

ARIMA

- `1956 1 1995 8` `(fma::elec)`
`1956 1 1995 8` `fma::elec` . [Figure 1](#) .

```
autoplot(elec) +  
  labs(x = NULL, y = NULL)
```

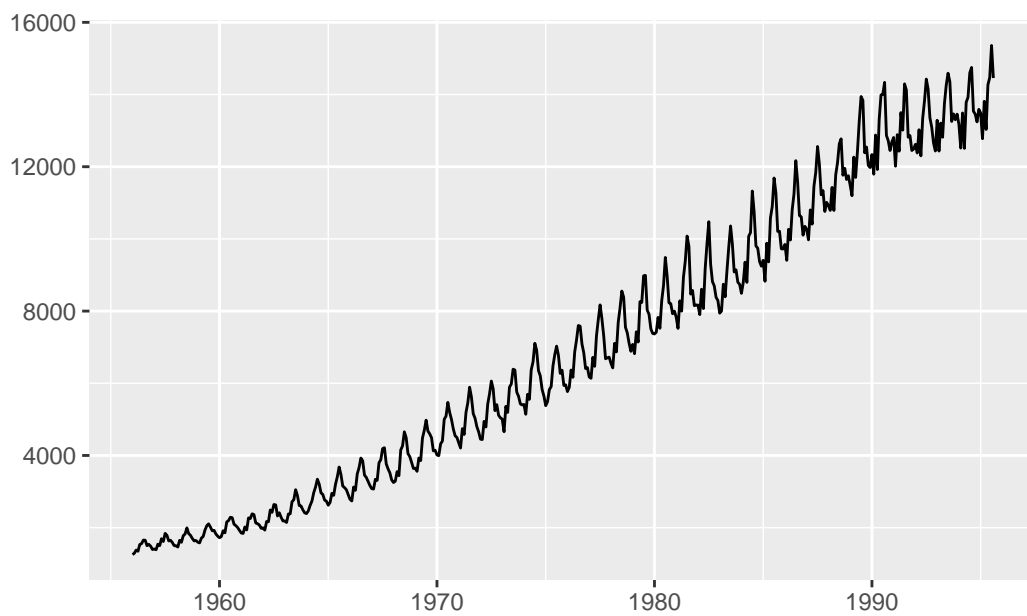


Figure 1: elec

```
,  
Box-Cox  
λ  
forecast  
BoxCox()  
BoxCox.lambda()  
λ  
BoxCox.lambda()
```

```
elec      Box-Cox      .

(lambda <- BoxCox.lambda(elec))
## [1] 0.2654076
```

Figure 2 .

```
autoplot(BoxCox(elec, lambda)) +
  labs(x = NULL, y = NULL)
```

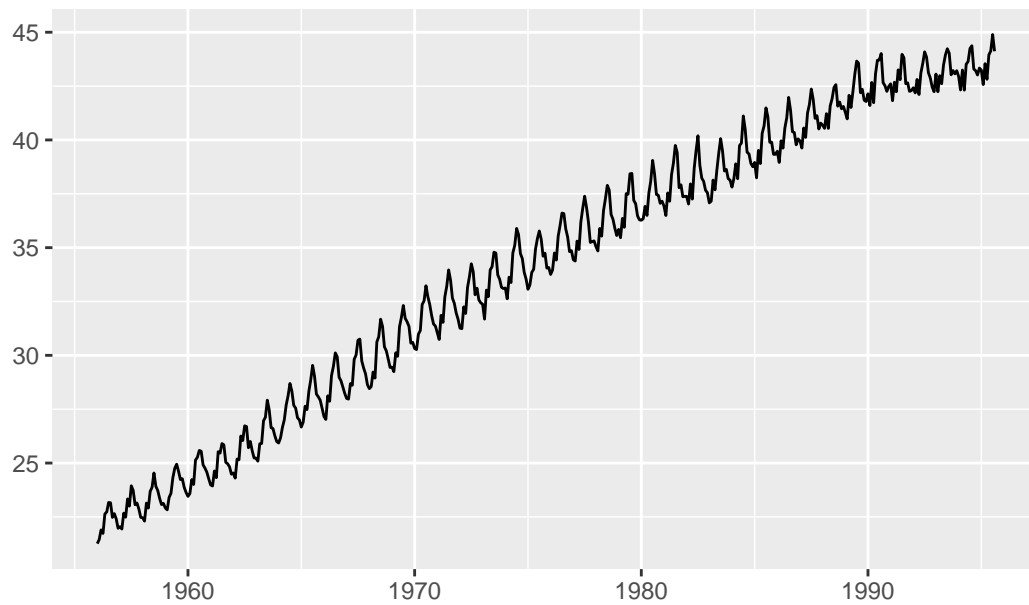


Figure 2: `elec` Box-Cox

Figure 2 Box-Cox . $y_t^{0.2654}$.

```
library(patchwork)

p1 <- autoplot(BoxCox(elec, BoxCox.lambda(elec))) +
  labs(x = NULL, y = NULL, title = "Box-Cox transformation")
p2 <- autoplot(log(elec)) +
  labs(x = NULL, y = NULL, title = "log transformation")
```

```
p1 + p2
```

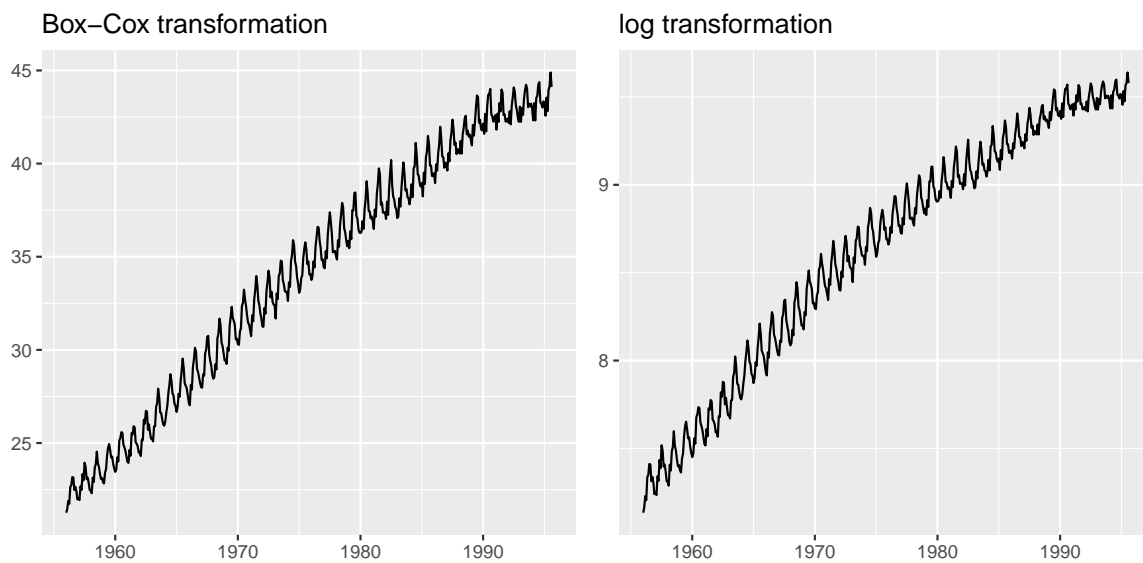


Figure 3: `elec`

Figure 3

- : Google (fpp2::goog200)

Google goog200 ACF . , ACF .

```
p1 <- autoplot(goog200) +
  labs(x = NULL, y = NULL, title = "Google stock price")
p2 <- ggAcf(goog200) + ggtitle("")
p1 + p2
```

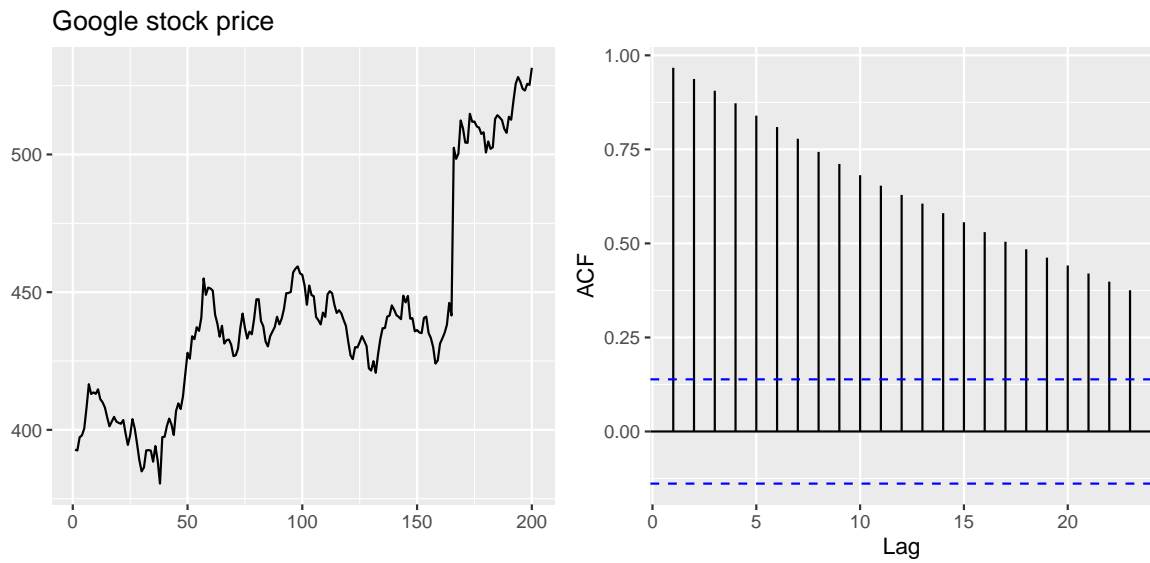


Figure 4: goog200 ACF

```
goog200 1 .

goog200_1 <- diff(goog200)
p3 <- autoplot(goog200_1) +
  labs(x = NULL, y = NULL, title = "Google stock price")
p4 <- ggAcf(goog200_1) + ggtitle("")
p3 + p4
```

