 \end{aligned}$$

CML procedure

- Numerical optimization of a function using an algorithm
- Input: function to be minimized and starting values for parameters, and data
- Output: vector of parameters and function value at minimum

CML procedure-CALL

$\{ x, f, g, cov, retcode \} = \text{CML}(\text{dataset}, \text{vars}, \&fct, \text{start})$

INPUT

dataset - name of data matrix

Important Note: the rows(dataset) needs to be equal to the number of likelihood contributions

DATA goes into the &fct as a global variable

vars - character vector of labels selected for analysis

take vars = 0;

fct - the name of a procedure that returns the log-likelihood,

ATS WT 08/09

e.g. `&malikeliproc`

start - a $K \times 1$ vector of start values

CML procedure-CALL

$$\{ x, f, g, cov, retcode \} = \text{CML}(\text{dataset}, \text{vars}, \&\text{fct}, \text{start})$$

OUTPUT

x - $K \times 1$ vector, estimated parameters

f - scalar, function at minimum (mean log-likelihood)

g - $K \times 1$ vector, gradient evaluated at x

cov - $K \times K$ matrix, covariance matrix of the parameters

retcode - scalar, return code

CML procedure-GLOBALS

Example:

```
_cml_Algorithm=1;  
_cml_LineSearch=1;  
_cml_DirTol = 1e-5;  
_cml_CovPar_=1;
```

CML Global variables I

CML global: `_cml_DirTol=0.000000001;`

`_cml_DirTol = scalar` is a convergence tolerance for gradient of estimated coefficients.

Default = $1e-5$.

When this criterion has been satisfied CML will exit the iterations.

Important!!

Some applications demand a small value in order to prevent convergence on a local minimum!!!! (local vs. global optima)

CML Global variables II

CML global: `_cml_Algorithm` = scalar indicator for optimization method

`_cml_Algorithm`

= 1, BFGS (Broyden, Fletcher, Goldfarb, Shanno)

= 2, DFP (Davidon, Fletcher, Powell)

= 3, NEWTON (Newton-Raphson)

= 4, BHHH

CML Global variables III

`_cml_LineSearch;`

= 1 One

= 2, STEPBT (default)

= 3, HALF (step-halving)

= 4, BRENT

= 5, BHHHSTEP

MA(1) Process

$$Y_t = c + \theta \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t = iidN(0, \sigma^2)$$

$$\boldsymbol{\theta} = (c, \theta, \sigma^2)'$$

Conditional density of the t^{th} observation

$$\begin{aligned}
 Y_t | \varepsilon_{t-1} &\sim N((c + \theta \varepsilon_{t-1}), \sigma^2) \\
 f_{Y_t | \varepsilon_{t-1}}(y_t | \varepsilon_{t-1}; \boldsymbol{\theta}) &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(y_t - c - \theta \varepsilon_{t-1})^2}{2\sigma^2} \right] \\
 \varepsilon_t &= y_t - c - \theta \varepsilon_{t-1} \\
 f_{Y_t | \varepsilon_{t-1}}(y_t | \varepsilon_{t-1}; \boldsymbol{\theta}) &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-\varepsilon_t^2}{2\sigma^2} \right]
 \end{aligned}$$

Writing the sample likelihood function MA(1)

$$\begin{aligned}
 & f_{Y_T, Y_{T-1}, \dots, Y_1 | \varepsilon_0 = 0}(y_T, y_{T-1}, \dots, y_1 | \varepsilon_0 = 0; \boldsymbol{\theta}) = \\
 & f_{Y_1 | \varepsilon_0 = 0}(y_1 | \varepsilon_0 = 0; \boldsymbol{\theta}) \prod_{t=2}^T f_{Y_t | Y_{t-1}, Y_{t-2}, \dots, Y_1, \varepsilon_0 = 0}(y_t | y_{t-1}, y_{t-2}, \dots, y_1, \varepsilon_0 = 0; \boldsymbol{\theta})
 \end{aligned}$$

