ARIMA Models

Lecture 09

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$MA(\infty)$

MA(q)

From last time,

$$\text{MA(q)}: \qquad y_t = \delta + w_t + \theta_1\, w_{t-1} + \theta_2\, w_{t-2} + \cdots + \theta_q\, w_{t-q}$$

Properties:

$$E(y_t) = \delta$$

$$\gamma(0) = Var(y_t) = (1 + \theta_1^2 + \theta_2 + \cdots + \theta_q^2)\, \sigma_w^2$$

$$\gamma(h) = \begin{cases} \theta_h + \theta_1\, \theta_{1+h} + \theta_2\, \theta_{2+h} + \cdots + \theta_{q-h}\, \theta_q & \text{if } h \in \{1, \ldots, q\} \\ 0 & \text{otherwise} \end{cases}$$

and is stationary for any values of $(\theta_1, \ldots, \theta_q)$

$MA(\infty)$

If we let $q \to \infty$ then process will be stationary if and only if the moving average coefficients (θ 's) are square summable, i.e.

$$\sum_{i=1}^{\infty} \theta_i^2 < \infty$$

which is necessary such that $Var(y_t) < \infty$ so that the weak stationarity conditions are met.

Sometimes, a slightly stronger condition known as absolute summability, $\sum_{i=1}^{\infty} |\theta_i| < \infty$ is necessary (e.g. for some CLT related asymptotic results).

Invertibility

If an $\text{MA}(q)$ process, $y_t = \delta + \theta_q(L) w_t$, can be rewritten as a stationary AR process then the process is said to be invertible.

$\text{MA}(1)$ w/ $\delta = 0$ example:

Invertibility vs Stationarity

A $\text{MA}(q)$ process is *invertible* if $y_t = \delta + \theta_q(L)\, w_t$ can be rewritten as an exclusively AR process (of possibly infinite order), i.e. $\phi(L)\, y_t = \alpha + w_t$.

Conversely, an $\text{AR}(p)$ process is *stationary* if $\phi_p(L)\, y_t = \delta + w_t$ can be rewritten as an exclusively MA process (of possibly infinite order), i.e. $y_t = \delta + \theta(L)\, w_t$.

So using our results w.r.t. $\phi(L)$ it follows that if all of the roots of $\theta_q(L)$ are outside the complex unit circle then the moving average process is invertible.

Differencing

Difference operator

We will need to define one more notational tool for indicating differencing

$$\Delta y_t = y_t - y_{t-1}$$

Just like the lag operator we will indicate repeated applications of this operator using exponents

$$\begin{aligned}
\Delta^2 y_t &= \Delta(\Delta y_t) \\
&= (\Delta y_t) - (\Delta y_{t-1}) \\
&= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\
&= y_t - 2y_{t-1} + y_{t-2}
\end{aligned}$$

Note that Δ can even be expressed in terms of the lag operator L,

$$\Delta^d = (1 - L)^d$$

Differencing and Stocastic Trend

Using the two component time series model

$$y_t = \mu_t + x_t$$

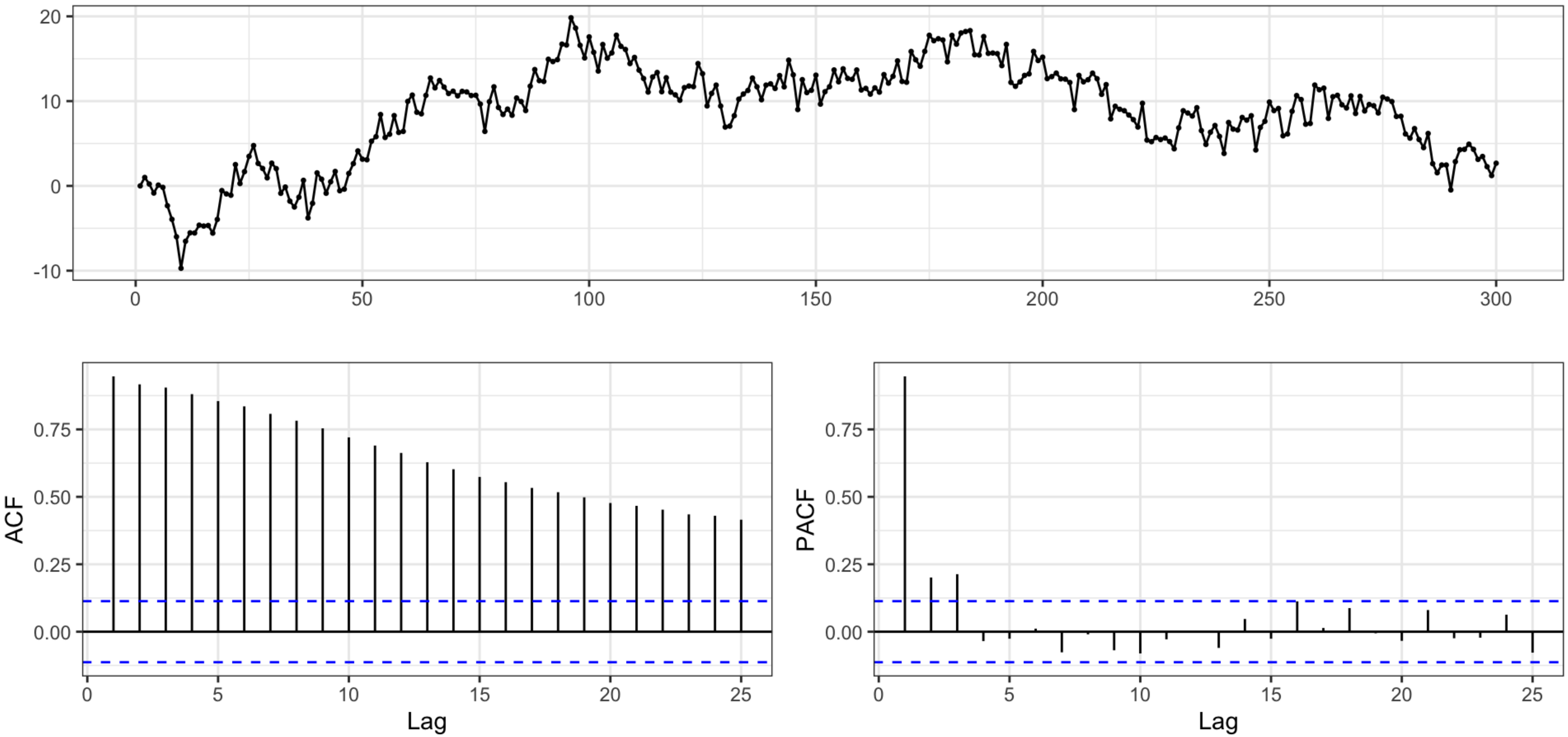
where μ_t is a non-stationary trend component and x_t is a mean zero stationary component.

We have already shown that differencing can address deterministic trend (e.g. $\mu_t = \beta_0 + \beta_1\, t$). In fact, if μ_t is any k-th order polynomial of t then $\Delta^k y_t$ is stationary.

Differencing can also address stochastic trend such as in the case where μ_t follows a random walk.

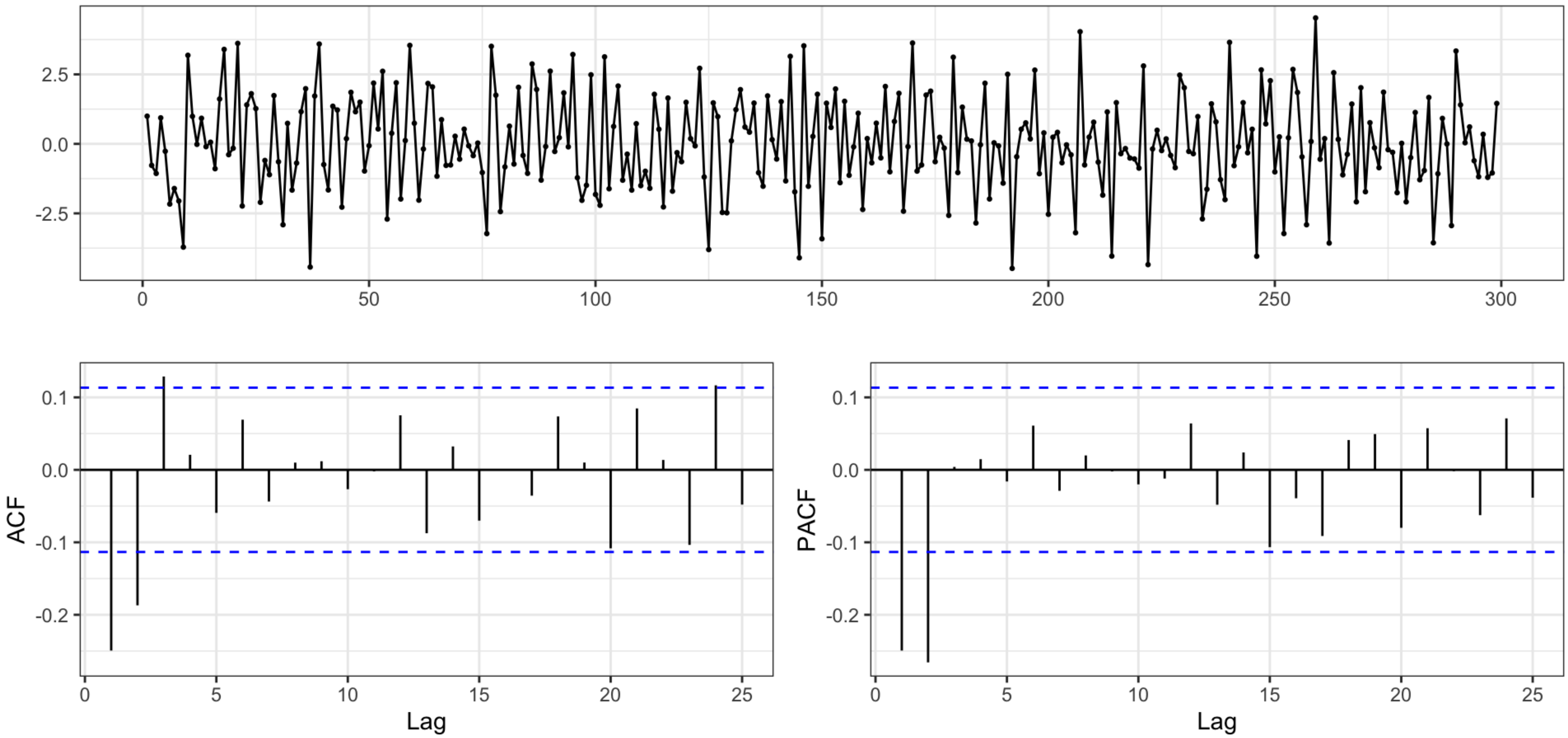
Stochastic trend - Example 1

Let $y_t = \mu_t + w_t$ where w_t is white noise and $\mu_t = \mu_{t-1} + v_t$ with v_t being a stationary process with mean 0.



Differenced stochastic trend

```r
forecast::ggtsdisplay(diff(d$y))
```



Stationary?