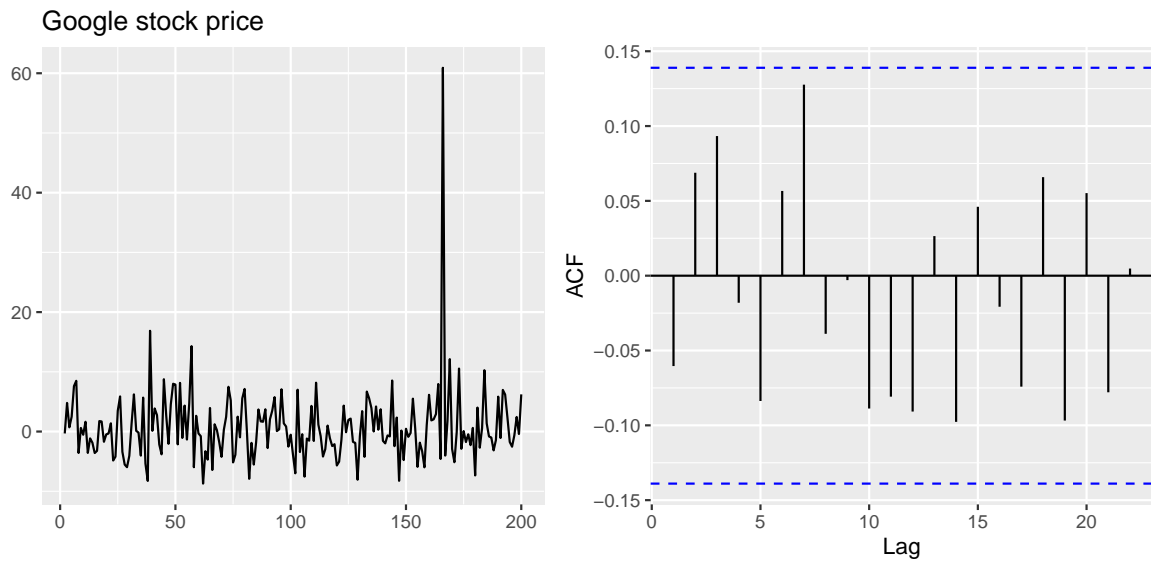


Figure 5: goog200 1 ACF

```

level      , ACF
.
.
goog200    .      urca::ur.kpss()      , forecast::ndiffs()
.

ndiffs(goog200)
## [1] 1

, 1      .      urca::ur.kpss()      . |> base R pipe
,      %>%      .

library(urca)
goog200 |>
  ur.kpss() |>
  summary()
##
## #####
## # KPSS Unit Root Test #
## #####
##
##
## Test is of type: mu with 4 lags.
##

```

```
## Value of test-statistic is: 2.7441
##
## Critical value for a significance level of:
##          10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463 0.574 0.739
```

1% . 1 , 1

```
goog200 |>
  diff() |>
  ur.kpss() |>
  summary()
##
## #####
## # KPSS Unit Root Test #
## #####
##
## Test is of type: mu with 4 lags.
##
## Value of test-statistic is: 0.1163
##
## Critical value for a significance level of:
##          10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463 0.574 0.739
```

```
• : 1956 1 1995 8 (fma::elec)
```

Figure 1 elec , .
ACF Figure 6 .

```
ln_elec <- log(elec)
p1 <- autoplot(ln_elec) +
  labs(x = NULL, y = NULL, title = "log transformed data")
p2 <- ggAcf(ln_elec) + ggtitle("")
p1 + p2
```

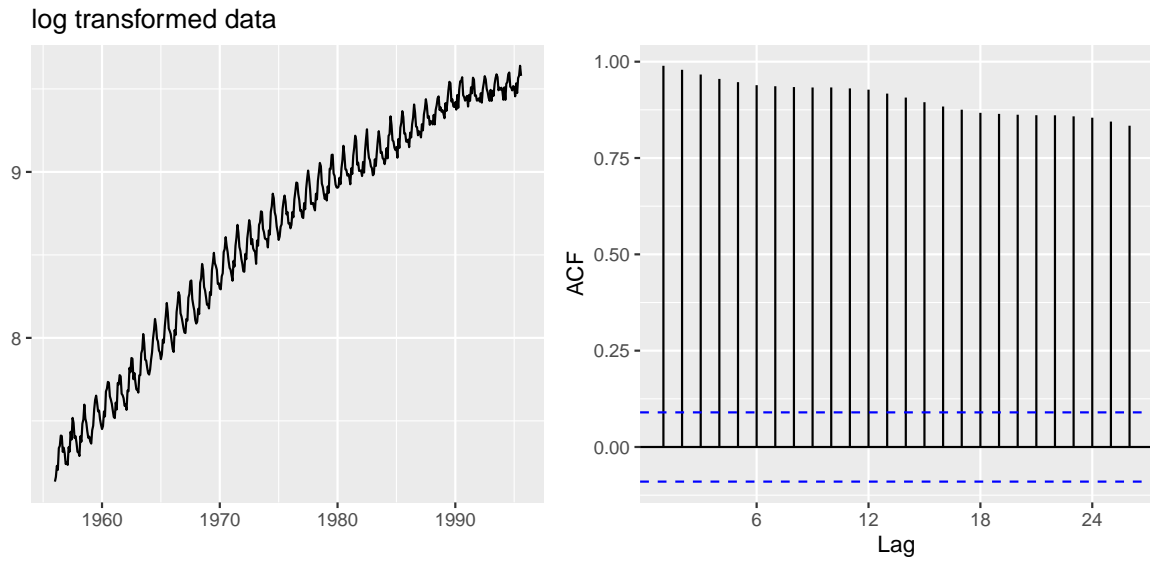


Figure 6: elec

ACF

```
. forecast::nsdiffs()
. nsdiffs() seasonal strength
```

```
elec |>
  log() |>
  nsdiffs()
## [1] 1
```

ACF

Figure 7

```
ln_elec_m <- log(elec) %>%
  diff(lag = 12)
p3 <- autoplot(ln_elec_m) +
  labs(x = NULL, y = NULL, title = "log transformed and seasonally differenced data")
p4 <- ggAcf(ln_elec_m) + ggtitle("")
p3 + p4
```

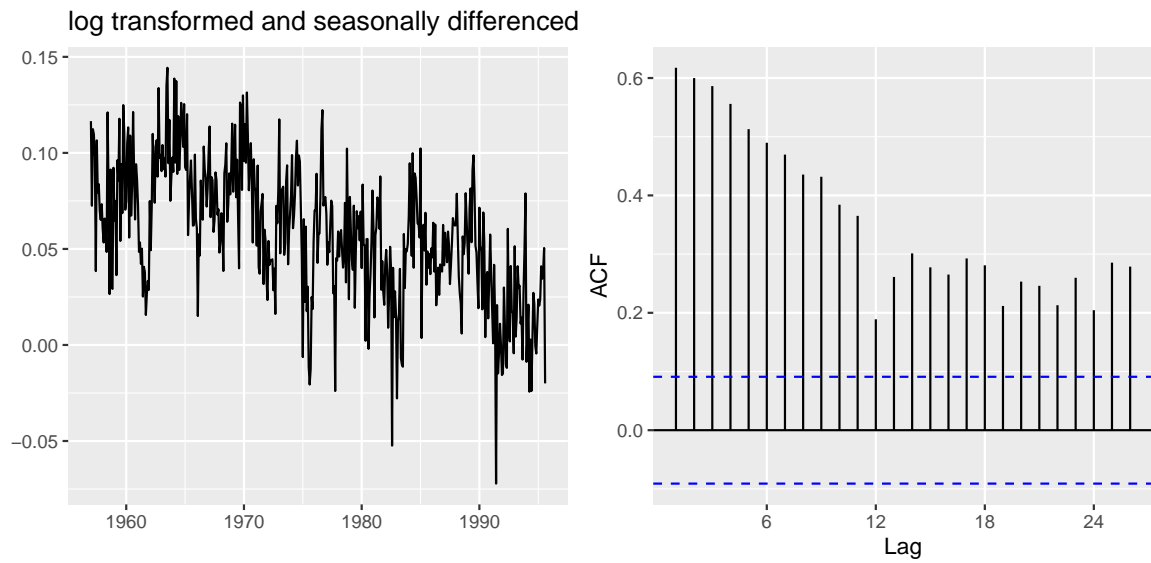


Figure 7: `elec` ACF

Figure 7 . 1 . Figure 8 ,

```
ln_elec_m_1 <- log(elec) %>%
  diff(lag = 12) %>%
  diff()
p5 <- autoplot(ln_elec_m_1) +
  labs(x = NULL, y = NULL, title = "log transformed and doubly differenced data")
p6 <- ggAcf(ln_elec_m_1) + ggtitle("")
p5 + p6
```

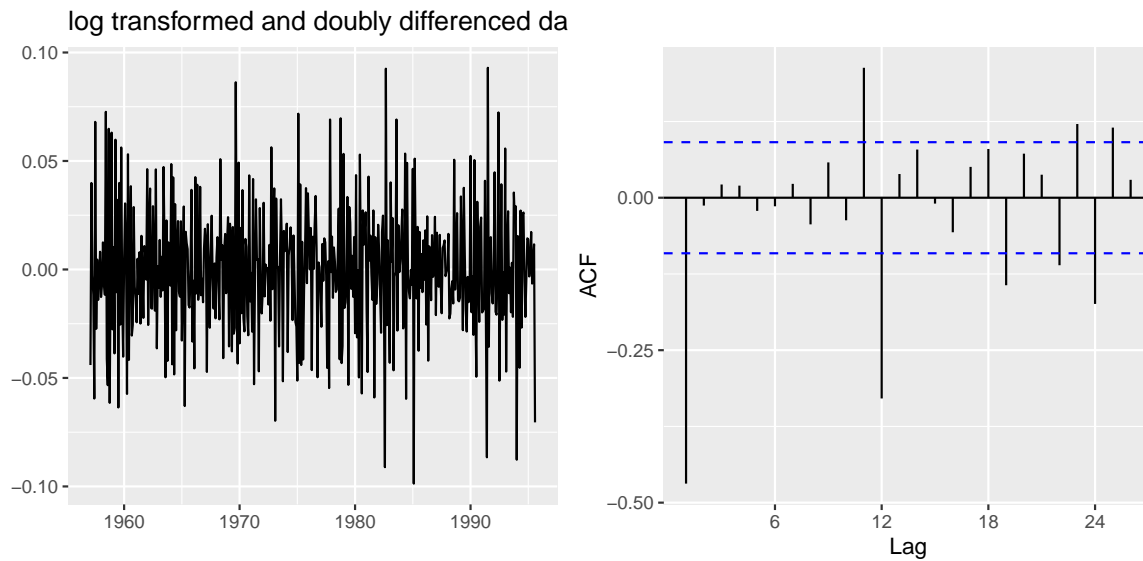



Figure 8: elec 1 ACF

ARIMA

- 1: gas

gas.csv 9 (rate) (co2) . .

```
gas <- read_csv("https://raw.githubusercontent.com/yjyjpark/TS-with-R/main/Data/gas.csv")
gas %>%
  print(n = 5)
## # A tibble: 296 x 2
##   rate co2
##   <dbl> <dbl>
## 1 -0.109 53.8
## 2 0      53.6
## 3 0.178 53.5
## 4 0.339 53.5
## 5 0.373 53.4
## # ... with 291 more rows
```

gas rate co2 . rate ts , $t = 1, 2, 3, \dots$
 1 . as.ts() .

