

Lezione 12 - 29/10/2019

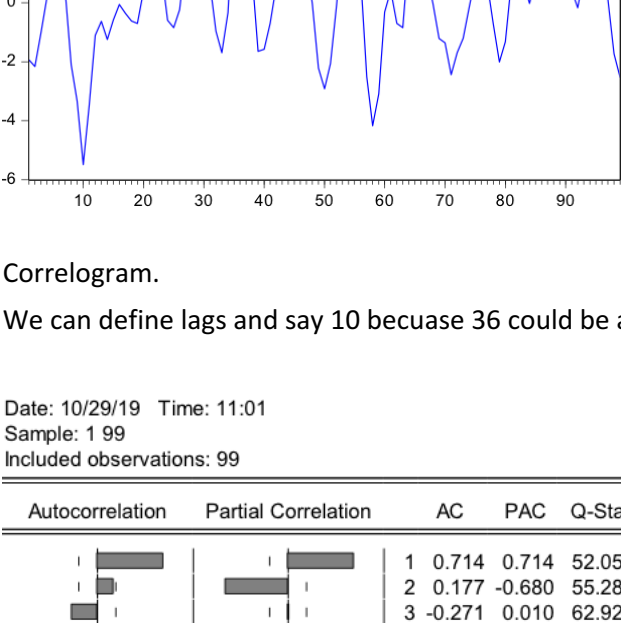
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Lezione 12 - 29/10/2019

Two dataset armas, one in txt and one in eview format. The way we exchange data is in text format because every app can read txt. Depending on what we have Eview will set on our data. Dated is timeseries, first one is cross section. Integer data because we don't have a fixed frequency. Data 1 99. Now import file and we got the preview of the data. Ha chiuso tutto : (

View -> graph

Copy to print in a file.



Correlogram.

We can define lags and say 10 because 36 could be a lot.

Date: 10/29/19 Time: 11:01
Sample: 1 99
Included observations: 99

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
1	1	1	0.714	0.714	52.052	0.000
1	1	2	0.177	-0.680	55.261	0.000
1	1	3	-0.271	0.010	62.922	0.000
1	1	4	-0.434	0.032	82.741	0.000
1	1	5	-0.327	-0.009	94.092	0.000
1	1	6	-0.074	0.072	94.678	0.000
1	1	7	0.162	0.029	97.537	0.000
1	1	8	0.309	0.171	108.03	0.000
1	1	9	0.333	0.080	120.38	0.000
1	1	10	0.250	0.057	127.39	0.000

Q-stat is the Portmanteau statistic.

If i'm interested in u^2 or y-1 ecc. Click generate button or Quick. Generate q = u^2

Qq = u^2-0.5*(abs(w))

Generate series that is aa = 0

aa=abs(w)-1 -->Sample 1 99 if abs(w)>1

Lagging variable

LY=y(-1)

Means y at time t-1

Quick -- Model

Write u c ar(1) ar(2)

I can tell what constant to estimate.

Dependent Variable: U
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/29/19 Time: 11:16
Sample: 1 99
Included observations: 99
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.076044	0.200841	0.378627	0.7058
AR(1)	1.238163	0.075154	16.47503	0.0000
AR(2)	-0.708478	0.071471	-9.912749	0.0000
SIGMASQ	0.813643	0.108459	7.501635	0.0000

R-squared	0.765285	Mean dependent var	0.067127
Adjusted R-squared	0.757873	S.D. dependent var	1.871332
S.E. of regression	0.920816	Akaike info criterion	2.734057
Sum squared resid	80.55063	Schwarz criterion	2.838910
Log likelihood	-131.3358	Hannan-Quinn criter.	2.776481
F-statistic	103.2486	Durbin-Watson stat	1.927609
Prob(F-statistic)	0.000000		

Inverted AR Roots	.62-.57i	.62+.57i
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Random variable with standard normal distribution.

The last two columns are t-statistics that are define on default if I want to test if a certain parameter is 0. Then there is the p value associated to it. P value coming from a t distribution, not a normal distribution.

At the end we have the roots. These are invertible and we got the root are smaller than 1 in absolute value.

We can use CLS on ESTIMATES --> options equation estimation

Put zero as a starting value

We check if we have residuals. View --> residual diagnostics and correlogram q-statistic(portmanteau)

If i use AR(1) I got all 0 nella prob poichè non è adatto.

View --> coefficient diagnostics --> wald test --> C(2)=1.2, C(3)=0.7

Forecasting (we are going to use z)

What we want to forecast? After the last observation. The enviroment is desine for 99 observations. We have to move the wall of the box a bit.

Proc --> ststructure/resi current page --> end date: 120 --> YES

Last 20 obs are NA.

QUICK --> Opntion equation estimation --> z MA(1) MA(2)

Now e have to do forecast: dynamic or statics

100 120

Yt+1|T =

I don't have theta2 but i have the estimate of it and i compute the residual of EpsT-1.

EpsT and theta1 --> i got estimate of it and i have the residual so i can use it.

