

Applied Time Series Analysis

FS 2013 – Week 07

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Looking Back & Outlook

We did consider shifted **AR(p)-models** $Y_t = m + X_t$ with:

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + E_t$$

where the correlation structure was as follows:

ACF: „exponential decay“

PACF: = 0 for all lags $k > p$

Now, in practice we could well observe a time series whose autocorrelation differs from the above structure.

We will thus discuss **ARMA(p,q) models**, a class that is suitable for modeling a wider spectrum of dependency structures.

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Moving Average Models

Whereas for AR(p) models, the current observation of a time series is written as a linear combination of its own past, **MA(q) models** can be seen as an extension of the „pure“ process

$$X_t = E_t, \text{ where } E_t \text{ is a white noise process,}$$

in the sense that past innovation terms E_{t-1}, E_{t-2}, \dots are included, too. We call this a **moving average** model:

$$X_t = E_t + \beta_1 E_{t-1} + \beta_2 E_{t-2} + \dots + \beta_q E_{t-q}$$

This is a time series process that is stationary, but not iid. In many respects, MA(q) models are complementary to AR(p).

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Notation for MA(q)-models

The backshift operator, and the characteristic polynomial, allow for convenient notation:

$$\text{MA}(q): \quad X_t = E_t + \beta_1 E_{t-1} + \beta_2 E_{t-2} + \dots + \beta_q E_{t-q}$$

$$\text{MA}(q) \text{ with BS:} \quad X_t = \left(1 + \beta_1 B + \beta_2 B^2 + \dots + \beta_q B^q\right) E_t$$

$$\text{MA}(q) \text{ with BS+CP:} \quad X_t = \Theta(B) E_t$$

where

$$\Theta(z) = 1 + \beta_1 z + \beta_2 z^2 + \dots + \beta_q z^q$$

is the characteristic polynomial

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Stationarity of MA(1)-Models

We first restrict ourselves to the simple MA(1)-model

$$X_t = E_t + \beta_1 E_{t-1}, \text{ where } E_t \text{ is a White Noise innovation}$$

The series X_t is weakly stationary, no matter what the choice of the parameter β_1 is.

Remember that for proving this, we have to show that:

- the expected value is 0
- the variance is constant and finite
- the autocovariance only depends on the lag k

→ **see the blackboard for the proof**

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ACF of the MA(1)-Process

We can deduct the ACF for the MA(1)-process:

$$\rho(1) = \frac{\gamma(1)}{\gamma(0)} = \frac{\beta_1}{(1 + \beta_1^2)} < 0.5$$

and

$$\rho(k) = 0 \quad \text{for all } k > 1.$$

Thus, we have a “cut-off” situation, i.e. a similar behavior to the one of the PACF in an AR(1) process. This is why and how AR(1) and MA(1) are complementary.

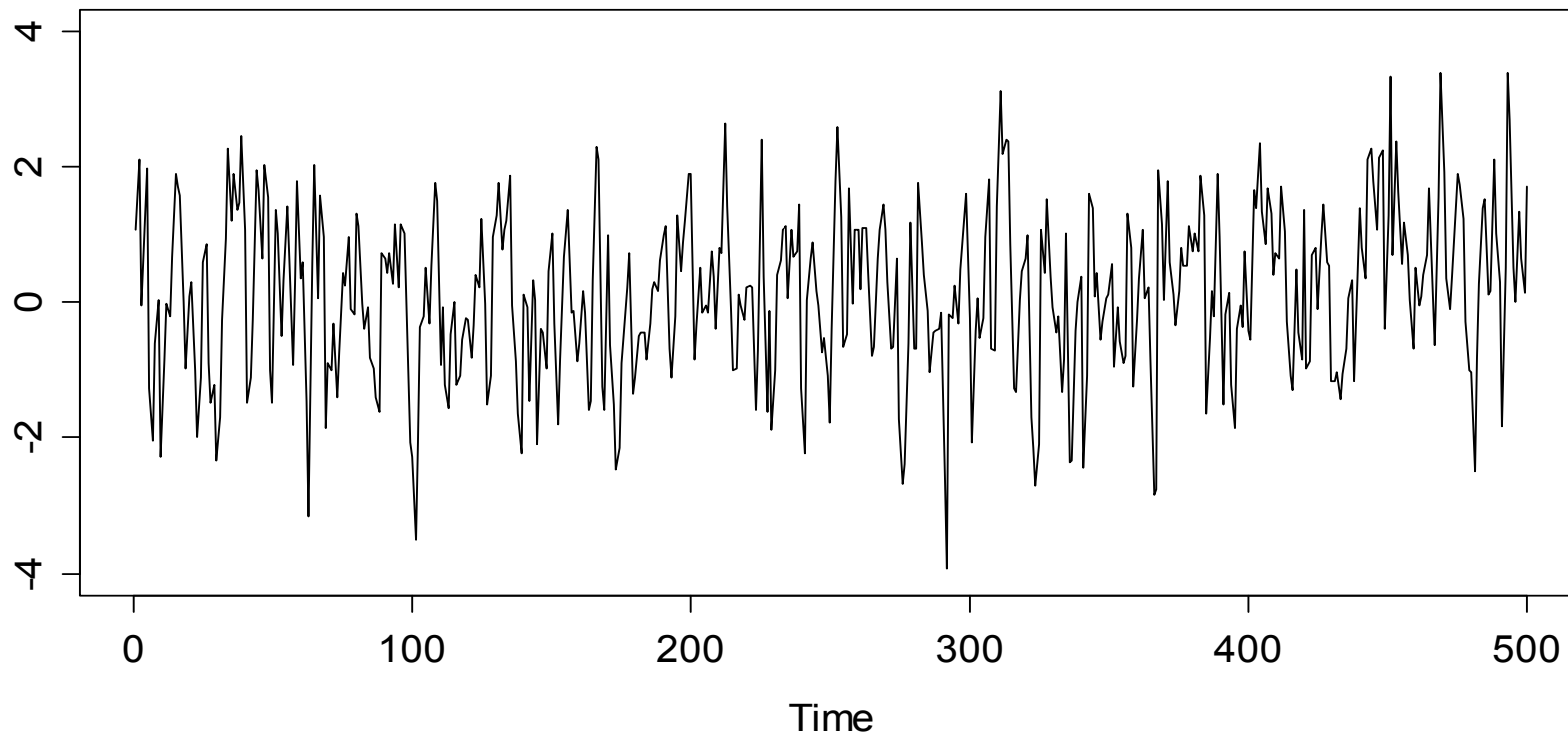
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Simulated Process with $\beta_1=0.7$

```
> ts.ma1 <- arima.sim(list(ma=0.7), n=500)  
> plot(ts.ma1, ylab="", ylim=c(-4,4))
```

Simulation from a MA(1) Process



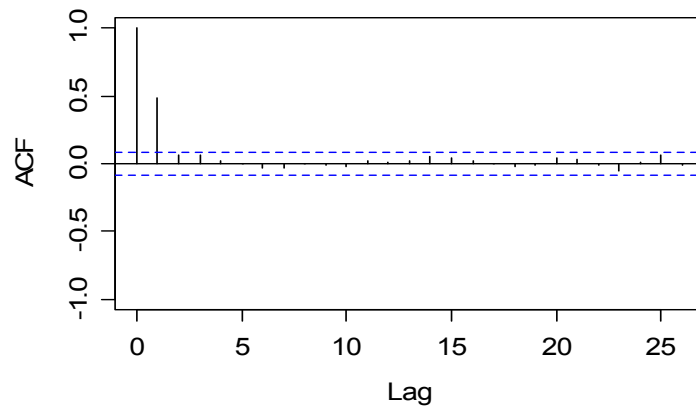
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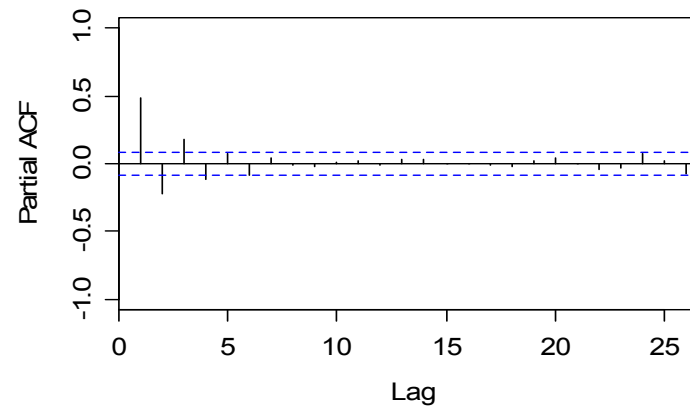
ACF and PACF of MA(1)

```
> acf.true <- ARMAacf(ma=0.7, lag.max=20)  
> pacf.true <- ARMAacf(ma=0.7, pacf=T, lag.m=20)
```

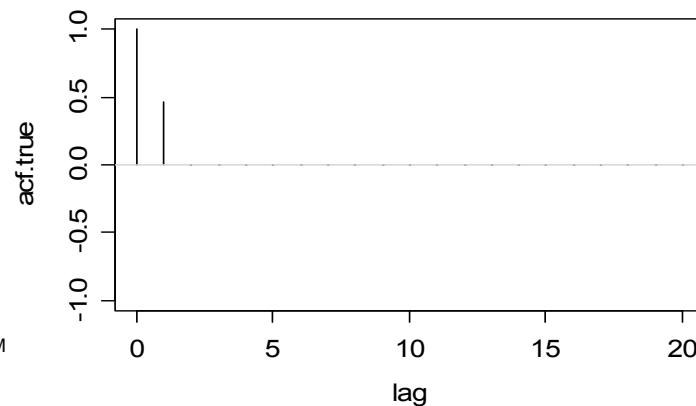
Estimated ACF



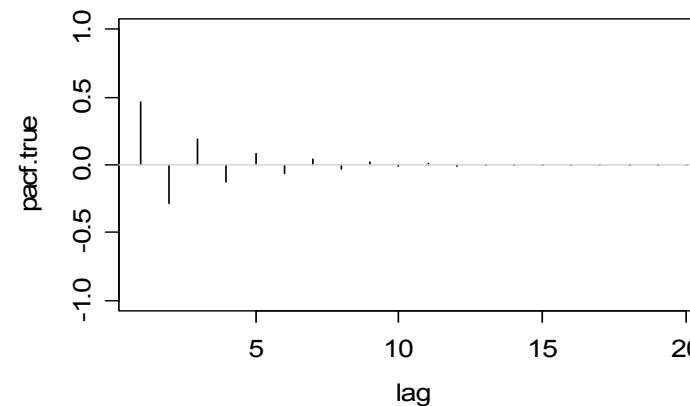
Estimated PACF



True ACF



True PACF



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MA(1): Remarks

Without additional assumptions, the ACF of an MA(1) doesn't allow identification of the generating model.

In particular, the two processes

$$X_t = E_t + 0.5 \cdot E_{t-1}$$

$$U_t = E_t + 2 \cdot E_{t-1}$$

have identical ACF:

$$\rho(1) = \frac{\beta_1}{1 + \beta_1^2} = \frac{1 / \beta_1}{1 + (1 / \beta_1^2)}$$

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MA(1): Invertibility

- An MA(1)-, or in general an MA(q)-process is said to be invertible if the roots of the characteristic polynomial $\Theta(B)$ lie outside of the unit circle.
- Under this condition, there exists only one MA(q)-process for any given ACF. But please note that any MA(q) is stationary, no matter if it is invertible or not.
- The condition on the characteristic polynomial translates to restrictions on the coefficients. For any MA(1)-model, $|\beta_1| < 1$ is required.
- R function `polyroot()` can be used for finding the roots.

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Practical Importance of Invertibility

The condition of invertibility is not only a technical issue, but has important practical meaning. Invertible MA(1)-processes can be written as an AR(∞):

$$\begin{aligned} X_t &= E_t + \beta_1 E_{t-1} \\ &= E_t + \beta_1 (X_{t-1} + E_{t-2}) \\ &= \dots \\ &= E_t + \beta_1 X_{t-1} + \beta_1^2 X_{t-2} + \beta_1^3 X_{t-3} + \dots \\ &= E_t + \sum_{i=1}^{\infty} \psi_i X_{t-i} \end{aligned}$$

Invertibility is practically relevant for model fitting!