Figure 9 .

```
rate.ts <- as.ts(gas$rate)
autoplot(rate.ts) + labs(y = NULL)
```

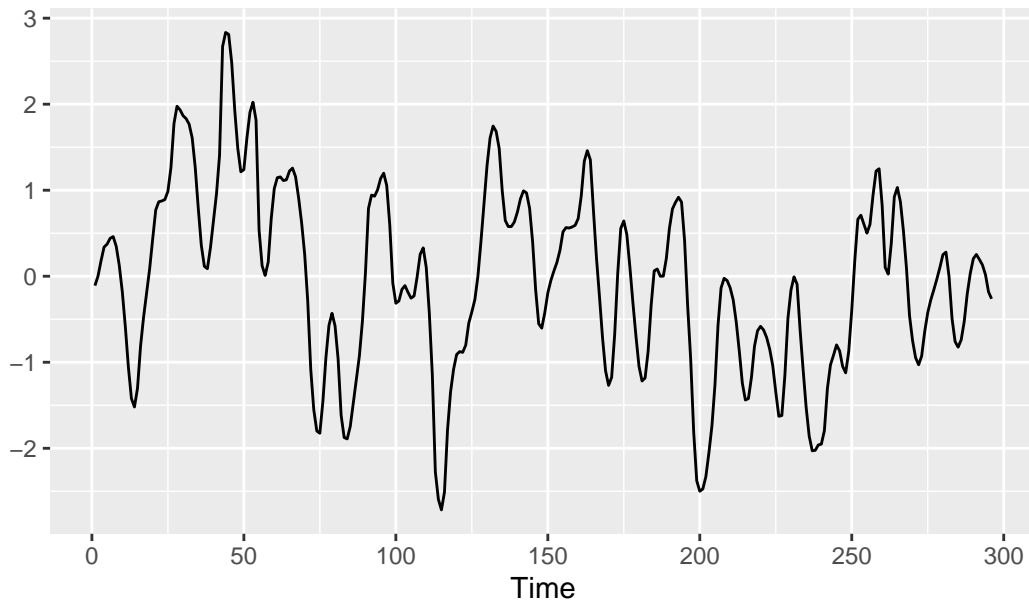


Figure 9: gas

```
rate.ts  ARIMA      .      training data test data      . Test data      10      .
```

```
train_r <- window(rate.ts, end = length(rate.ts) - 10)
test_r  <- window(rate.ts, start = length(rate.ts) - 9)
```

```
Training data      .      ACF      .      Figure 10      .
```

```
ggtsdisplay(train_r)
```

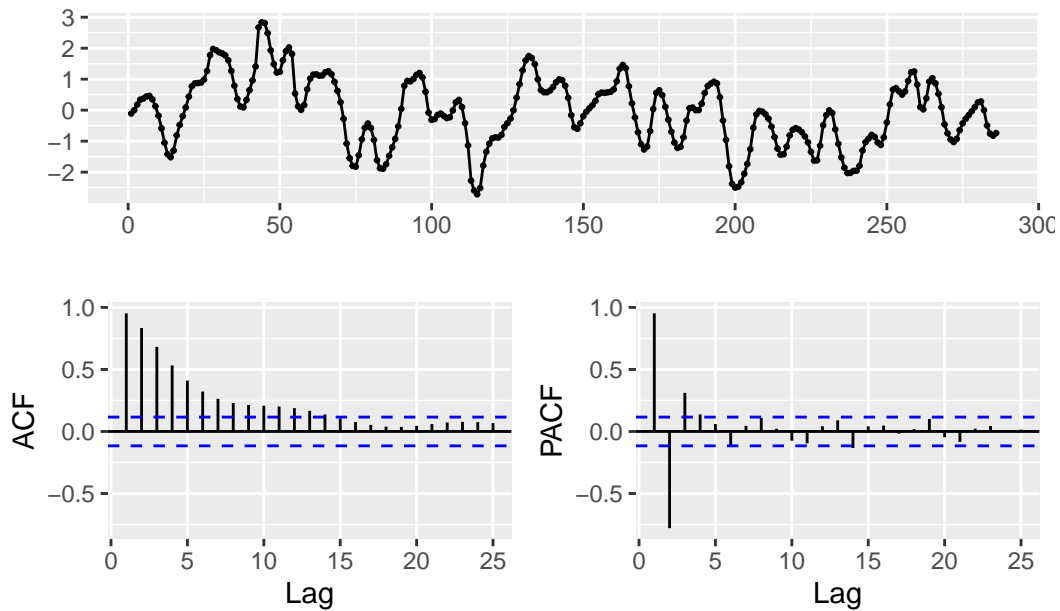


Figure 10: train_r

Figure 10

, ACF

.

.

```
ndiffs(train_r)
## [1] 1
```

, ACF

,

.

```
FALSE . trace = TRUE d = 0 , stepwise, approximation, seasonal
AICc .
```

```
fit1 <- auto.arima(train_r, d = 0, stepwise = FALSE,
                    approximation = FALSE, seasonal = FALSE,
                    trace = TRUE)
```

```
##
## ARIMA(0,0,0) with zero mean : 862.9984
## ARIMA(0,0,0) with non-zero mean : 864.2264
## ARIMA(0,0,1) with zero mean : 502.5603
## ARIMA(0,0,1) with non-zero mean : 503.849
## ARIMA(0,0,2) with zero mean : 245.7837
## ARIMA(0,0,2) with non-zero mean : 247.1783
```

```

## ARIMA(0,0,3) with zero mean      : 81.487
## ARIMA(0,0,3) with non-zero mean  : 83.02667
## ARIMA(0,0,4) with zero mean      : -20.65077
## ARIMA(0,0,4) with non-zero mean  : -19.01766
## ARIMA(0,0,5) with zero mean      : -84.62715
## ARIMA(0,0,5) with non-zero mean  : -82.85418
## ARIMA(1,0,0) with zero mean      : 184.3482
## ARIMA(1,0,0) with non-zero mean  : 186.3166
## ARIMA(1,0,1) with zero mean      : -16.72114
## ARIMA(1,0,1) with non-zero mean  : -14.73886
## ARIMA(1,0,2) with zero mean      : -74.34891
## ARIMA(1,0,2) with non-zero mean  : -72.35703
## ARIMA(1,0,3) with zero mean      : -115.7122
## ARIMA(1,0,3) with non-zero mean  : -113.7137
## ARIMA(1,0,4) with zero mean      : -133.8983
## ARIMA(1,0,4) with non-zero mean  : -131.9025
## ARIMA(2,0,0) with zero mean      : -89.86221
## ARIMA(2,0,0) with non-zero mean  : -88.00051
## ARIMA(2,0,1) with zero mean      : -113.8044
## ARIMA(2,0,1) with non-zero mean  : -111.8785
## ARIMA(2,0,2) with zero mean      : -116.6196
## ARIMA(2,0,2) with non-zero mean  : -114.6669
## ARIMA(2,0,3) with zero mean      : -130.7106
## ARIMA(2,0,3) with non-zero mean  : -128.7274
## ARIMA(3,0,0) with zero mean      : -123.114
## ARIMA(3,0,0) with non-zero mean  : -121.1507
## ARIMA(3,0,1) with zero mean      : -125.3355
## ARIMA(3,0,1) with non-zero mean  : -123.3294
## ARIMA(3,0,2) with zero mean      : -123.8663
## ARIMA(3,0,2) with non-zero mean  : -121.8527
## ARIMA(4,0,0) with zero mean      : -125.2705
## ARIMA(4,0,0) with non-zero mean  : -123.2711
## ARIMA(4,0,1) with zero mean      : -123.4833
## ARIMA(4,0,1) with non-zero mean  : -121.4641
## ARIMA(5,0,0) with zero mean      : -124.0066
## ARIMA(5,0,0) with non-zero mean  : -121.9828
##
##
## Best model: ARIMA(1,0,4) with zero mean

```

, ARMA(1,4) .

```

fit1
## Series: train_r
## ARIMA(1,0,4) with zero mean
##
## Coefficients:
##          ar1          ma1          ma2          ma3          ma4
##          0.7769  1.1456  1.0384  0.7892  0.3022
## s.e.    0.0450  0.0657  0.0922  0.0880  0.0627
##
## sigma^2 = 0.03511:  log likelihood = 73.1
## AIC=-134.2  AICc=-133.9  BIC=-112.26

, ARIMA(3,1,1)

fit2 <- auto.arima(train_r, stepwise = FALSE,
                    approximation = FALSE, seasonal = FALSE)

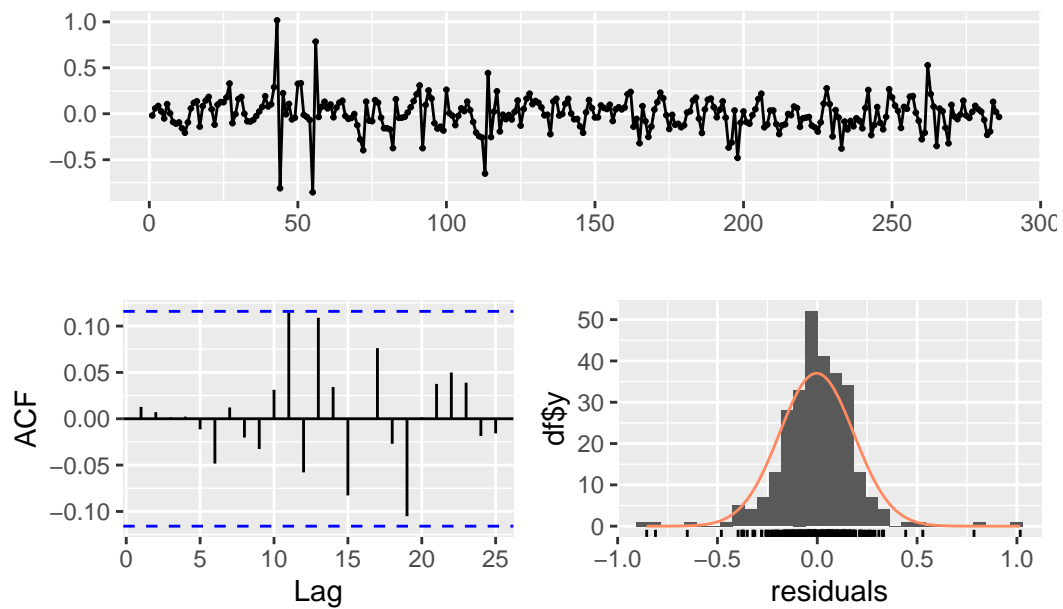
fit2
## Series: train_r
## ARIMA(3,1,1)
##
## Coefficients:
##          ar1          ar2          ar3          ma1
##          1.9589  -1.3503  0.3304  -0.9855
## s.e.    0.0580  0.1032  0.0576  0.0148
##
## sigma^2 = 0.03717:  log likelihood = 65.4
## AIC=-120.81  AICc=-120.59  BIC=-102.55

fit1

checkresiduals(fit1)

```

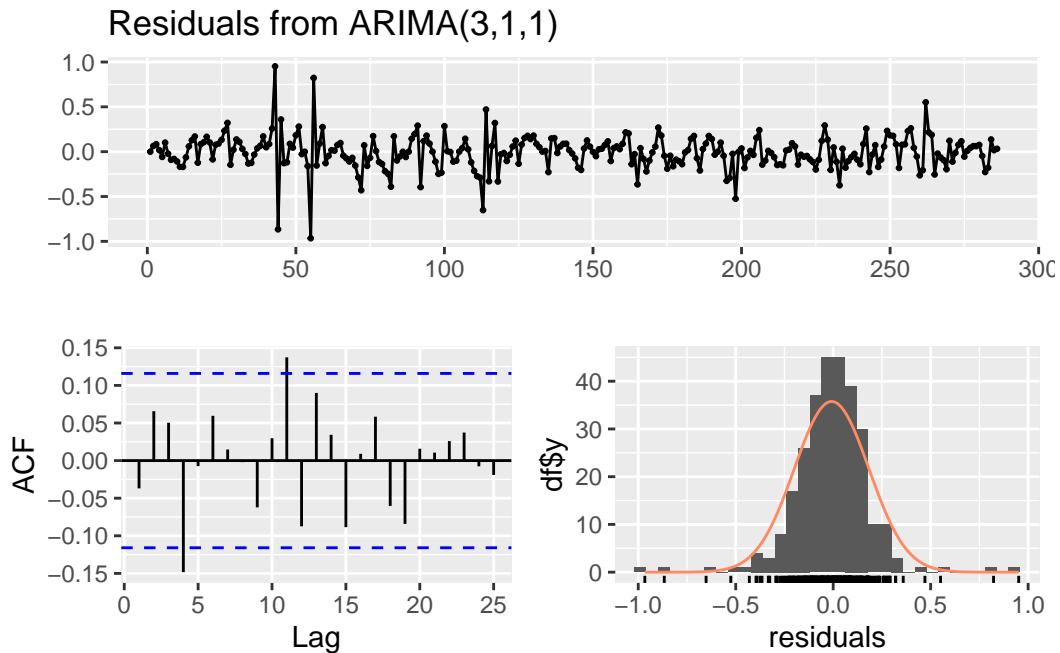
Residuals from ARIMA(1,0,4) with zero mean