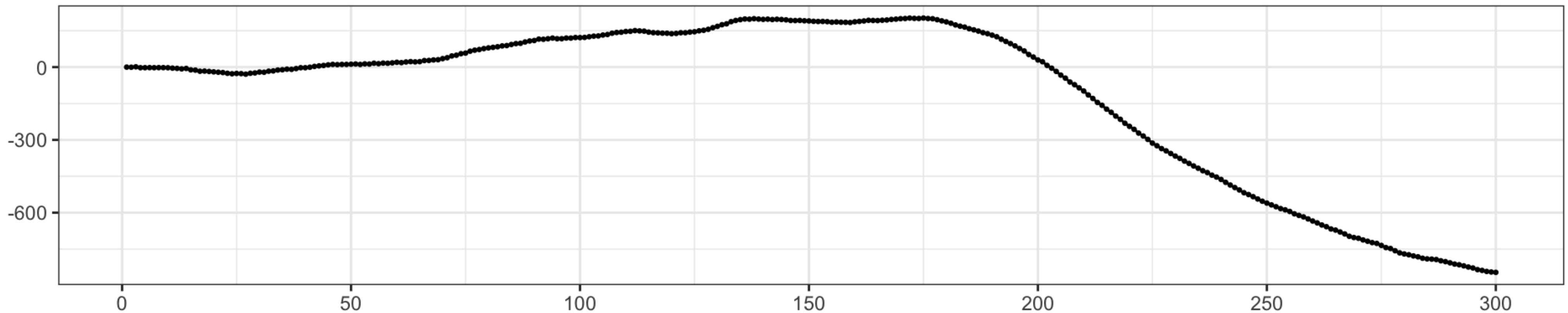
Is y_t stationary?

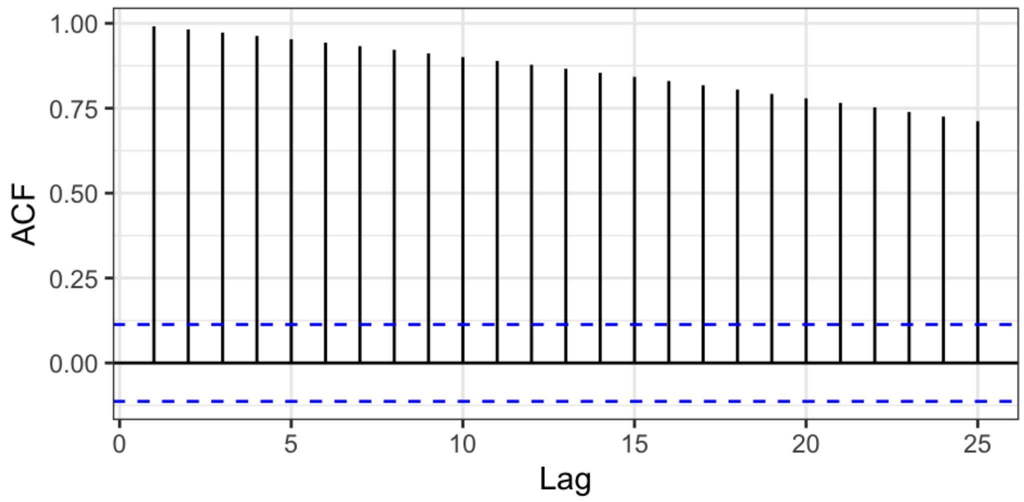
Difference Stationary?

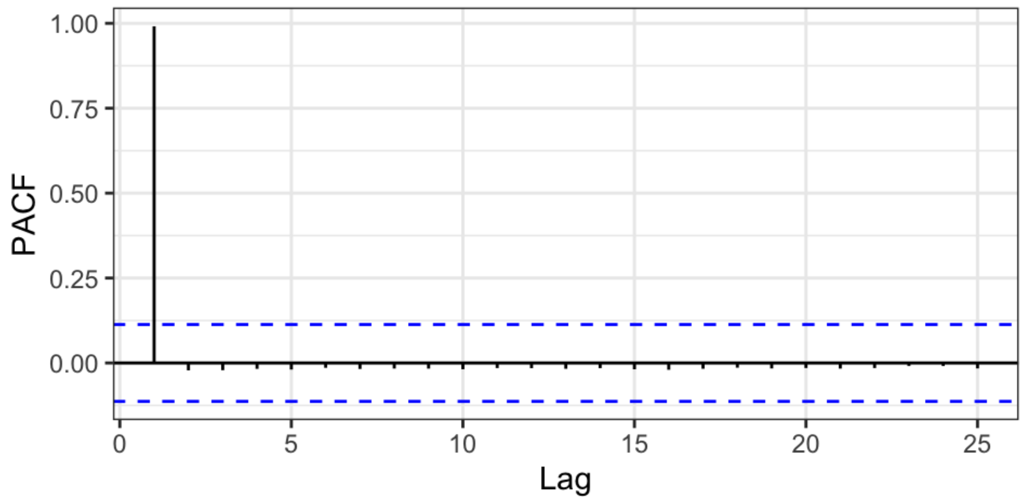
Is Δy_t stationary?

Stochastic trend - Example 2

Let $y_t = \mu_t + w_t$ where w_t is white noise and $\mu_t = \mu_{t-1} + v_t$ but now $v_t = v_{t-1} + e_t$ with e_t being stationary.

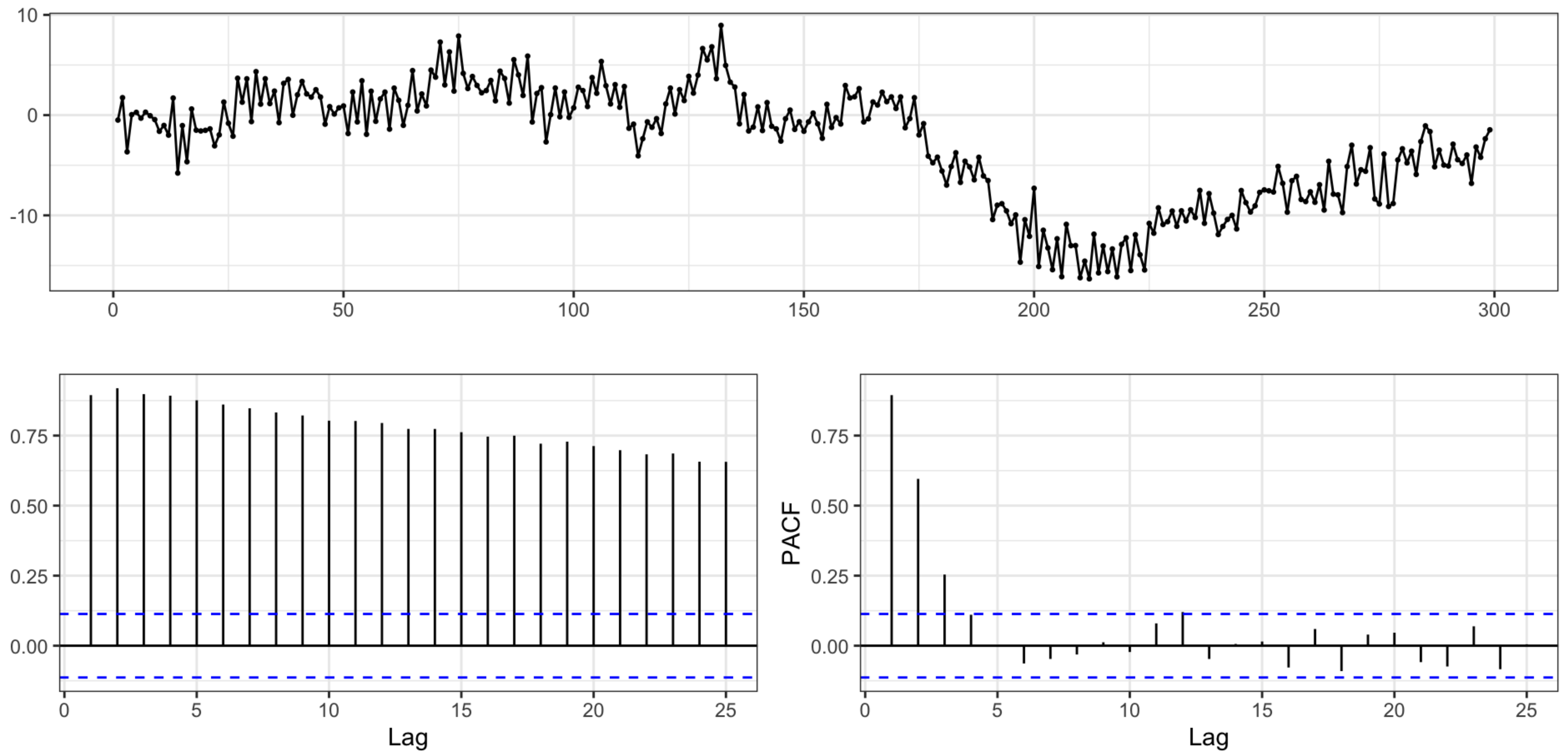






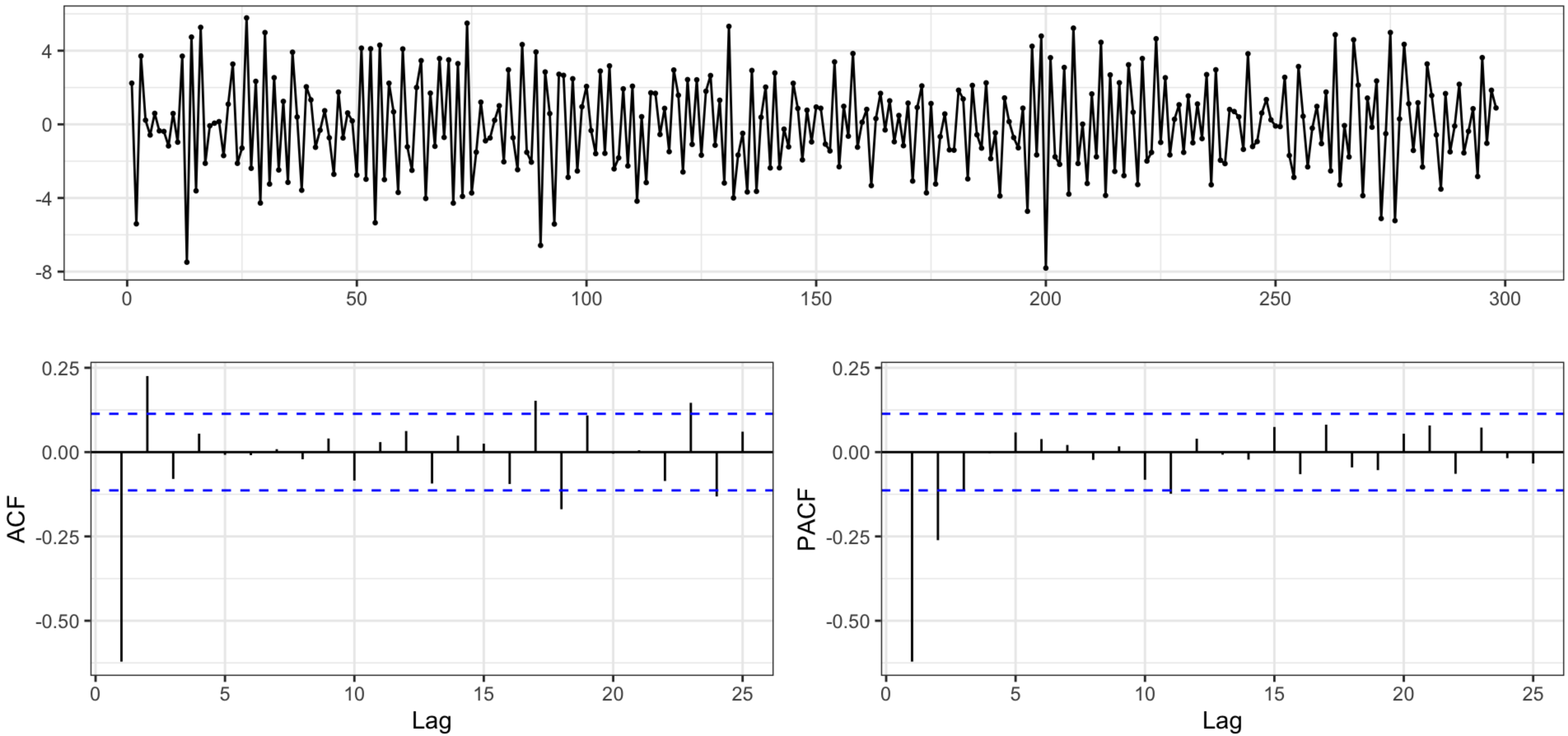
Differenced stochastic trend

```r
forecast::ggtsdisplay(diff(d$y))
```



Twice differenced stochastic trend

```r
forecast::ggtsdisplay(diff(d$y,differences = 2))
```



Difference stationary?