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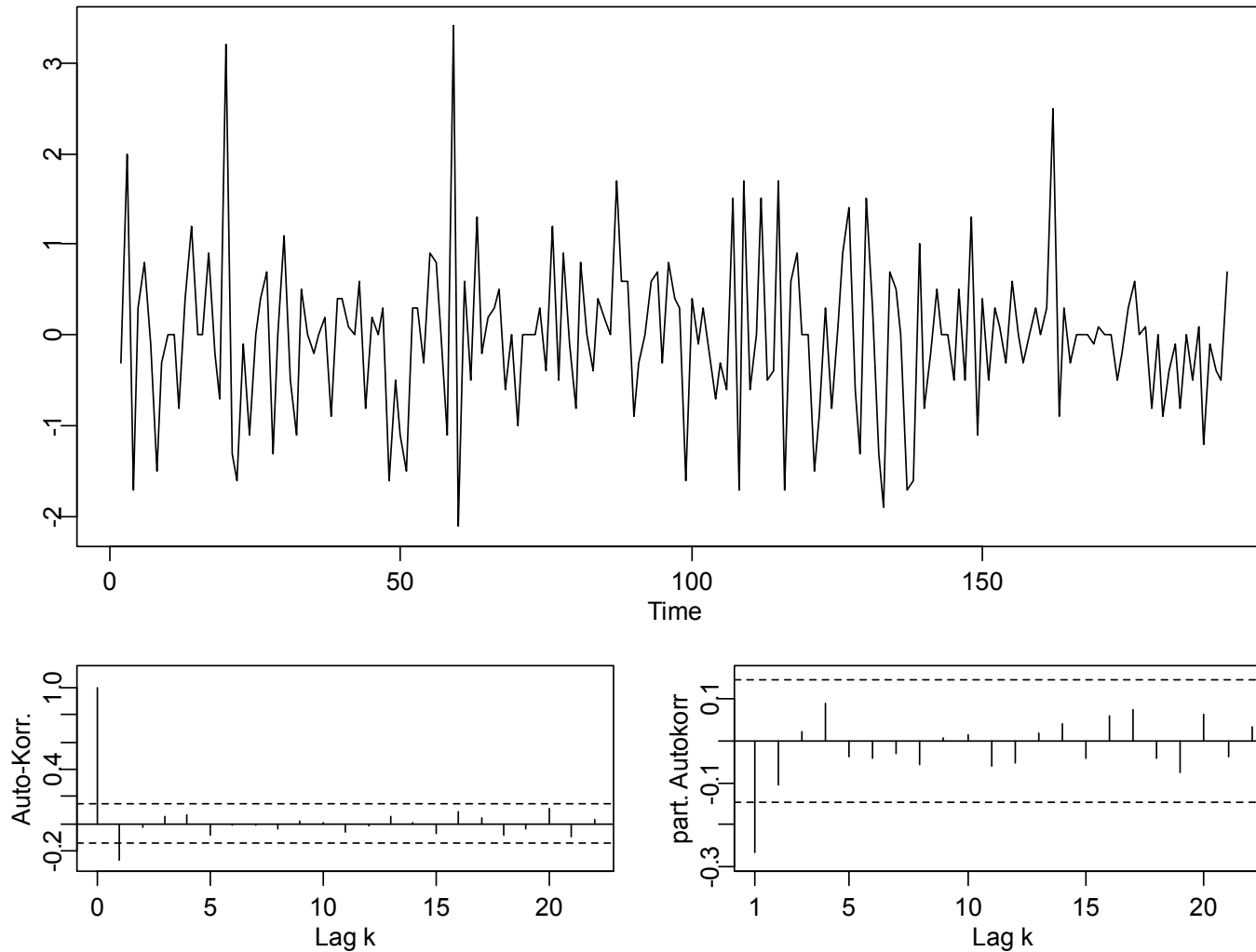
MA(1): Example

- daily return of an AT&T bond from 04/1975 to 12/1975
- the time series has 192 observations
- we are looking at the first-order differences
- an MA(1) model seems to fit the data (→ next slide)
- since we are looking at a differenced series, this is in fact an ARIMA(0,1,1) model (→ will be discussed later...)

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MA(1): Example



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MA(q)-Models

The MA(q)-model is defined as follows:

$$X_t = E_t + \beta_1 E_{t-1} + \beta_2 E_{t-2} + \dots + \beta_q E_{t-q} ,$$

where E_t are i.i.d. innovations (=a white noise process).

The ACF of this process can be computed from the coefficients:

$$\rho(k) = \frac{\sum_{i=0}^{q-k} \beta_i \beta_{i+k}}{\sum_{i=0}^q \beta_i^2} , \quad \text{for all } k=1, \dots, q \text{ with } \beta_0 = 1$$

$$\rho(k) = 0 , \quad \text{for all } k > q$$

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ACF/PACF of MA(q)

ACF

- the ACF of an MA(q) has a cut-off at lag $k=q$
- it behaves thus like the PACF of an AR(q)-model

PACF

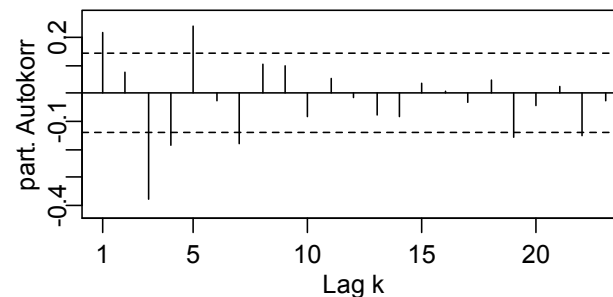
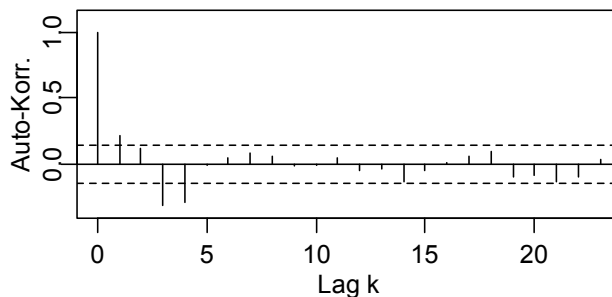
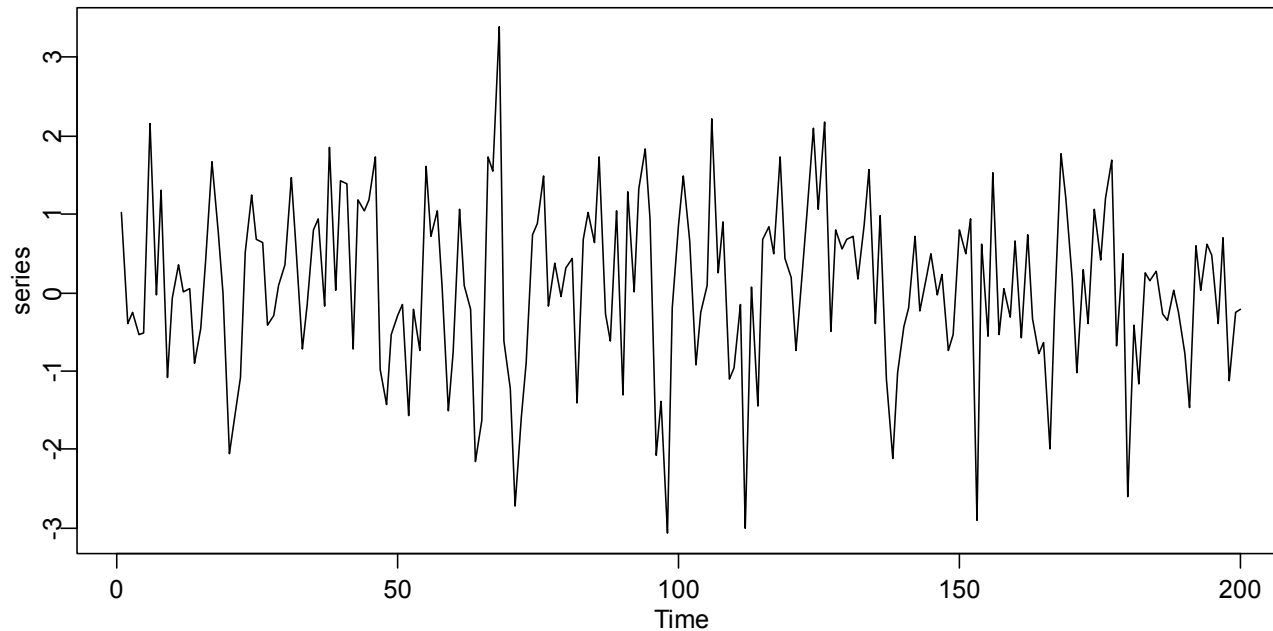
- the PACF is (again) complicated to determine, but:
- the PACF of an MA(q) has an „exponential decay“
- it behaves thus like the ACF of an AR-model

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MA(4): Example

$$X_t = E_t + 0.3 \cdot E_{t-1} + 0.3 \cdot E_{t-2} - 0.2 \cdot E_{t-3} - 0.2 \cdot E_{t-4}, \quad E_t \sim N(0,1)$$



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ARMA(p,q)-Models

An ARMA(p,q)-model combines AR(p) and MA(q):

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + E_t + \beta_1 E_{t-1} + \dots + \beta_q E_{t-q}$$

where E_t are i.i.d. innovations (=a white noise process).

It's easier to write an ARMA(p,q) with the characteristic polynomial:

$$\Phi(B)X_t = \Theta(B)E_t, \text{ where}$$

$$\Phi(z) = 1 - \alpha_1 z - \dots - \alpha_p z^p \quad \text{is the cP of the AR-part, and}$$

$$\Theta(z) = 1 - \beta_1 z - \dots - \beta_q z^q \quad \text{is the cP of the MA-part}$$

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Stationarity/Invertibility of ARMA(p,q)

