dtli1

Zurich University
of Applied Sciences

Applied Time Series Analysis
SS 2013 – Week 09

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Folie 1

dtli1 Dieses Folienset ist etwas langfädig. Zudem kommt man in 2 Lektionen nur knapp durch. Änderungen:

Einführung knapper und knackiger machen
ZR-Regressionsproblem kompakter fassen
Probleme ganz klar auflisten
Beispiele vorstellen
Rezept geben für ZR-Regression
Bsp. für GLS-Transformation muss unbedingt rein
Verallgemeinerung OK

Dettling Marcel (dtli); 03.04.2012

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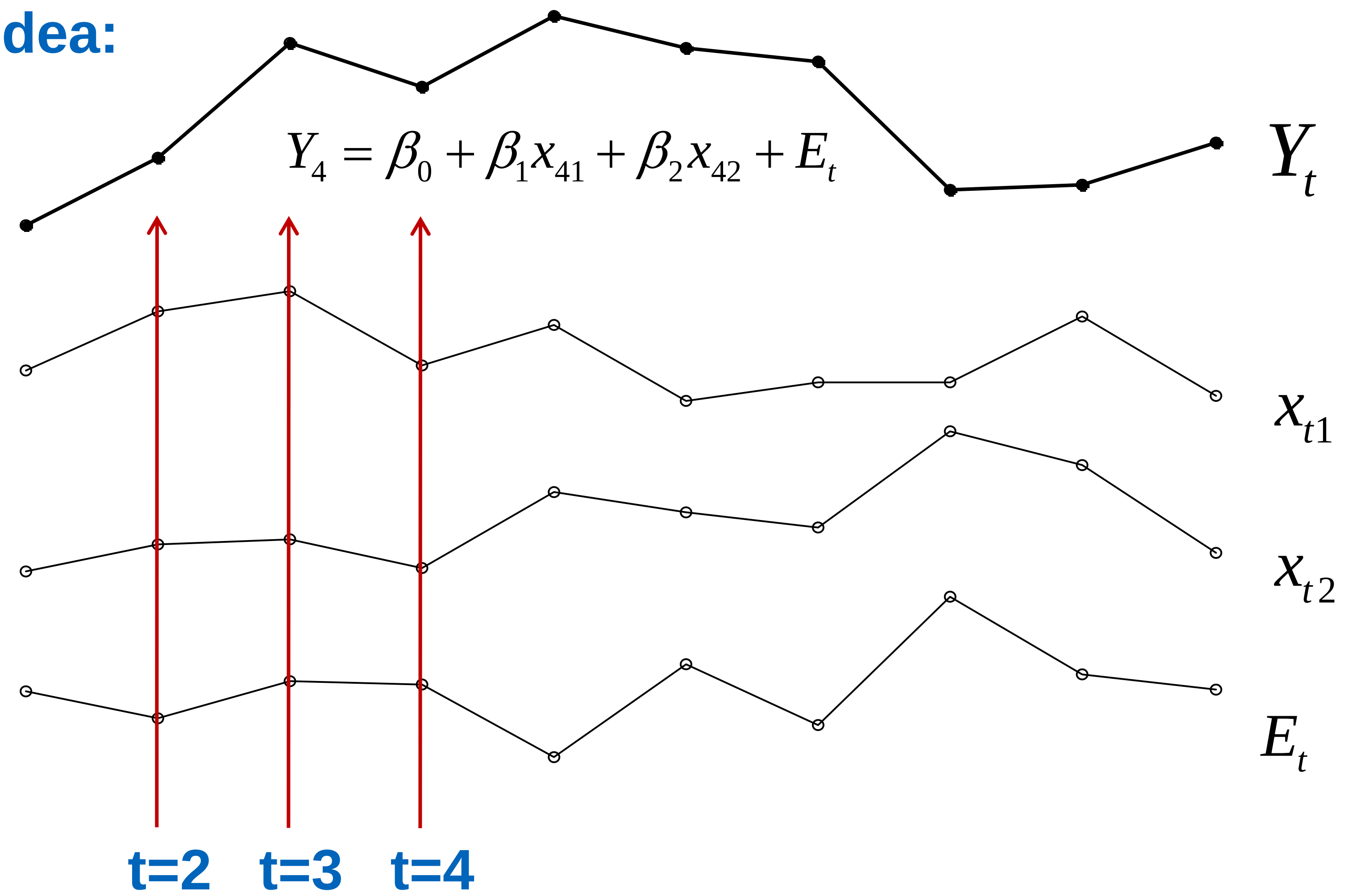
Time Series Regression

Idea:



The Setup

- There is a response time series Y_t
- There is one or several explanatory/descriptive time series $x_{t1},...,x_{tp}$
- The goal is to infer the relation $Y_t \sim x_{t1} + ... + x_{tp}$, i.e. find β_j
- As long as the error series E_t is i.i.d, the usual regression setup with LS-estimates is perfectly fine

→ **Caution and specific procedures are required if the errors are correlated!**

Dealing with Correlated Errors

- In case of time series regression, the error term E_t is usually correlated and not i.i.d.
- Then, the estimates $\hat{\beta}_j$ are still unbiased, but the usual LS-procedure is no longer efficient and the standard errors can be grossly wrong
- There are procedures that correct for correlated errors:
  - **Cochrane-Orcutt-Method**
  - **Generalized Least Squares**
- **They must be applied in case of correlated errors!**

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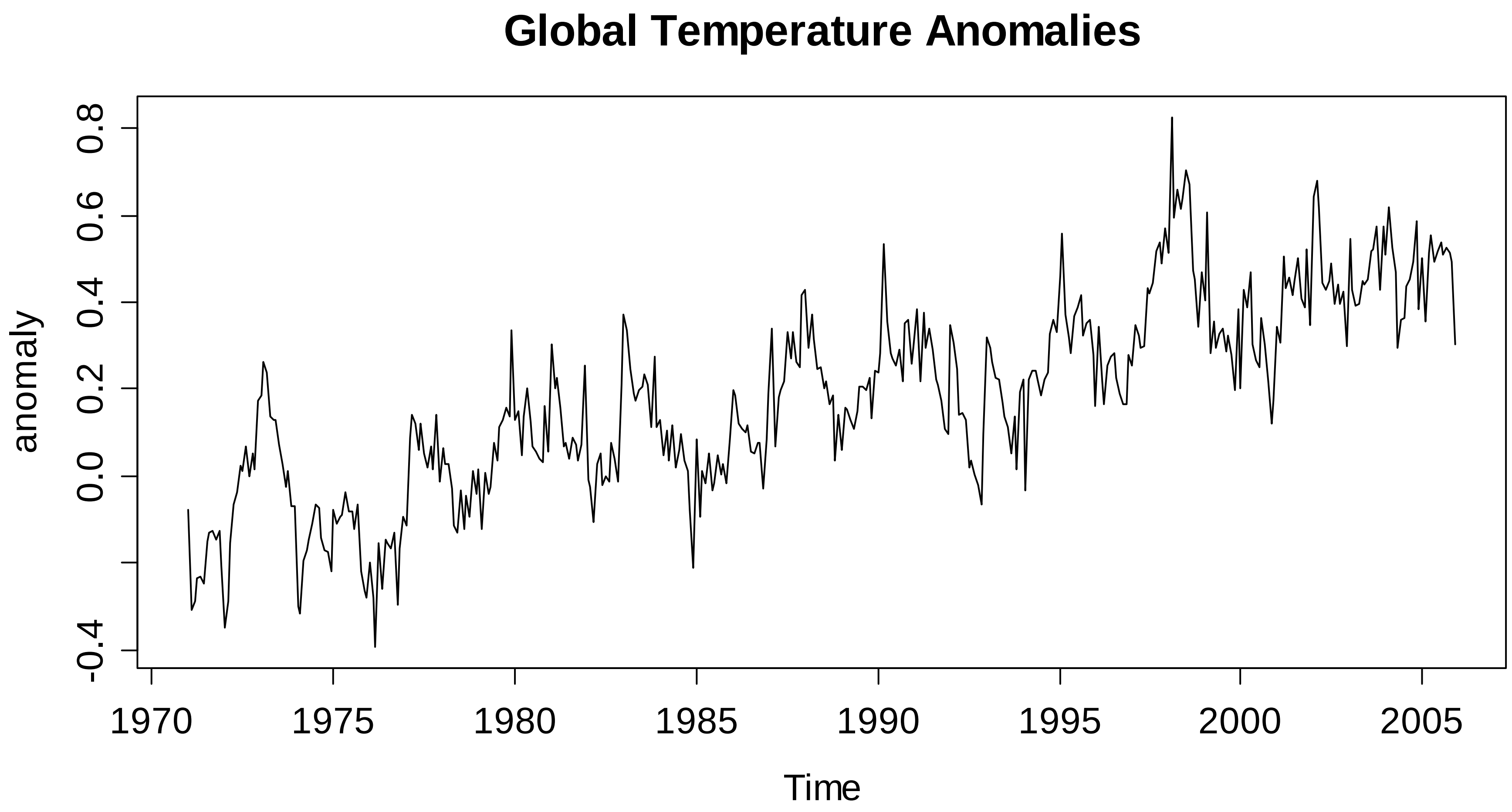
Example 1: Global Temperature



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Example 1: Global Temperature

Temperature = Trend + Seasonality + Remainder

$$Y_t = \beta_0 + \beta_1 \cdot t + \beta_2 \cdot 1_{[month="Feb"]} + \ldots + \beta_{12} \cdot 1_{[month="Dec"]} + E_t,$$

→ Recordings from 1971 to 2005, $n = 420$

→ The remainder term is usually a stationary time series, thus it would not be surprising if the regression model features correlated errors.

→ The applied question which is of importance here is whether there is a significant trend, and a significant seasonal variation

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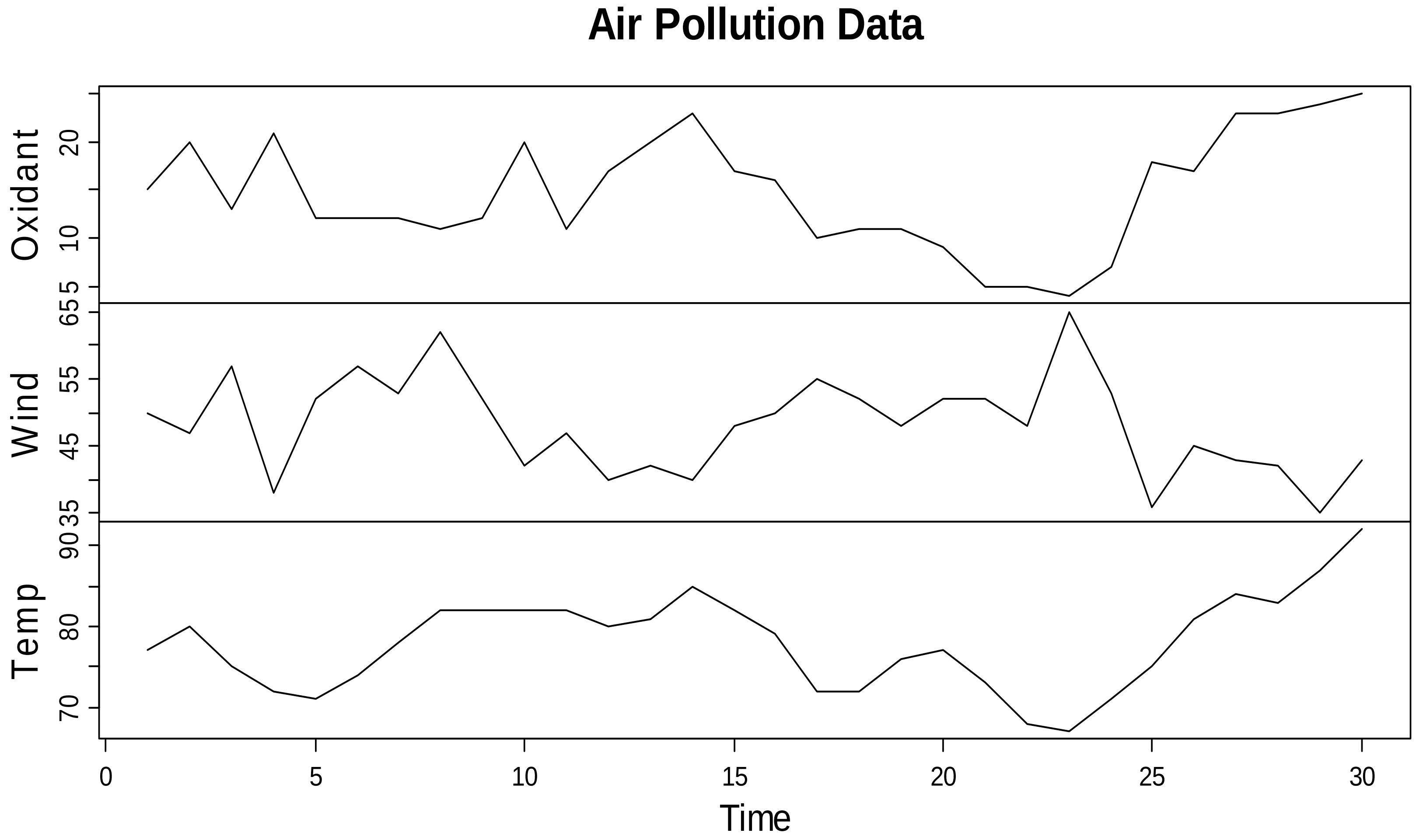
Example 2: Air Pollution



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Example 2: Air Pollution

Oxidant = Wind + Temperature + Error

$$Y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + E_t$$

→ Recordings from 30 consecutive days, $n = 30$

→ The data are from the Los Angeles basin, USA

→ The pollutant level is influence by both wind and temperature, plus some more, unobserved variables.