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,4) with zero mean
## Q* = 1.5628, df = 5, p-value = 0.9057
##
## Model df: 5.   Total lags used: 10
```

```
fit2      .      .
```

```
checkresiduals(fit2)
```



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(3,1,1)
## Q* = 11.352, df = 6, p-value = 0.07809
##
## Model df: 4.   Total lags used: 10
```

```

,               , fit1               , fit2
,               , AICc               , test data
,               , test data          ,

```

```
fc1 <- forecast(fit1)
fc2 <- forecast(fit2)
```

```
accuracy(fc1, test_r)
```

```
##               ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.003485182 0.1857419 0.1308396      NaN      Inf 0.5071232
## Test set     0.197714969 0.2984918 0.2589217 261.7854 282.7786 1.0035587
##               ACF1 Theil's U
## Training set 0.01278907      NA
## Test set     0.63693511 1.231509
```

```
accuracy(fc2, test_r)
##               ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.008064075 0.1911149 0.1333927      NaN      Inf 0.5170188
## Test set      0.325580419 0.3713446 0.3255804 390.3076 437.7347 1.2619224
##               ACF1 Theil's U
## Training set -0.03694615      NA
## Test set      0.57275035 1.400976
```

```
accuracy()      , ARMA(1,4)  fit1      .      .      .
```

$$(1 - 0.7769B) y_t = (1 + 1.145B + 1.038B^2 + 0.789B^3 + 0.302B^4) \varepsilon_t$$

. Test data , Figure 11 .

```
autoplot(fc1, include = 20) +
  autolayer(test_r, color = "red", size = .8) +
  labs(y = "rate")
```

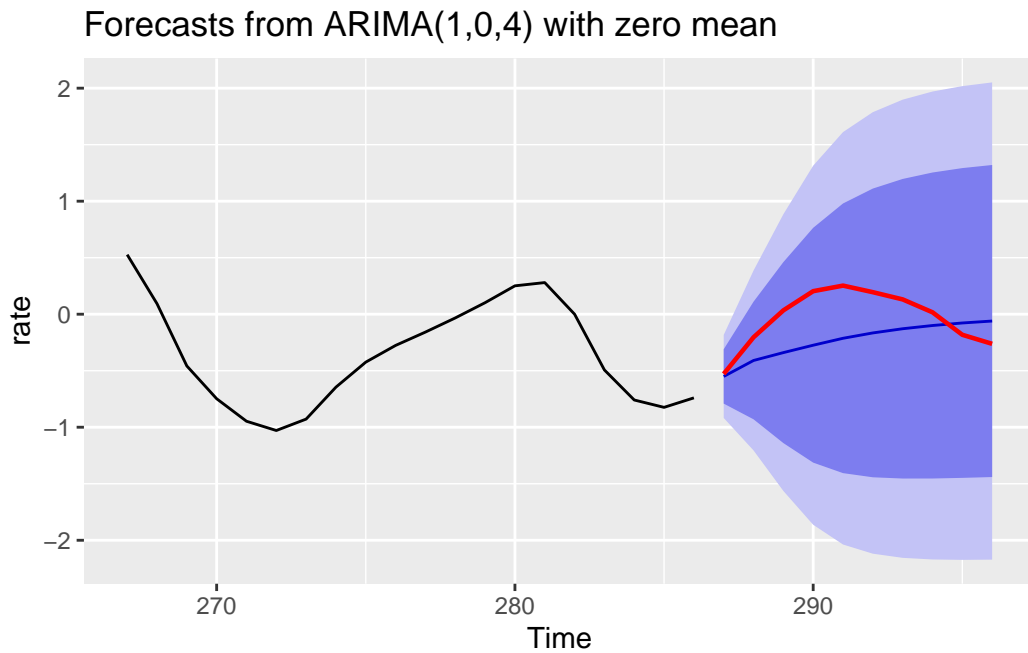


Figure 11: rate

- 2 : 1996 1 2012 3 Euro (fpp2::elecequip)


```

elecequip ~ ARIMA ~ stl() ,
forecast::seasadj()

```

```

elecequip_desea <- stl(elecequip, s.window="periodic") %>%
  seasadj()

```

Figure 12

```

autoplot(elecequip, series = "Monthly data") +
  autolayer(elecequip_desea,
    series = "Seasonally adjusted", size = .8) +
  scale_color_manual(values = c("Monthly data" = "blue",
    "Seasonally adjusted" = "red")) +
  theme(legend.position = "top") +
  labs(y = NULL, color = NULL)

```

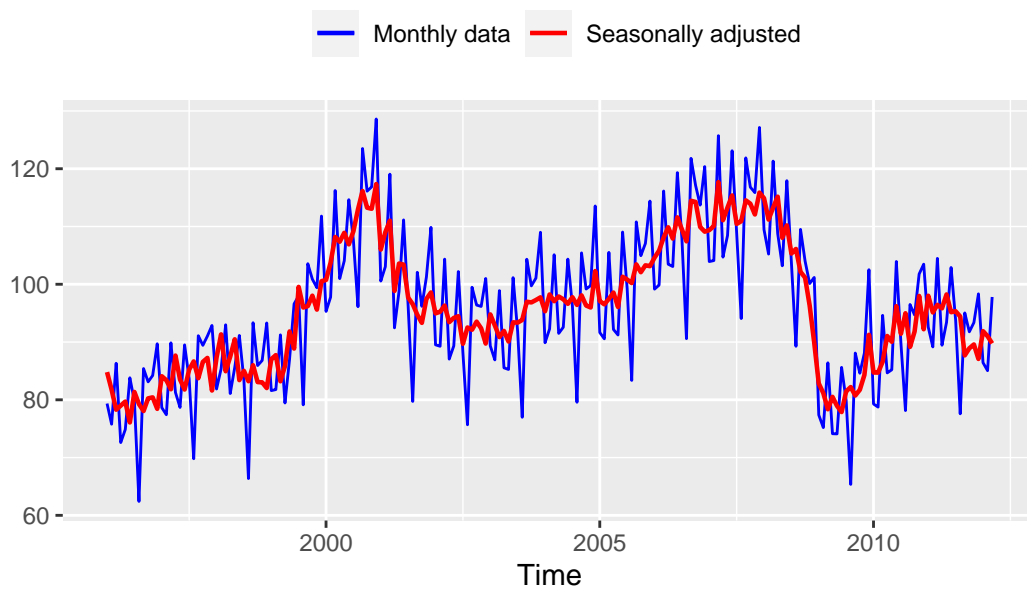


Figure 12: elecequip

. Test data 2 .

```

train_eq <- window(elecequip_desea, end = c(2010,3))
test_eq <- window(elecequip_desea, start = c(2010,4))

```

Figure 13 .

```
ggtsdisplay(train_eq)
```

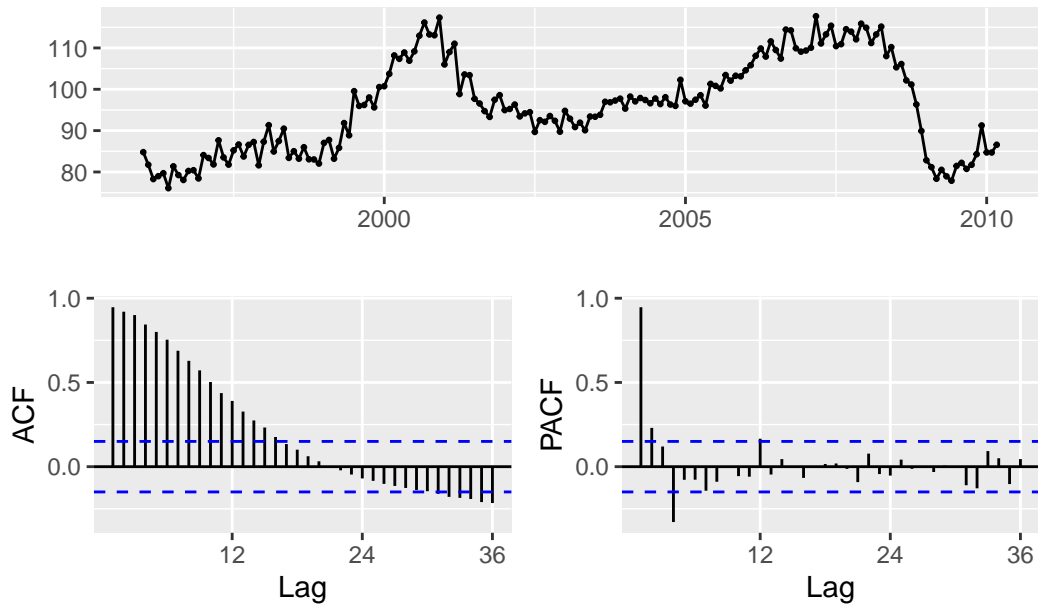


Figure 13: train_eq

level , ACF .

```
ndiffs(train_eq)
## [1] 1
```

ACF Figure 14 .

```
train_eq %>%
  diff() %>%
  ggtsdisplay()
```

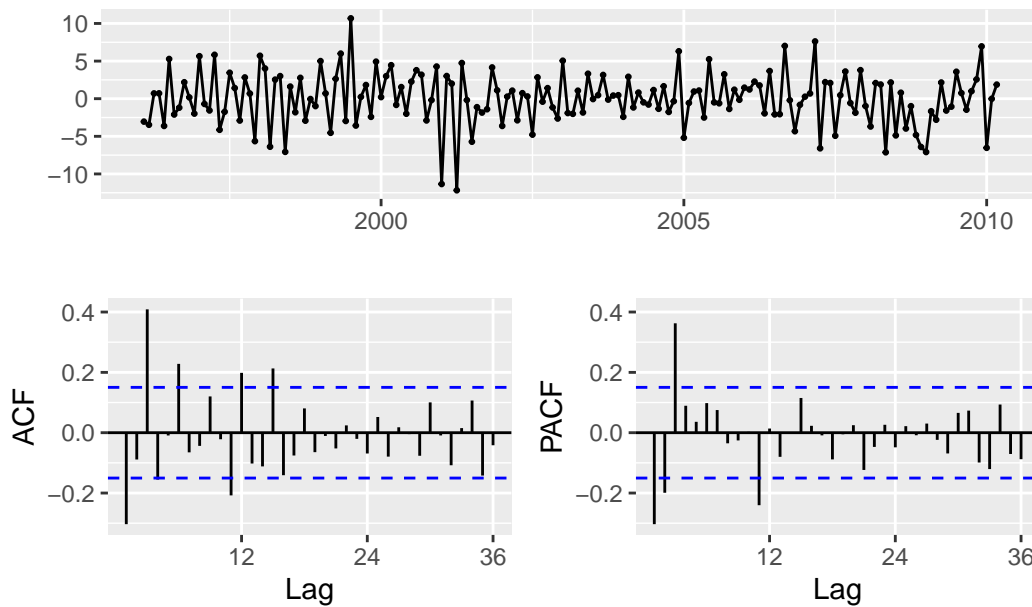


Figure 14: train_eq

. ACF , PACF 3 AR(3) , ARIMA(3,1,0)

auto.arima()