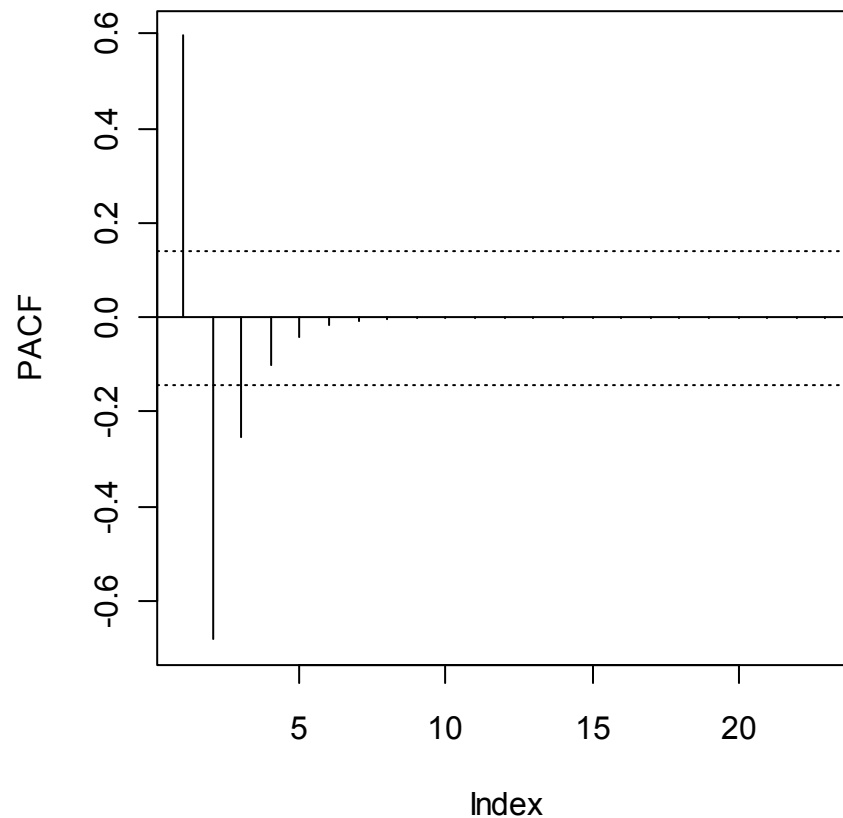
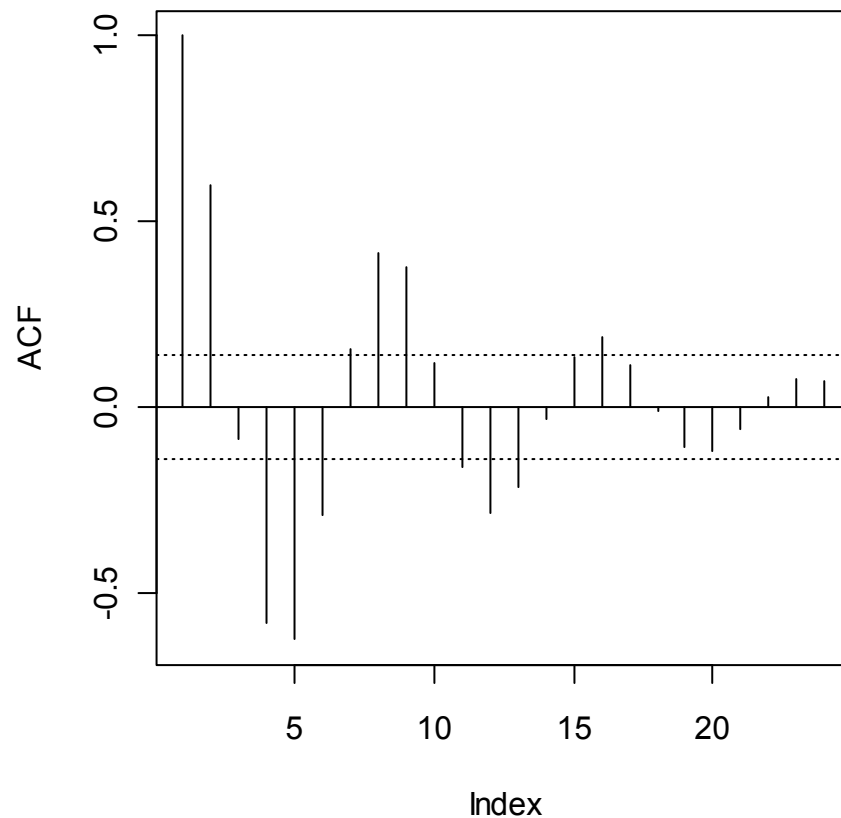
- both properties are determined by the cP
- the AR-cP determines stationarity
- the MA-cP determines invertibility
- condition: roots of the cP outside of the unit circle
- stationarity: model can be written as a $MA(\infty)$
- invertibility: model can be written as an $AR(\infty)$

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True ACF/PACF of an ARMA(2,1)

$$X_t = 1.2 \cdot X_{t-1} - 0.8 \cdot X_{t-2} + E_t + 0.4 \cdot E_{t-1}, \quad E_t \sim N(0,1)$$

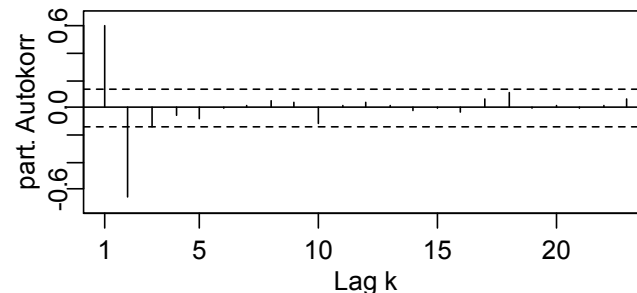
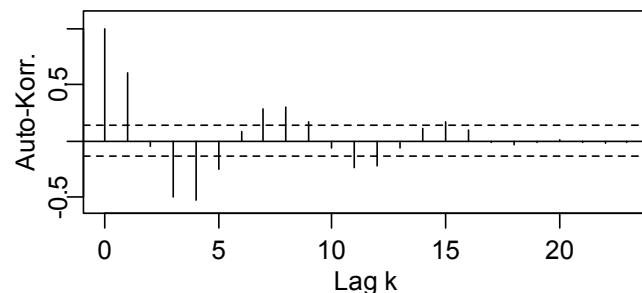
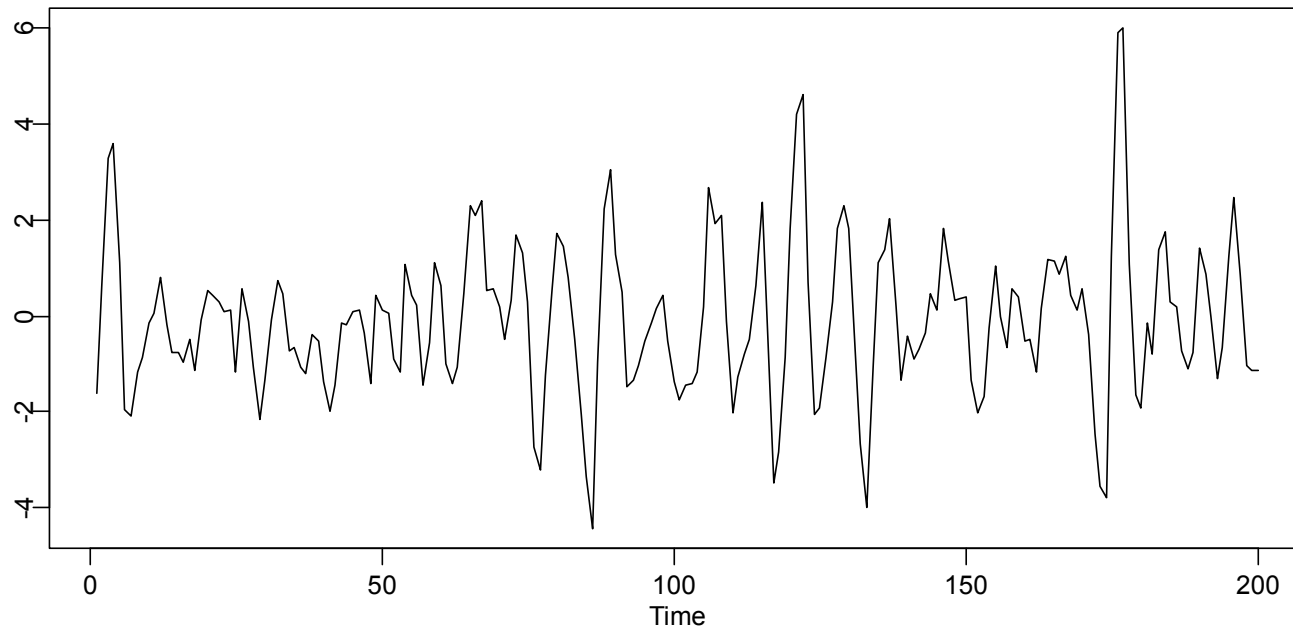


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Simulated ACF/PACF of an ARMA(2,1)

$$X_t = 1.2 \cdot X_{t-1} - 0.8 \cdot X_{t-2} + E_t + 0.4 \cdot E_{t-1}, \quad E_t \sim N(0,1)$$



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Properties of ACF/PACF in ARMA(p,q)

	ACF	PACF
AR(p)	exponential decay	cut-off at lag p
MA(q)	cut-off at lag q	exponential decay
ARMA(p,q)	mix decay/cut-off	mix decay/cut-off

→ all linear time series processes can be approximated by an ARMA(p,q) with possibly large p,q. They are thus are very rich class of models.

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Fitting ARMA(p,q)

What needs to be done?

- 1) **Achieve stationarity**
→ transformations, differencing, modeling, ...
- 2) **Choice of the order**
→ determining (p,q)
- 3) **Parameter estimation**
→ Estimation of α , β , μ , σ_E^2
- 4) **Residual analysis**
→ if necessary, repeat 1), and/or 2)-4)

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Identification of the Order (p,q)

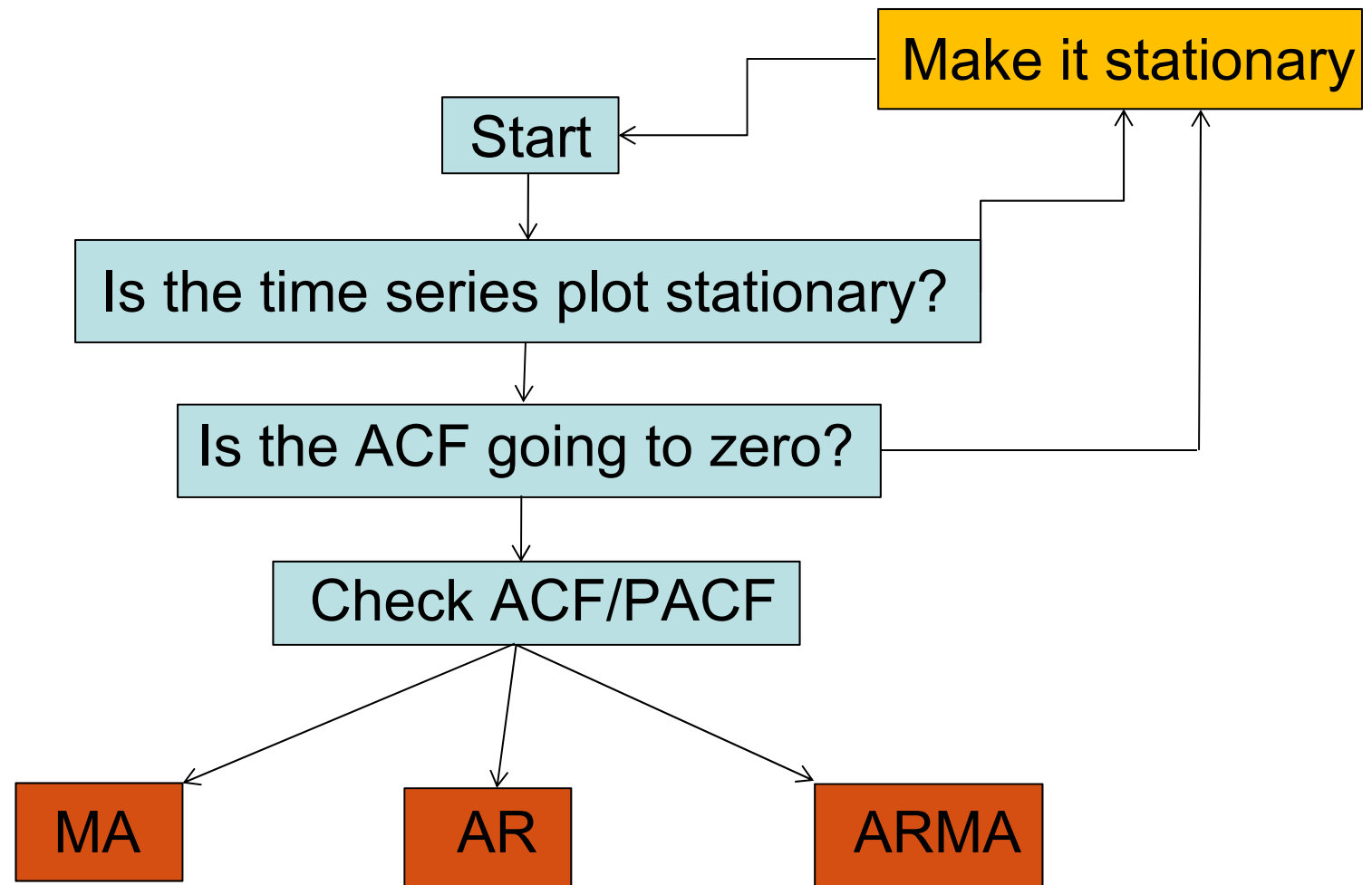
Please note:

- We only have one single realization of the time series with finite length.
 - The plots (etc.) we base the order choice on are not „facts“, but are estimations with uncertainty.
 - This holds especially for the ACF/PACF plots.
 - Every ARMA(p,q) can be written as $AR(\infty)$ or $MA(\infty)$
- **There is usually >1 model that describes the data well.**

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ARMA(p,q)-Modeling



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Parameter Estimation

For parameter estimation with AR(p) models, we had 4 choices:

- a) Regression
- b) Yule-Walker
- c) Maximum-Likelihood
- d) Burg's Algorithm

For ARMA(p,q) models, only two options are remaining, and both of them require numerical optimization:

- 1) Conditional Sum of Squares**
- 2) Maximum-Likelihood**

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Conditional Sum of Squares

Idea: This is an iterative approach where the parameters are determined such that the sum of squared errors (between observations and fitted values) are minimal.

$$S(\hat{\beta}_1, \dots, \hat{\beta}_q) = \sum_{t=1}^n \hat{E}_t^2 = \sum_{t=1}^n (X_t - (\hat{\beta}_1 \hat{E}_{t-1} - \dots - \hat{\beta}_q \hat{E}_{t-q}))^2$$

This requires starting values which are chosen as:

$$\hat{E}_0 = 0, \hat{E}_{-1} = 0, \dots, \hat{E}_{1-q} = 0$$

A numerical search is used to find the parameter values that minimize the entire conditional sum of squares. They also serve as starting values for MLE.