→ It is well conceivable that there is "day-to-day memory" in the pollutant levels, i.e. there are correlated errros.

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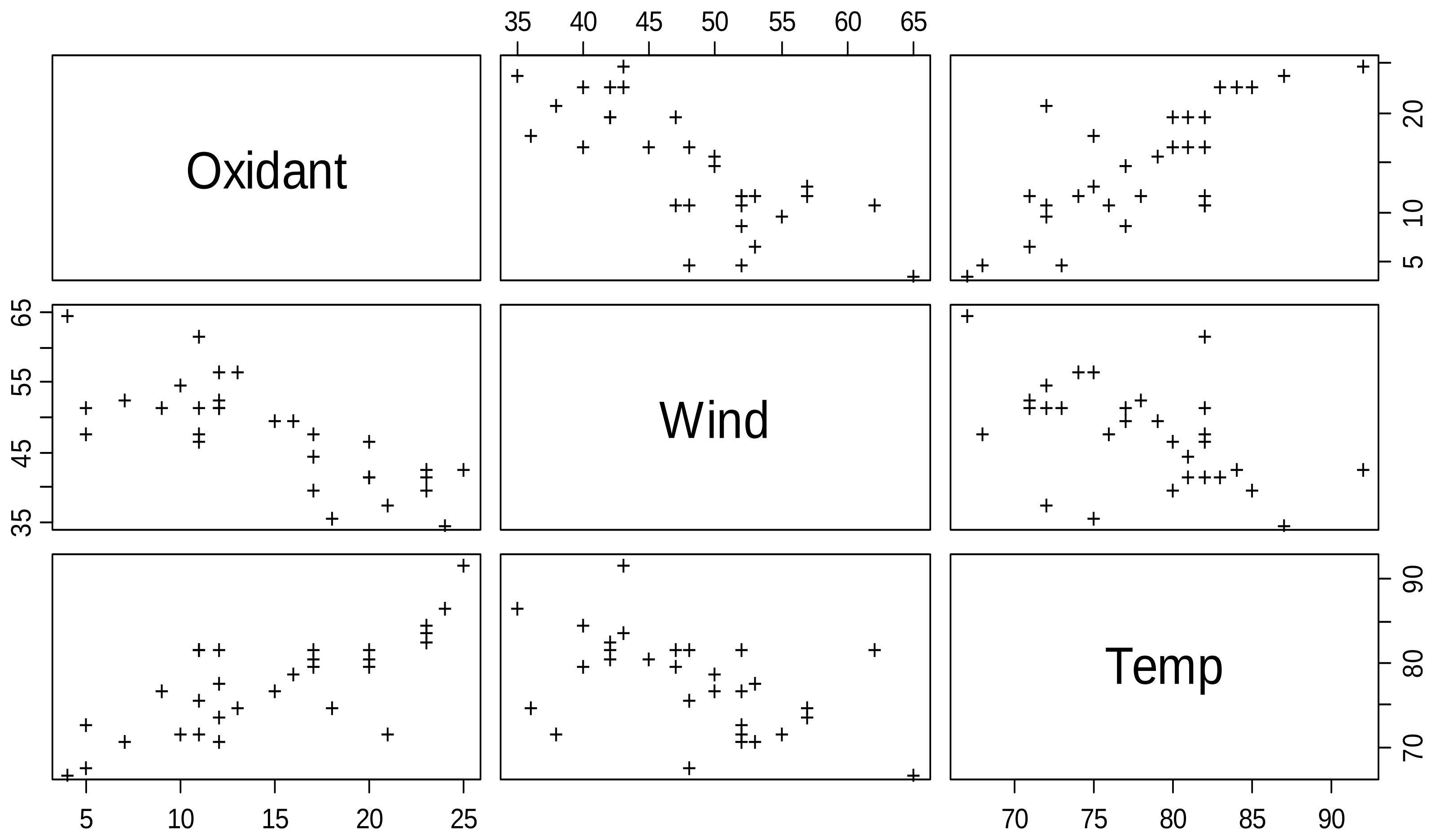
Example 2: Air Pollution



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Time Series Regression Model

$$Y_t = \beta_0 + \beta_1 x_{t1} + \ldots + \beta_q x_{tp} + E_t$$

- $t = 1, \ldots, N$
- no feedback from Y_t onto the predictors (i.e. input series)
- E_t are independent from x_{sj} for all j and all s, t
- E_t (generally) are dependent (e.g. an ARMA(p,q)-process)

Facts When Using Least Squares

In case of correlated errors, the effect on point estimates is:

- the estimated coefficients $\beta_1, ..., \beta_q$ are unbiased
- the estimates are no longer optimal: $Var\left(\hat{\beta}_j\right) > \min_* Var\left(\hat{\beta}_j^*\right)$

Important is the effect on the standard errors of the estimates:

- $\hat{Var}\left(\hat{\beta}_j\right)$ can be grossly wrong!
- often, the standard errors are underestimated
- too small CIs & spuriously significant test results

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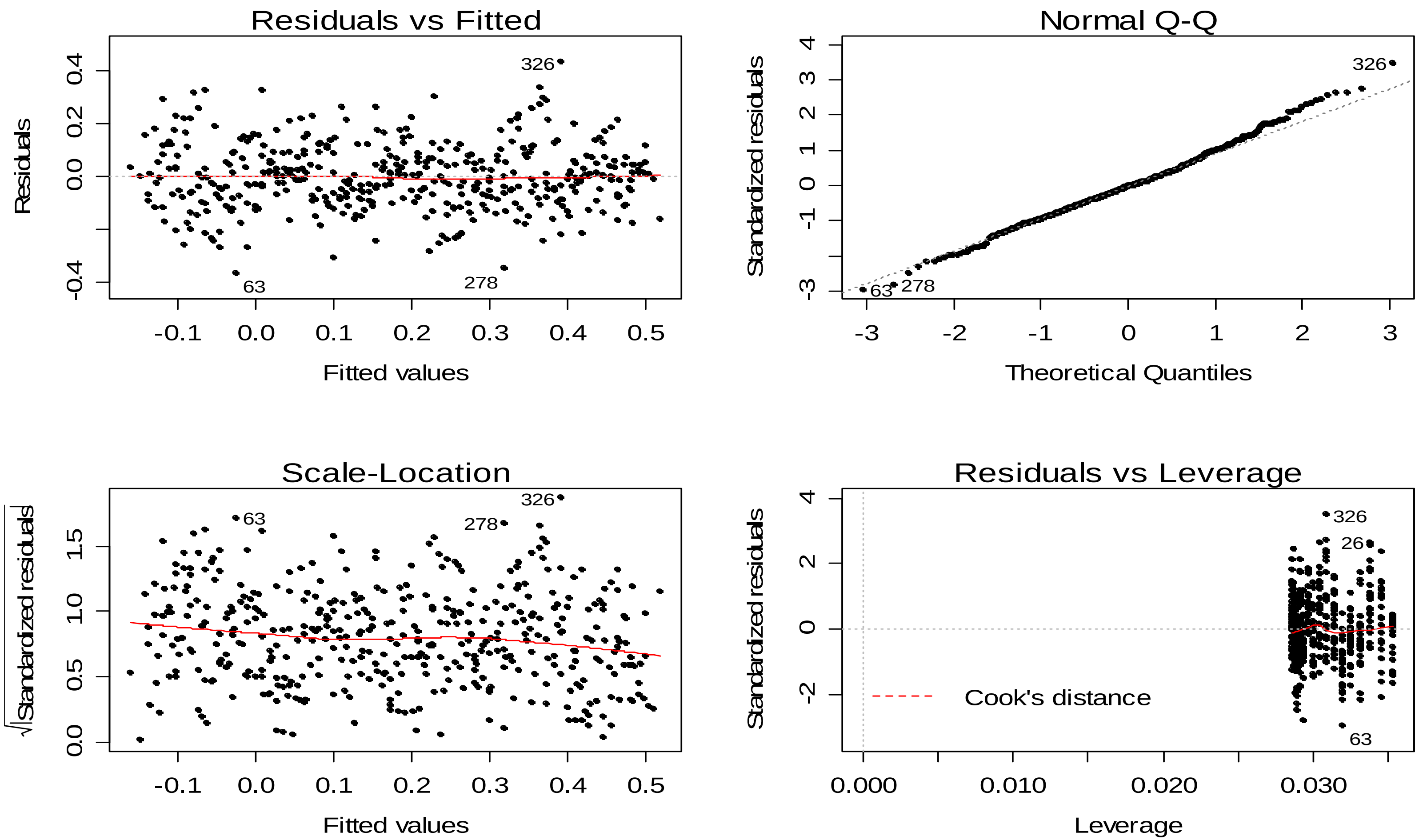
Finding Correlated Errors