Conditional log likelihood function MA(1)

$$\begin{aligned}
 \mathcal{L}(\boldsymbol{\theta}) &= \\
 \log f_{Y_T, Y_{T-1}, \dots, Y_1 | \varepsilon_0 = 0}(y_T, y_{T-1}, \dots, y_1 | \varepsilon_0 = 0; \boldsymbol{\theta}) &= \\
 -T \log(\sqrt{2\pi\sigma^2}) - \sum_{t=1}^T \frac{\varepsilon_t^2}{2\sigma^2}
 \end{aligned}$$

How to get ε_t ? - Recursion

$$\varepsilon_1 = y_1 - c \quad \text{with} \quad \varepsilon_0 = 0$$

$$\varepsilon_2 = y_2 - c - \theta\varepsilon_1$$

...

$$\varepsilon_T = y_T - c - \theta\varepsilon_{T-1}$$

Writing the conditional log-likelihood function MA(1)

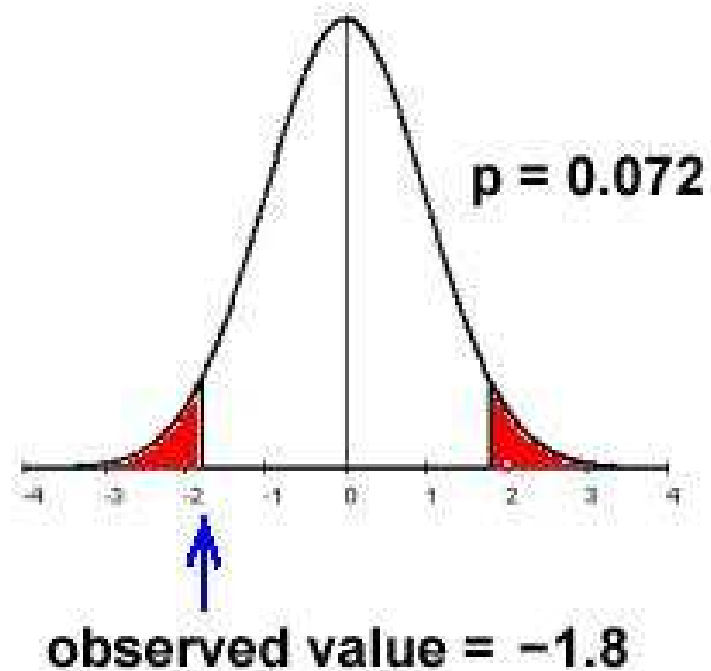
$$\begin{aligned}
 \mathcal{L}(\boldsymbol{\theta}) &= f_{Y_1|\varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_1)^2}{2\sigma^2} \right] \right) \\
 &+ \log f_{Y_2|Y_1, \varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_2)^2}{2\sigma^2} \right] \right) \\
 &\dots \\
 &+ \log f_{Y_T|Y_{T-1}, \dots, Y_1, \varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(\varepsilon_T)^2}{2\sigma^2} \right] \right)
 \end{aligned}$$

Writing the conditional log-likelihood function MA(1)

$$\begin{aligned}
 \mathcal{L}(\boldsymbol{\theta}) &= f_{Y_1|\varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow -\log\left(\sqrt{2\pi\sigma^2}\right) - \left[\frac{\varepsilon_1^2}{2\sigma^2}\right] \\
 &+ \log f_{Y_2|Y_1, \varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow -\log\left(\sqrt{2\pi\sigma^2}\right) - \left[\frac{\varepsilon_2^2}{2\sigma^2}\right] \\
 &\dots \\
 &+ \log f_{Y_T|Y_{T-1}, \dots, Y_1, \varepsilon_0=0}(\cdot; \boldsymbol{\theta}) \rightarrow -\log\left(\sqrt{2\pi\sigma^2}\right) - \left[\frac{\varepsilon_T^2}{2\sigma^2}\right]
 \end{aligned}$$

Reminder: P -value

Two Sided Test: Example



Reminder: P-value

```
se = sqrt(diag(cov));  
t_test = thx./se;  
p_val = 2*cdfnc(t_test);
```

General:

One-sided `p_val = cdfnc(t_test);`

Two-sided `p_val = 2*cdfnc(t_test);`