Is Δy_t stationary?

2nd order difference stationary?

What about $\Delta^2 y_t$, is it stationary?

ARIMA

ARIMA Models

Autoregressive integrated moving average are just an extension of an ARMA model to include differencing of degree d to y_t before including the autoregressive and moving average components.

$$\text{ARIMA}(p, d, q): \qquad \phi_p(L)\, \Delta^d\, y_t = \delta + \theta_q(L) w_t$$

Box-Jenkins approach:

1. Transform data if necessary to stabilize variance
2. Choose order (p, d, q) of ARIMA model
3. Estimate model parameters (δ, ϕs, and θs)
4. Diagnostics

Using `forecast` - random walk with drift

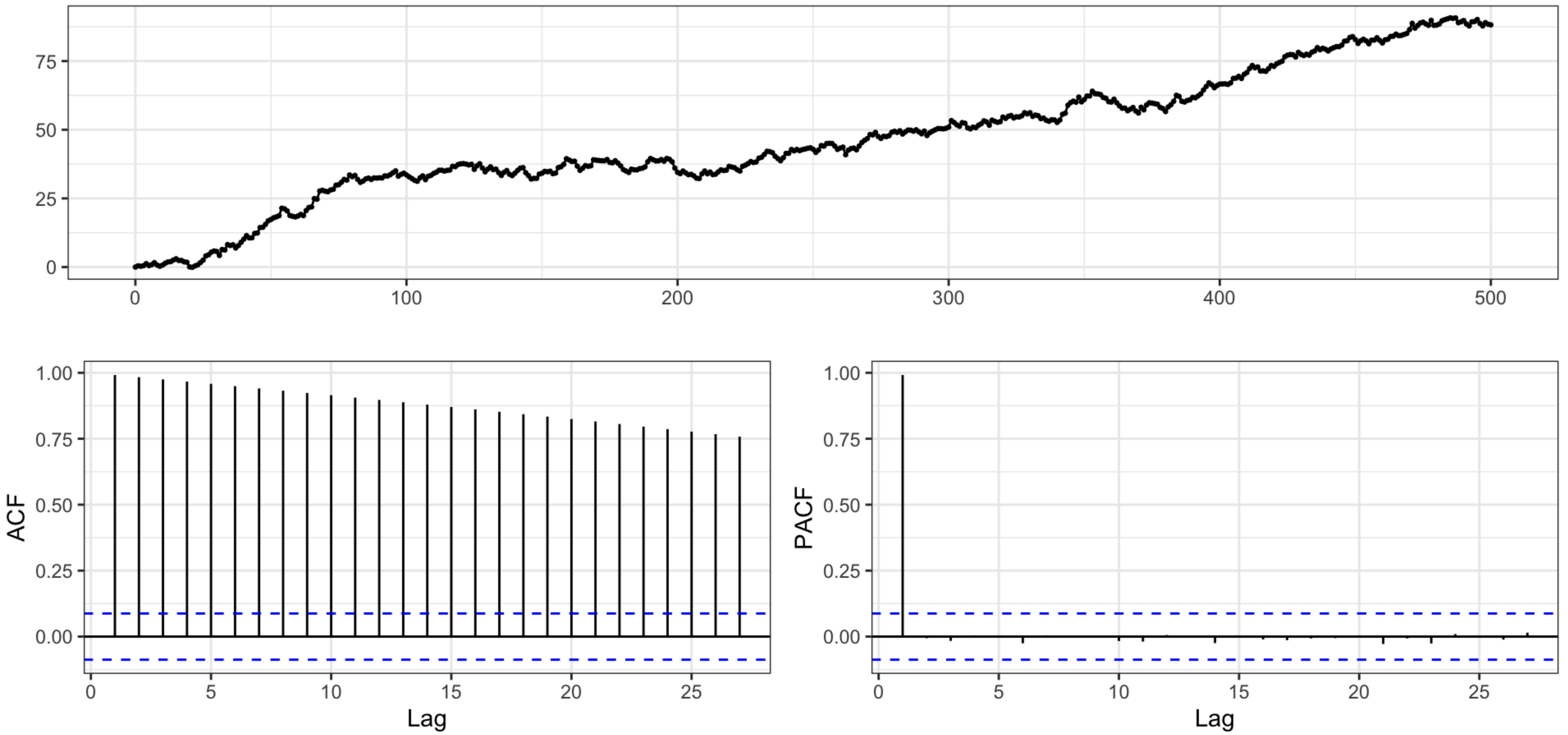
Some of R's base timeseries handling is a bit wonky, the `forecast` package offers some useful alternatives and additional functionality.

```r
rwd = arima.sim(n=500, model=list(order=c(0,1,0)), mean=0.1)

forecast::Arima(rwd, order = c(0,1,0), include.constant = TRUE)
```

```
Series: rwd
ARIMA(0,1,0) with drift

Coefficients:
       drift
      0.1764
s.e.  0.0416

sigma^2 = 0.8649:  log likelihood = -672.69
AIC=1349.39   AICc=1349.41   BIC=1357.81
```