1) Start by fitting an OLS regression and analyze residuals



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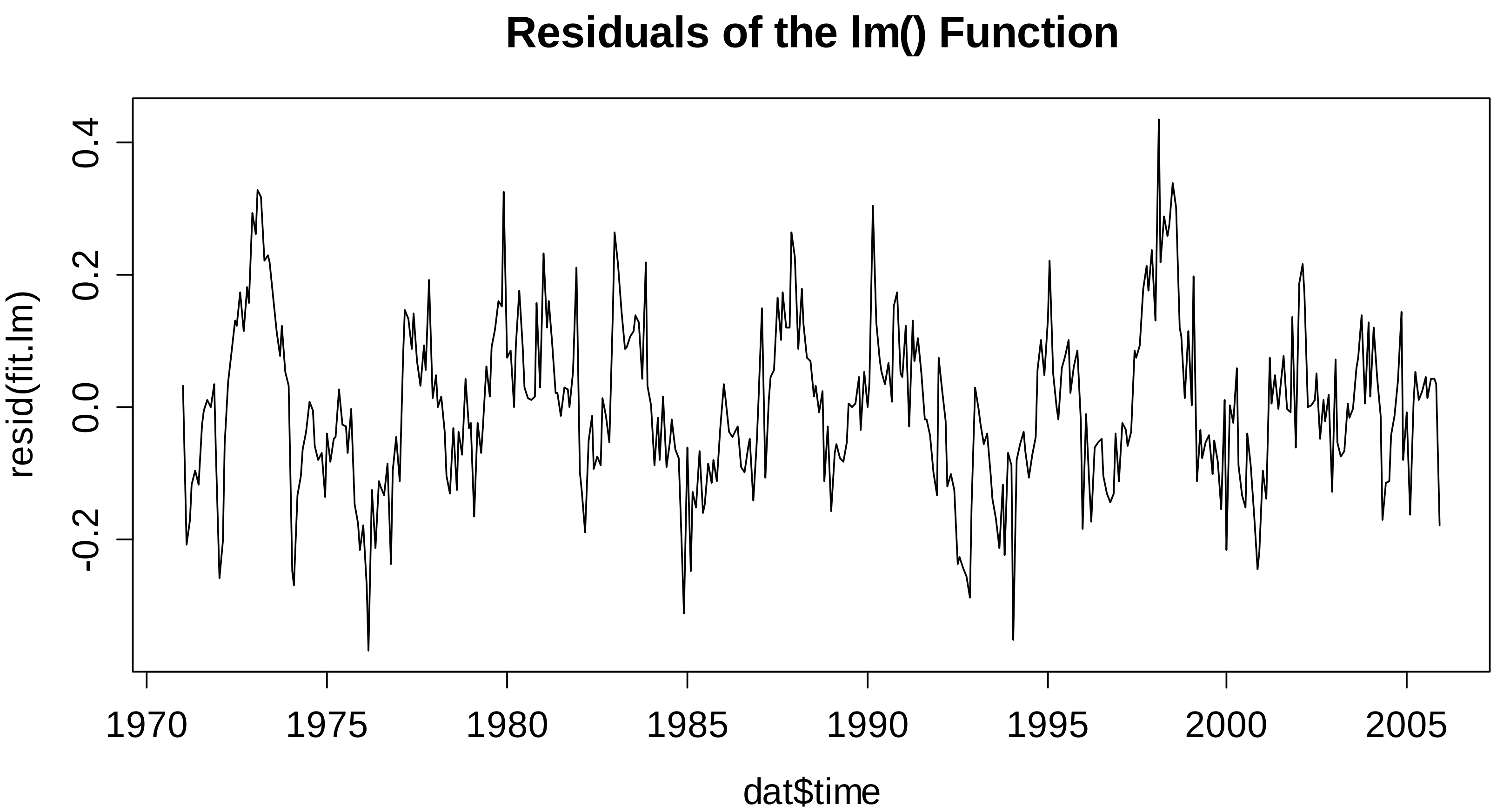
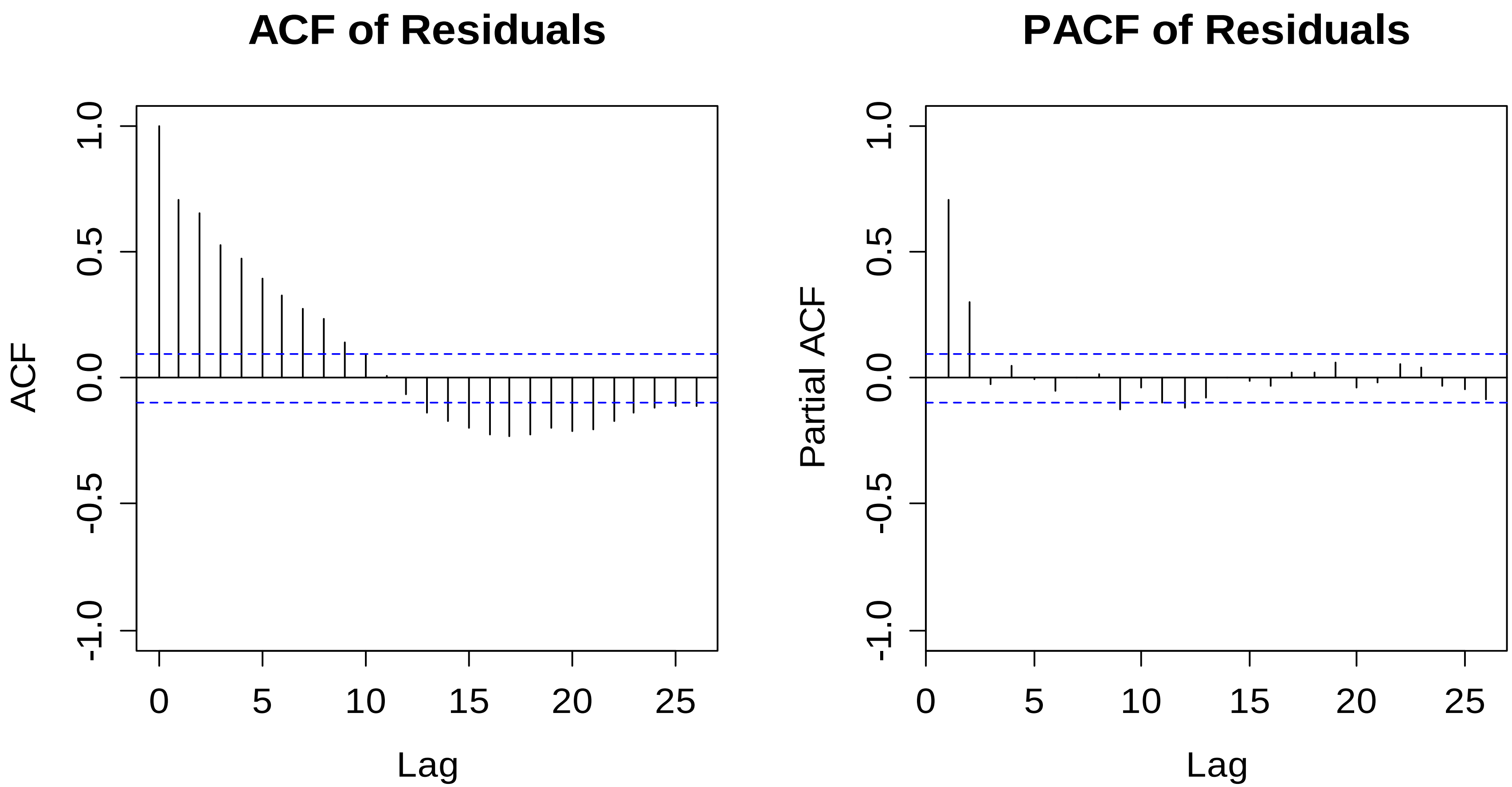
Finding Correlated Errors

2) Continue with a time series plot of OLS residuals



Finding Correlated Errors

3) Also analyze ACF and PACF of OLS residuals



Model for Correlated Errors

→ It seems as if an AR(2) model provides an adequate model for the correlation structure observed in the residuals of the OLS regression model.

```
> fit.ar2 <- ar.burg(resid(fit.lm)); fit.ar2

Call: ar.burg.default(x = resid(fit.lm))

Coefficients:
     1       2
0.4945  0.3036

Order selected 2  sigma^2 estimated as  0.00693
```

→ Residuals of this AR(2) model must look like white noise!

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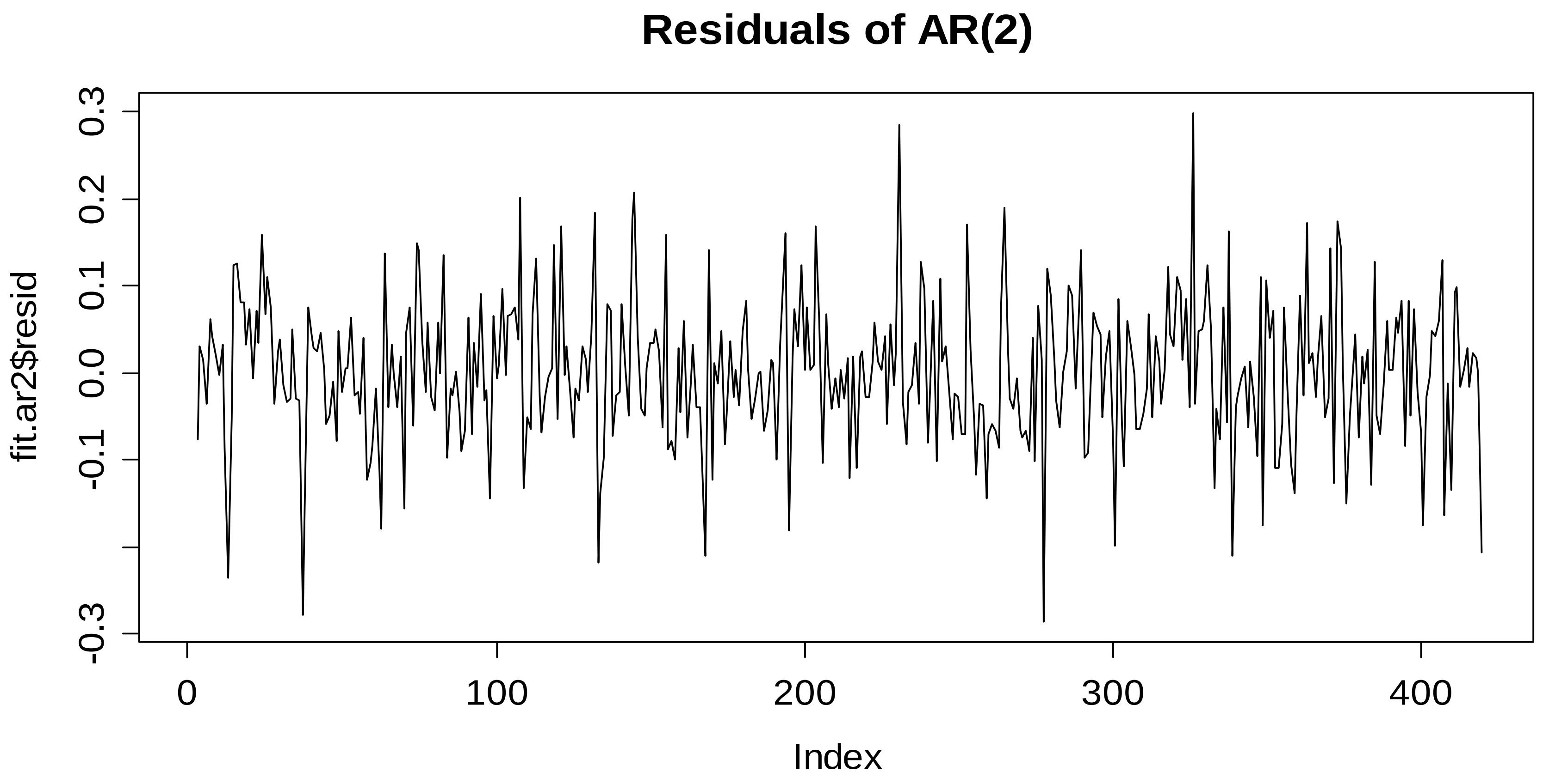
Does the Model Fit?

