

# **Quantitative Macroeconomics**

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**Week 5**

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## Contents

1	Information Criteria For AR(p)	1
2	Portmanteau Test For Residual Autocorrelation	2
3	Bootstrap Confidence Interval For AR(1) Coefficient	3

# 1 Information Criteria For AR(p)

Consider the following information criteria to estimate the order  $p$  of an  $AR(p)$  model:

$$AIC(n) = \log \tilde{\sigma}^2(n) + \frac{2}{T^{eff}}n$$

$$SIC(n) = \log \tilde{\sigma}^2(n) + \frac{\log T^{eff}}{T^{eff}}n$$

$$HQC(n) = \log \tilde{\sigma}^2(n) + \frac{2 \log \log T^{eff}}{T^{eff}}n$$

where  $\tilde{\sigma}^2$  denotes the ML estimate of the variance term based on the OLS residuals  $\hat{u}_t(n)$  of the corresponding estimated  $AR(p)$  model.  $n$  is the number of estimated parameters and  $T^{eff} = T - p^{max}$ , where  $p^{max}$  is the maximum number of lags to consider.

1. Provide intuition between the different criteria. Which one (asymptotically) over- or underestimates the correct order?
2. Write a function `nlag = LagOrderSelectionARp(y, const, pmax, crit)` that computes the different order criteria for  $p = 1, \dots, p^{max}$  using data vector  $y$  and possible constant term ( $const = 1$ ) or constant term and linear trend ( $const = 2$ ). `nlag` should output the recommended lag according to criteria `crit`, which takes a string (`AIC`, `SIC` or `HQC`) as input value.
3. Load the dataset of the simulated AR(4) process given in the CSV file `AR4.csv`. Which model is preferred according to the order selection criteria?

## Readings

- Lütkepohl (2004).

## 2 Portmanteau Test For Residual Autocorrelation

The portmanteau test checks the null hypothesis that there is no remaining residual autocorrelation at lags 1 to  $h$  against the alternative that at least one of the autocorrelations is nonzero. In other words, the pair of hypotheses:

$$H_0 : \rho_u(1) = \rho_u(2) = \dots = \rho_u(h) = 0$$

versus:

$$H_1 : \rho_u(j) \neq 0 \text{ for at least one } j = 1, \dots, h$$

where  $\rho_u(j) = \text{Corr}(u_t, u_{t-j})$  denotes an autocorrelation coefficient of the residual series.

Consider the Box-Pierce test statistic  $Q_h$

$$Q_h = T \sum_{j=1}^h \hat{\rho}_u^2(j)$$

which has an approximate  $\chi^2(h-p)$ -distribution if the null hypothesis holds and  $T$  is the length of the residual series. The null hypothesis of no residual autocorrelation is rejected for large values of the test statistic.

- Load quarterly data for the price index of US Gross National Product given in `gnpdeflator.csv`. This is a chain-type price index with basis year 2005. The data is seasonally adjusted and spans the period from 1954.Q4 to 2007.Q4.
- Compute the inflation series. That is, take the first difference of the log of `gnpdeflator`.
- Use the Akaike information criteria to determine the lag length  $\hat{p}$ .
- Estimate two models with OLS: (i) an  $AR(\hat{p})$  model and (ii) an  $AR(1)$  model.
- Set  $h = \hat{p} + 10$  and compute  $Q_h$  as well as the corresponding p-value for both models.
- Comment, based on your findings, whether the residuals are white noise.

### Readings:

- Lütkepohl (2004).

### 3 Bootstrap Confidence Interval For AR(1) Coefficient

Consider the AR(1) model with constant

$$y_t = c + \phi y_{t-1} + u_t$$

for  $t = 1, \dots, T$  with iid error terms  $u_t$  and  $E(u_t|y_{t-1}) = 0$ . Usually, we construct a  $(1-\alpha)\%$ -confidence interval for  $\phi$  using the normal (or student's t) approximation:

$$\left[ \hat{\phi} - z_{\alpha/2} \cdot SE(\hat{\phi}); \hat{\phi} + z_{1-\alpha/2} \cdot SE(\hat{\phi}) \right]$$

with  $\hat{\phi}$  denoting the OLS estimate,  $SE(\hat{\phi})$  the estimated standard error of  $\phi$  and  $z_{\alpha/2}$  the  $\alpha/2$  quantile of the standard normal distribution (or t-distribution). If one does not know the asymptotic distribution of a test statistic (or it has a very complicated form), one often relies on a nonparametric simulation approach. To this end, we are going to do a so-called “*bootstrap*”, i.e. we recompute the t-statistics a large number of times on artificial data generated from resampled residuals.

1. What is a “Bootstrap approximation”? Provide insight into the basic idea and possible applications of this statistical technique.

2. Write a program for the following:

- Simulate  $T = 100$  observations with  $c = 1$ ,  $\phi = 0.8$  and errors drawn from e.g. the exponential distribution such that  $E(u_t) = 0$ .
- Estimate the model with OLS and calculate the t-statistic  $\tau = \frac{\hat{\phi}}{SE(\hat{\phi})}$ .
- Store the OLS residuals in a vector  $\hat{u} = (\hat{u}_2, \dots, \hat{u}_T)'$ .
- Set  $B = 10000$  and initialize the output vector  $\tau^* = (\tau_1^*, \dots, \tau_B^*)$ .
- For  $b = 1, \dots, B$ :
  - Draw a sample **with replacement** from  $\hat{u}$  and save it as  $u^* = u_2^*, \dots, u_T^*$ .
  - Initialize an artificial time series  $y_t^*$  with  $T$  observations and set  $y_1^* = y_1$ .
  - For  $t = 2, \dots, T$  generate

$$y_t^* = \hat{c} + \hat{\phi} y_{t-1}^* + u_t^*$$

- On this artificial dataset estimate an AR(1) model. Denote the estimated OLS coefficient  $\phi^*$  and corresponding estimated standard deviation  $SE(\phi^*)$ . Store the following t-statistic in your output vector at position  $b$ :

$$\tau^* = \frac{\phi^* - \hat{\phi}}{SE(\phi^*)}$$

- Sort the output vector such that  $\tau_{(1)}^* \leq \dots \leq \tau_{(B)}^*$ .
- The “*bootstrap approximate*” confidence interval for  $\phi$  is then given by

$$\left[ \hat{\phi} - \tau_{((1-\alpha/2)B)}^* \cdot SE(\hat{\phi}); \hat{\phi} - \tau_{((\alpha/2)B)}^* \cdot SE(\hat{\phi}) \right]$$

Set  $\alpha = 0.05$  and compare this with the normal approximation.

- Redo the exercise for  $T = 30$  and  $T = 10000$ . Comment on your findings.

#### Readings

- Kilian and Lütkepohl (2017, Ch. 12)

## References

- Kilian, Lutz and Helmut Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Themes in Modern Econometrics. Cambridge: Cambridge University Press. ISBN: 978-1-107-19657-5. URL: <https://doi.org/10.1017/9781108164818>.
- Lütkepohl, Helmut (2004). “Univariate Time Series Analysis”. In: *Applied Time Series Econometrics*. Ed. by Helmut Lütkepohl and Markus Krätzig. First. Cambridge University Press, pp. 8–85. ISBN: 978-0-521-83919-8 978-0-521-54787-1 978-0-511-60688-5. DOI: 10.1017/CB09780511606885.003.