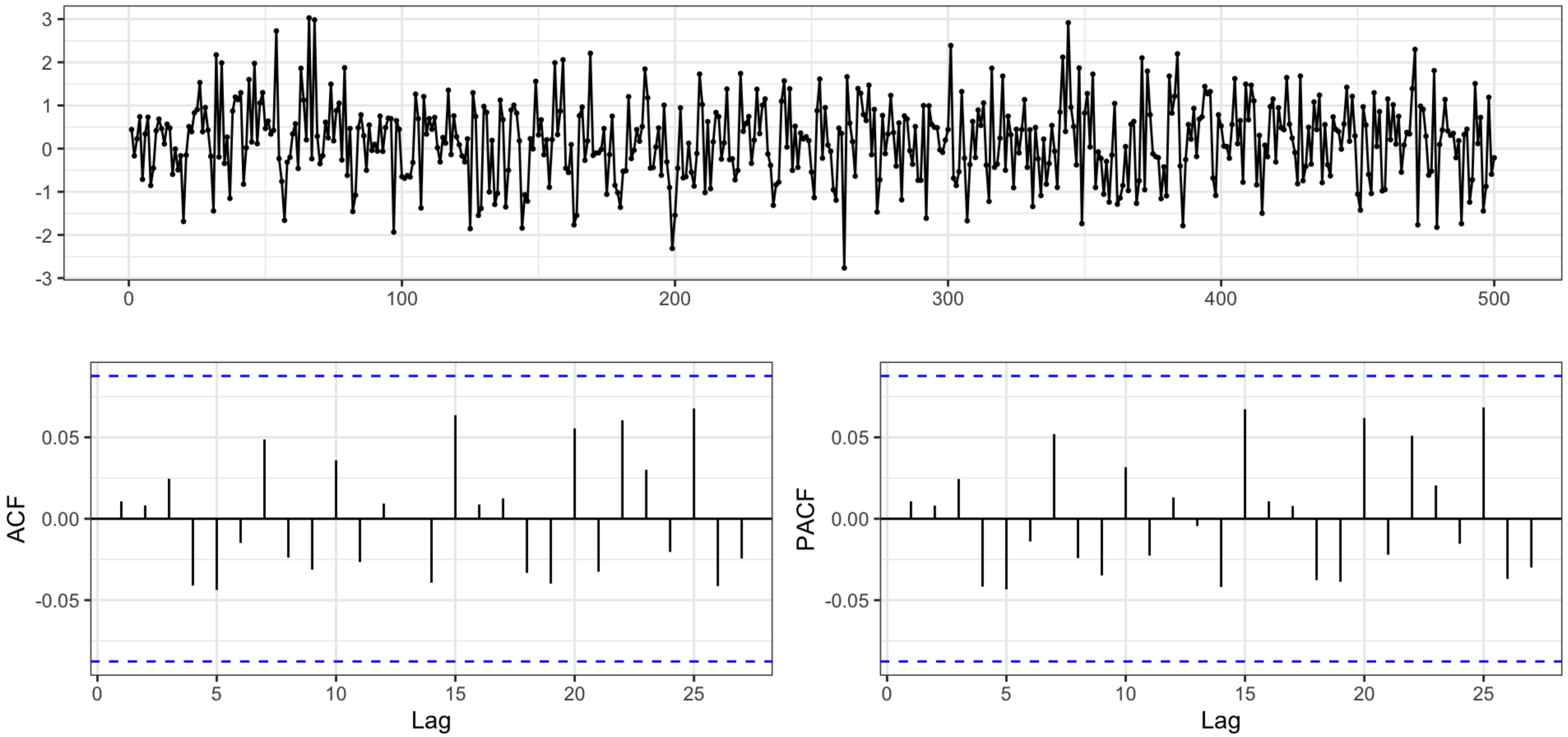
EDA

```
forecast::ggtsdisplay(rwd)
```



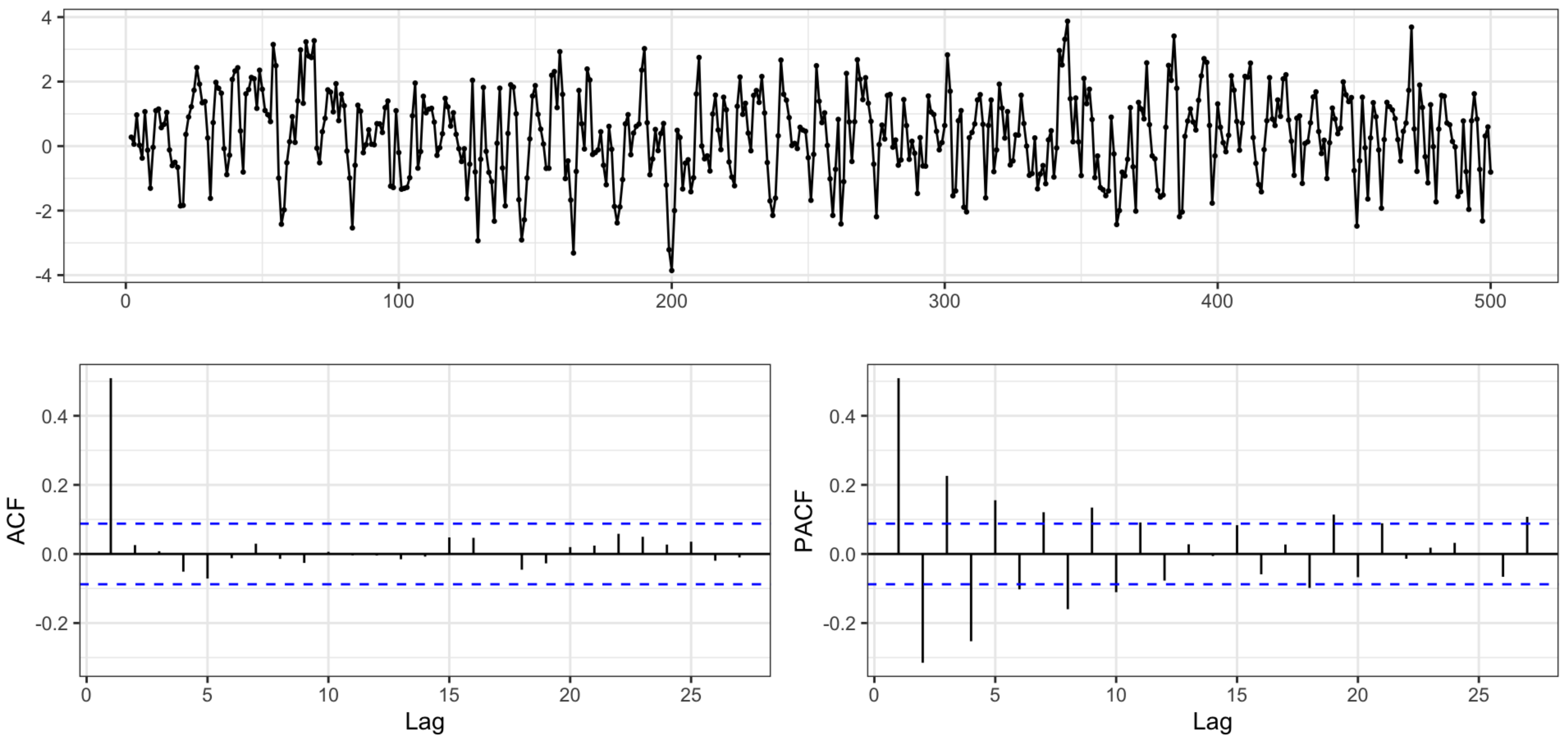
Differencing - Order 1

```r
forecast::ggtsdisplay(diff(rwd))
```



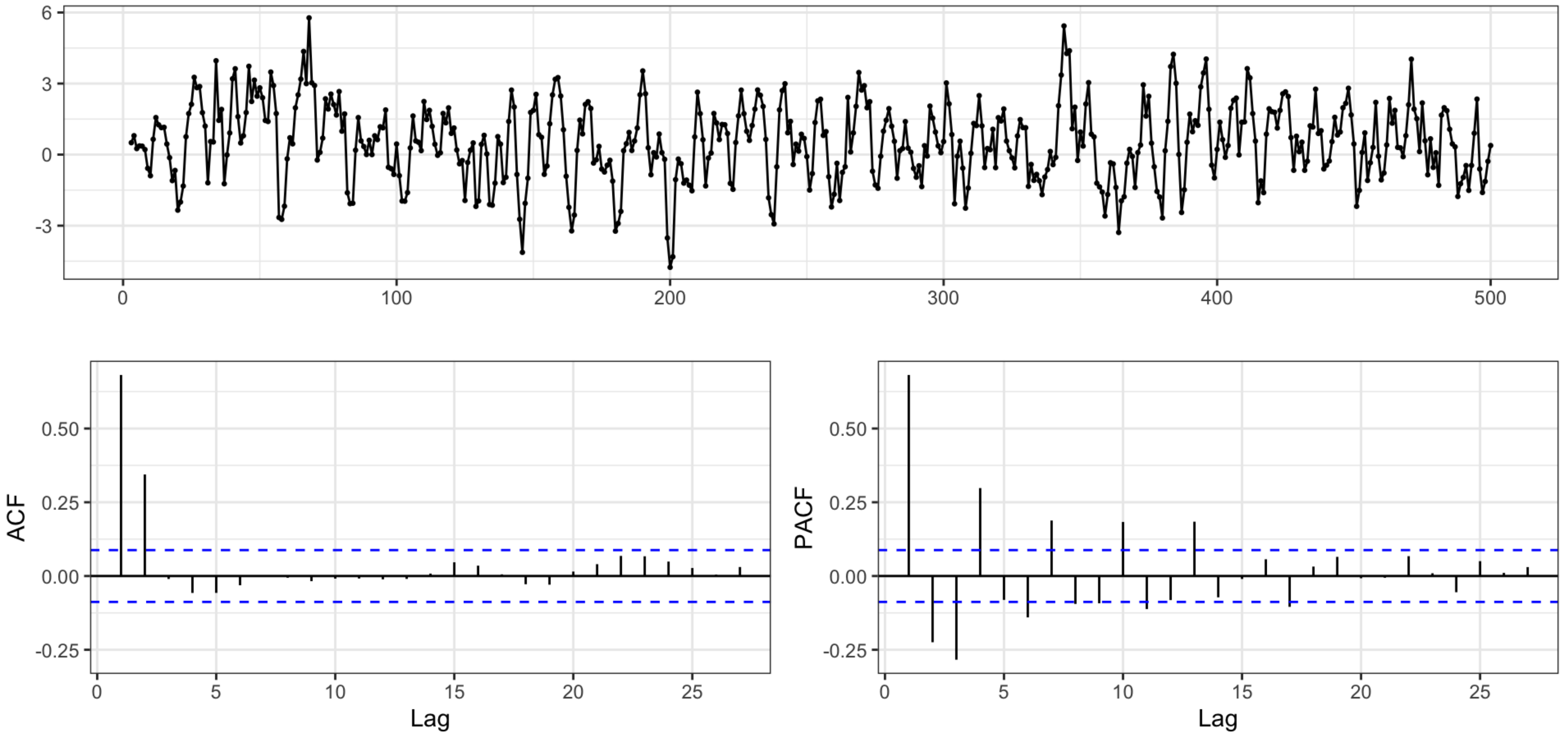
Differencing - Order 2

```r
forecast::ggtsdisplay(diff(rwd, 2))
```

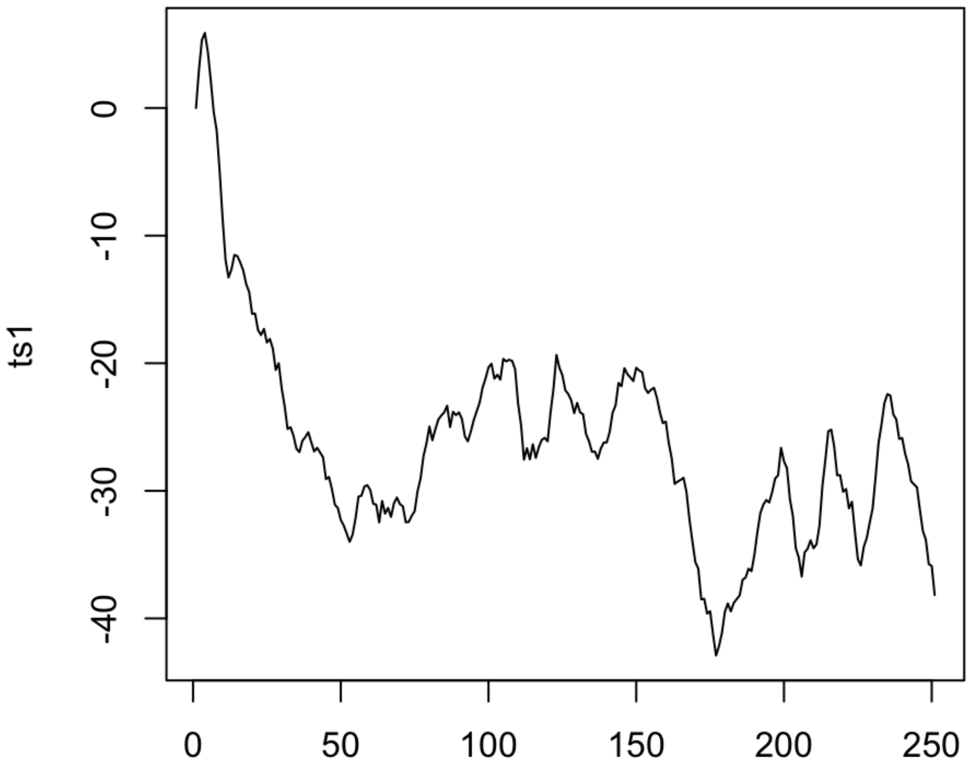


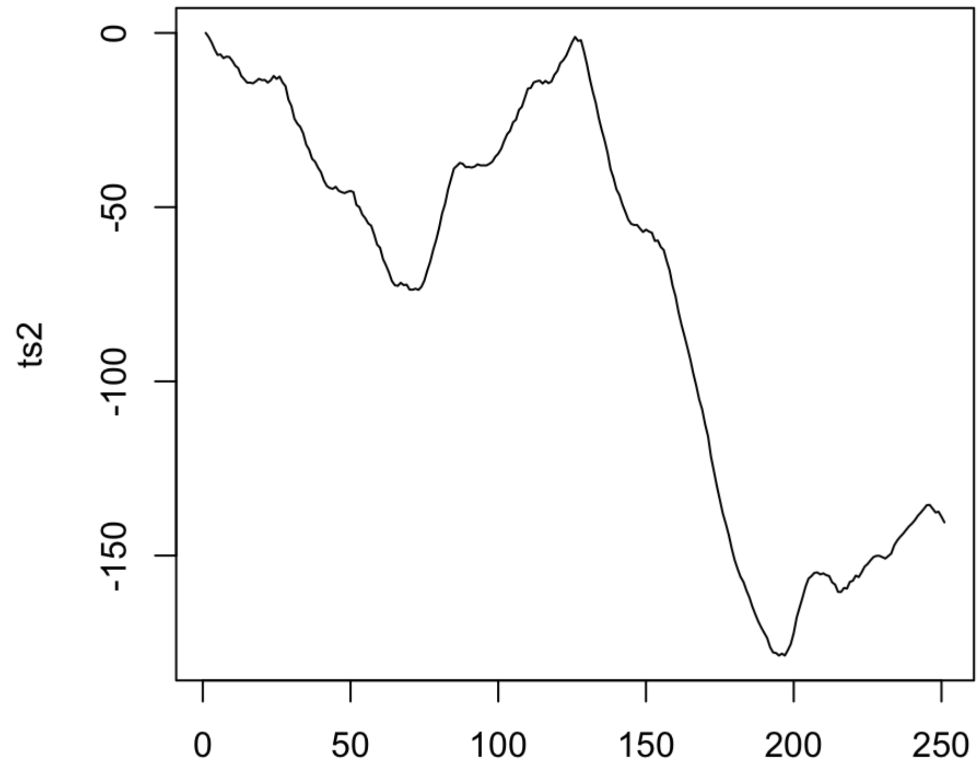
Differencing - Order 3

```
forecast::ggtsdisplay(diff(rwd, 3))
```