5) Visualize a time series plot of the AR(2) residuals



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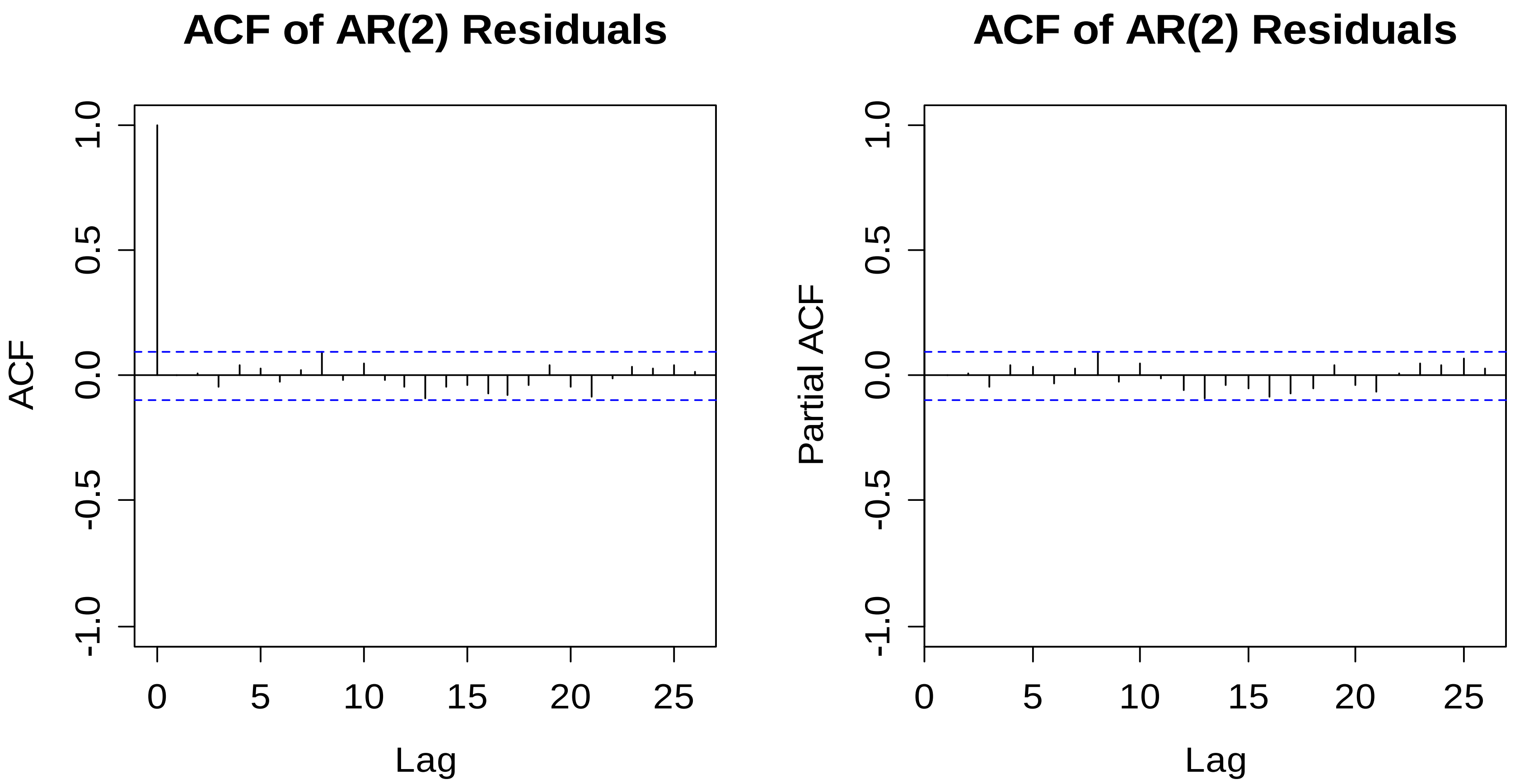
Does the Model Fit?

5) ACF and PACF plots of AR(2) residuals



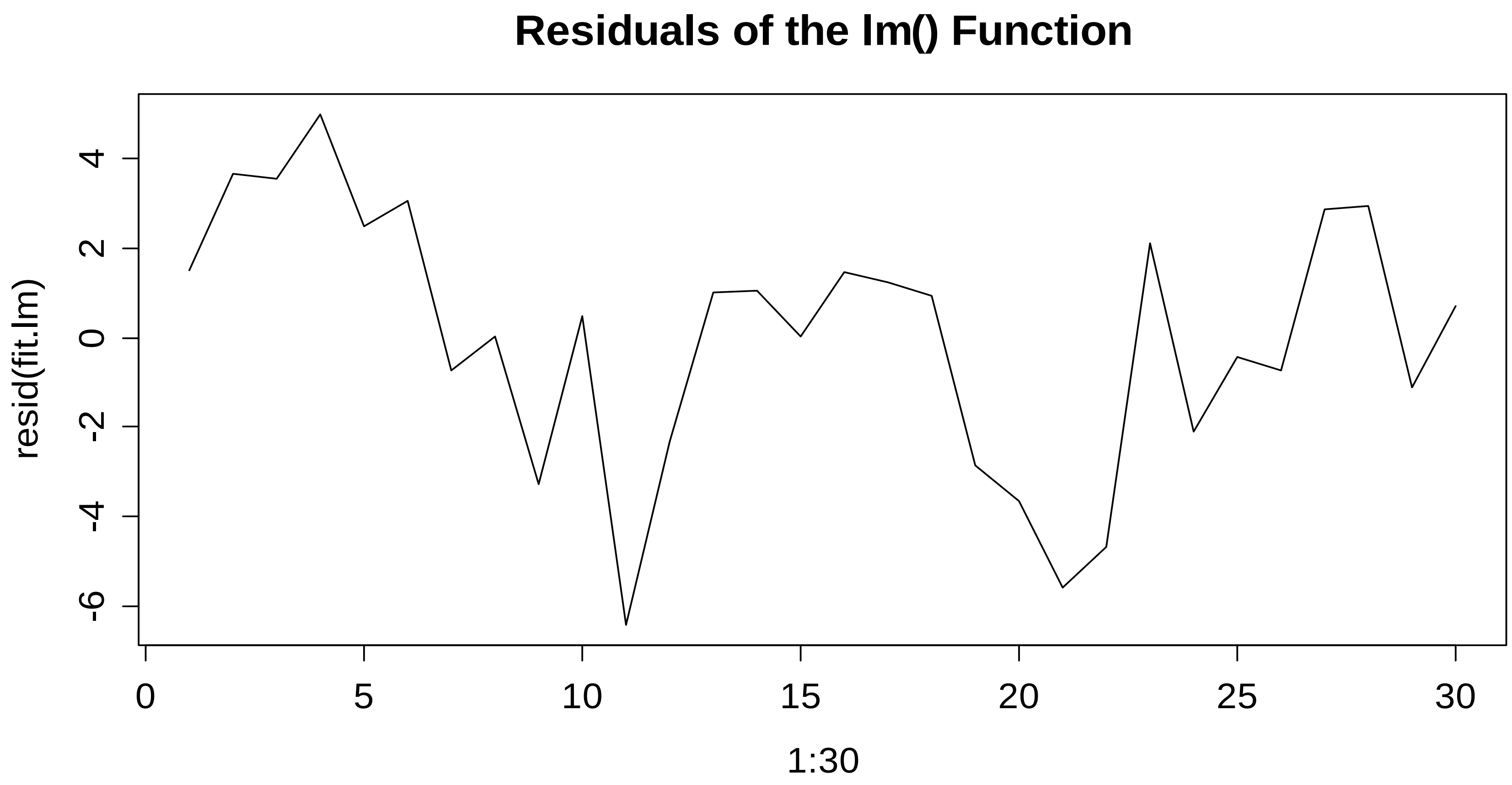
Global Temperature: Conclusions

- The residuals from OLS regression are visibly correlated.
- An AR(2) model seems appropriate for this dependency.
- The AR(2) yields a good fit, because its residuals have White Noise properties. We have thus understood the dependency of the regression model errros.

→ We need to account for the correlated errors, else the coefficient estimates will be unbiased but inefficient, and the standard errors are wrong, preventing successful inference for trend and seasonality

Air Pollution: OLS Residuals

Time series plot: dependence present or not?



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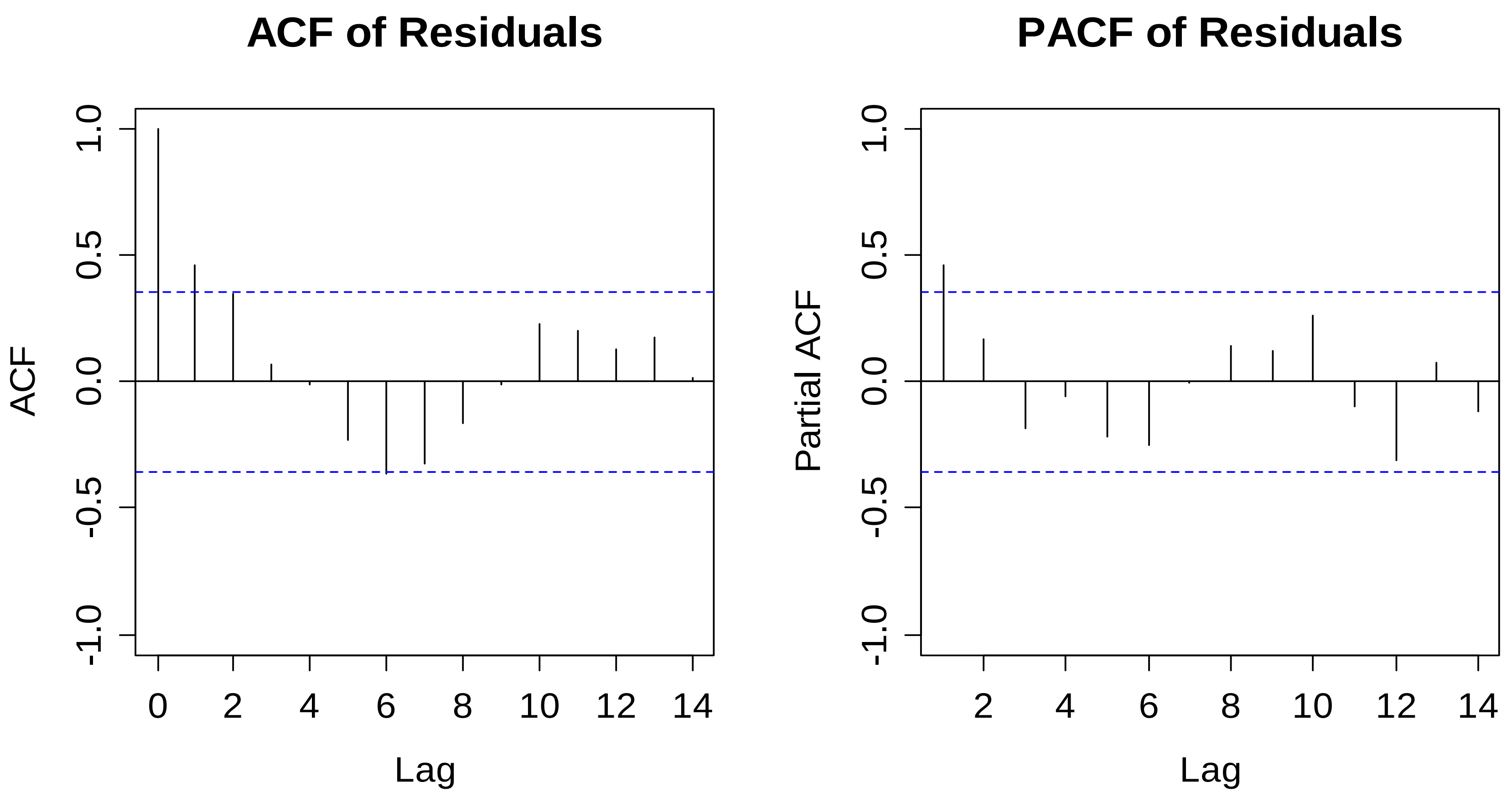
Air Pollution: OLS Residuals

ACF and PACF suggest: *there is AR(1) dependence*



Pollutant Example

```
> summary(erg.poll,corr=F)
Call: lm(formula = Oxidant ~ Wind + Temp, data = pollute)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)

(Intercept) -5.20334   11.11810  -0.468    0.644
Wind        -0.42706    0.08645  -4.940 3.58e-05 ***
Temp         0.52035    0.10813   4.812 5.05e-05 ***

Residual standard error: 2.95 on 27 degrees of freedom
Multiple R-squared: 0.7773, Adjusted R-squared: 0.7608
F-statistic: 47.12 on 2 and 27 DF,  p-value: 1.563e-09
```

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Durbin-Watson Test

- The Durbin-Watson approach is a test for autocorrelated errors in regression modeling based on the test statistic:

$$D = \frac{\sum_{t=2}^{N} (r_t - r_{t-1})^2}{\sum_{t=1}^{N} r_t^2}$$

- This is implemented in R: `dwtest()` in `library(lmtest)`. A p-value for the null of no autocorrelation is computed.

- This test does not detect all autocorrelation structures. If the null is not rejected, the residuals may still be autocorrelated.

→ **Never forget to check ACF/PACF of the residuals!**

Durbin-Watson Test

Example 1: Global Temperature

```
> library(lmtest)
> dwtest(fit.lm)
data:  fit.lm
DW = 0.5785, p-value < 2.2e-16
alt. hypothesis: true autocorrelation is greater than 0
```

Example 2: Air Pollution

```
> dwtest(fit.lm)
data:  fit.lm
DW = 1.0619, p-value = 0.001675
alt. hypothesis: true autocorrelation is greater than 0
```

Generalized Least Squares

→ **See the blackboard for full explanation**

- OLS regression assumes a diagonal error covariance matrix, but there is a generalization to $Var(E) = \sigma^2 \Sigma$.