EpsT-1? I don't know it. Do i have residual? Not it's in the future. This guy is a white noise so we stick zero on it. So the forecast is Yt+1|T = Theta1^t EpsT^t + THeta2^t epsT-1^t

So this is my forecast for point 100. For point 101?

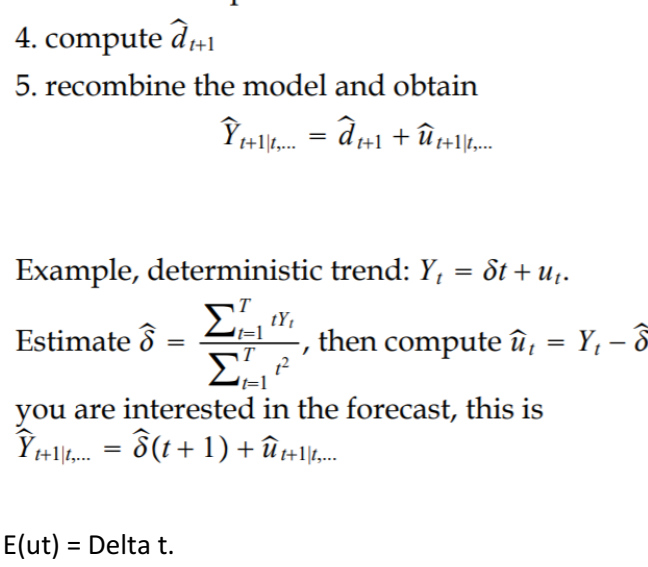
$$Y_{t+2} = \theta_1 z + \theta_2 \epsilon_{t+1} + \theta_3 \epsilon_t$$

$$\hat{Y}_{t+2|t} = 0 \quad 0 \quad \theta_2 \hat{\epsilon}_t$$

$$Y_{t+3} = \theta_1 \epsilon_3 + \theta_2 \epsilon_{t+2} + \theta_3 \epsilon_{t+1}$$

$$\hat{Y}_{t+3|t} = 0 \rightarrow \text{MUNE CF INDEP AR(2) CBSSTZ VARS(2)}$$

So forecast is 0 after 3.



We can use ARMA to ZEP 2,3 step but after that we don't know anything else.

Chapter 9

Exercise 3 on Monday

We are moving to the non stationary world. Mean depend on time or variance depends on time so non stationary. If i fail one of them i'm not in a stionary process

Modelling nonstationarity, deterministic components

What if data have a deterministic trend (linear, quadratic...) or another deterministic component (such as a deterministic cycle or a seasonal effect)?

Consider

$$Y_t = d_t + u_t$$

where

- d_t is a deterministic component
- u_t is a stationary ARMA(p,q) model

Then we can:

1. estimate \hat{d}_t ,
2. compute $\hat{u}_t = Y_t - \hat{d}_t$,
3. model \hat{u}_t as if it was our observables.

For example, if we want to forecast $Y_{t+1|t}$, we

proceed as before and we

1. compute \hat{u}_t .
2. choose an appropriate ARMA model for \hat{u}_t
3. forecast $\hat{u}_{t+1|t}$, using the standard approach to forecast ARMA processes
4. compute \hat{d}_{t+1}
5. recombine the model and obtain

$$\hat{Y}_{t+1|t} = \hat{d}_{t+1} + \hat{u}_{t+1|t}$$

Example, deterministic trend: $Y_t = \delta t + u_t$.

Estimate $\hat{\delta} = \frac{\sum_{t=1}^T Y_t}{\sum_{t=1}^T t}$, then compute $\hat{u}_t = Y_t - \hat{\delta}t$; if

you are interested in the forecast, this is

$$\hat{Y}_{t+1|t} = \hat{\delta}(t+1) + \hat{u}_{t+1|t}$$

E(u) = Delta t.

$$Y_t = \delta t + u_t \quad \text{when stationary ARMA with } E(u_t) = 0$$

$$E(Y_t) = \delta t \quad \text{this depends on time}$$

$$Y_t = \delta t + u_t \quad \text{when we know } u_t \text{ we can forecast it}$$

so we know δ but, on estimates (T)

We just have to take away stationarity, model the stationarity part and put the stationarity back.

Nonstationarity, stochastic components

Consider

$$Y_t = Y_{t-1} + \epsilon_t, \epsilon_t \text{ i.i.d.}(0, \sigma^2) \text{ when } t \geq 1; Y_0 = 0$$

Clearly, the model is not stationary (notice the dependence on t in the definition). We can also notice this by checking, for example, the variance:

$$\begin{aligned} V(Y_t) &= V(Y_{t-1} + \epsilon_t) = V(Y_{t-1}) + V(\epsilon_t) + 2E(Y_{t-1}\epsilon_t) \\ &= V(Y_{t-1}) + \sigma^2 = V(Y_{t-2} + \epsilon_{t-1}) + \sigma^2 \\ &= V(Y_{t-2}) + V(\epsilon_{t-1}) + 2E(Y_{t-2}\epsilon_{t-1}) + \sigma^2 \\ &= V(Y_{t-2}) + 2\sigma^2 = \dots = V(Y_0) + t\sigma^2. \end{aligned}$$