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Maximum-Likelihood-Estimation

Idea: Determine the parameters such that, given the observed time series x_1, \dots, x_n , the resulting model is the most plausible (i.e. the most likely) one.

→ **This requires the choice of a probability distribution for the time series $X = (X_1, \dots, X_n)$**

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Maximum-Likelihood-Estimation

If we assume the ARMA(p,q)-model

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + E_t + \beta_1 E_{t-1} + \dots + \beta_q E_{t-q}$$

and i.i.d. normally distributed innovations

$$E_t \sim N(0, \sigma_E^2)$$

the time series vector has a multivariate normal distribution

$$X = (X_1, \dots, X_n) \sim N(\mu \cdot \underline{1}, V)$$

with covariance matrix V that depends on the model parameters α , β and σ_E^2 .

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Maximum-Likelihood-Estimation

We then maximize the density of the multivariate normal distribution with respect to the parameters

$$\alpha, \beta, \mu \text{ and } \sigma_E^2.$$

The observed x-values are hereby regarded as fixed values.

→ **This is a highly complex non-linear optimization problem that requires sophisticated algorithms and starting values which are usually provided by CSS (at least that's the default in R's `arima()`).**

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Maximum-Likelihood-Estimation

```
> r.Pmle <- arima(d.Psqrt,order=c(2,0,0),include.mean=T)
> r.Pmle
```

```
Call: arima(x=d.Psqrt, order=c(2,0,0), include.mean=T)
```

Coefficients:

	ar1	ar2	intercept
	0.275	0.395	3.554
s.e.	0.107	0.109	0.267

```
sigma^2 = 0.6: log likelihood = -82.9, aic = 173.8
```

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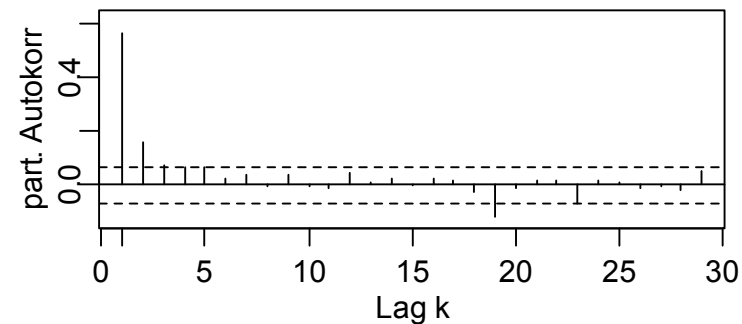
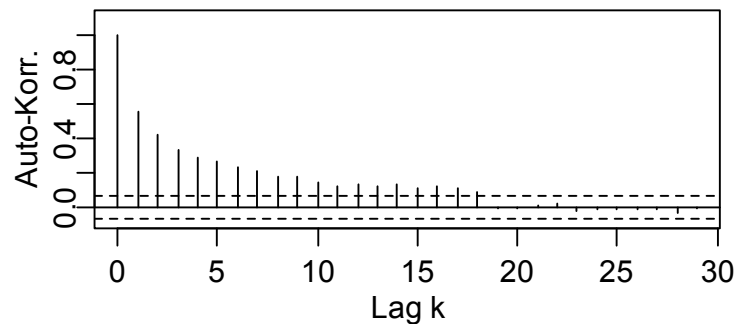
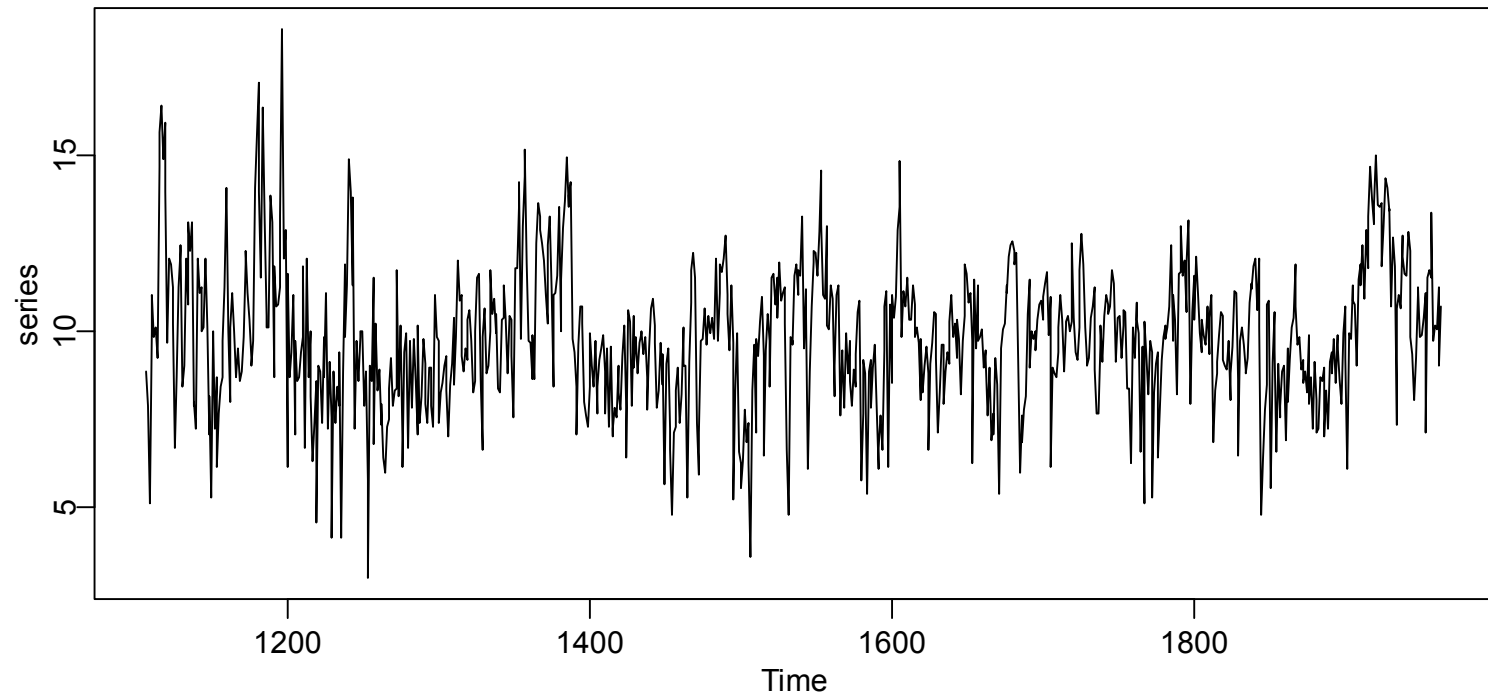
MLE: Remarks

- The MLE approach would work for any distribution. However, for innovation distributions other than Gaussian, the joint distribution might be „difficult“.
- For „reasonable“ deviations from the normality assumption, MLE still yields „good“ results.
- Besides the parameter estimates, we also obtain an estimate of their standard error
- Other software packages such as for example SAS don't rely on MLE, but use CSS, which is in spirit similar to Burg's algorithm.

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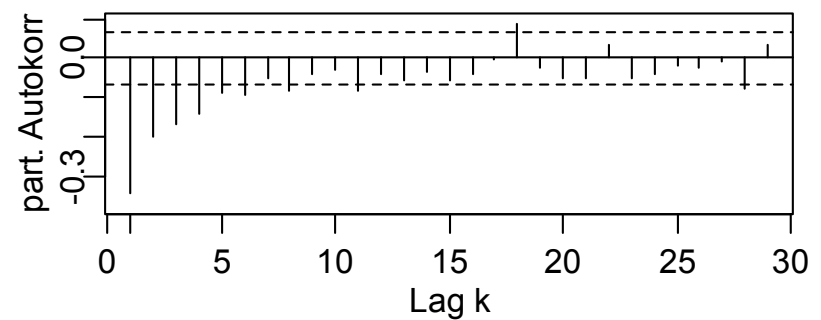
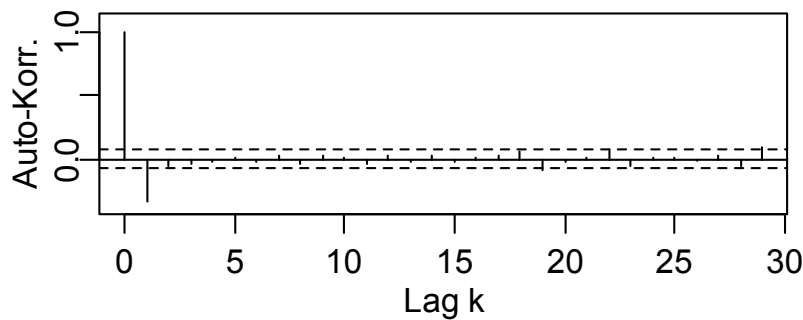
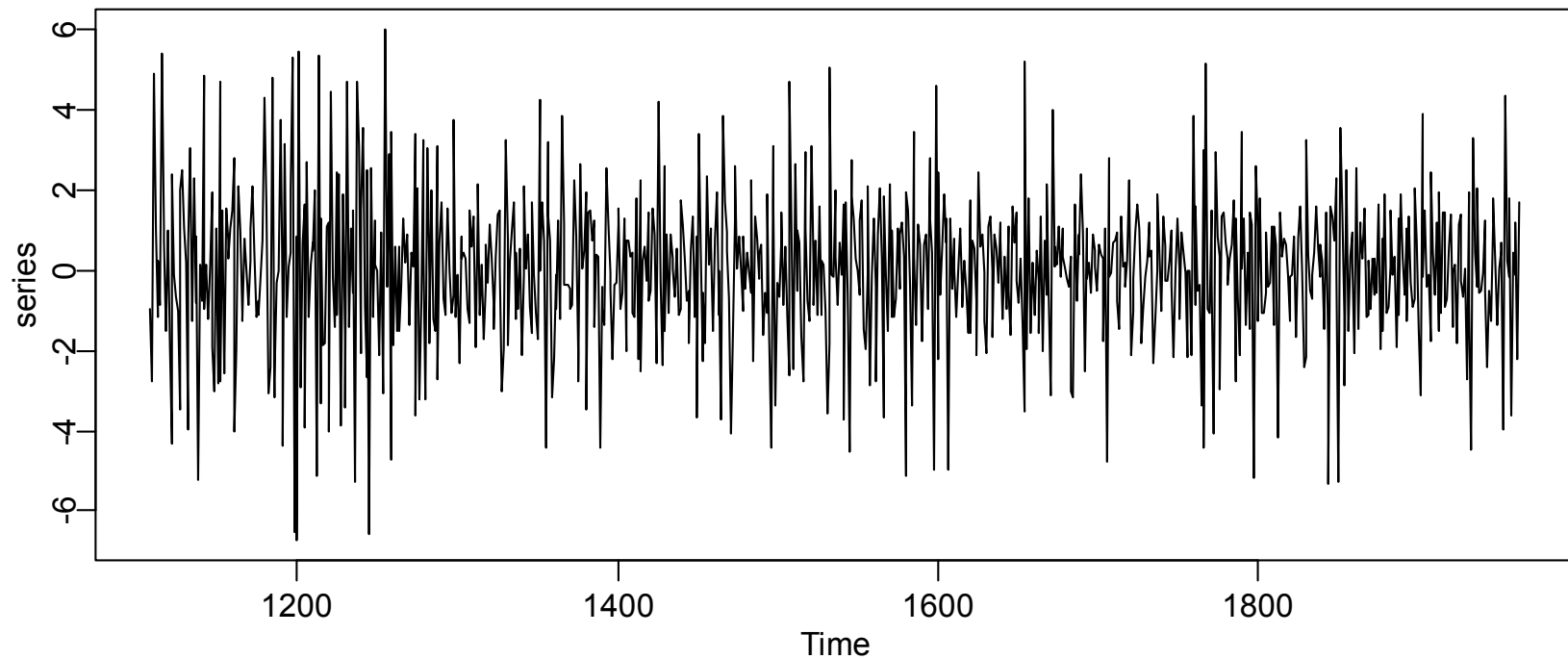
Douglas Fir: Original Data