- If we find $\Sigma = SS^T$, the regression model can be rewritten as:

$$\begin{aligned} y &= X\beta + E \\ S^{-1}y &= S^{-1}X\beta + S^{-1}E \\ y^* &= X^*\beta + E^* \qquad \text{with } Var(E^*) = \sigma^2 I \end{aligned}$$

- One obtains the generalized least square estimates:

$\hat{\beta} = (X^T\Sigma^{-1}X)X^T\Sigma^{-1}y$ with $Var(\hat{\beta}) = (X^T\Sigma^{-1}X)^{-1}\sigma^2$

Generalized Least Squares

For using the GLS approach, i.e. for correcting the dependent errors, we need an estimate of the error covariance matrix Σ.

The two major options for obtaining it are:

1) **Cochrane-Orcutt (for AR(p) correlation structure only)**
   iterative approach: i) β, ii) α, iii) β

2) **GLS (Generalized Least Squares, for ARMA(p,q))**
   simultaneous estimation of β and α

→ **Full explanation of the two different approaches is provided on the blackboard!**

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GLS: Syntax

Package `nlme` has function `gls()`. It does only work if the correlation structure of the errors is provided. This has to be deterimined from the residuals of an OLS regression first.

```
> library(nlme)
> corStruct <- corARMA(form=~time, p=2)
> fit.gls <- gls(temp~time+season, data=dat,
                 correlation=corStruct)
```

The output contains the **regression coefficients** and their **standard errors**, as well as the **AR-coefficients** plus some further information about the model (Log-Likeli, AIC, ...).

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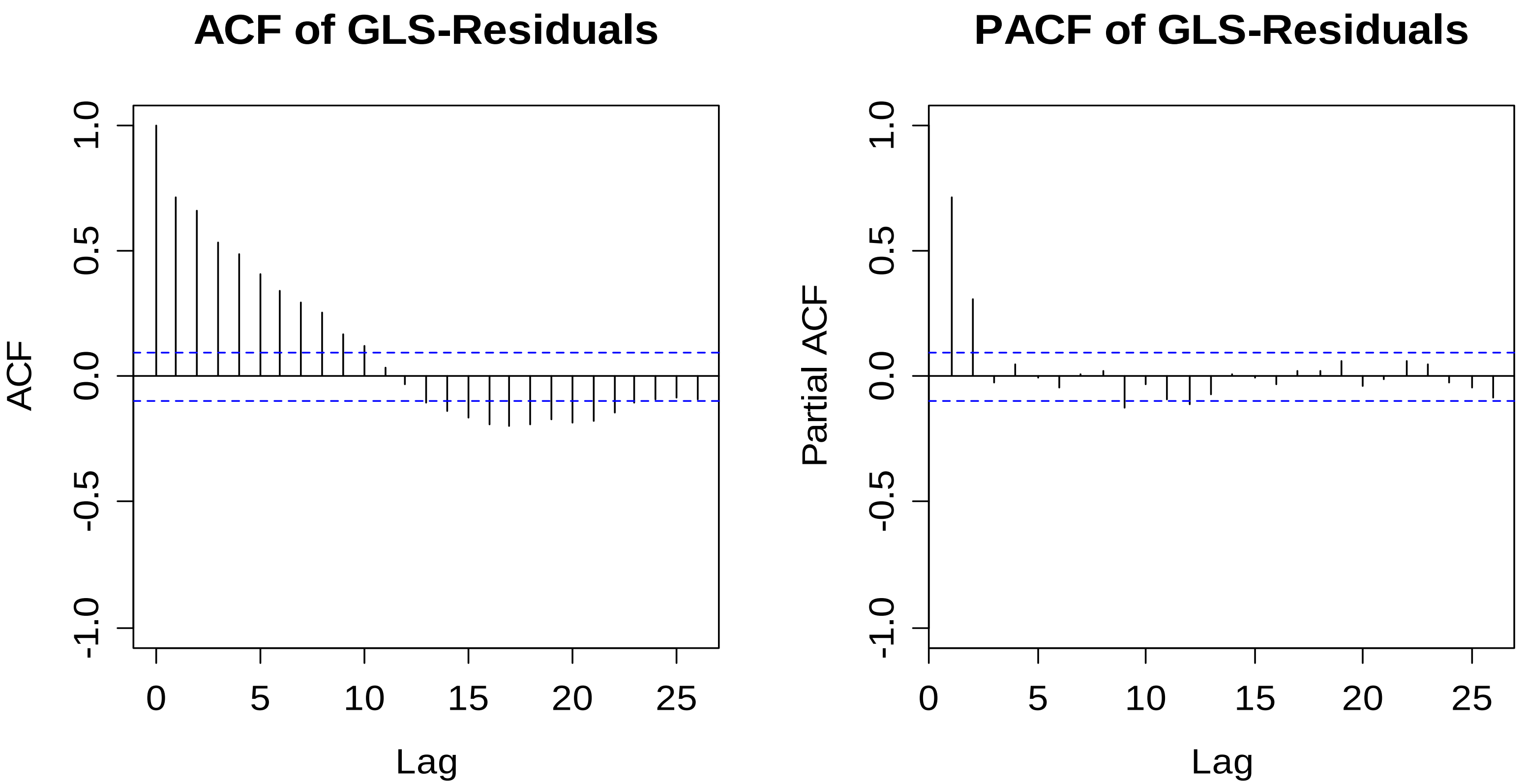
GLS: Residual Analysis

The residuals from a GLS must look like coming from a time series process with the respective structure:



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GLS/OLS: Comparison of Results

→ **The trend in the global temperature is significant!**

OLS

```
> coef(fit.lm)["time"]
      time
0.01822374
> confint(fit.lm, "time")
          2.5 %     97.5 %
time 0.01702668 0.0194208
```

GLS

```
> coef(fit.gls)["time"]
      time
0.02017553
> confint(fit.gls, "time")
          2.5 %      97.5 %
time 0.01562994 0.02472112
```

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GLS/OLS: Comparison of Results

→ The seasonal effect is not significant!

OLS

```
> drop1(fit.lm, test="F")
 temp ~ time + season
       Df Sum of Sq     RSS     AIC  F value  Pr(F)
<none>               6.4654 -1727.0
time    1   14.2274 20.6928 -1240.4 895.6210 <2e-16 ***
season 11    0.1744  6.6398 -1737.8   0.9982 0.4472
```

GLS

```
> anova(fit.gls)
Denom. DF: 407
            numDF  F-value p-value
(Intercept)     1 78.40801  <.0001
time            1 76.48005  <.0001
season         11  0.64371  0.7912
```

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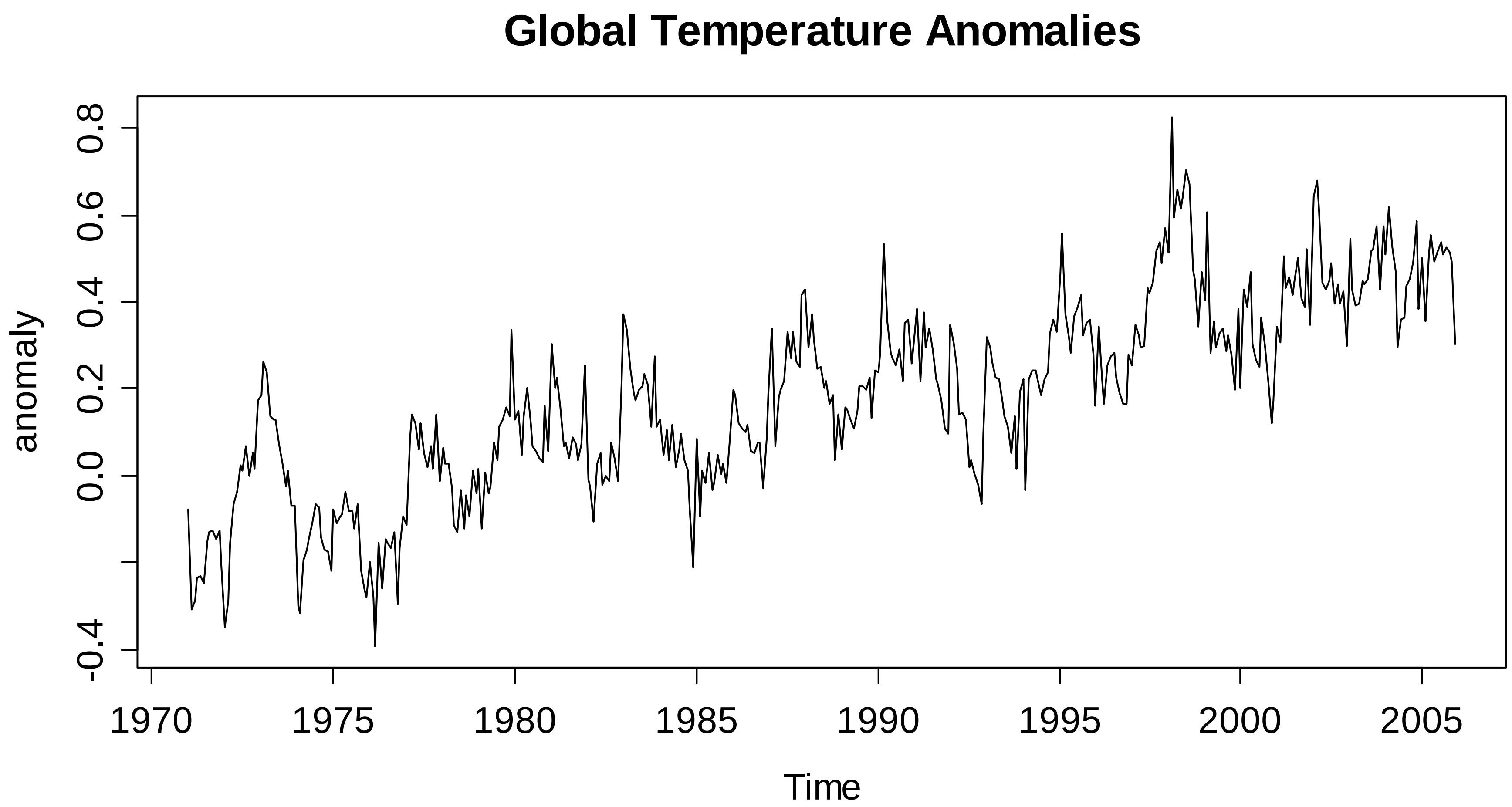
Example 1: Global Temperature



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Air Pollution: Results

Both predictors are significant with both approaches...

OLS

```
> confint(fit.lm, c("Wind", "Temp"))
          2.5 %     97.5 %
Wind -0.6044311 -0.2496841
Temp  0.2984794  0.7422260
```

GLS

```
> confint(fit.gls, c("Wind", "Temp"))
          2.5 %     97.5 %
Wind -0.5447329 -0.2701709
Temp  0.2420436  0.7382426
```

→ But still, it is important to use GLS with correlated errors!

Simulation Study: Model

We want to study the effect of correlated errors on the quality of estimates when using the least squares approach:

$$x_t = t/50$$

$$y_t = x_t + 2x_t^2 + E_t$$

where E_t is from an AR(1)-process with $\alpha = -0.65$ and $\sigma = 0.1$.