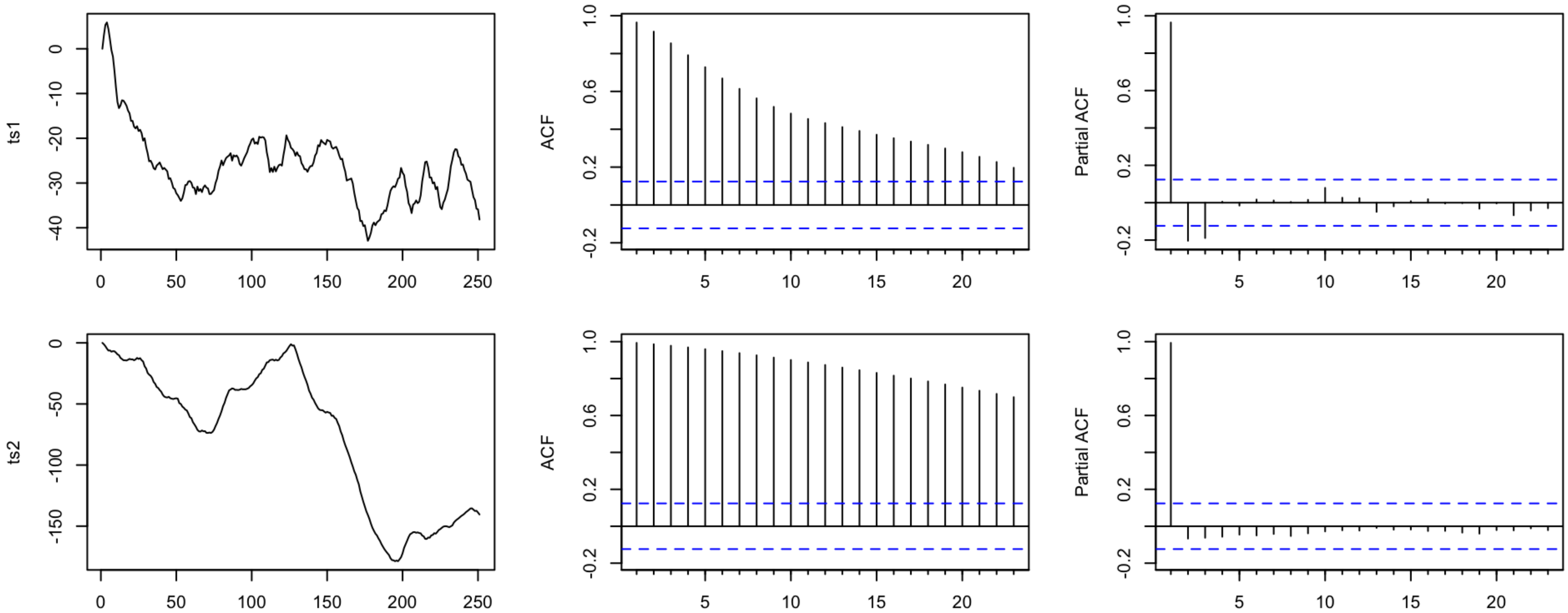


AR or MA?

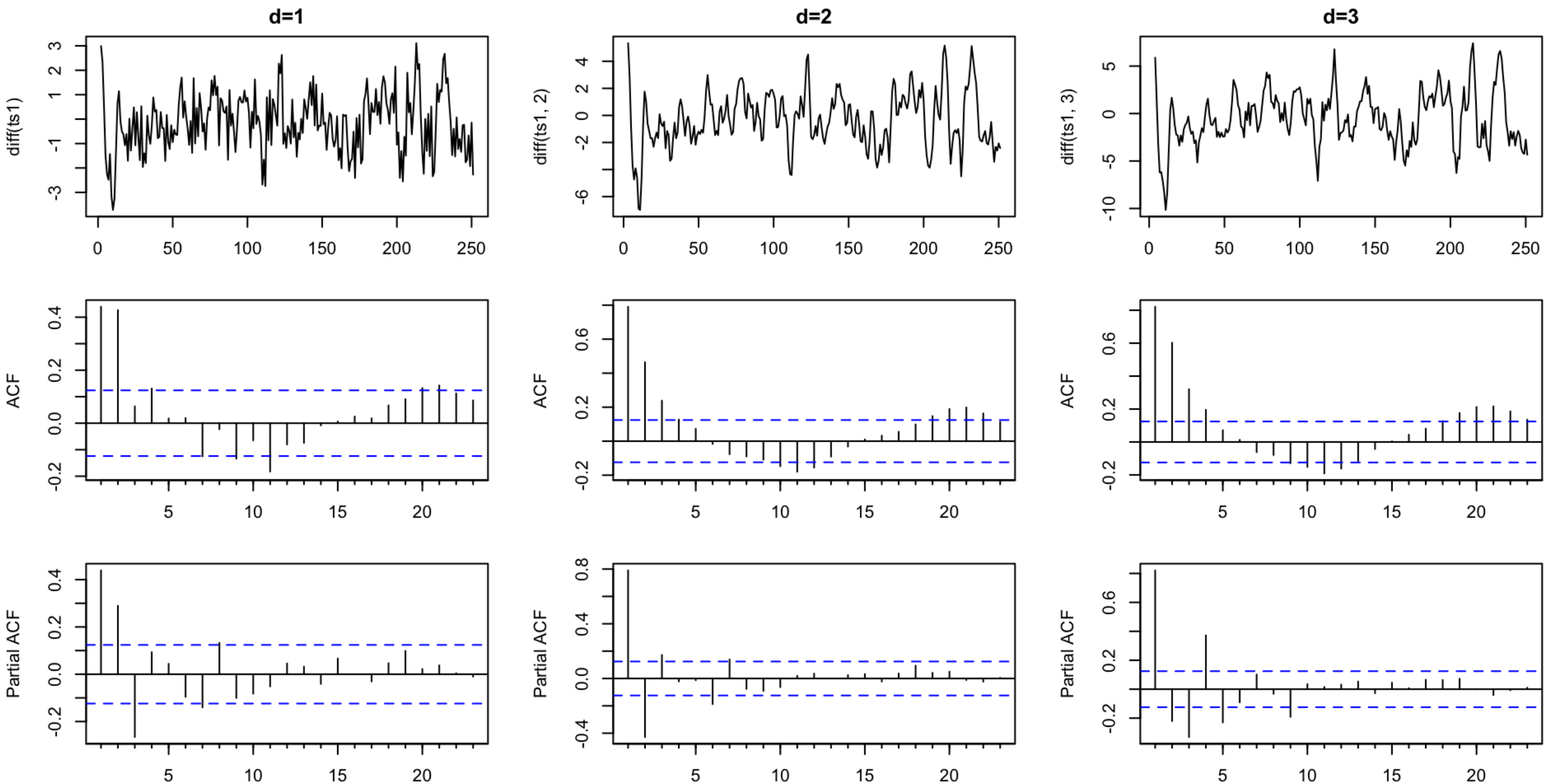

ts1
0
-10
-20
-30
-40
0
50
100
150
200
250


ts2
0
-50
-100
-150
0
50
100
150
200
250

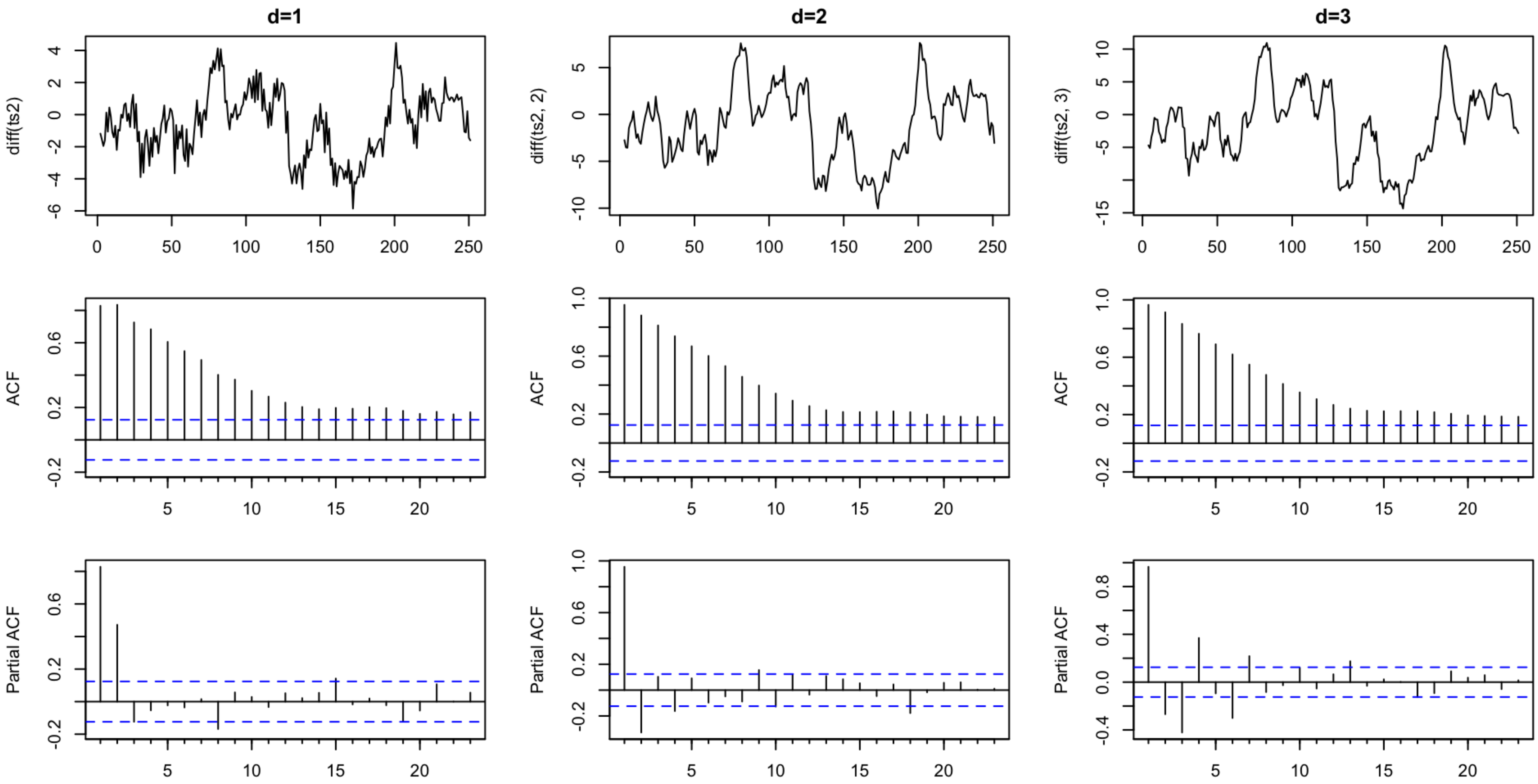
EDA


ts1
0
-10
-20
-30
-40
0
50
100
150
200
250
ACF
Partial ACF
1.0
0.6
0.2
-0.2
5
10
15
20
ts2
-50
-100
-150

`ts1` - Finding d



`ts2` - Finding d



`ts1` - Models

p	d	q	aic	aicc	bic
0	1	0	814.14	814.16	817.66
1	1	0	757.83	757.88	764.87
2	1	0	735.41	735.51	745.98
0	1	1	784.81	784.86	791.86
1	1	1	748.57	748.67	759.13
2	1	1	720.70	720.87	734.79
0	1	2	710.79	710.89	721.36
1	1	2	712.75	712.92	726.84
2	1	2	714.00	714.24	731.61