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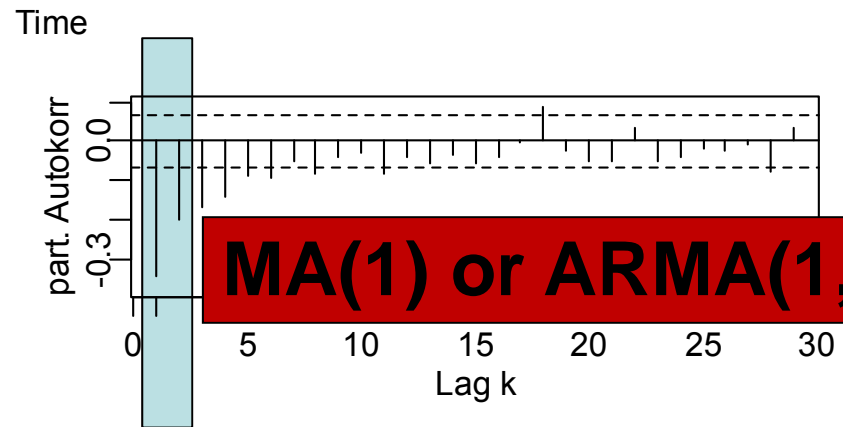
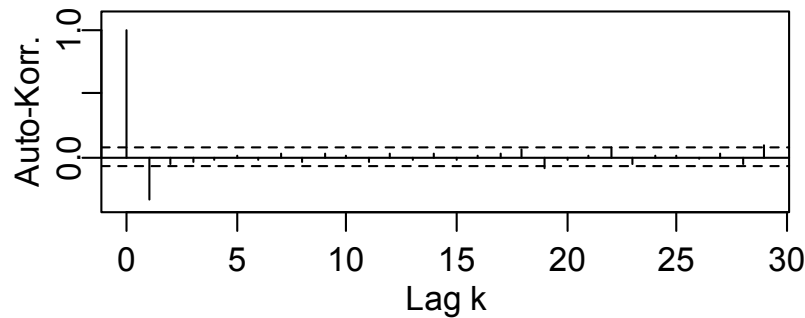
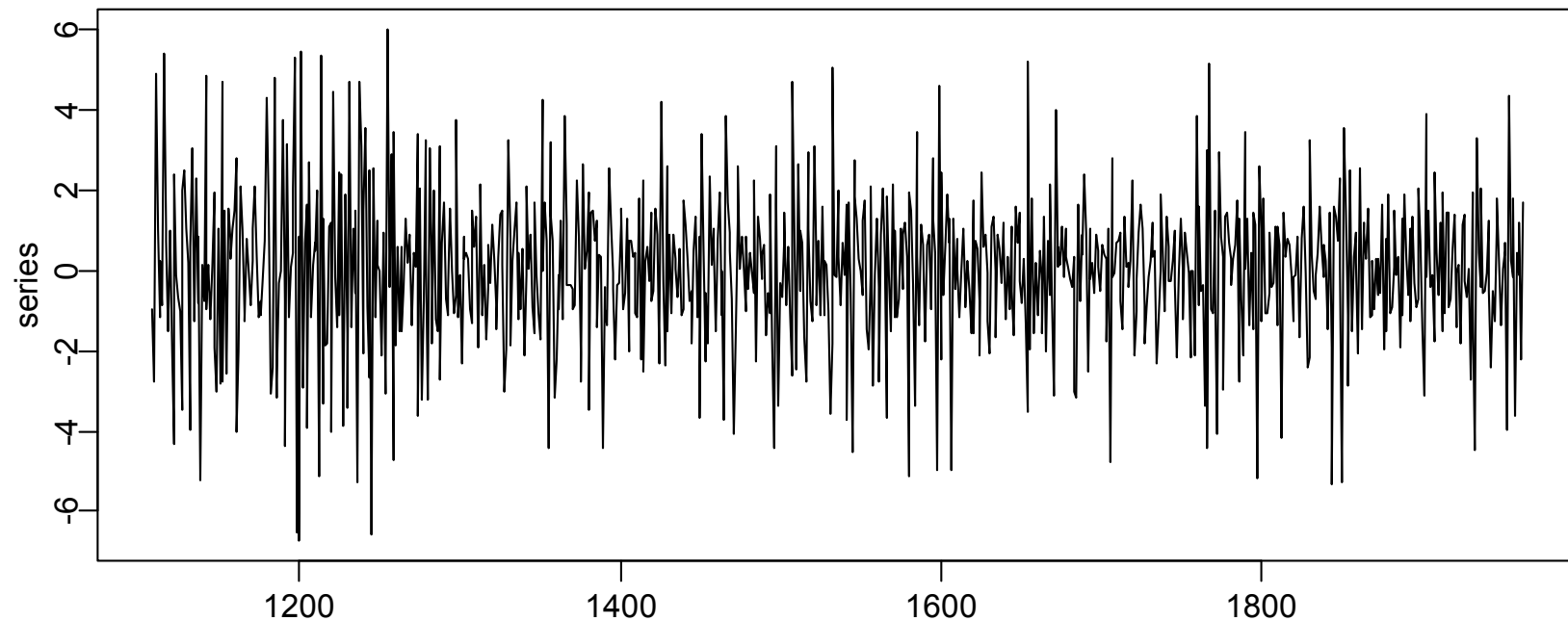
Douglas Fir: Differenced Series



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Douglas Fir: Differenced Series

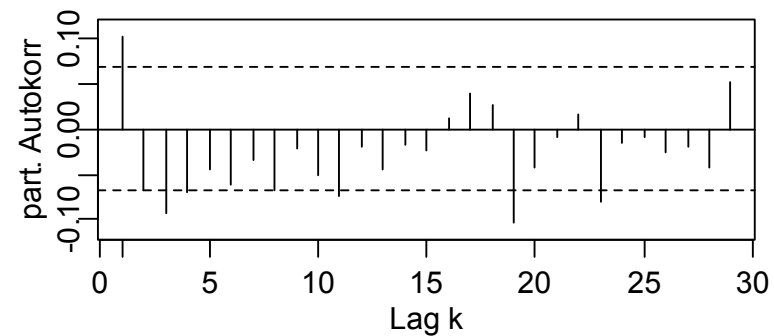
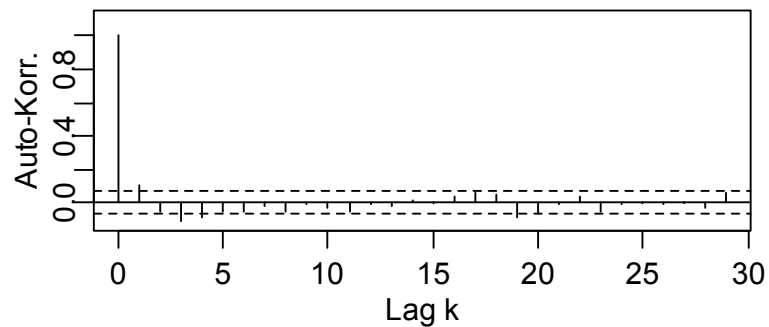
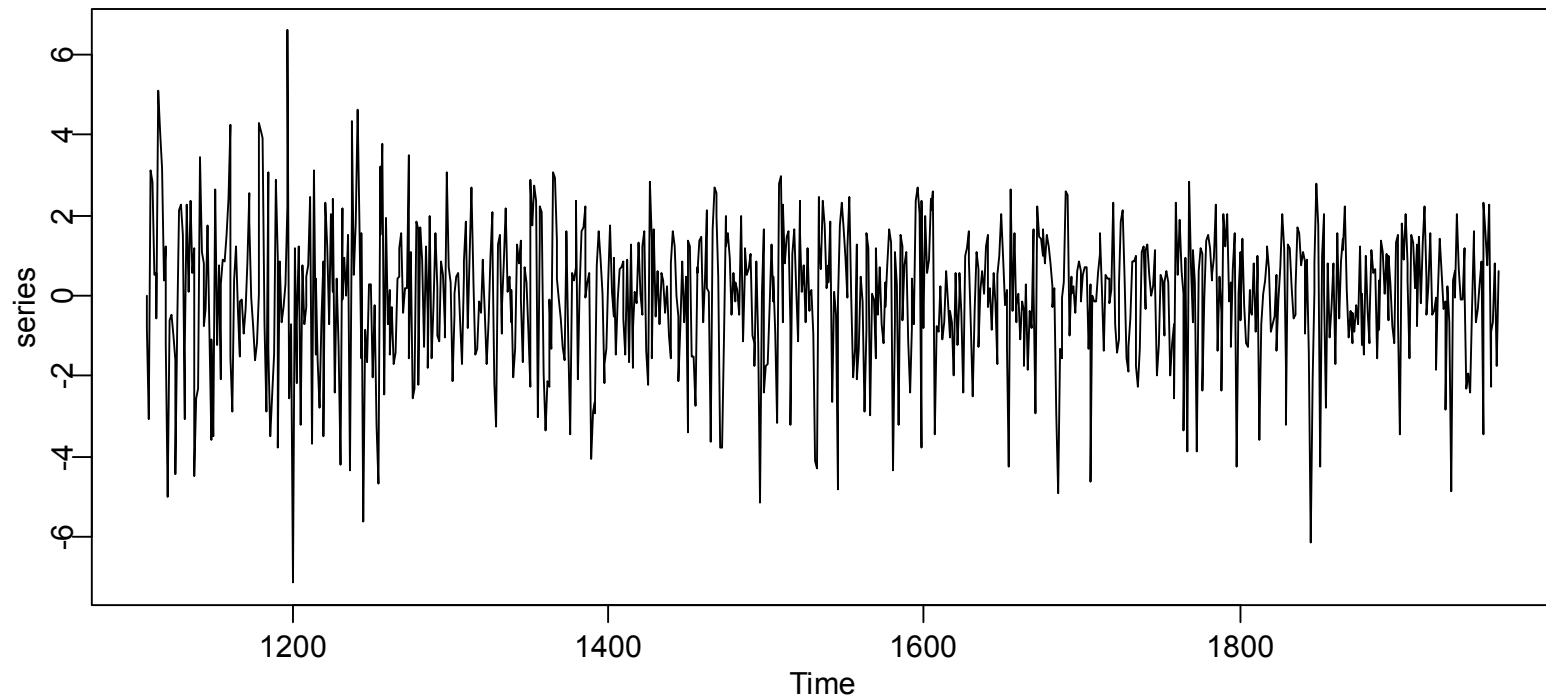


MA(1) or ARMA(1,1)???