We generate 100 realizations from this model and estimate the regression coefficient and its standard error by:

1) LS
2) GLS

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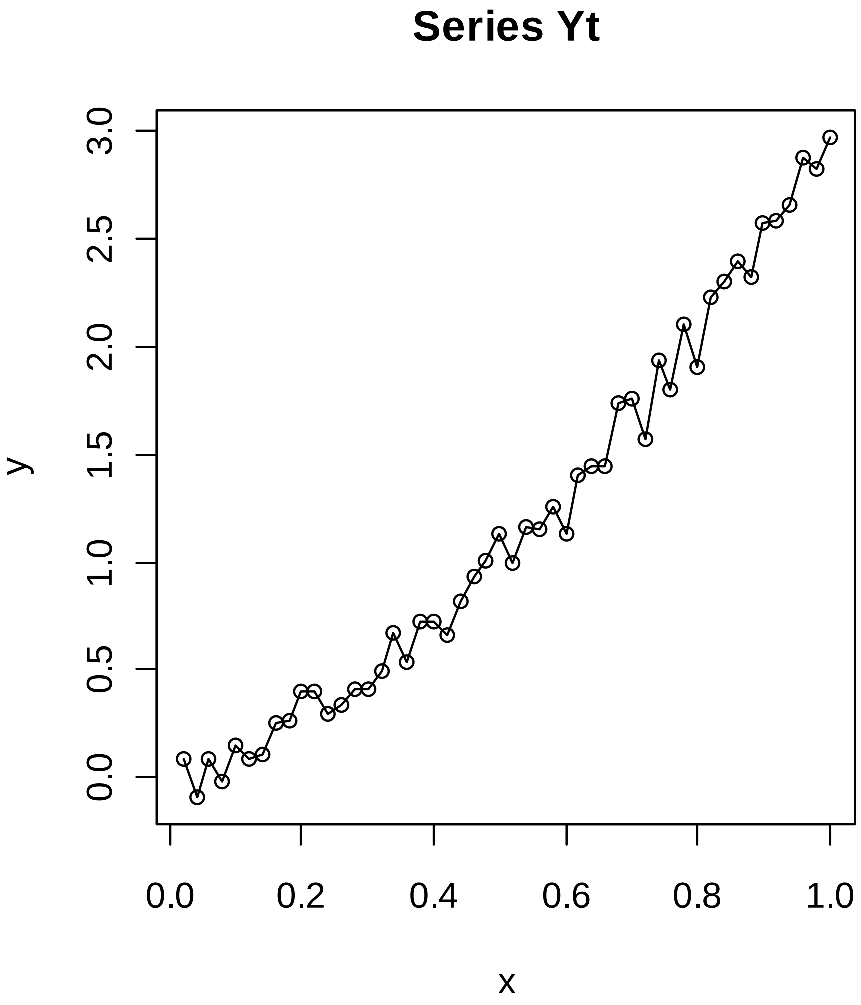
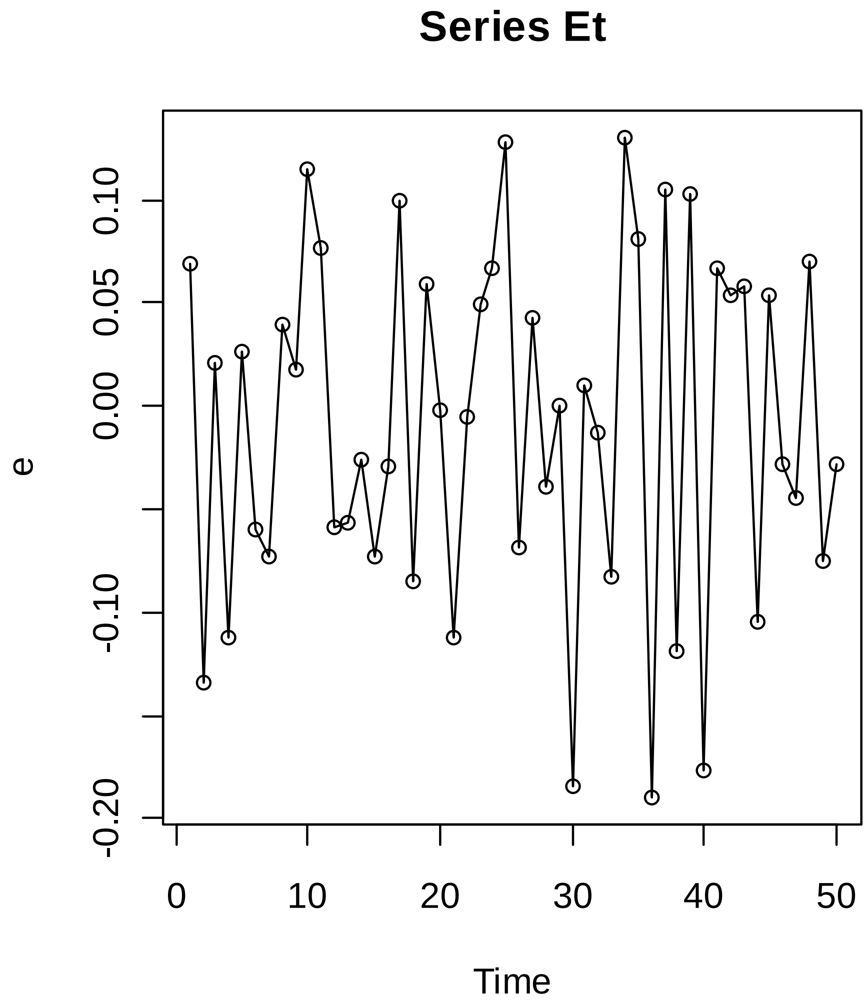
Simulation Study: Series





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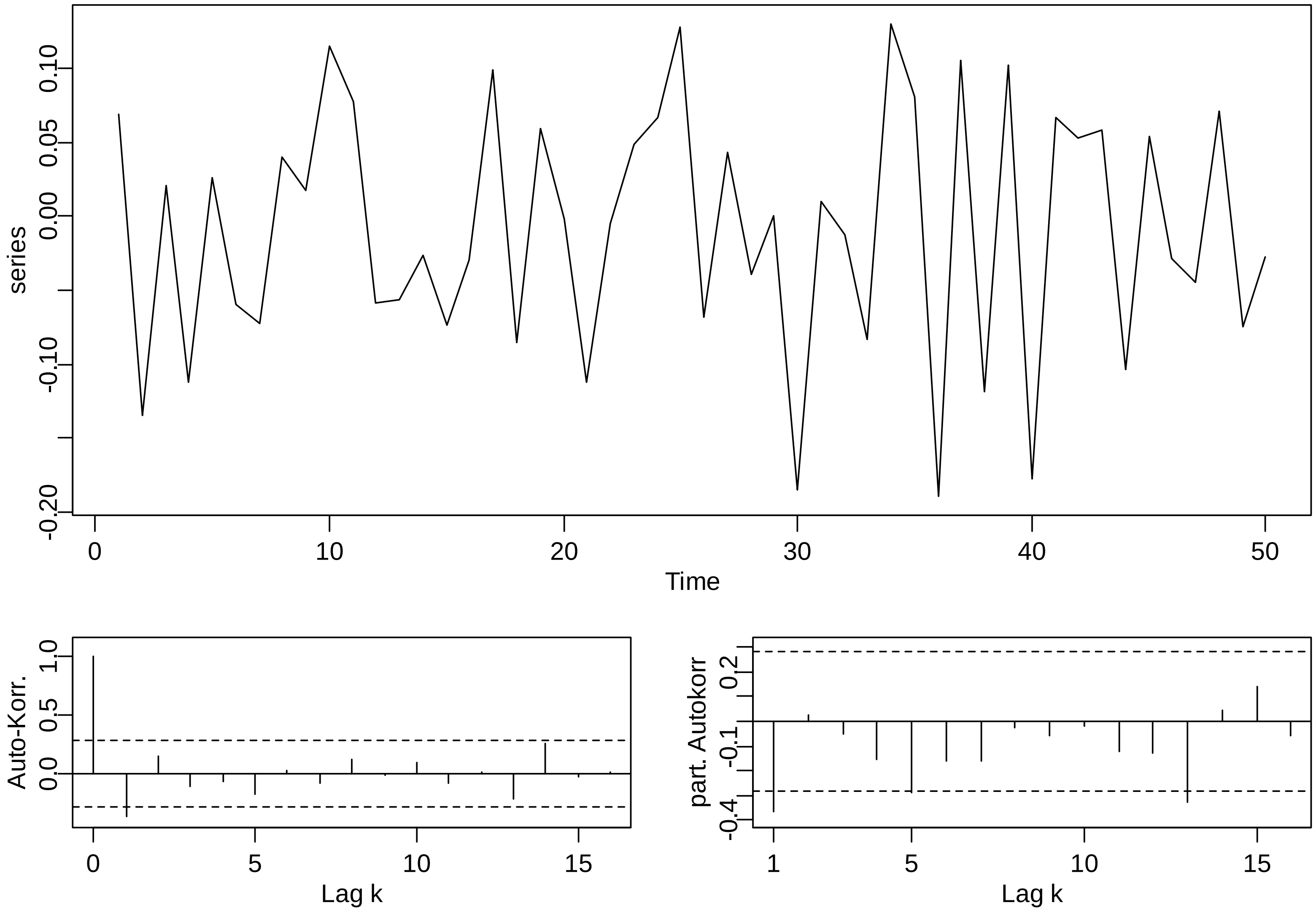
Simulation Study: ACF of the Error Term



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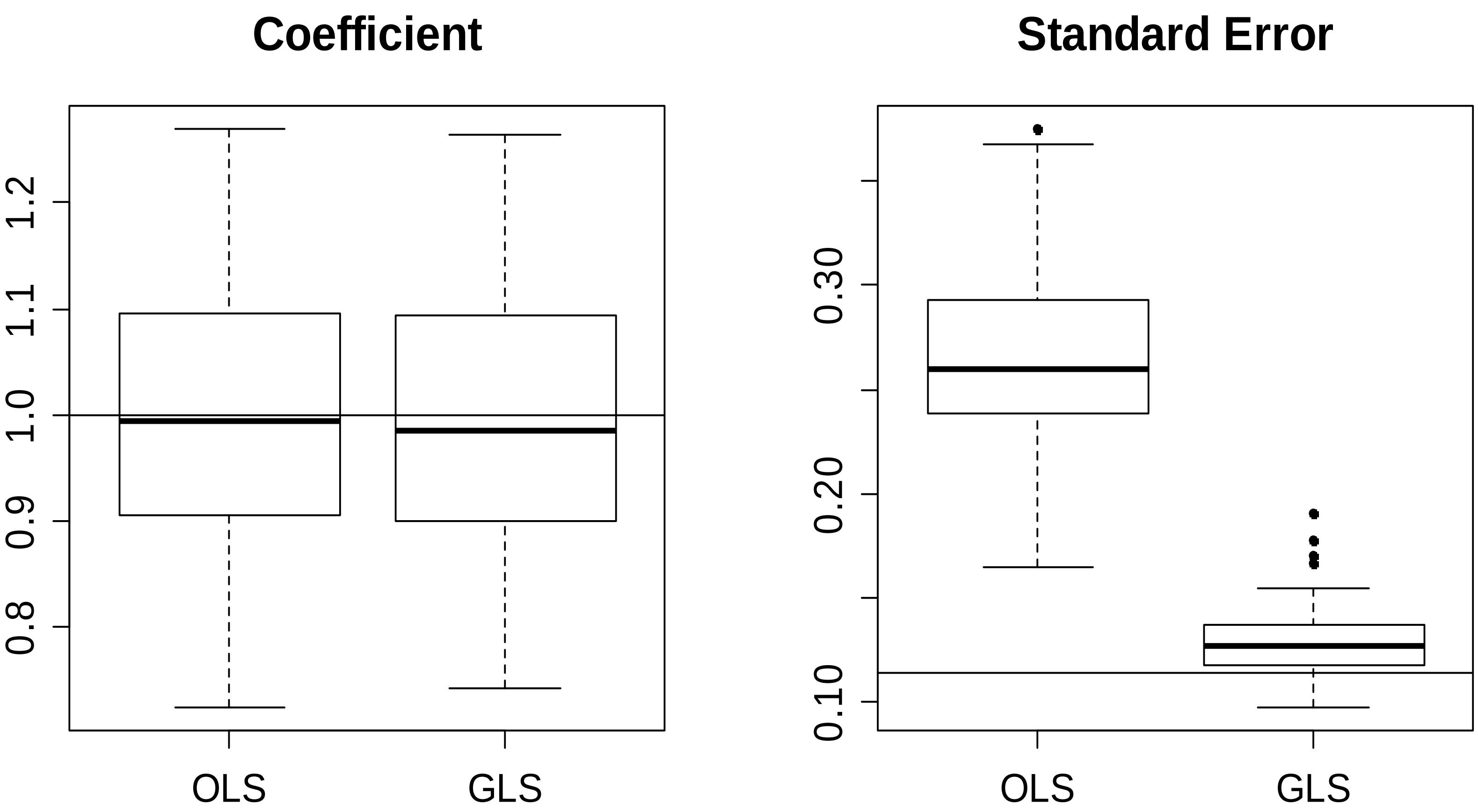
Simulation Study: Results