`ts2` - Models

p	d	q	aic	aicc	bic
0	1	0	1072.99	1073.01	1076.51
1	1	0	768.43	768.48	775.47
2	1	0	705.91	706.00	716.47
0	1	1	951.02	951.06	958.06
1	1	1	728.80	728.89	739.36
2	1	1	704.81	704.97	718.90
0	1	2	839.03	839.13	849.59
1	1	2	709.16	709.32	723.24
2	1	2	705.68	705.92	723.28

ts1 - final model

Fitted:

```r
forecast::Arima(ts1, order = c(0,1,2))
```

```
Series: ts1
ARIMA(0,1,2)

Coefficients:
         ma1     ma2
      0.4421  0.5849
s.e.  0.0495  0.0547

sigma^2 = 0.9858:  log likelihood = -352.4
AIC=710.79   AICc=710.89   BIC=721.36
```

Truth:

```r
ts1 = arima.sim(n=250, model=list(order=c(0,1,2), ma=c(0.4,0.5)))
```

ts2 - final model

Fitted:

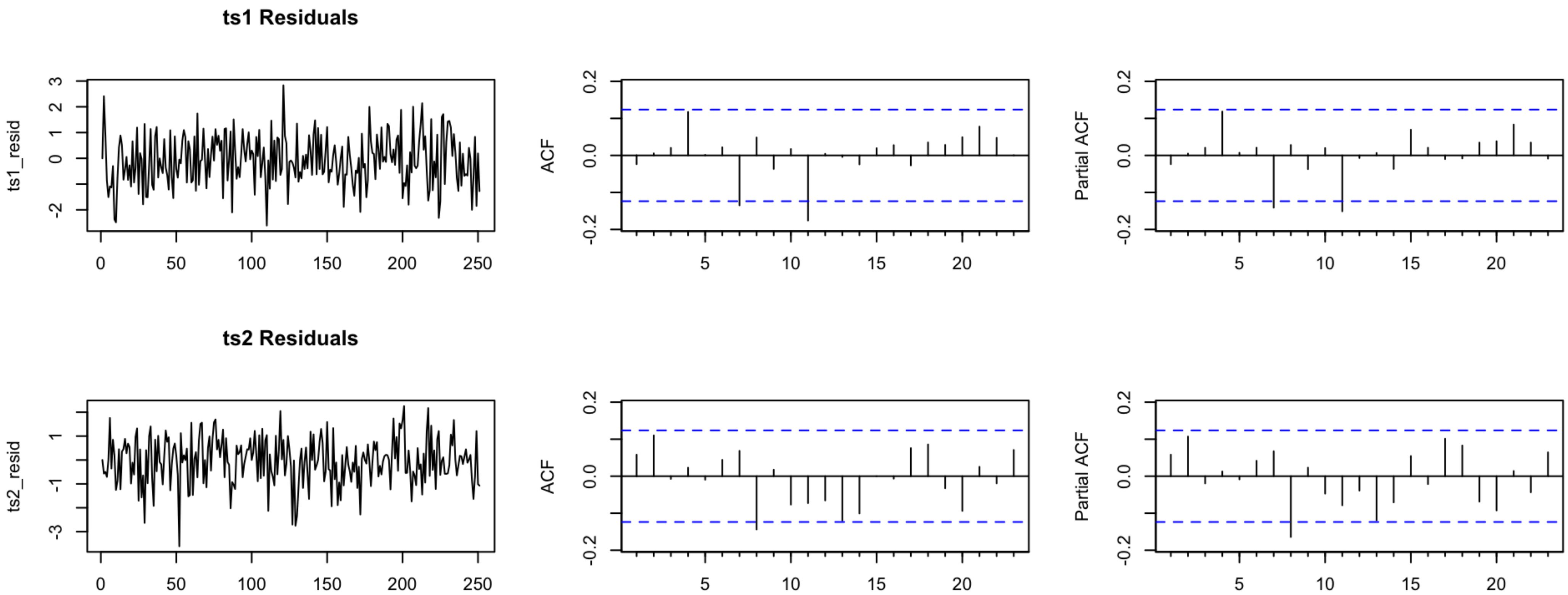
```r
forecast::Arima(ts2, order = c(2,1,0))
```

```
Series: ts2
ARIMA(2,1,0)

Coefficients:
         ar1     ar2
      0.4388  0.4760
s.e.  0.0552  0.0553

sigma^2 = 0.9636:  log likelihood = -349.95
AIC=705.91   AICc=706   BIC=716.47
```

Truth:

```r
ts2 = arima.sim(n=250, model=list(order=c(2,1,0), ar=c(0.4,0.5)))
```

Residuals


ts1 Residuals
ts1_resid
ACF
Partial ACF
ts2 Residuals
ts2_resid
ACF
Partial ACF

Automatic model selection

`ts1`:

```
forecast::auto.arima(ts1)
```

```
Series: ts1
ARIMA(2,1,2)

Coefficients:
          ar1     ar2     ma1     ma2
      -0.0532  0.1291  0.4878  0.4983
s.e.   0.1100  0.1468  0.0936  0.1240

sigma^2 = 0.9908:  log likelihood = -352
AIC=714   AICc=714.24   BIC=731.61
```

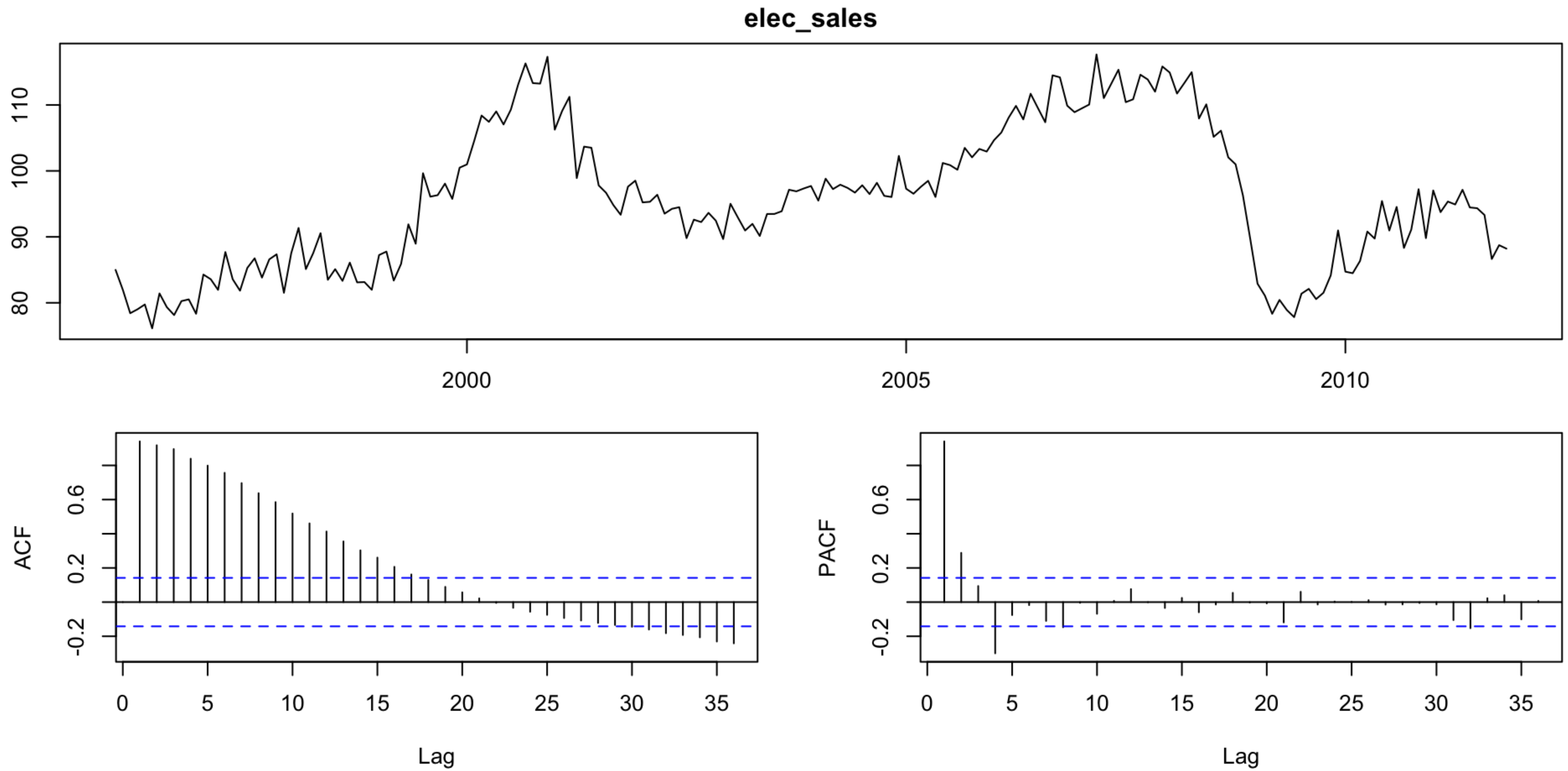
`ts2`:

```
forecast::auto.arima(ts2)
```

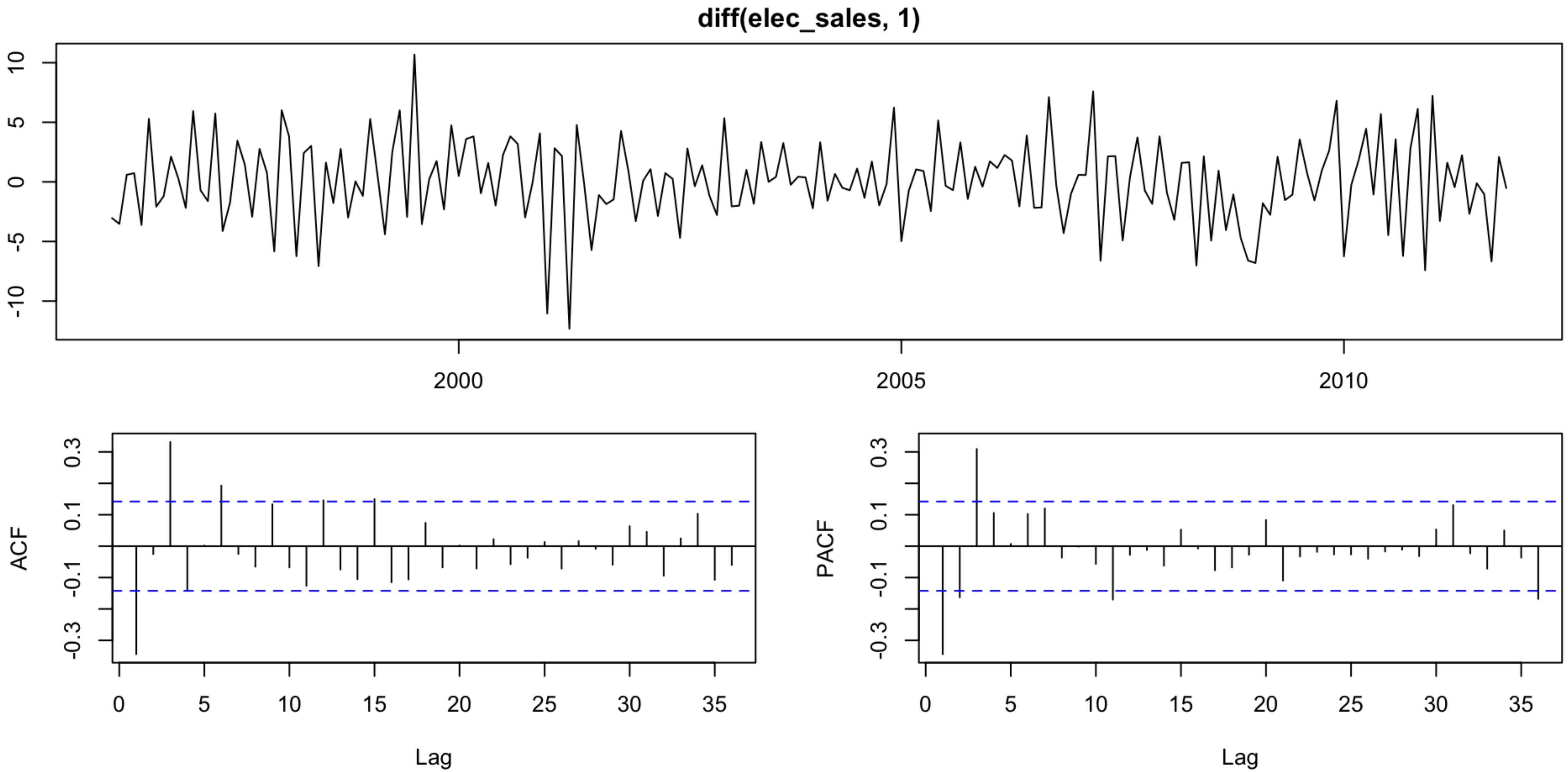
```
Series: ts2
ARIMA(3,1,0)

Coefficients:
         ar1     ar2      ar3
      0.4990  0.5305  -0.1246
s.e.  0.0626  0.0613   0.0629

sigma^2 = 0.9524:  log likelihood = -348.01
AIC=704.02   AICc=704.18   BIC=718.11
```

