

**Université Toulouse 1 Capitole  
Ecole d'économie de Toulouse**

**Année universitaire 201**

**2016-2017**

**Session 1**

**Semestre 2**

Master 1 Economics, Econometrics & Statistics

Epreuve : Time Series

Date de l'épreuve : 30 mars 2017

Durée de l'épreuve : 1h30

Liste des documents autorisés : aucun document

Liste des matériels autorisés : calculatrice

Nombre de pages (y compris page de garde) : 8 pages (7+1)

**Toulouse School of Economics**  
2016-2017

Master 1

**Time series Exam**  
30th March 2017 - 9.00am-10.30am

The exam is composed of a set of eight MCQs (1 point each) and three exercises (4 points each).

**MCQ**

MCQ 1: Properties of stationary time series, select the right statement(s)

- A A strictly stationary time series has a bounded variance
- B A covariance stationary time series may be deterministic
- C A strictly stationary time series is always a covariance stationary time series
- D A weak white noise with variance  $\sigma^2$  is a strong white noise

MCQ 2: Properties of stationary time series, select the right statement(s)

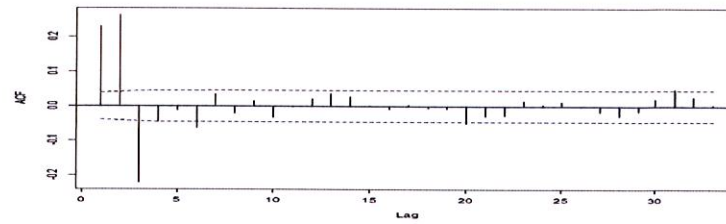
- A The autocovariance function of a covariance stationary time series is even
- B When it exists, the autocorrelation function of a strictly stationary time series takes its values in  $[-1, 1]$ .
- C The sum of two weak noises is a weak noise.
- D The spectral density of a weak white noise is a constant.

MCQ 3: Properties of stationary time series, select the right statement(s)

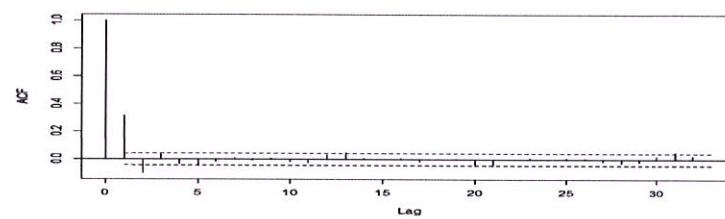
- A A covariance stationary time series that satisfies a MA(2) representation satisfies several MA(2) representations with the same innovation process.
- B A covariance stationary time series satisfies an AR representation. The roots of the polynomial  $\Phi(L)$  associated to the AR equation must be of modulus strictly less than 1, if the weak white noise associated to this equation is the innovation process.
- C The canonical representation of an ARMA( $p, q$ ) covariance stationary time series must be used when computing its forecasts.
- D The characterization of covariance stationary ARMA, AR and MA time series is based on more or less complicated functions of the values at various lags of the autocovariance function.

MCQ 4: Which ACF or PACF is consistent with an AR(3) time series ?

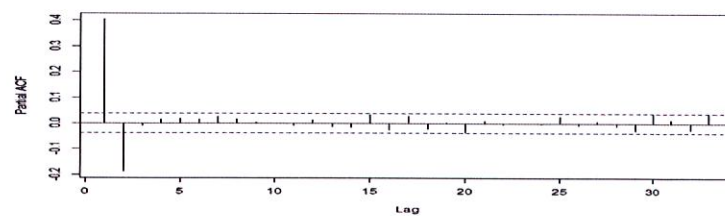
A ACF



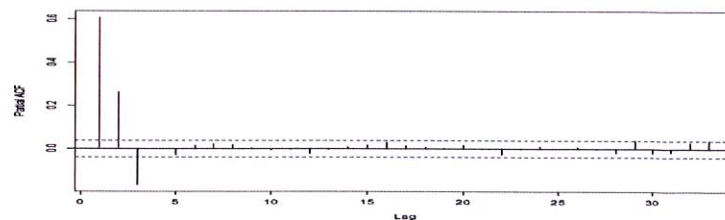
B ACF



C Partial ACF



D Partial ACF



MCQ 6: From the eacf table from R, which model do you consider for estimation ?

```
> eacf(x)
AR/MA
  0  1  2  3  4  5  6  7  8  9 10 11 12 13
0 x x o x x o o o o o o o x x
1 x x x x x o o o o o o o o o
2 x x o o o o o o o o o o x o
3 x x o o o o o o o o o o x o
4 x x x x o o o o o o o o o o
5 x x x o o o o o o o o o o o
6 x x x o o o o o x o o o o o
7 x x o o o o x o x o o o o o
```

- A ARMA(1,1)
- B ARMA(2,1)
- C ARMA(3,2)
- D ARMA(2,2)

MCQ 7: From the following output (from R),

```
> xarma<- arima(x, order=c(3,0,2))
> xarma
call:
arima(x = x, order = c(3, 0, 2))
Coefficients:
      ar1      ar2      ar3      ma1      ma2  intercept
s.e.    0.9854   -0.4733   -0.0018   0.0447   0.5551     0.3724
      0.0882    0.1232    0.0758    0.0763    0.0617     0.1363
sigma^2 estimated as 0.8735:  log likelihood = -676.7, aic = 1365.4
> Box.test(xarma$residuals, lag=20, type="Ljung-Box")
Box-Ljung test
data:  xarma$residuals
X-squared = 21.036, df = 20, p-value = 0.395
```