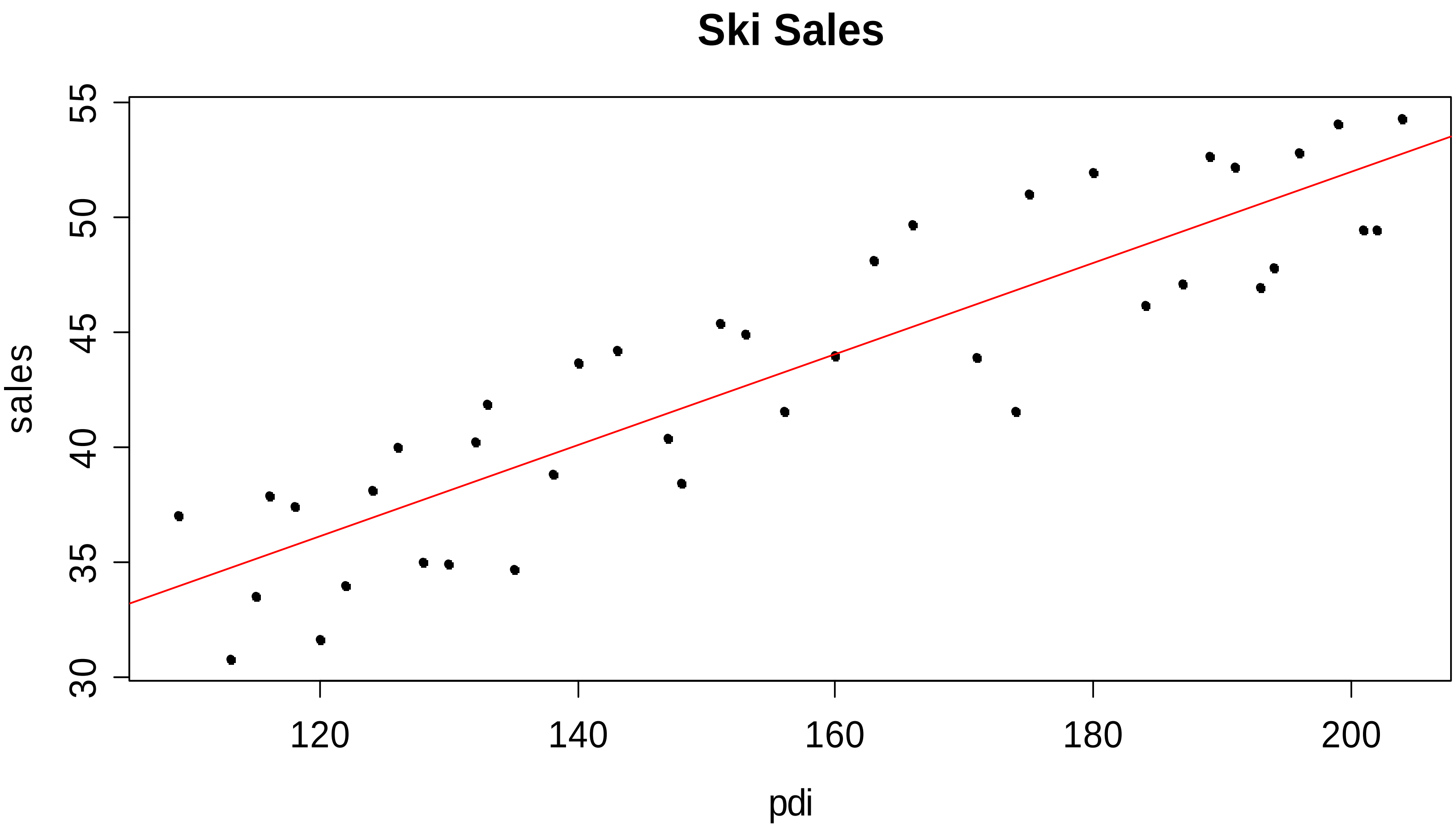


Missing Input Variables

- (Auto-)correlated errors are often caused by the non-presence of crucial input variables.
- In this case, it is much better to identify the not-yet-present -variables and include them in the analysis.
- However, this isn't always possible.

→ **regression with correlated errors can be seen as a sort of emergency kit for the case where the non-present variables cannot be added.**

Example: Ski Sales



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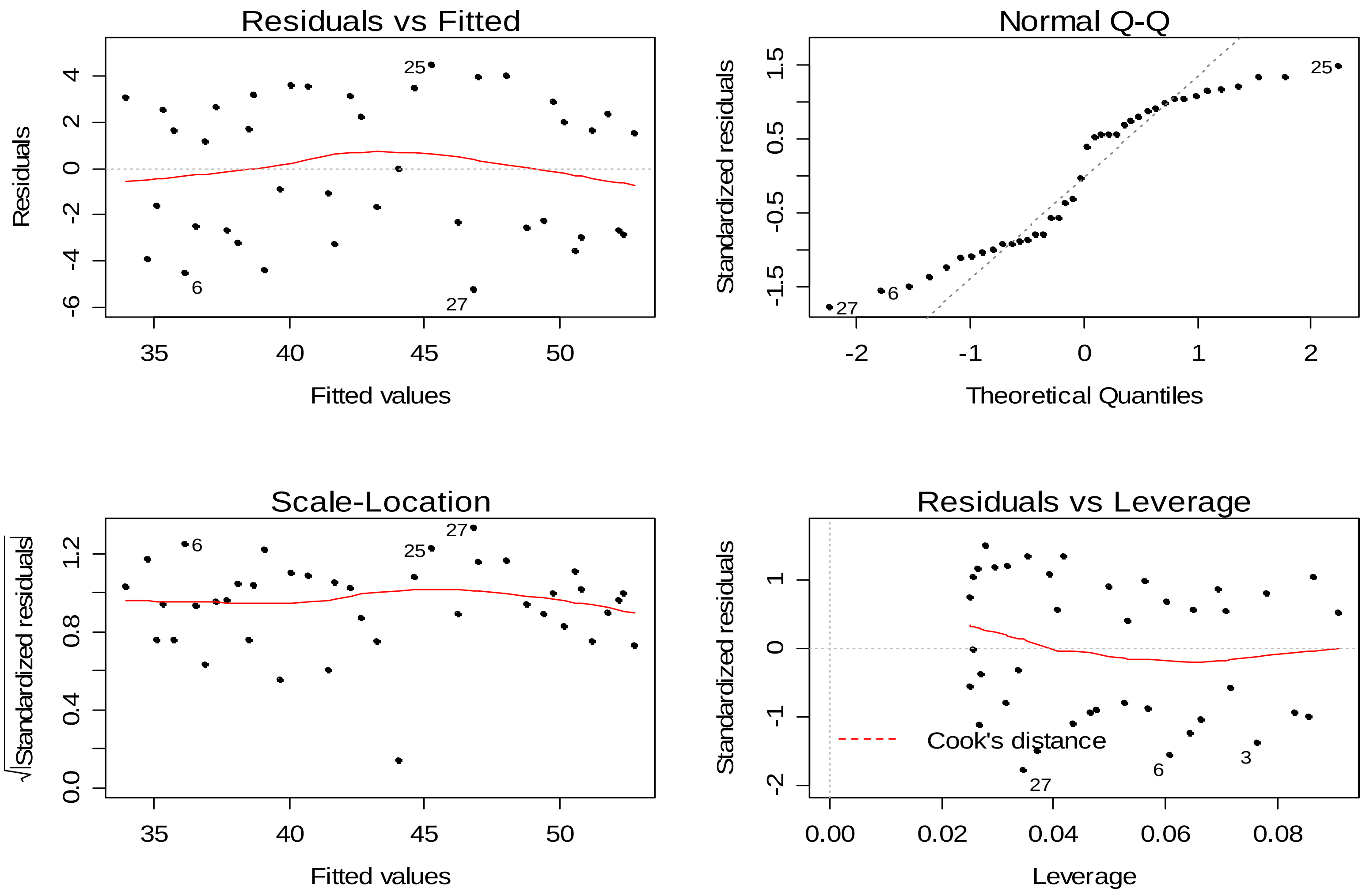
Ski Sales: Residual Diagnostics



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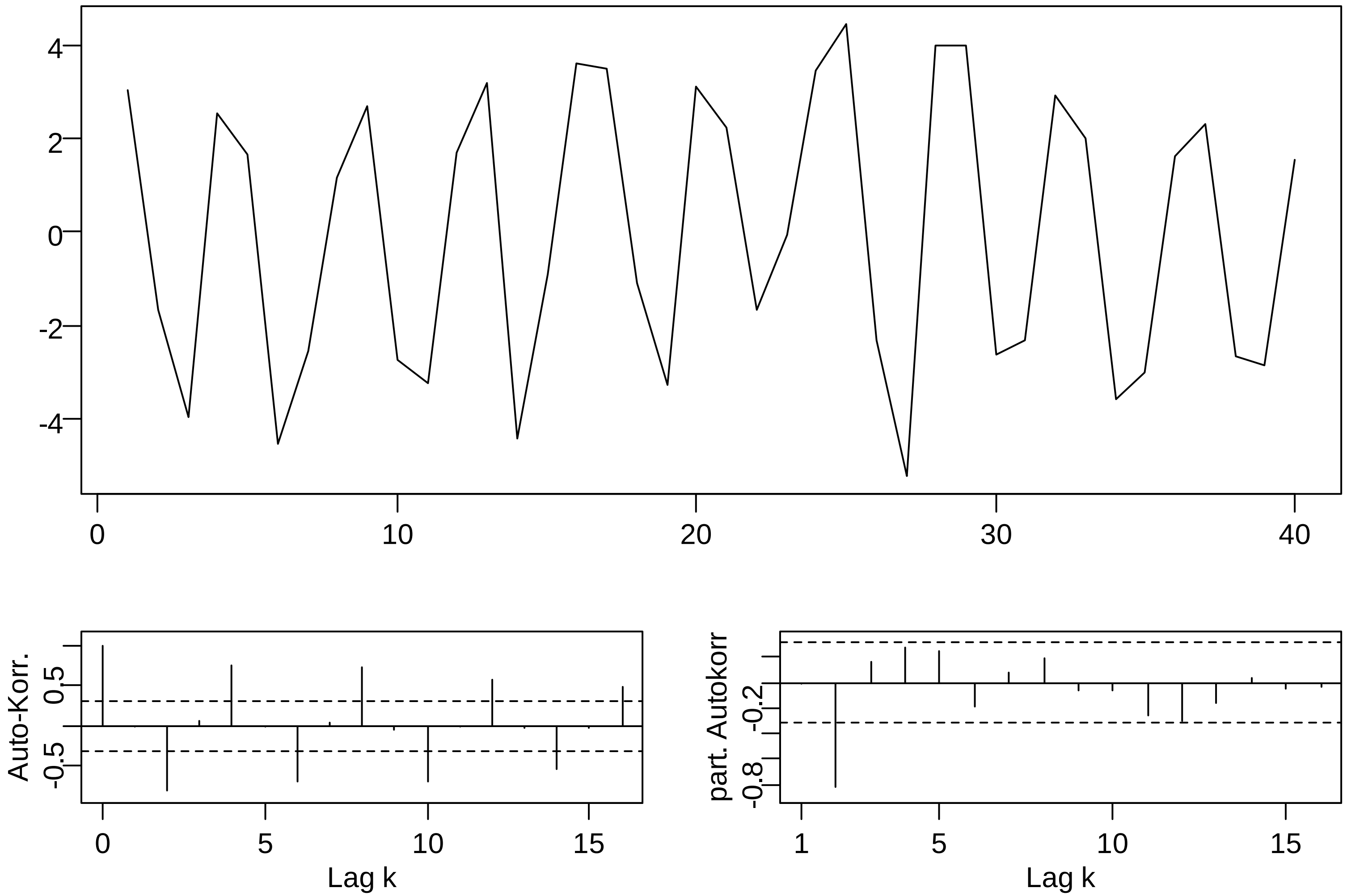
Ski Sales: ACF/PACF of Residuals