Electrical Equipment Sales

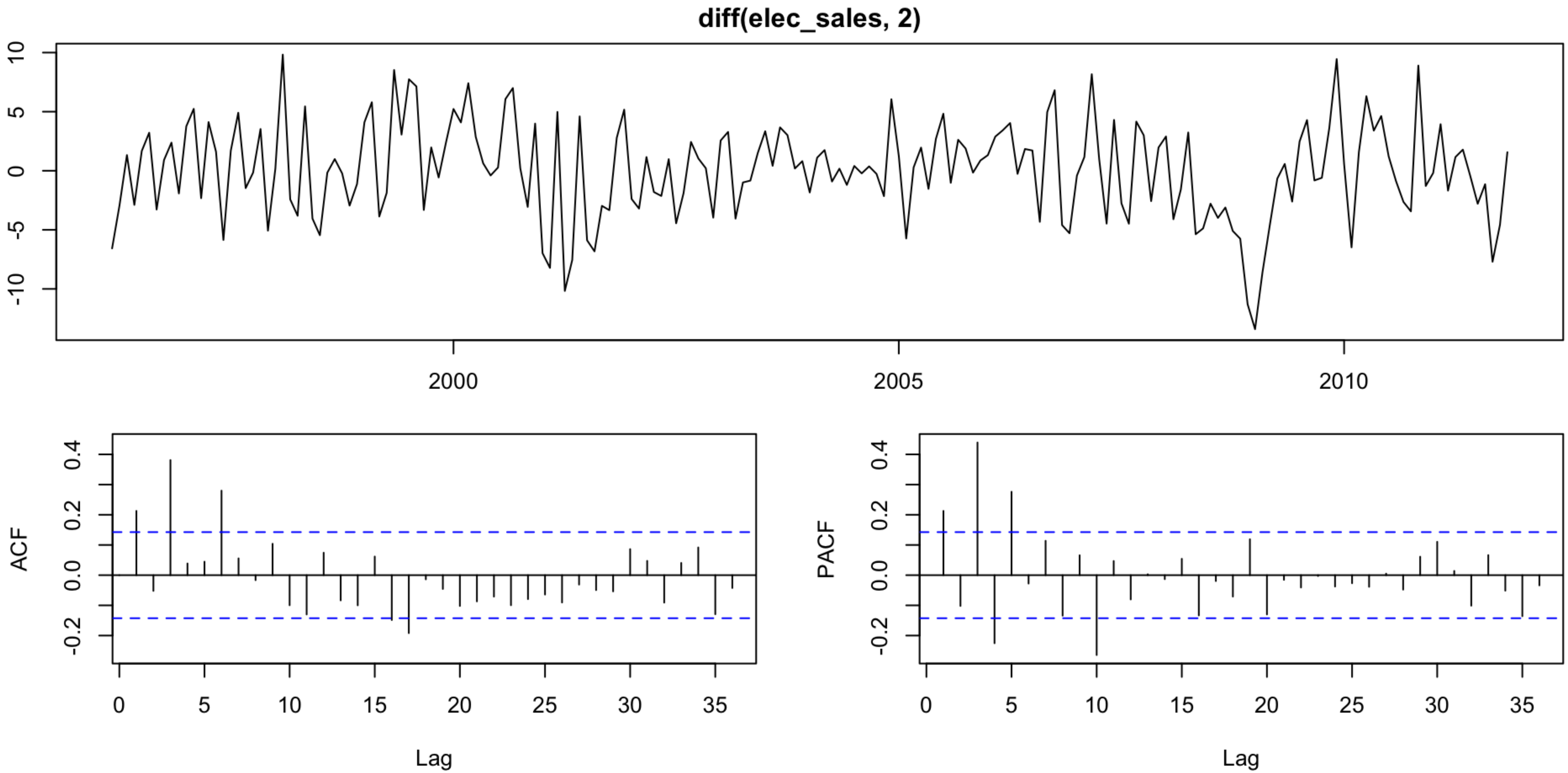
Data


elec_sales
80
90
100
110
2000
2005
2010
ACF
-0.2
0.2
0.6
0
5
10
15
20
25
30
35
Lag
PACF
-0.2
0.2
0.6
0
5
10
15
20
25
30
35
Lag

1st order differencing



2nd order differencing



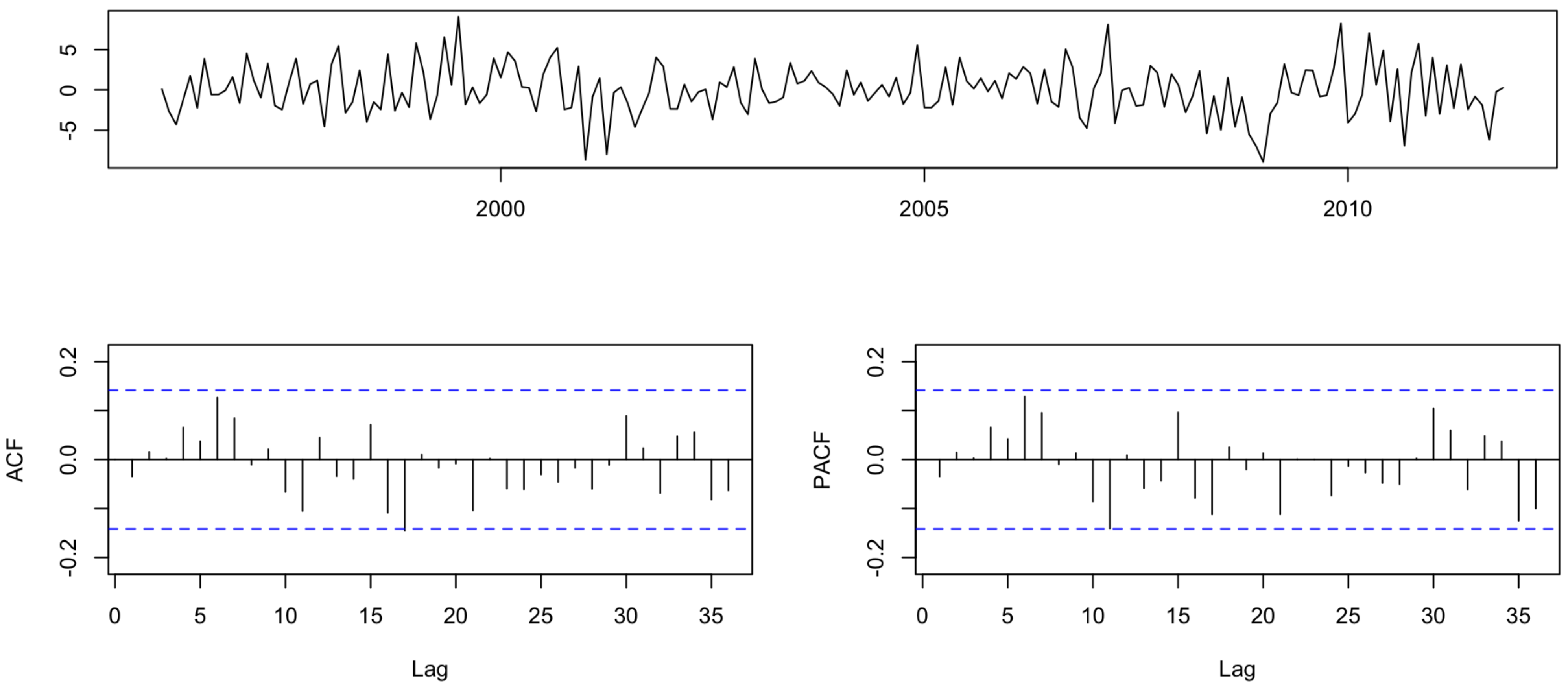
Model

```r
forecast::Arima(elec_sales, order = c(3,1,0))
```

```
Series: elec_sales
ARIMA(3,1,0)

Coefficients:
          ar1      ar2     ar3
      -0.3488  -0.0386  0.3139
s.e.   0.0690   0.0736  0.0694

sigma^2 = 9.853:  log likelihood = -485.67
AIC=979.33   AICc=979.55   BIC=992.32
```

Residuals

```r
forecast::Arima(elec_sales, order = c(3,1,0)) %>% residuals() %>%
  forecast::tsdisplay(points=FALSE)
```



Model Comparison

Model choices:

```r
forecast::Arima(elec_sales, order = c(3,1,0))$aicc
```

```
[1] 979.5477
```

```r
forecast::Arima(elec_sales, order = c(3,1,1))$aicc
```

```
[1] 978.4925
```

```r
forecast::Arima(elec_sales, order = c(4,1,0))$aicc
```

```
[1] 979.2309
```

```r
forecast::Arima(elec_sales, order = c(2,1,0))$aicc
```

```
[1] 996.8085
```

Automatic selection:

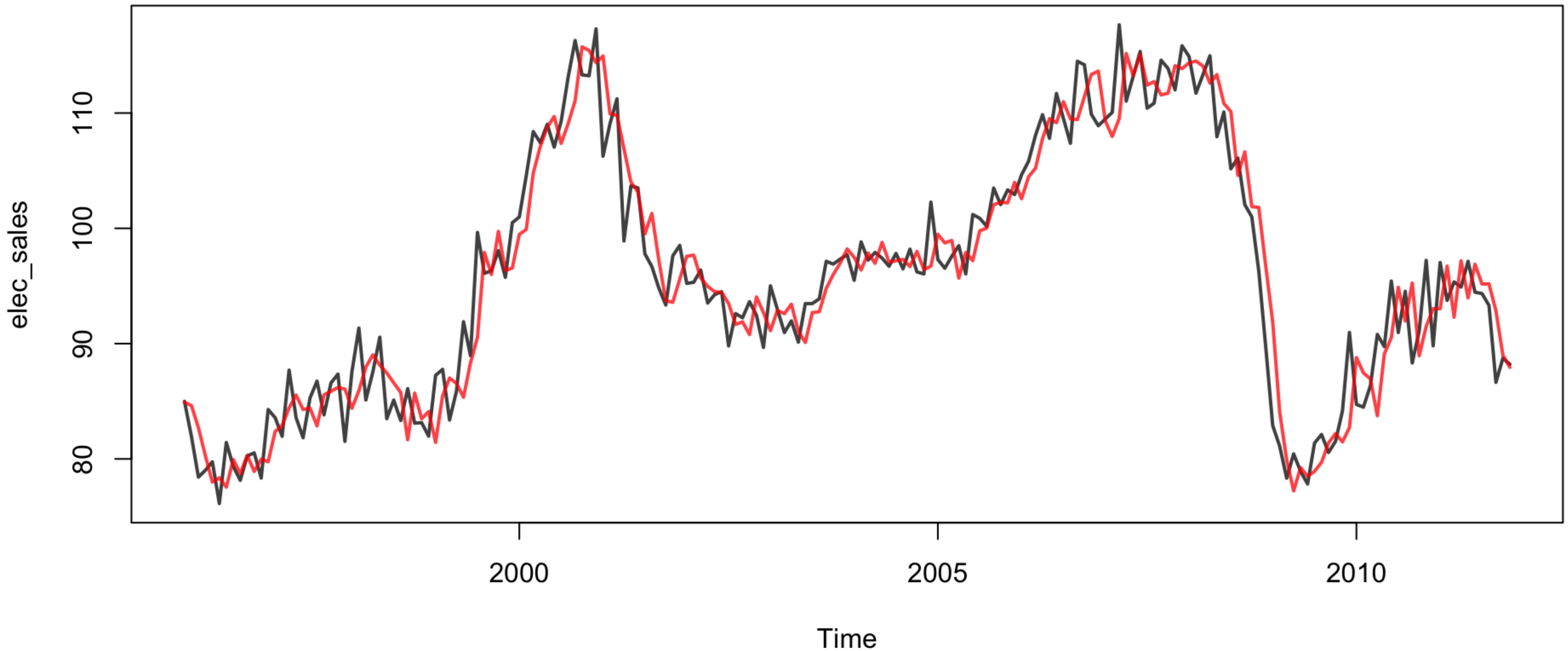
```r
forecast::auto.arima(elec_sales)
```

```
Series: elec_sales
ARIMA(3,1,1)
```

```
Coefficients:
         ar1     ar2     ar3      ma1
      0.0519  0.1191  0.3730  -0.4542
s.e.  0.1840  0.0888  0.0679   0.1993

sigma^2 = 9.737:  log likelihood = -484.08
AIC=978.17   AICc=978.49   BIC=994.4
```

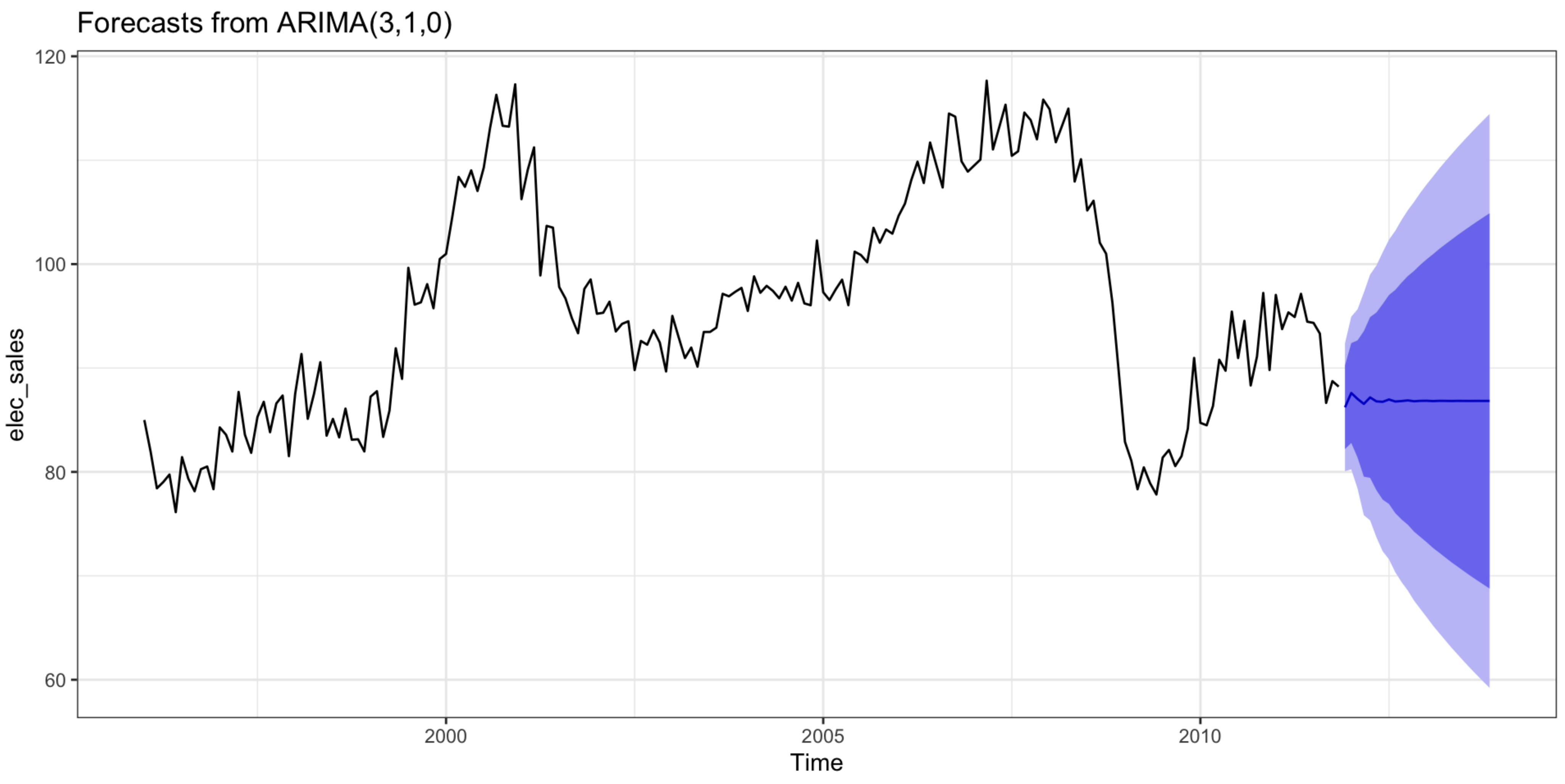
Model fit

```r
plot(elec_sales, lwd=2, col=adjustcolor("black", alpha.f=0.75))
forecast::Arima(elec_sales, order = c(3,1,0)) %>% fitted() %>%
  lines(col=adjustcolor('red',alpha.f=0.75),lwd=2)
```



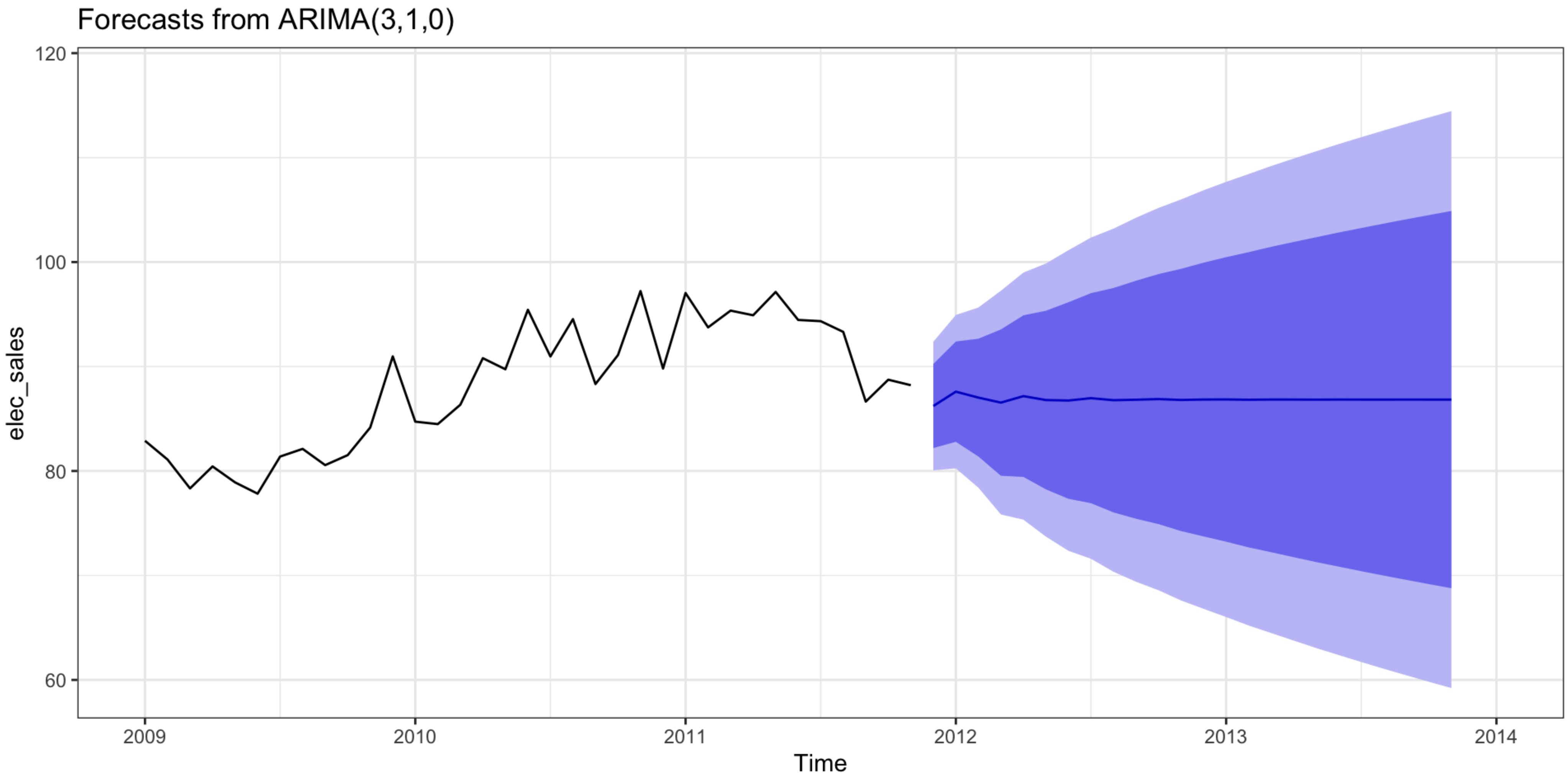
Model forecast

```
forecast::Arima(elec_sales, order = c(3,1,0)) %>%
  forecast::forecast() %>% autoplot()
```



Model forecast - Zoom

```r
forecast::Arima(elec_sales, order = c(3,1,0)) %>%
  forecast::forecast() %>% autoplot() + xlim(2009,2014)
```



General Guidance

1. Positive autocorrelations out to a large number of lags usually indicates a need for differencing
2. Slightly too much or slightly too little differencing can be corrected by adding AR or MA terms respectively.
3. A model with no differencing usually includes a constant term, a model with two or more orders (rare) differencing usually does not include a constant term.
4. After differencing, if the PACF has a sharp cutoff then consider adding AR terms to the model.
5. After differencing, if the ACF has a sharp cutoff then consider adding an MA term to the model.
6. It is possible for an AR term and an MA term to cancel each other's effects, so try models with fewer AR terms and fewer MA terms.

Based on guidance in Robert Nau's notes on regression and time series analysis - Chapter 5