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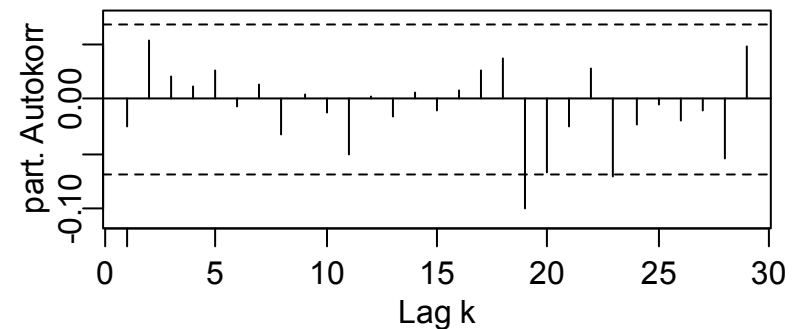
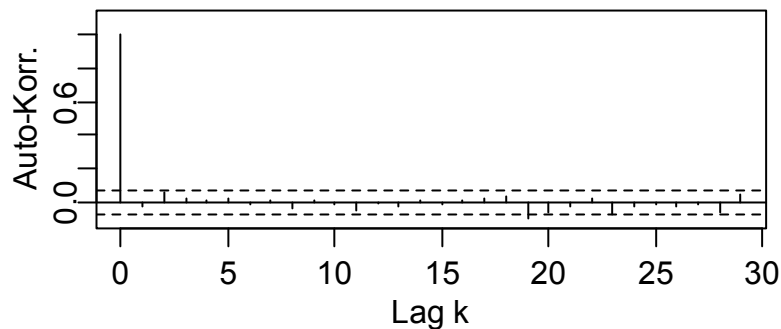
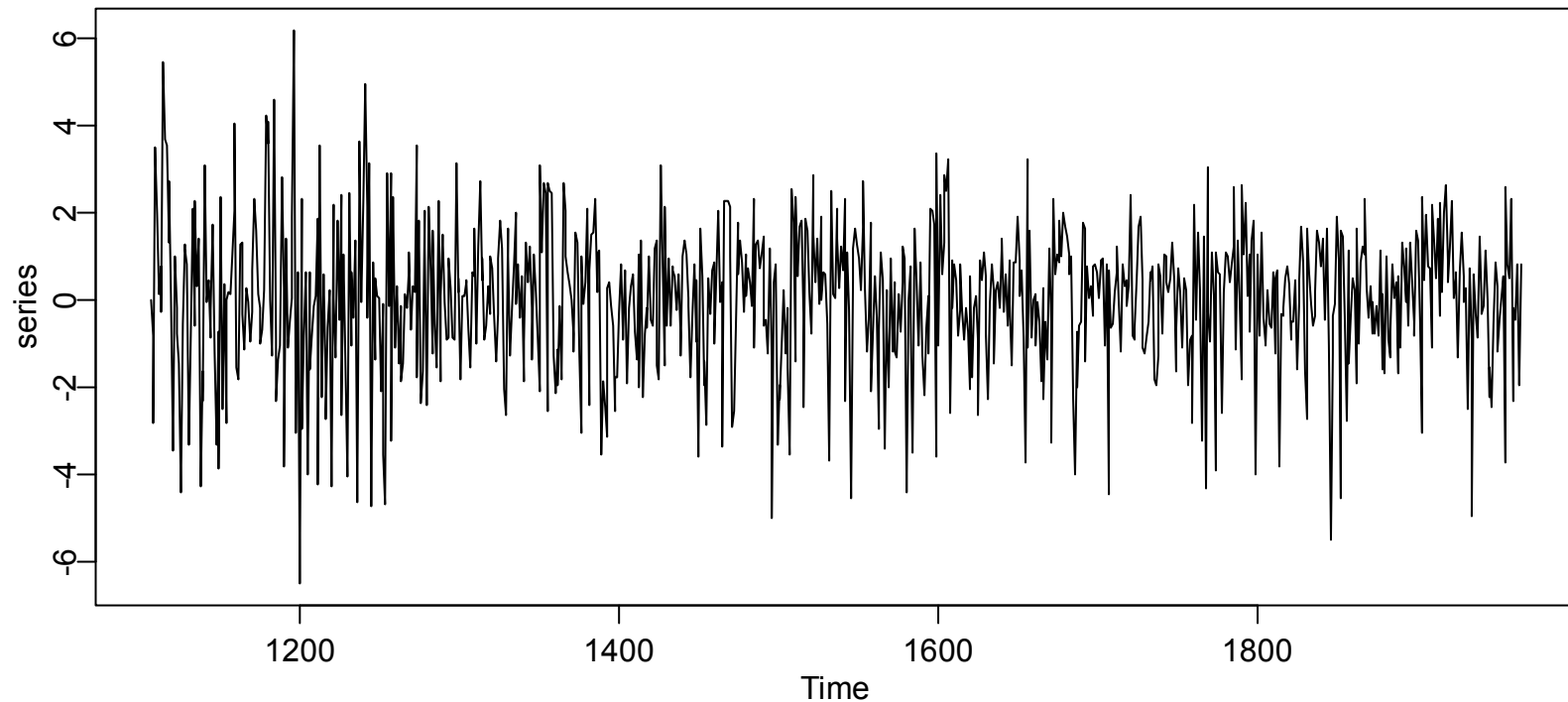
Residuals of MA(1)



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Residuals of ARMA(1,1)



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Another Example: Fitting ARMA(p,q)

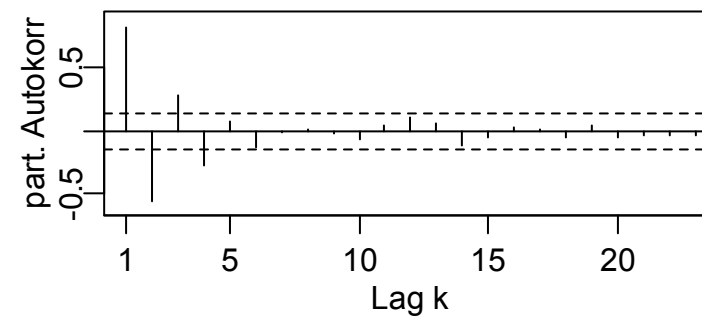
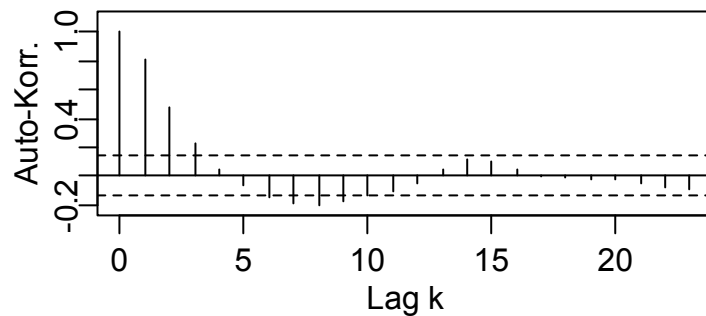
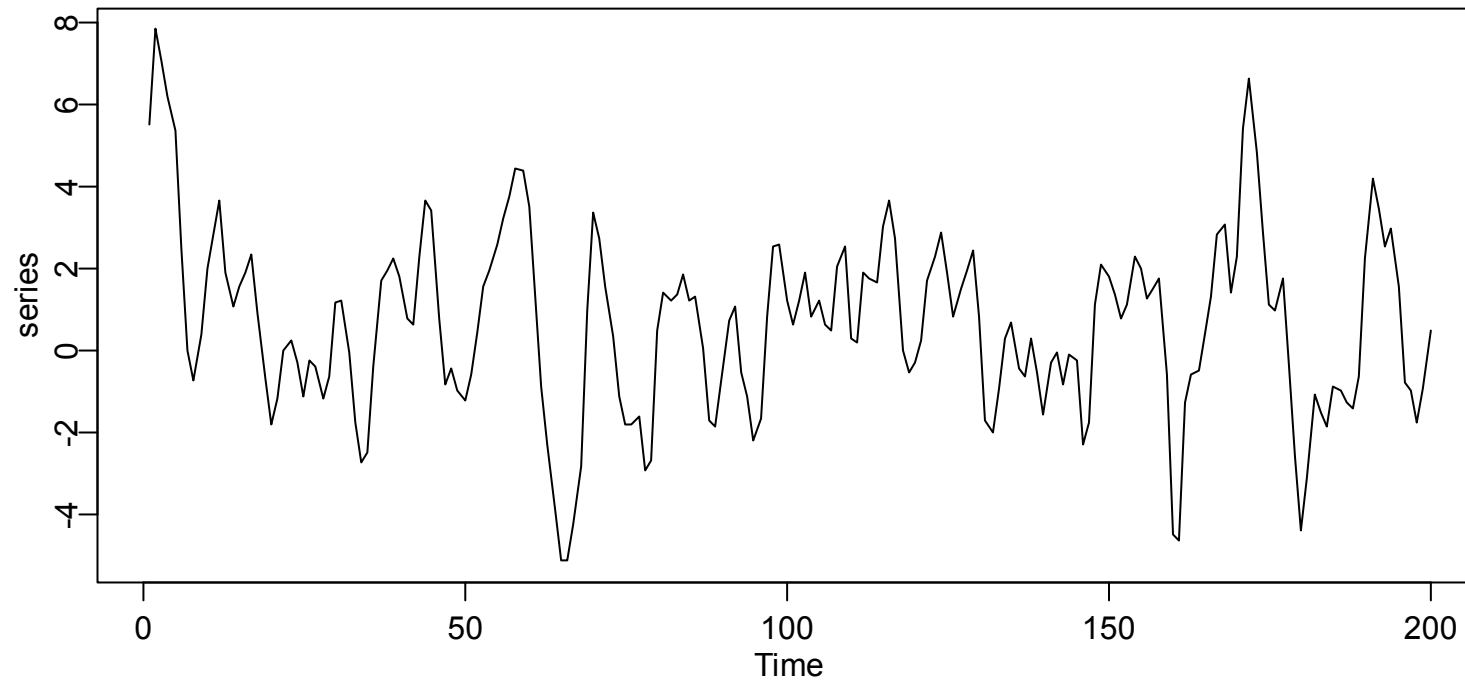
What needs to be done?

- 1) Achieve stationarity
→ transformations, differencing, modeling, ...
- 2) Choice of the order
→ determining (p,q), plus integration order d for ARIMA
- 3) Parameter estimation
→ ML-estimation of $\alpha, \beta, \mu, \sigma_E^2$
- 4) Residual analysis
→ if necessary, repeat 1), and/or 2)-4)

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The Series, ACF and PACF



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Model 1: AR(4)

```
> fit1
```

```
Call: arima(x = my.ts, order = c(4, 0, 0))
```

```
Coefficients:
```