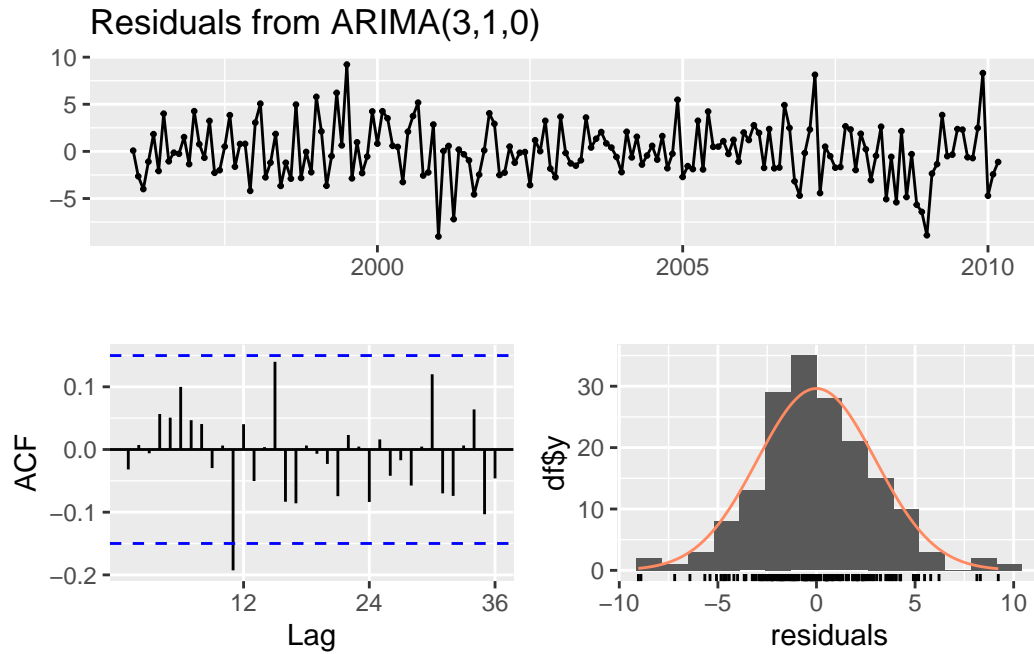
```
fit1 <- auto.arima(train_eq, stepwise = FALSE,
                  approximation = FALSE, seasonal = FALSE)

fit1
## Series: train_eq
## ARIMA(3,1,0)
##
## Coefficients:
##          ar1      ar2      ar3
##      -0.2922  -0.0635   0.3710
## s.e.   0.0713   0.0748   0.0718
##
## sigma^2 = 9.169: log likelihood = -428.36
## AIC=864.73  AICc=864.97  BIC=877.27
```

ACF PACF ARIMA(3,1,0) . .

$$(1 + 0.292B + 0.064B^2 - 0.371B^3)(1 - B) y_t = \varepsilon_t$$

```
checkresiduals(fit1)
```



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(3,1,0)
## Q* = 20.702, df = 21, p-value = 0.4772
##
## Model df: 3.   Total lags used: 24
```

```
fc1 <- forecast(fit1)
```

```
accuracy(fc1, test_eq)
```

```
##           ME           RMSE          MAE          MPE          MAPE          MASE
```

```
## Training set -0.002219982 2.992424 2.301026 -0.05081691 2.411491 0.2786977
## Test set      8.727507127 9.330976 8.727507 9.28015517 9.280155 1.0570657
##
##              ACF1 Theil's U
## Training set -0.03178277      NA
## Test set      0.38874430 2.481532
```

Figure 15 . test data .

```
autoplot(fc1, include = 20) +
  autolayer(test_eq, color = "red", size = .8) +
  ylab("Electrical equipment manufactured")
```

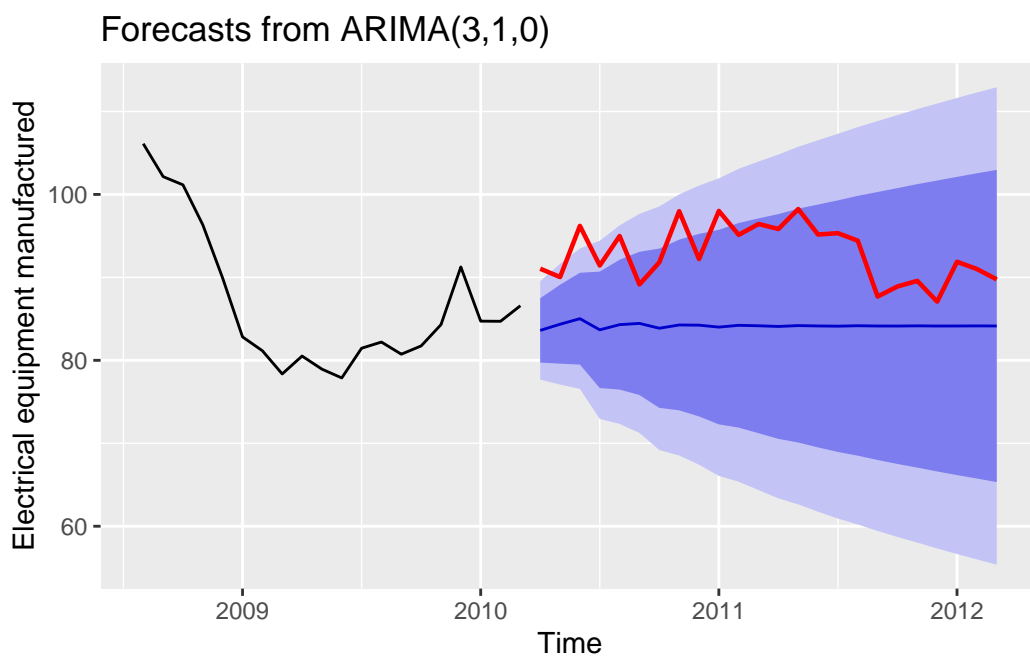


Figure 15: elecequip

ARIMA

- 1 : 1984 1 1988 12

```
1984 1 1988 12      ARIMA      .      training data test
data      .      ts      .
```

```
depart <- scan("https://raw.githubusercontent.com/yjyjpark/TS-with-R/main/Data/depart.txt")
depart.ts <- ts(depart, start = 1984, freq = 12)
```

depart.ts . Figure 16 .

```
autoplot(depart.ts) +
  ylab(NULL)
```

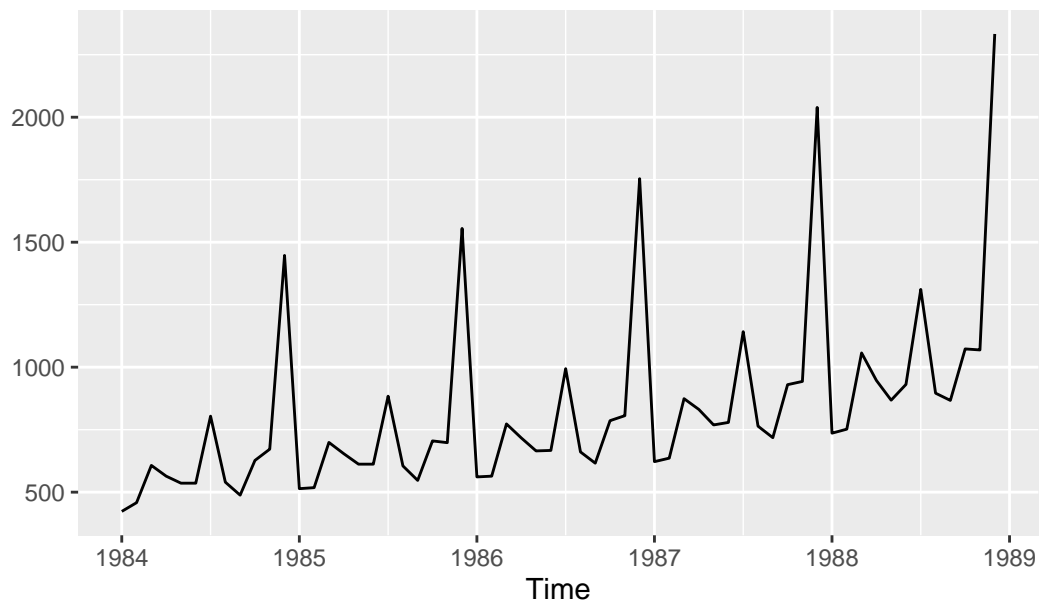


Figure 16:

Figure 17 .

```
lndepart <- log(depart.ts)
autoplot(lndepart) +
  labs(title = "log(depart.ts)", y = NULL)
```

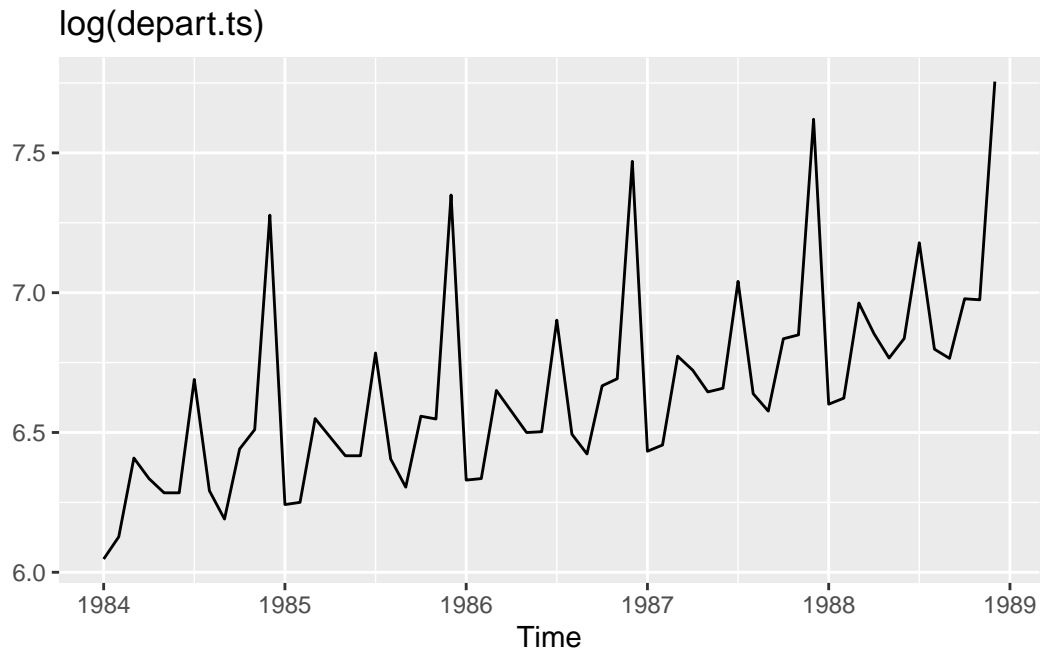


Figure 17:

ACF,

. 1 .