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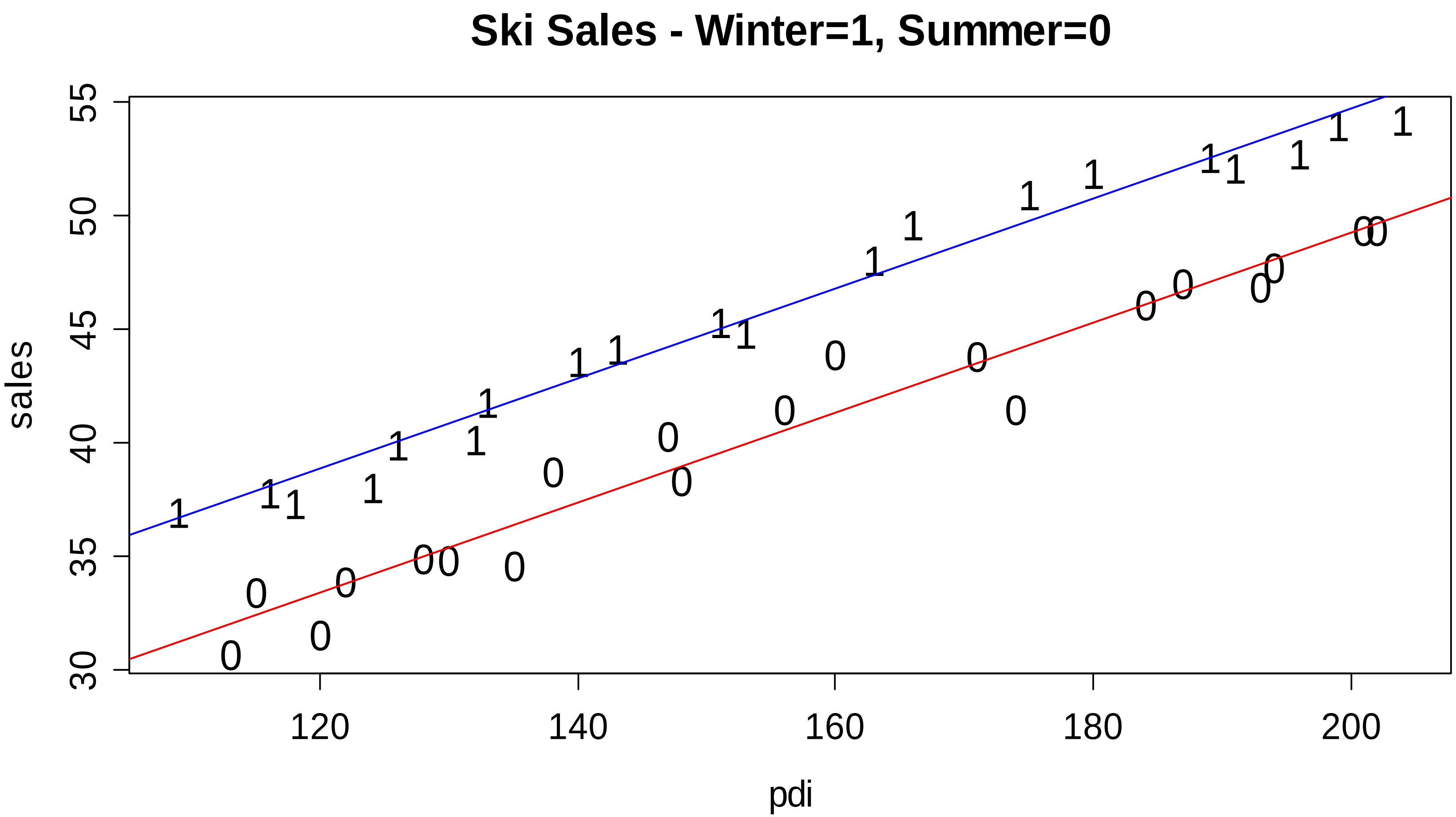
Ski Sales: Model with Seasonal Factor



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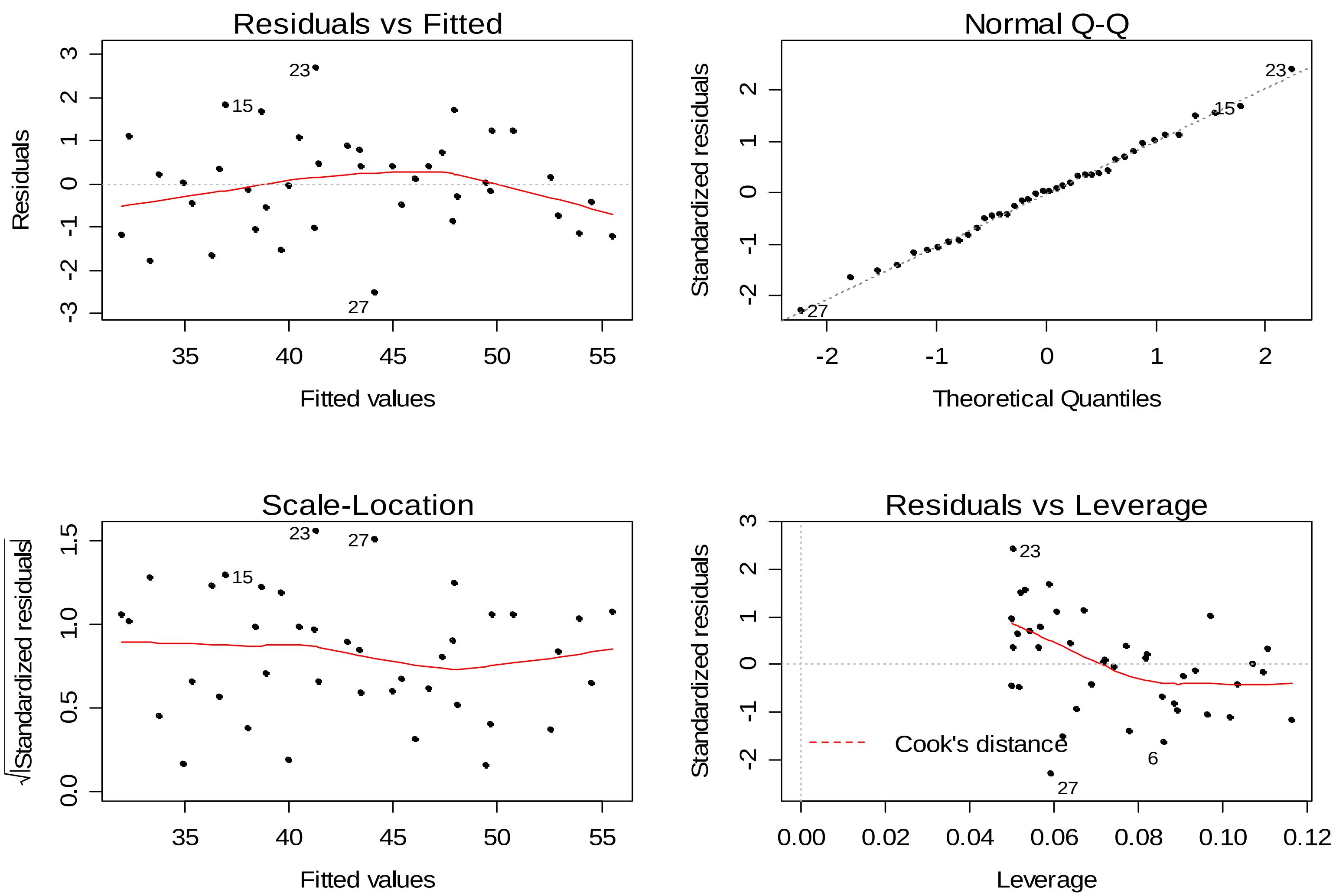
Residuals from Seasonal Factor Model



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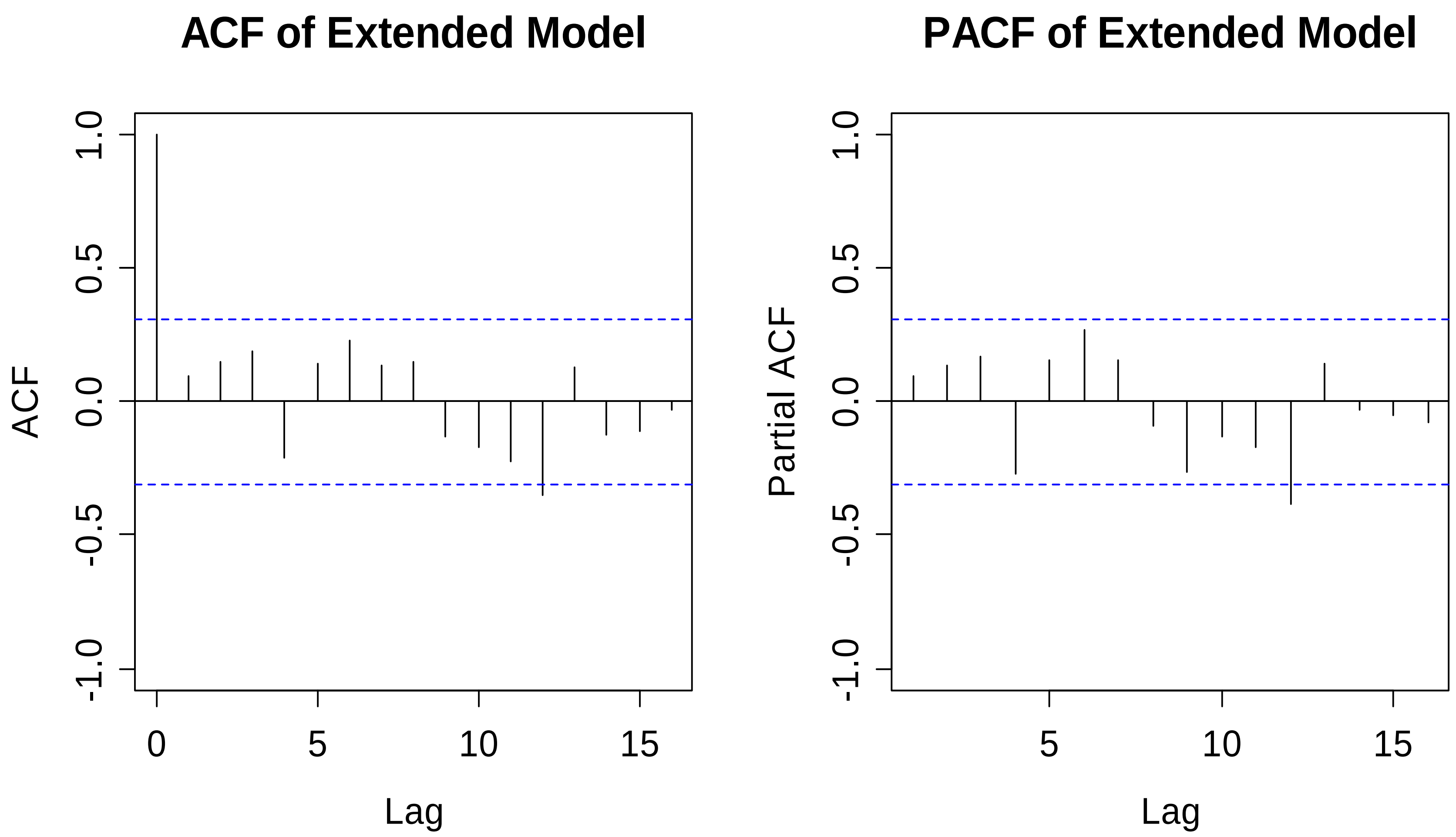
Residuals from Seasonal Factor Model



Ski Sales: Summary

- the first model (sales vs. PDI) showed correlated errors
- the Durbin-Watson test failed to indicate this correlation
- this apparent correlation is caused by ommitting the season
- adding the season removes all error correlation!

→ ***the emergency kit „time series regression" is, after careful modeling, not even necessary in this example. This is quite often the case!***