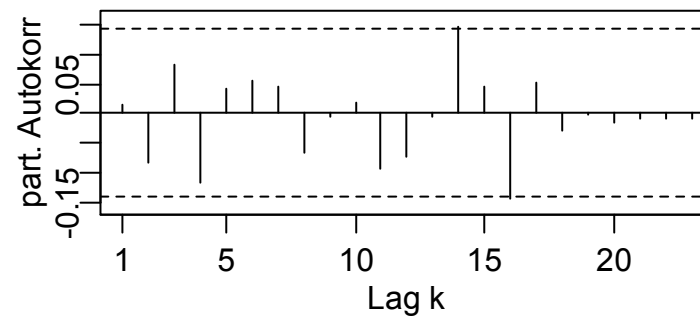
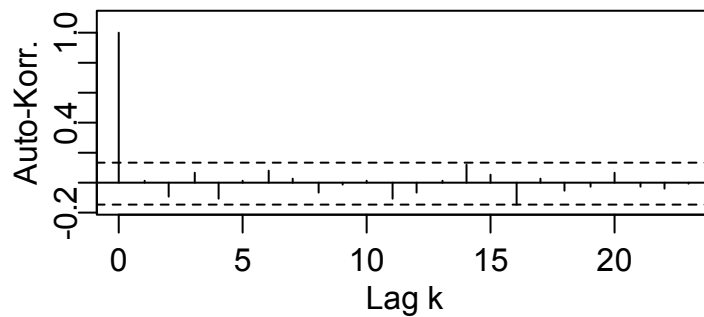
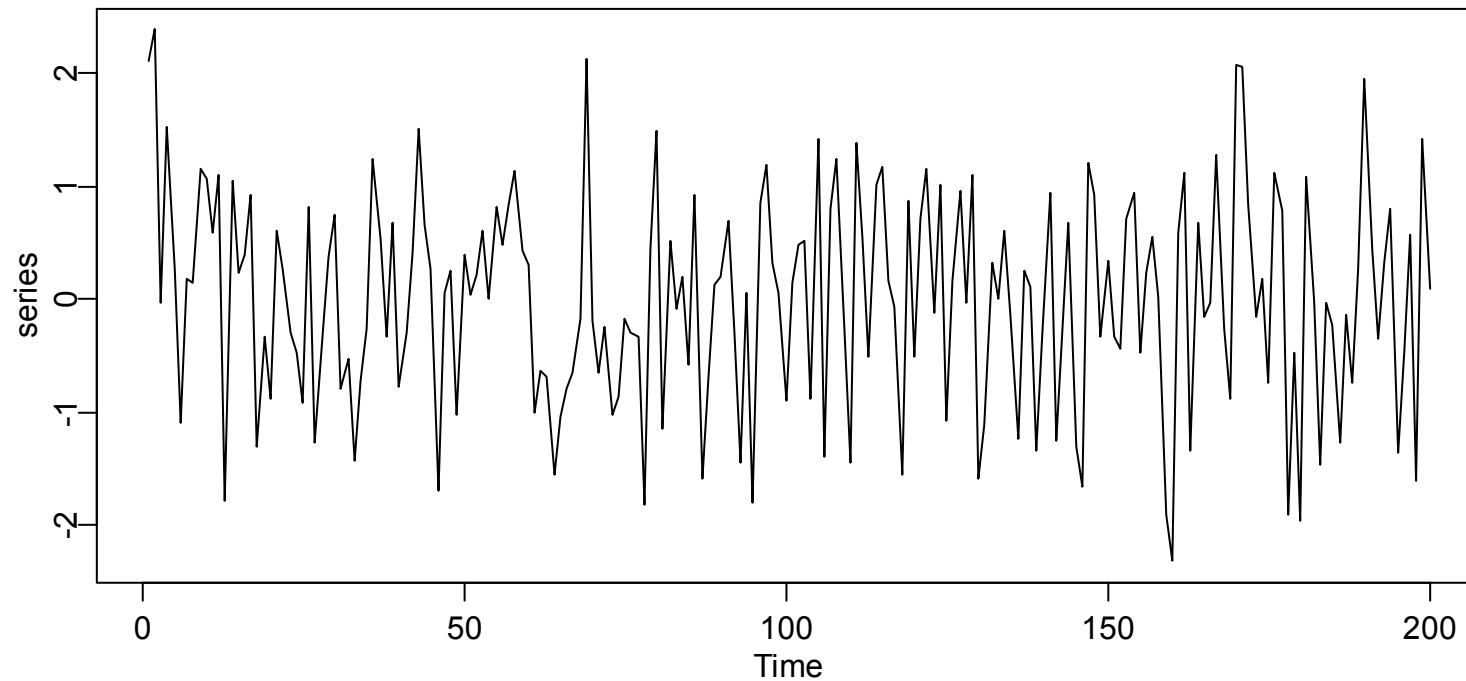
	ar1	ar2	ar3	ar4	intercept
	1.5430	-1.2310	0.7284	-0.3000	0.6197
s.e.	0.0676	0.1189	0.1189	0.0697	0.2573

```
sigma^2=0.8923, log likelihood=-273.67, aic=559.33
```

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Residuals of Model 1: AR(4)



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Model 2: MA(3)

```
> fit2
```

```
Call: arima(x = my.ts, order = c(0, 0, 3))
```

```
Coefficients:
```

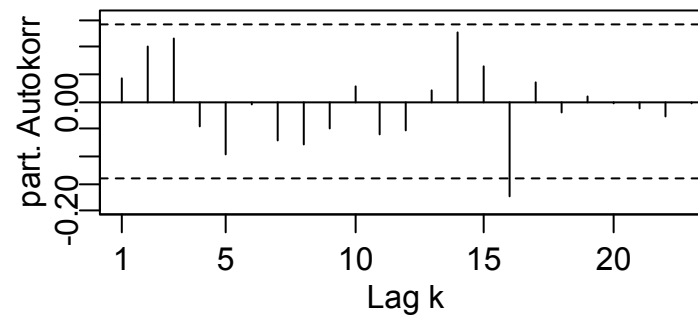
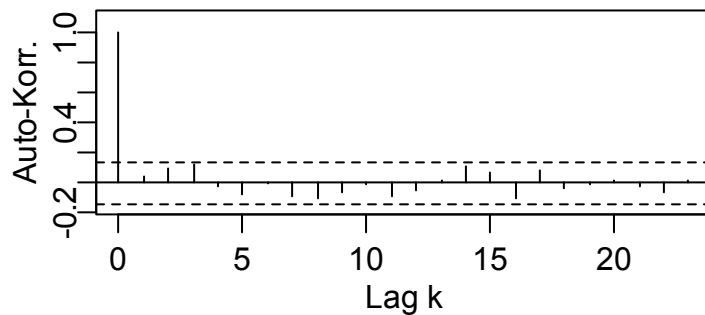
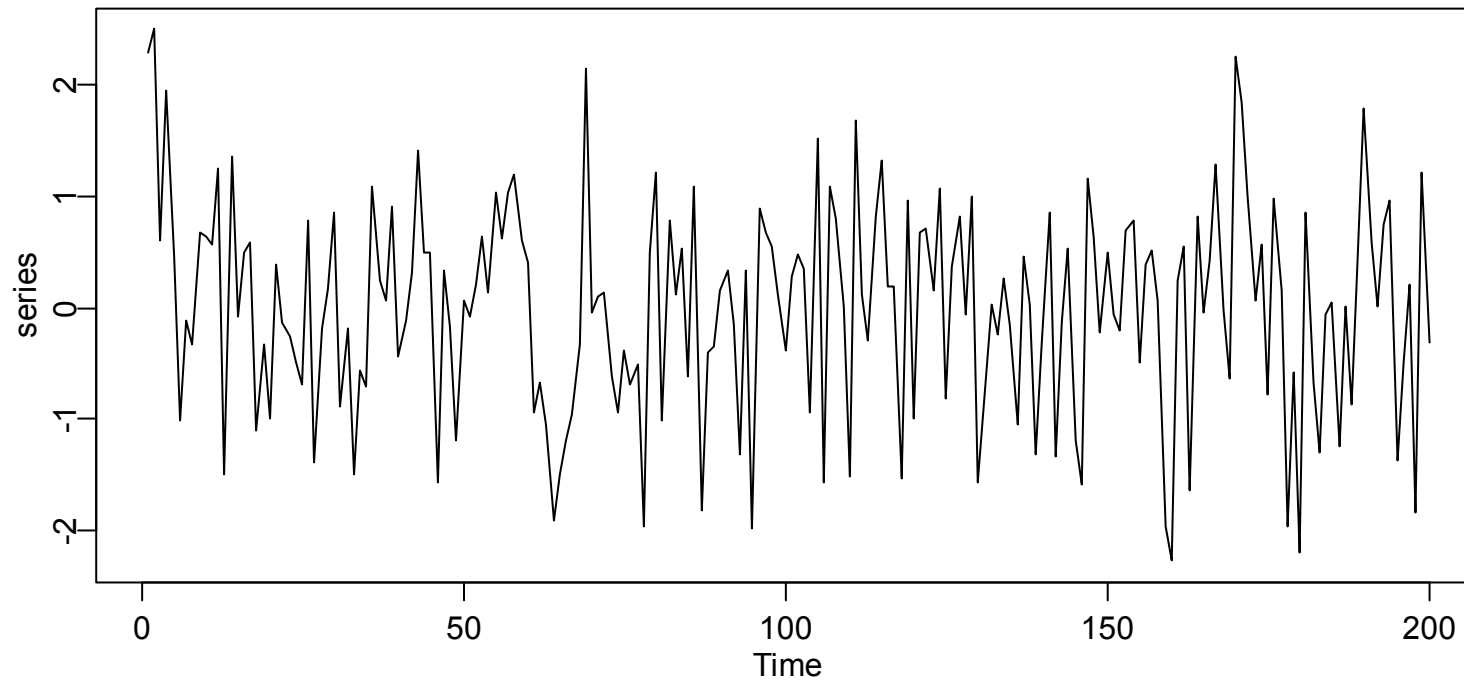
	ma1	ma2	ma3	intercept
	1.5711	1.0056	0.3057	0.6359
s.e.	0.0662	0.0966	0.0615	0.2604

```
sigma^2=0.9098, log likelihood=-275.64, aic=561.29
```

Applied Time Series Analysis

FS 2013 – Week 07

Residuals of Model 2: MA(3)



Applied Time Series Analysis

FS 2013 – Week 07

Model 3: ARMA(1,1)

```
> fit3
```

```
Call: arima(x = my.ts, order = c(1, 0, 1))
```

```
Coefficients:
```

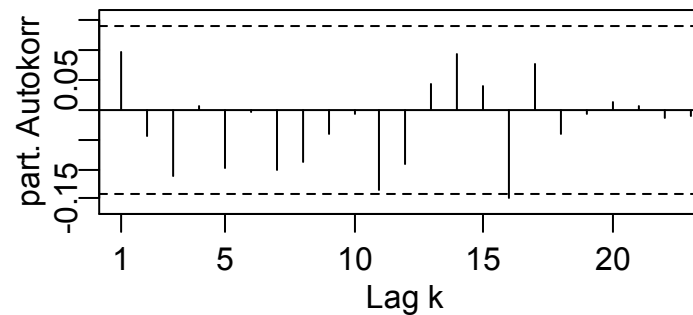
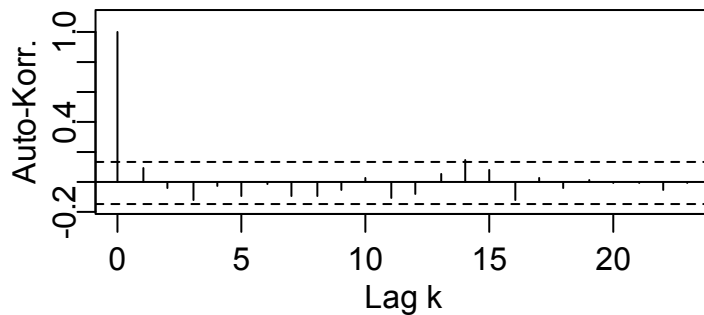
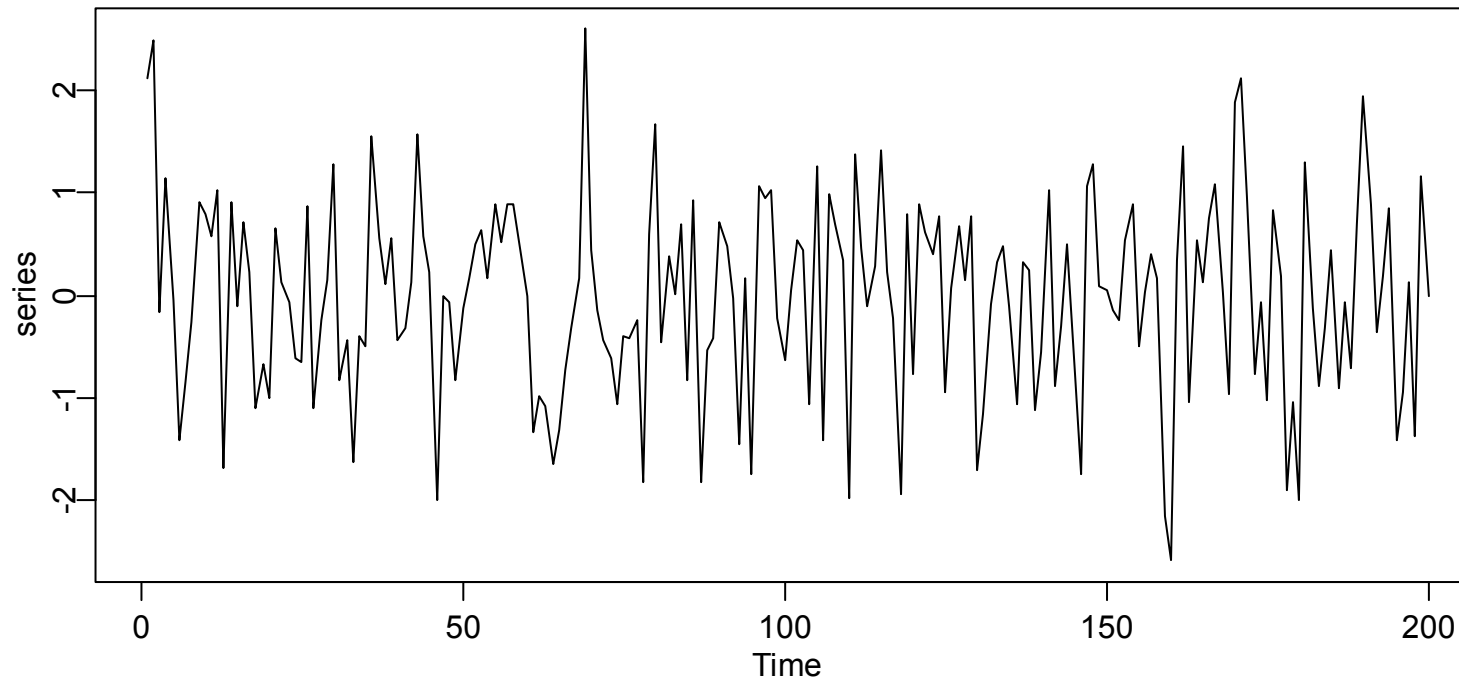
	ar1	ma1	intercept
	0.6965	0.7981	0.6674
s.e.	0.0521	0.0400	0.3945

```
sigma^2=0.9107, log likelihood=-275.72, aic=559.43
```