```
ndiffs(lndepart)
## [1] 1
nsdiffs(lndepart)
## [1] 1
```

ACF Figure 17 .

```
ggtsdisplay(lndepart, lag.max = 36,
            main = "lndepart: log transformed data")
```

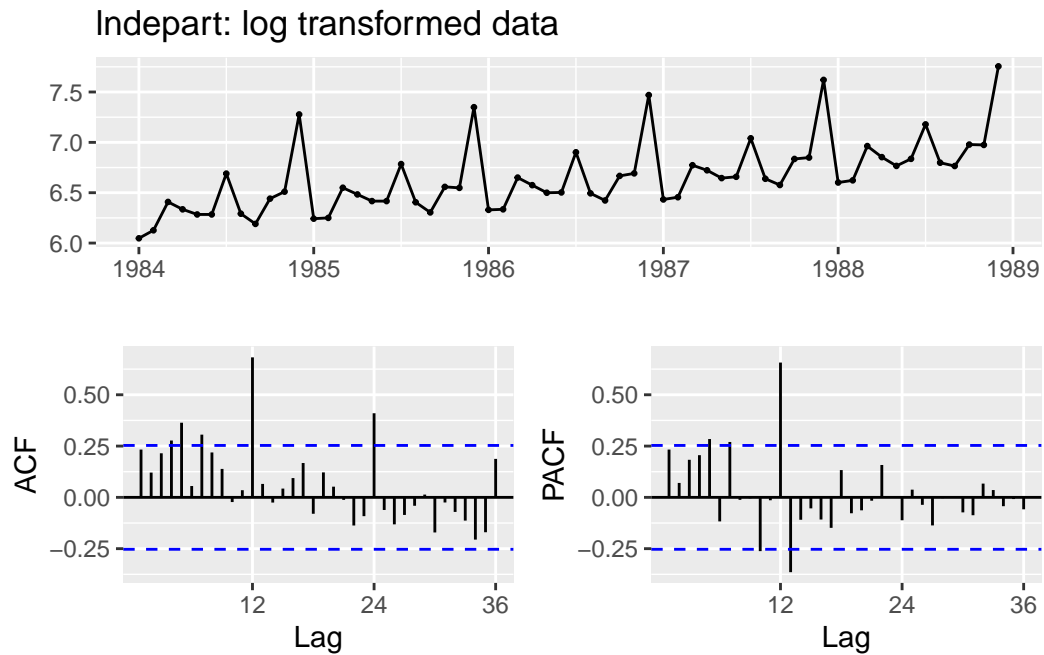


Figure 18: `Indepart` , ACF PACF

6

ACF . Figure 19 ACF 1

```
Indepart_12 <- diff(Indepart, lag = 12)
ggtsdisplay(Indepart_12, lag.max = 36,
  main = "Seasonally differenced Indepart")
```

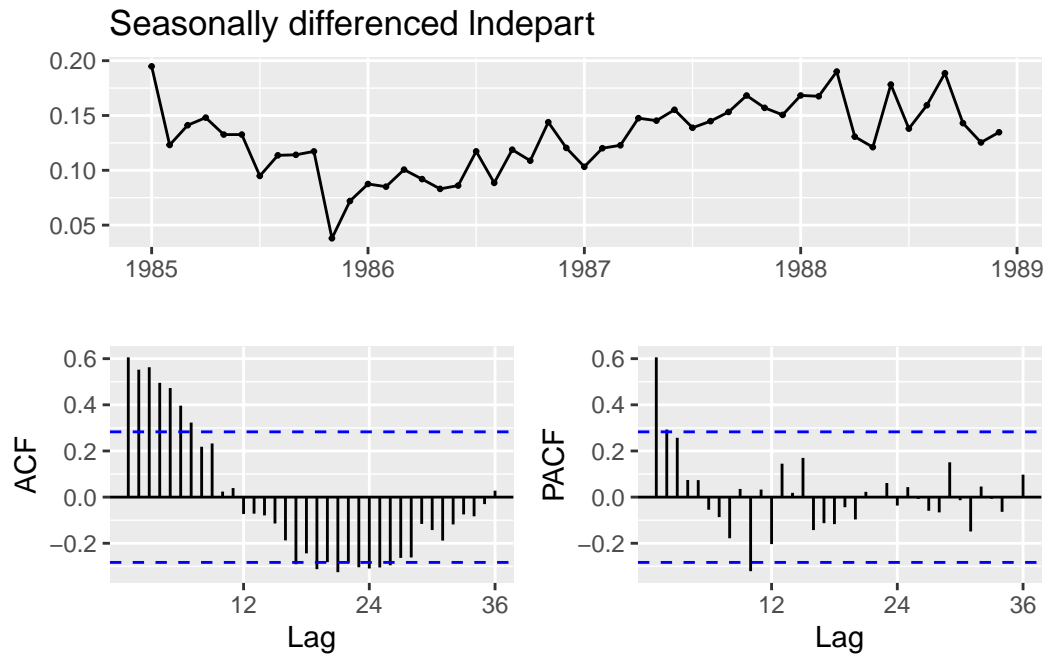



Figure 19: lndepart , ACF PACF

1 ACF 1 . Figure 20 . , ,

```
lndepart_12_1 <- diff(lndepart_12)
ggtsdisplay(lndepart_12_1, lag.max = 36,
            main = "Doubly differenced lndepart")
```

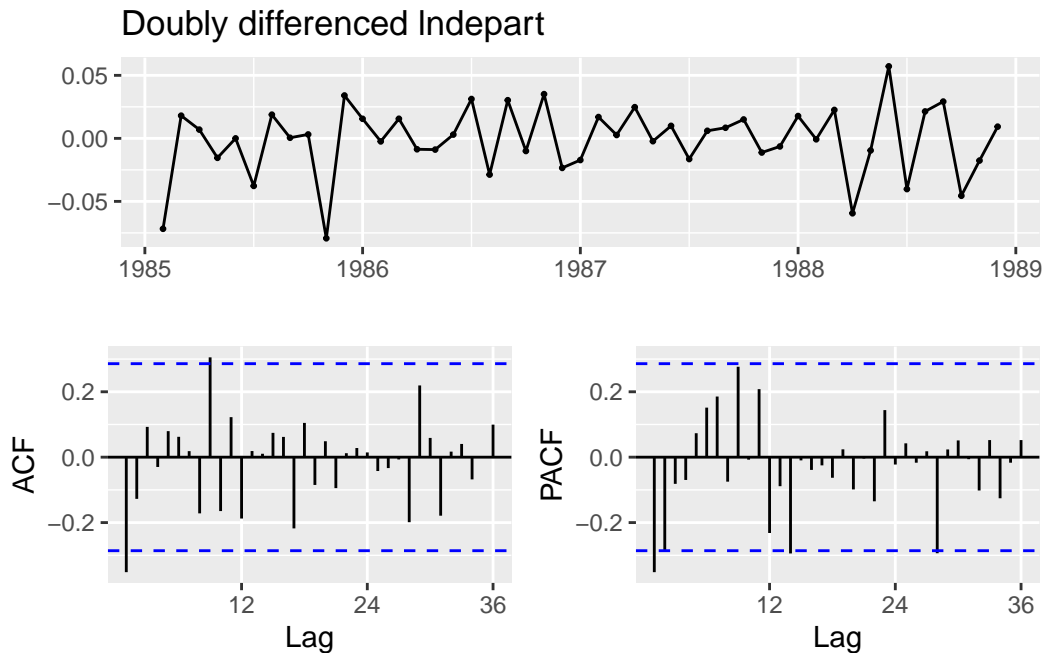


Figure 20: 1 Indepart , ACF PACF

AR 1 MA 1 6 , ACF 1 , PACF 1, 2
 , ACF 1 , PACF , p=0, q=1 MA(1)
 .
 12, 24, 36 , ACF PACF 12, 24, 36 . P=0, Q=0
 , P=1, Q=0 P=0, Q=1 .

ACF PACF , ARIMA(0,1,1)(0,1,0)₁₂ ARIMA(0,1,1)(1,1,0)₁₂ ,
 ARIMA(0,1,1)(0,1,1)₁₂ .
 auto.arima() . auto.arima()
 , d D . lambda 0 .

```
fit_d <- auto.arima(depart.ts, lambda = 0,
                    stepwise = FALSE, approximation = FALSE)
```

```
summary(fit_d)
## Series: depart.ts
## ARIMA(0,1,1)(0,1,1)[12]
## Box Cox transformation: lambda= 0
```

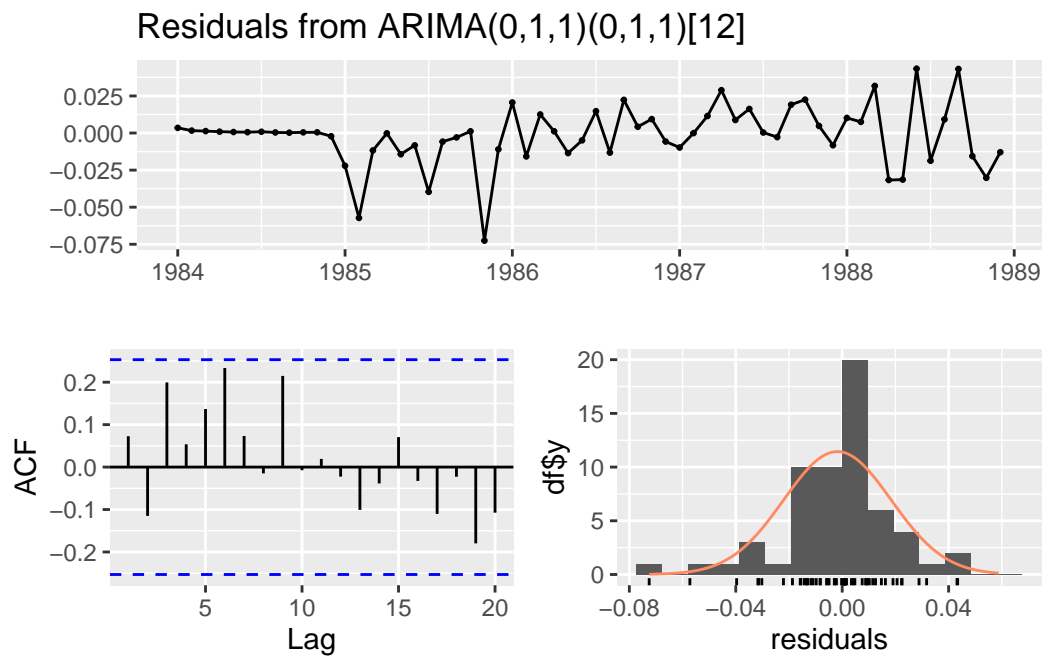
```
##
## Coefficients:
##          ma1      sma1
##      -0.5840  -0.4159
## s.e.   0.1093   0.1946
##
## sigma^2 = 0.0005401:  log likelihood = 110.29
## AIC=-214.59  AICc=-214.03  BIC=-209.04
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
## Training set -1.937472 16.9307 11.60509 -0.200563 1.36766 0.1084166 0.04358066
```

ACF PACF ARIMA(0,1,1)(0,1,1)₁₂ .

$$(1 - B^{12})(1 - B) \log y_t = (1 - 0.584B)(1 - 0.4159B^{12}) \varepsilon_t$$

fit_d . , .

`checkresiduals(fit_d)`



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,1)(0,1,1)[12]
## Q* = 12.817, df = 10, p-value = 0.2341
##
## Model df: 2.   Total lags used: 12
```