In the same way, the covariances too depend on time: for $j > 0$,

$$\begin{aligned} Cov(Y_t, Y_{t+j}) &= Cov(Y_t, Y_t + \epsilon_{t+1} + \dots + \epsilon_{t+j}) \\ &= Cov(Y_t, Y_t) + Cov(Y_t, \epsilon_{t+1}) + \dots + Cov(Y_t, \epsilon_{t+j}) \\ &= V(Y_t) + 0 + \dots + 0 = t\sigma^2. \end{aligned}$$

This model can also be rewritten, using recursive substitution t times,

$$Y_t = Y_0 + \sum_{j=0}^{t-1} \epsilon_{t-j}$$

(notice here that the initial condition is not irrelevant, in the sense that it still affects Y_t and does not fade away; by setting $Y_0 = 0$, we do not "rule it out", but we "normalise for it").

This particular process is called "integrated": it is not stationary nor ergodic, it is not mean reverting, and all the properties we discussed for stationary ARMA(p,q) do not apply here.

Rearranging the indices, and replacing $Y_0 = 0$,

$$Y_t = \sum_{j=1}^t \epsilon_j$$

this last notation motivates the fact that processes of this type are called "integrated", or, more precisely, "integrated of order 1", I(1).

If i have a shock 1000 years ago i can't change it --> is not reverting. This idea is called **Random walk**.

We can think the summation as a integral. So integrating of order 1 this epsilon. Infact, there need to consider only independent identica distributed eps. Also stationary and invertible ARMA model

The concept of integration may be extended, to

$$\begin{aligned} Y_t &= Y_{t-1} + u_t, \text{ when } t \geq 1, \text{ where} \\ u_t &= \phi_1 u_{t-1} + \dots + \phi_p u_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}, \\ &u_t \text{ stationary and invertible} \\ &\epsilon_t \text{ i.i.d.}(0, \sigma^2); \\ Y_0 &= 0 \end{aligned}$$

then $Y_t = \sum_{j=0}^t u_j$ is again an "integrated" I(1) process, $Y_t \in I(1)$

(and it could be further generalised to u_t MA(x), **SUM OF AUTOCORREANCE (LT)**) provided that $0 < \sum_{j=-\infty}^{\infty} \gamma_j < \infty$)

On the other hand, since $\Delta Y_t = u_t$, then $u_t \in I(0)$.

The process is I(0) if we take the difference of integrated of order 1.

Notice that in our definition, $E(Y_t) = 0$ because we set $Y_0 = 0$.

When $Y_0 \neq 0$, say $Y_0 = \kappa$, using recursive substitutions,

$$Y_t = \kappa + \sum_{j=1}^t u_j$$

and $E(Y_t) = \kappa \neq 0$.

Most authors consider Y_t as defined here as I(1), especially in empirical work. For our purpose, it may be convenient to refer to this as "I(1)" with non-zero mean", especially when the presence of a non-zero mean may change the limit distribution of estimators or test statistics.

Sum of a constant to a I(1) process. What is important is that the process is I(1) when i integrate stationary and invertible ARMA model (summation non zero autocorvariances)

~~A process integrated when you integrate~~

~~First differences any it is stationary~~

~~Not true!~~

why? counter example

$$\epsilon_t \sim N(0, \sigma^2) \text{ stationary } \int(0)$$

$$Y_t = \epsilon_t \text{ stationary } \int(0)$$

first difference

$$\Delta Y_t = \epsilon_t - \epsilon_{t-1} \text{ MA(1) stationary } \int(0)$$

sum of all autocorvariances = 0

so it's I(1).

$$\text{stationary } \not\Rightarrow \int(0)$$

$$\int(0) \not\Rightarrow \text{stationary}$$

I can observe u and compute u straight away. So just add the forecast of ut. The solution is the same in both situations. If stationary for mean of variance is the same. I can take away stationarity source and then take back at the end. In many situation i can do it. GDP i can't use ARMA's but i can take away trend!

Combining stochastic and non stochastic forms on non stationarity

One model of particular interest is

$$\begin{aligned} Y_t &= c + Y_{t-1} + u_t, \text{ when } t \geq 1, \text{ where} \\ u_t &= \phi_1 u_{t-1} + \dots + \phi_p u_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}, \\ &u_t \text{ stationary and invertible} \\ &\epsilon_t \text{ i.i.d.}(0, \sigma^2); \\ Y_0 &= 0 \end{aligned}$$

In this case,

$$Y_t = ct + \sum_{j=1}^t u_j$$

so both the linear trend and the integration are present. Some authors consider Y_t as defined here as I(1); we will be more specific, and we will refer to this as "I(1) and with a deterministic trend".

* If $Y_0 = \kappa$ instead,

$$Y_t = \kappa + ct + \sum_{j=1}^t u_j$$

* Recalling that $Y_t = c + Y_{t-1} + u_t$, the forecast of $\hat{Y}_{t+1|t} = c + Y_t + \hat{u}_{t+1|t}$.

Forecasting a trend.