Applied Time Series Analysis

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Residuals of Model 3: ARMA(1,1)



Applied Time Series Analysis

FS 2013 – Week 07

Model 4: ARMA(2,1)

```
> fit4
```

```
Call: arima(x = my.ts, order = c(2, 0, 1))
```

```
Coefficients:
```

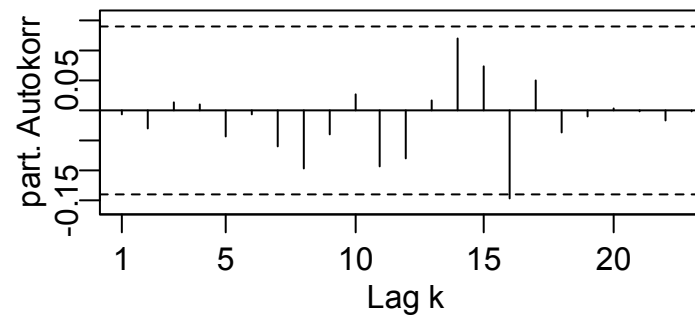
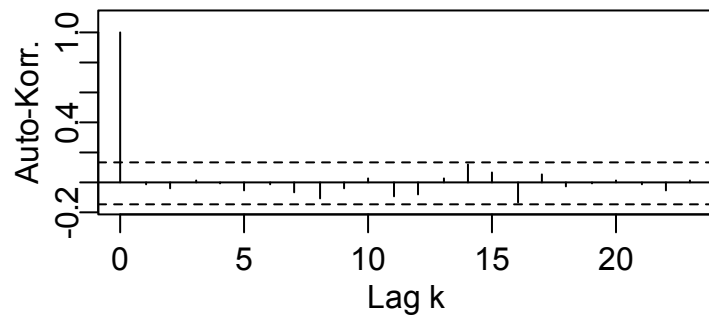
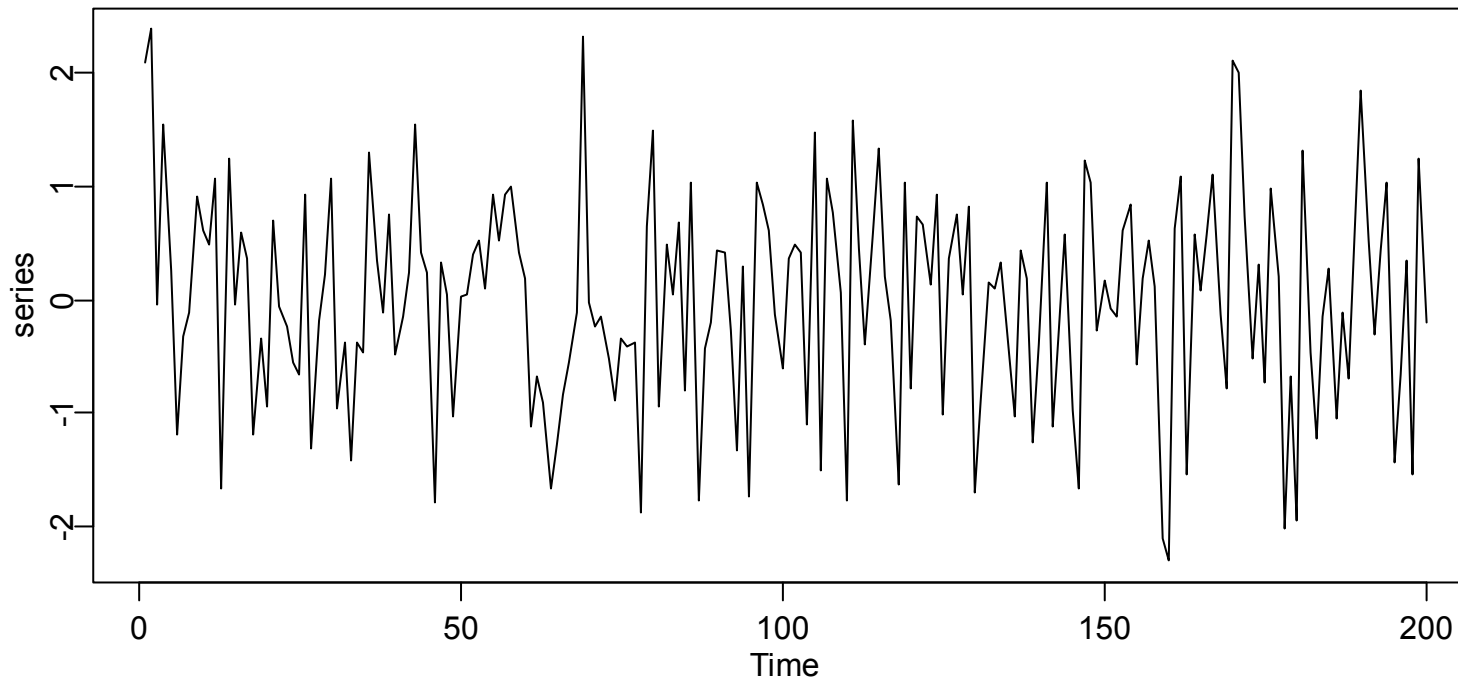
	ar1	ar2	ma1	intercept
	0.8915	-0.2411	0.7061	0.6420
s.e.	0.0855	0.0856	0.0625	0.3208

```
sigma^2=0.8772, log likelihood=-272.01, aic=554.02
```

Applied Time Series Analysis

FS 2013 – Week 07

Residuals of Model 4: ARMA(2,1)



Applied Time Series Analysis

FS 2013 – Week 07

Model 5: ARMA(4,1)

```
> fit5
```

```
Call: arima(x = my.ts, order = c(4, 0, 1))
```

```
Coefficients:
```

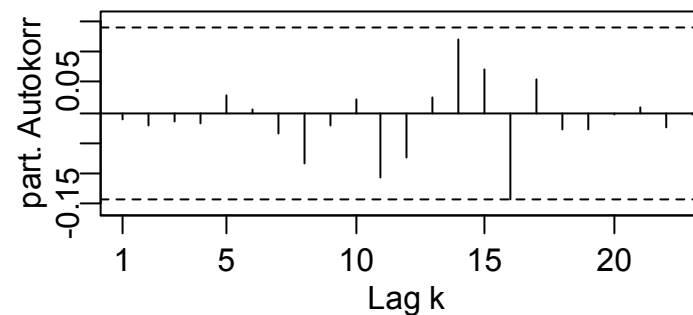
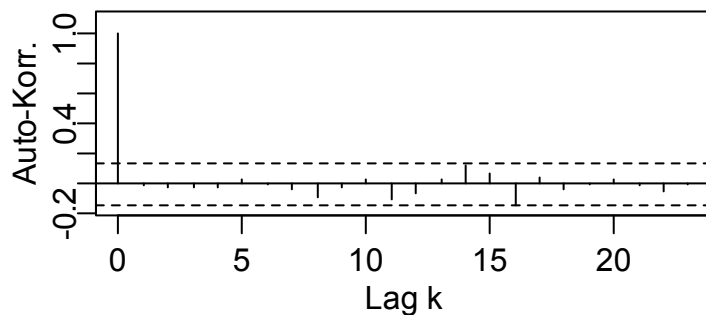
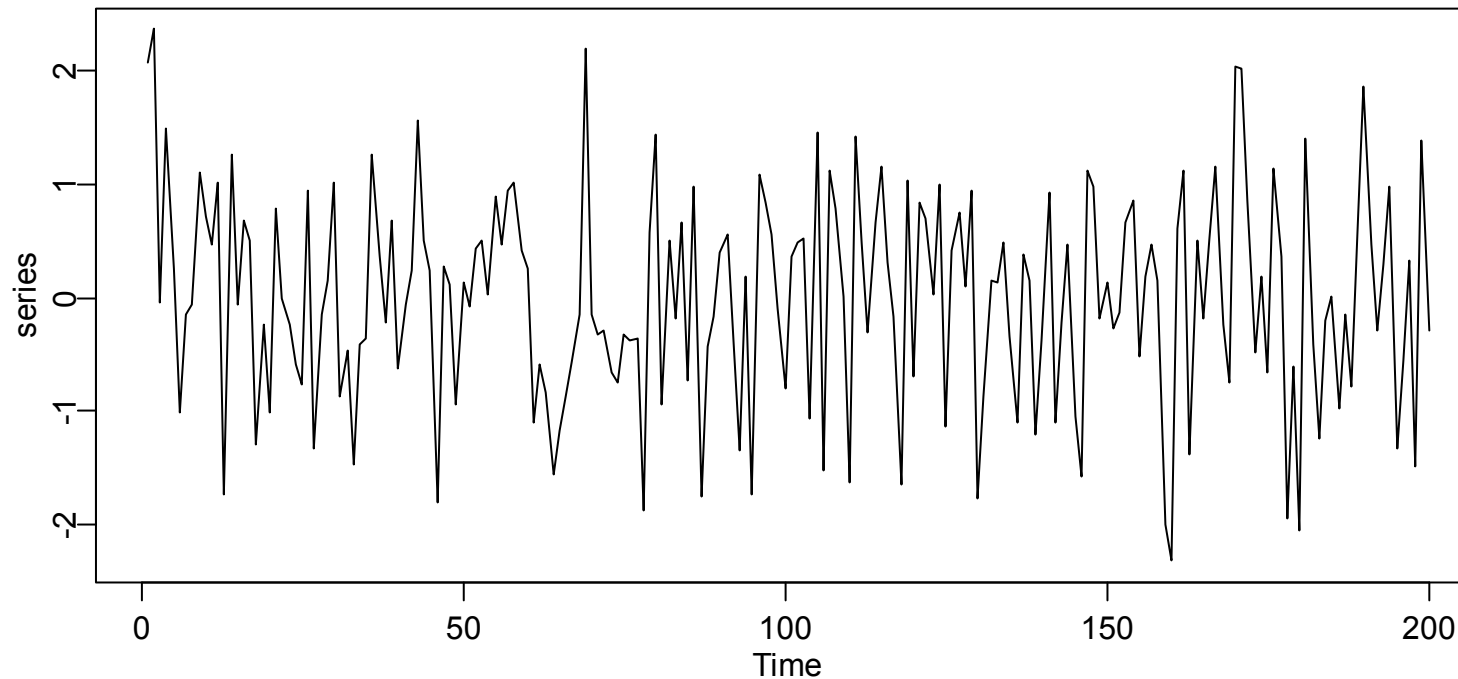
	ar1	ar2	ar3	ar4	ma1	intercept
	1.0253	-0.4693	0.2190	-0.1280	0.5733	0.6312
s.e.	0.1725	0.2658	0.2124	0.1062	0.1653	0.2930

```
sigma^2=0.8708, log likelihood=-271.3, aic = 556.59
```

Applied Time Series Analysis

FS 2013 – Week 07

Residuals of Model 5: ARMA(4,1)



Applied Time Series Analysis

FS 2013 – Week 07

Summary of the Order Choice Problem

- Regarding ACF/PACF, all 5 models are plausible
→ ARMA(2,1) would be my favorite
- The residuals look fine (i.e. independent) for all 5 models
→ no further evidence for a particular model
- Regarding AIC, the ARMA models do better
→ ARMA(2,1) would be my favorite
- Significance of the coefficients
→ excludes the ARMA(4,1) as the last contender

Best choice: ARMA (2,1)