Figure 21

```
forecast(fit_d) %>%
  autoplot() + ylab(NULL)
```

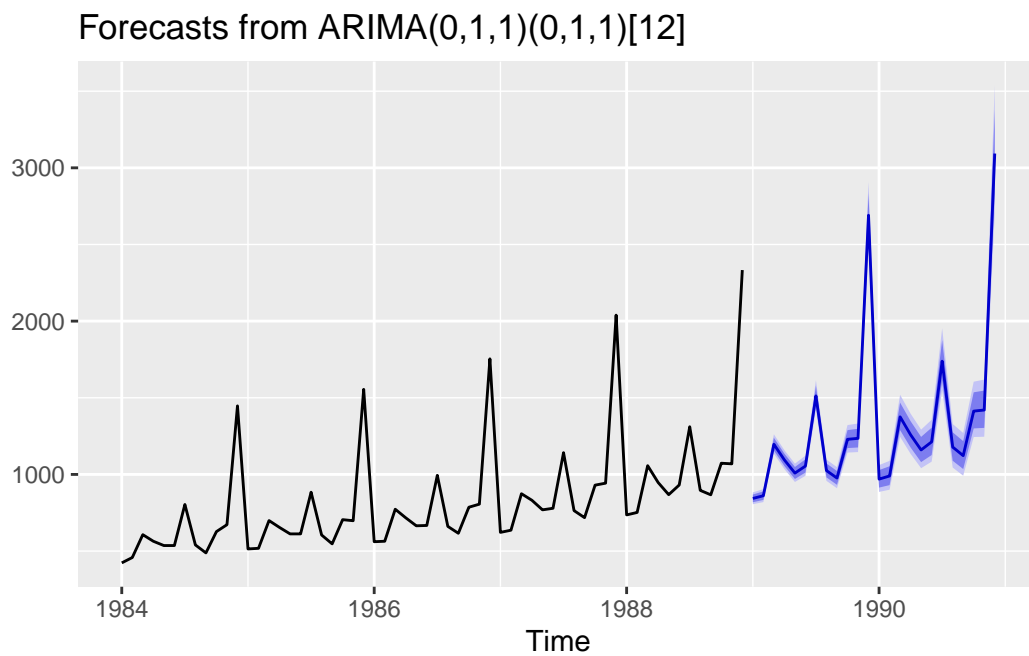


Figure 21:

- 2 : 1981 1 1992 12

```
1981 1 1992 12 12          ARIMA  ETS          ,          .
2    test data    , 10    .
```

```
tour <- scan("https://raw.githubusercontent.com/yjyjpark/TS-with-R/main/Data/Ktour.txt")
tour.ts <- ts(tour, start = 1981, freq = 12)
```

```
train_K <- window(tour.ts, end = c(1990,12))
test_K <- window(tour.ts, start = c(1991,1))
```

Training data

Figure 22

```
autoplot(train_K) +
  ylab(NULL)
```

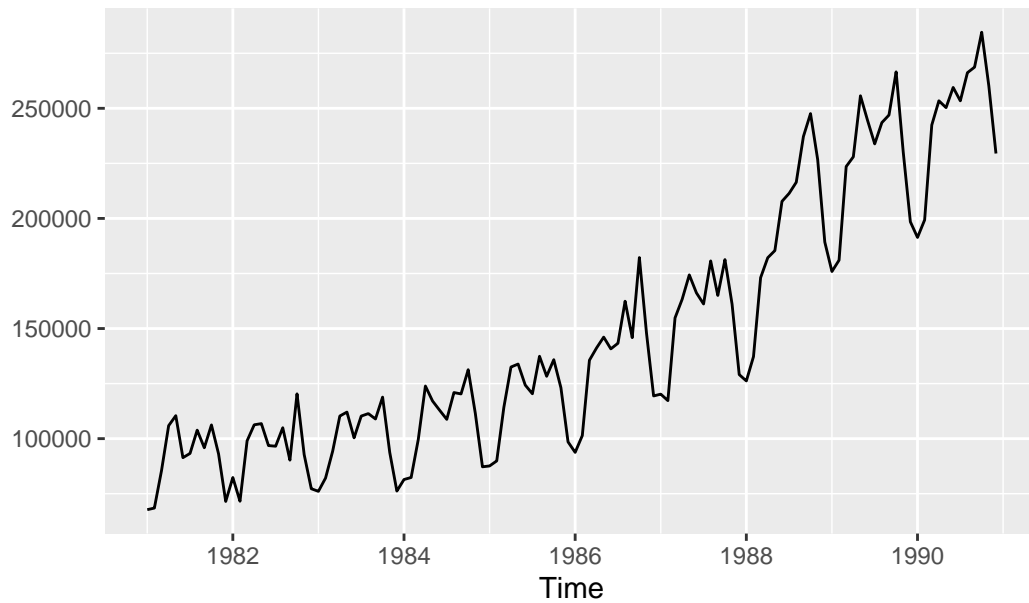


Figure 22:

ARIMA , , ,
Box-Cox λ .

```
BoxCox.lambda(train_K)
## [1] 0.09573094
```

$\hat{\lambda} = 0.096$, $y_t^{0.09}$ λ $\hat{\lambda} = 0$.

ACF Figure 23

```
lntrain_K <- log(train_K)
ggtsdisplay(lntrain_K,
            main = "log transformed:lntrain_K")
```

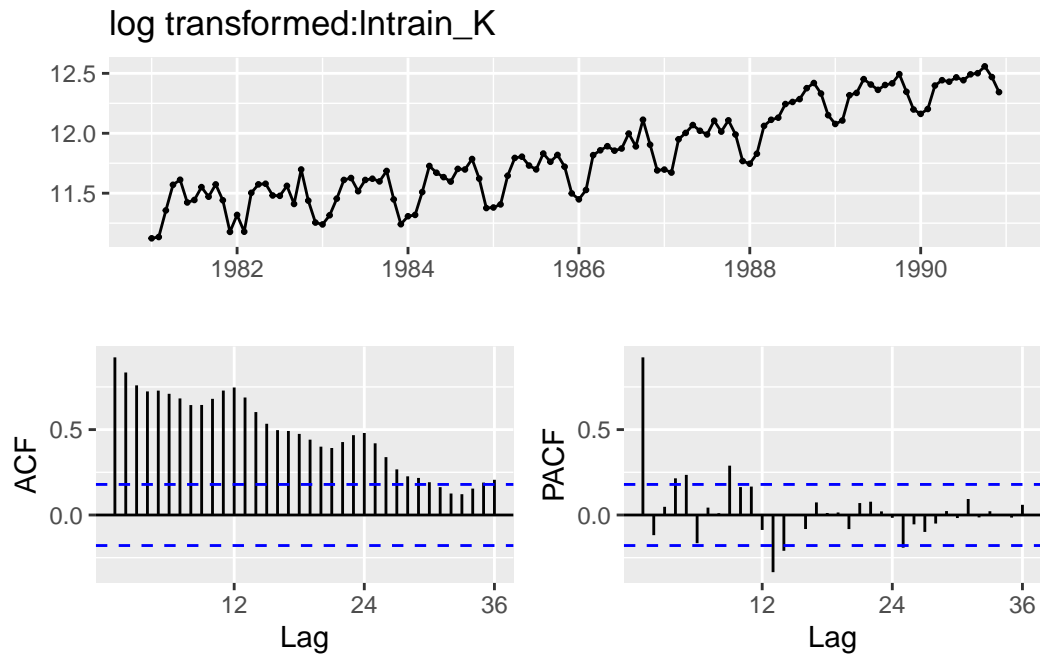


Figure 23: lntrain_K , ACF PACF

, . Figure 24 , ACF 1~6 . 1 .

```
lntrain_K_12 <- diff(lntrain_K, lag = 12)
ggtsdisplay(lntrain_K_12,
            main = "Seasonally differenced")
```

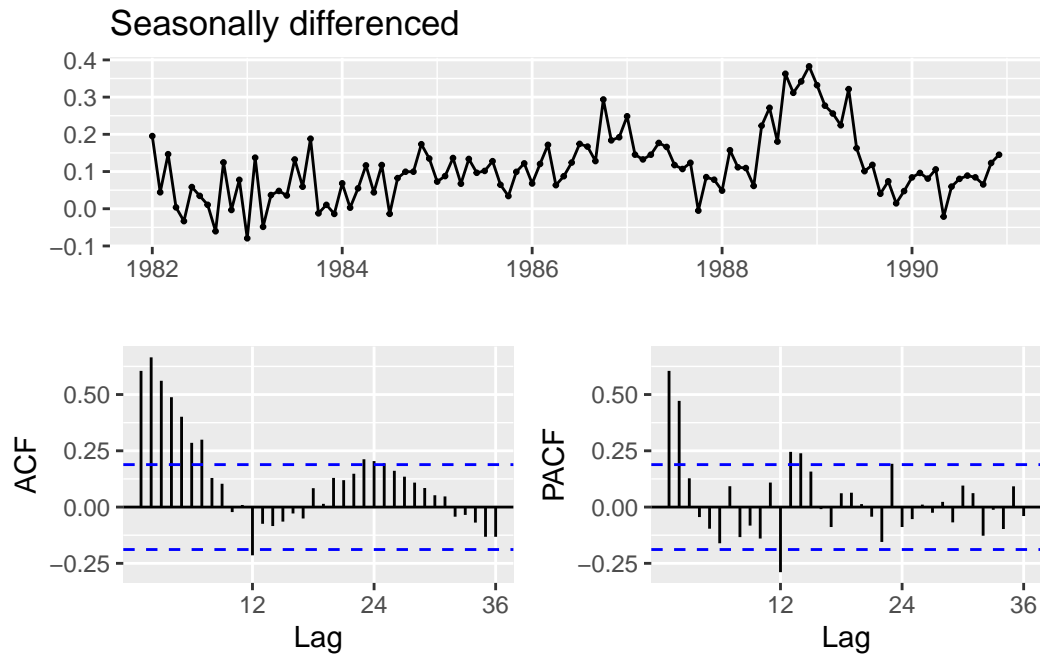


Figure 24: `lntrain_K`, ACF PACF

1, . Figure 25.

```
lntrain_K_12_1 <- diff(lntrain_K_12)
ggtsdisplay(lntrain_K_12_1,
            main = "Doubly differenced")
```