- A you decide to use this model in a forecast exercise
- B you decide to increase the polynomial degrees of the MA part or AR part
- C you decide to reduce the polynomial degree of the AR part
- D you decide to reduce the polynomial degree of the MA part

MCQ 8: From the following output (from R),

```
> xarma<- arima(x, order=c(1,0,1))
> xarma

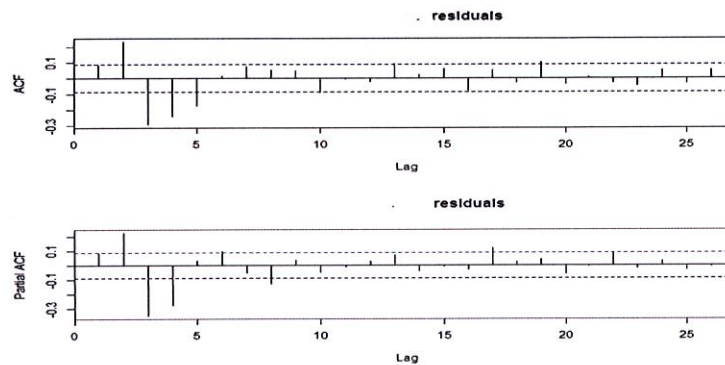
Call:
arima(x = x, order = c(1, 0, 1))

Coefficients:
      ar1      ma1  intercept
0.6906  0.2834  0.3739
s.e.  0.0361  0.0374  0.1993

sigma^2 estimated as 1.166: log likelihood = -748.32,
aic = 1502.65
> Box.test(xarma$residuals, lag=20, type="Ljung-Box")
[1] TRUE

Box-Ljung test

data:  xarma$residuals
X-squared = 146.01, df = 20, p-value < 2.2e-16
```



- A you decide to use this model for forecast
- B you decide to increase the polynomial degrees of the MA part or AR part
- C you decide to reduce the polynomial degree of the AR part
- D you decide to reduce the polynomial degree of the MA part

### Exercise 1

Let  $(y_t)_{t \in \mathbb{Z}}$  be a covariance stationary time series that satisfies the following equation

$$y_t = \mu + \Phi y_{t-1} + \varepsilon_t + \theta \varepsilon_{t-1}$$

where  $(\varepsilon_t)_{t \in \mathbb{Z}}$  is a strong white noise with variance  $\sigma^2$ ,  $\mu \in \mathbb{R}$ .

1. Give the conditions under which the above equation is the canonical representation of the time series ? We consider these conditions satisfied in the sequel of the exercise.

2. Give the mean of  $y$ .
3. Give the Yule-Walker recurrence equation satisfied by the autocovariance function of  $y$ .
4. Give the forecast of  $y_{T+1}$  based on the information set  $\{y_T, y_{T-1}, \dots\}$ .
5. A statistician proposes to use an instrumental approach to estimate the parameter  $\Phi$  and to use  $y_{t-2}$  as an instrument for  $y_{t-1}$ . Does that seem reasonable? Why?

### Exercise 2

Let consider  $y$  a covariance stationary time series that satisfies the following ARMA equation

$$y_t - 2y_{t-1} = \varepsilon_t - 2\varepsilon_{t-1} + 4\varepsilon_{t-2}$$

where  $(\varepsilon_t)_{t \in \mathbb{Z}}$  is a white noise with variance  $\sigma^2$ .

1. Give the polynomials  $\Phi(L)$  and  $\Theta(L)$  that are associated to this data generating equation.
2. If this representation is not the canonical representation of the time series  $y$ , give the canonical representation of  $y$ .
3. Give the forecast function  $P_{H_y^T} y_{T+h}$  as a function of the horizon  $h$  and random variables in the space spanned by the r.v.s  $y_s$  for  $s \leq T$ .

### Exercise 3

Let consider the time series  $y$  and  $x$  that respectively satisfy the following equations

$$y_t = \Phi_1 y_{t-1} + \varepsilon_t$$

and

$$x_t = \Phi_2 x_{t-1} + \eta_t$$

where  $(\varepsilon_t)_{t \in \mathbb{Z}}$  and  $(\eta_t)_{t \in \mathbb{Z}}$  are two strong white noises with variance  $\sigma_\varepsilon^2$  and  $\sigma_\eta^2$  and that are independent (so that  $\forall (s, t) \in \mathbb{Z}, E\varepsilon_t \eta_s = 0$ ).

1. Give the condition(s) under which  $(\varepsilon_t)_{t \in \mathbb{Z}}$  and  $(\eta_t)_{t \in \mathbb{Z}}$  are the innovation processes of  $y$  and  $x$  (we assume that these conditions will be satisfied in the sequel.)
2. We define a new time series  $z$  by the following set of equations

$$\begin{aligned} z_{2t} &= y_t \\ z_{2t+1} &= x_t \end{aligned}$$

- (a) Show that  $\forall (s, t) \in \mathbb{Z}, Ey_t x_s = 0$ .
- (b) Compute the variance of  $z$ . Give a condition to ensure that the variance is not time dependent. We will assume that this condition is satisfied in the sequel.
- (c) Compute the autocovariance function of  $z$ . Give a condition to ensure that the covariance function is invariant by translation. We will assume that this condition is satisfied in the sequel.
- (d) Give the model satisfied by  $z$ .