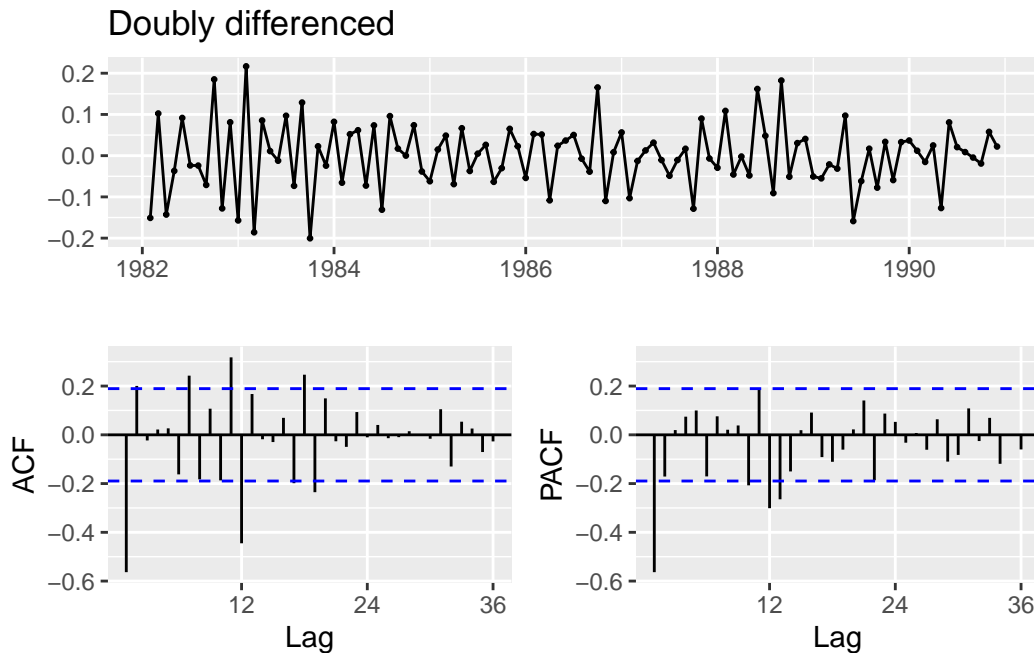


Figure 25: 1 lntrain_K , ACF PACF

```
ndiffs(lntrain_K)
## [1] 1
nsdiffs(lntrain_K)
## [1] 1
```

ACF PACF Figure 25 . 1 6 ARIMA . ACF
 2 , PACF 1 , 2
 AR(1), AR(2), MA(2), ARMA(1,1)
 ARIMA ACF PACF 12 , 24 36 ACF PACF ,
 , AR(1)₁₂, MA(1)₁₂, ARMA(1,1)₁₂
 , ARIMA(1,1,0)(1,1,0)₁₂ , ARIMA(1,1,0)(0,1,1)₁₂ ,
 ARIMA(1,1,0)(1,1,1)₁₂ ARIMA(2,1,0)(1,1,0)₁₂ , ARIMA(2,1,0)(0,1,1)₁₂ , ARIMA(2,1,0)(1,1,1)₁₂ ,
 ARIMA(1,1,1)(1,1,0)₁₂ , ARIMA(1,1,1)(0,1,1)₁₂ , ARIMA(1,1,1)(1,1,1)₁₂
 ACF PACF ,
 . , auto.arima() ACF PACF
 .
 auto.arima() .


```
fit_K <- auto.arima(train_K, lambda = 0,
                    stepwise = FALSE, approximation = FALSE)
```

```
summary(fit_K)
## Series: train_K
## ARIMA(2,1,0)(1,1,1)[12]
## Box Cox transformation: lambda= 0
##
## Coefficients:
##          ar1          ar2          sar1          sma1
##       -0.6995   -0.2496   -0.2892   -0.3817
## s.e.    0.0956    0.0947    0.1695    0.1736
##
## sigma^2 = 0.002917:  log likelihood = 159.82
## AIC=-309.63   AICc=-309.04   BIC=-296.27
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -117.8446 8079.833 5752.686 -0.1325567 3.815935 0.3223641
##              ACF1
## Training set 0.1387895
```

ARIMA(2,1,0)(1,1,1)₁₂ , ACF PACF . .

$$(1 + 0.69B + 0.25B^2)(1 + 0.29B^{12})(1 - B)(1 - B^{12}) \log y_t = (1 - 0.382^{12}) \varepsilon_t$$

ETS . ETS . ETS ETS

```
fit_K_ets1 <- ets(train_K, lambda = 0)
```

```
summary(fit_K_ets1)
## ETS(A,Ad,A)
##
## Call:
## ets(y = train_K, lambda = 0)
##
## Box-Cox transformation: lambda= 0
##
```

```

## Smoothing parameters:
##   alpha = 0.3998
##   beta  = 0.0242
##   gamma = 1e-04
##   phi   = 0.978
##
## Initial states:
##   l = 11.3617
##   b = 0.0098
##   s = -0.2089 -0.0012 0.1585 0.0577 0.1123 0.035
##       0.0516 0.1154 0.0989 0.0121 -0.2092 -0.2221
##
## sigma: 0.0548
##
##           AIC           AICc           BIC
## -104.72171  -97.94943  -54.54685
##
## Training set error measures:
##           ME           RMSE           MAE           MPE           MAPE           MASE           ACF1
## Training set 1116.089 8322.678 5764.589 0.4909287 3.788076 0.3230311 0.09314822

```

ETS(A,Ad,A)

```
fit_K_ets2 <- ets(train_K)
```

```

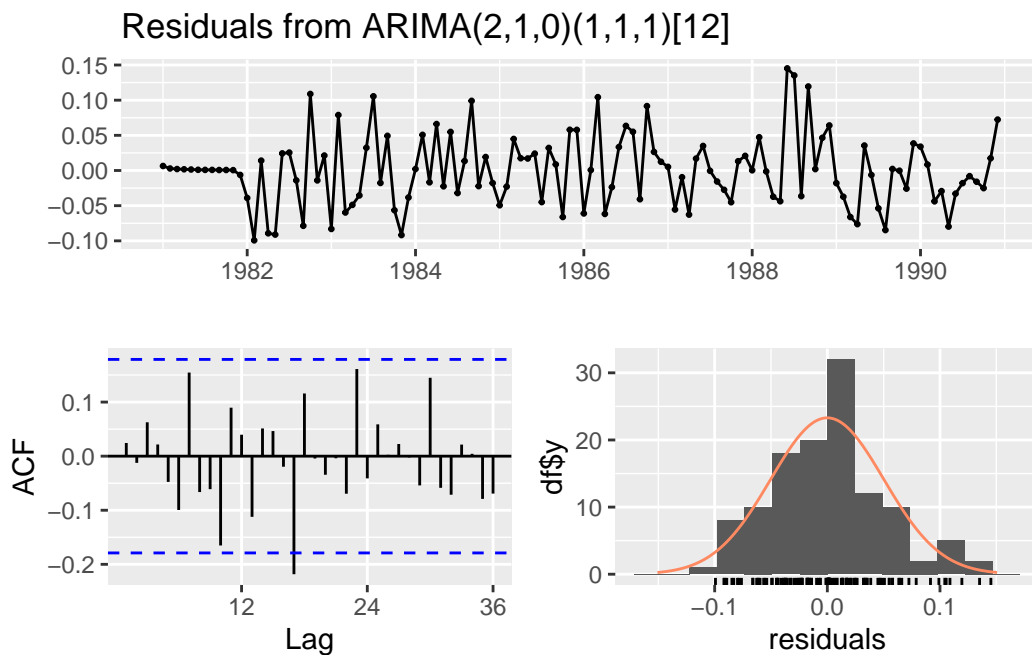
summary(fit_K_ets2)
## ETS(M,Ad,M)
##
## Call:
## ets(y = train_K)
##
## Smoothing parameters:
##   alpha = 0.4275
##   beta  = 0.0306
##   gamma = 1e-04
##   phi   = 0.9799
##
## Initial states:
##   l = 89459.3204

```

```
##      b = 291.8495
##      s = 0.808 0.9953 1.172 1.0557 1.1073 1.0353
##          1.0453 1.1046 1.0949 0.9939 0.7992 0.7886
##
##      sigma: 0.0562
##
##      AIC      AICc      BIC
## 2738.255 2745.028 2788.430
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
## Training set 1147.204 8155.819 5774.677 0.5763675 3.839131 0.3235964 0.02357097
```

```
ETS(M,Ad,M)      .      ETS      'damped additive'      ,      'additive'      ,
                  'multiplicative'      .
      ARIMA      ETS      .      ARIMA      .
```

```
checkresiduals(fit_K)
```

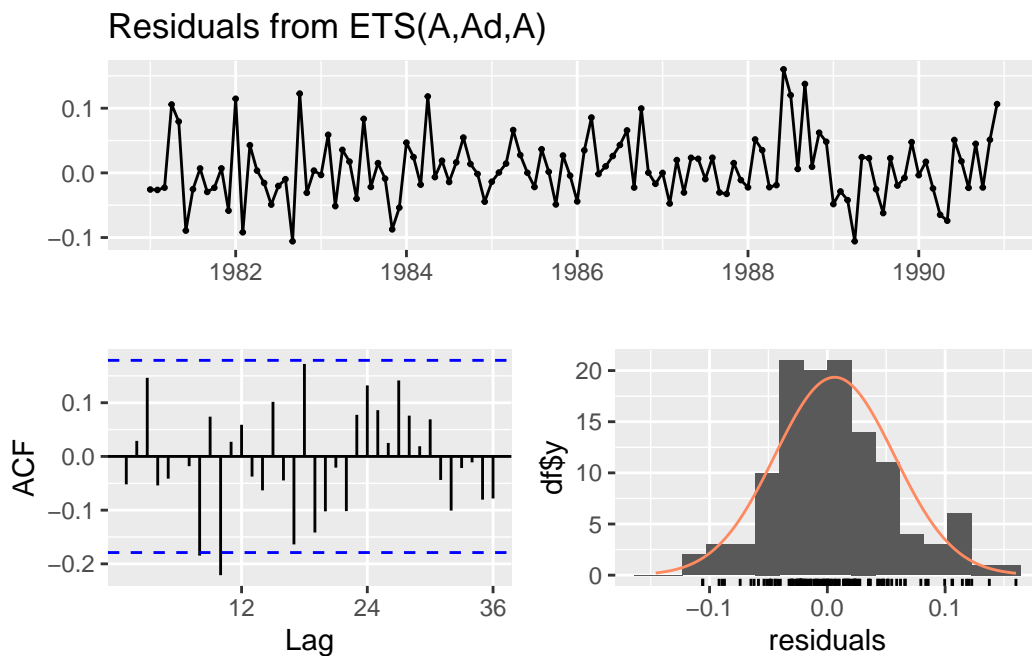


```
##
## Ljung-Box test
```

```
##
## data: Residuals from ARIMA(2,1,0)(1,1,1)[12]
## Q* = 27.495, df = 20, p-value = 0.1219
##
## Model df: 4. Total lags used: 24
```

```
ETS      Ljung-Box  p-value      ,      .      ETS      ,
.      ETS(A,Ad,A)  fit_K_ets1      .
```

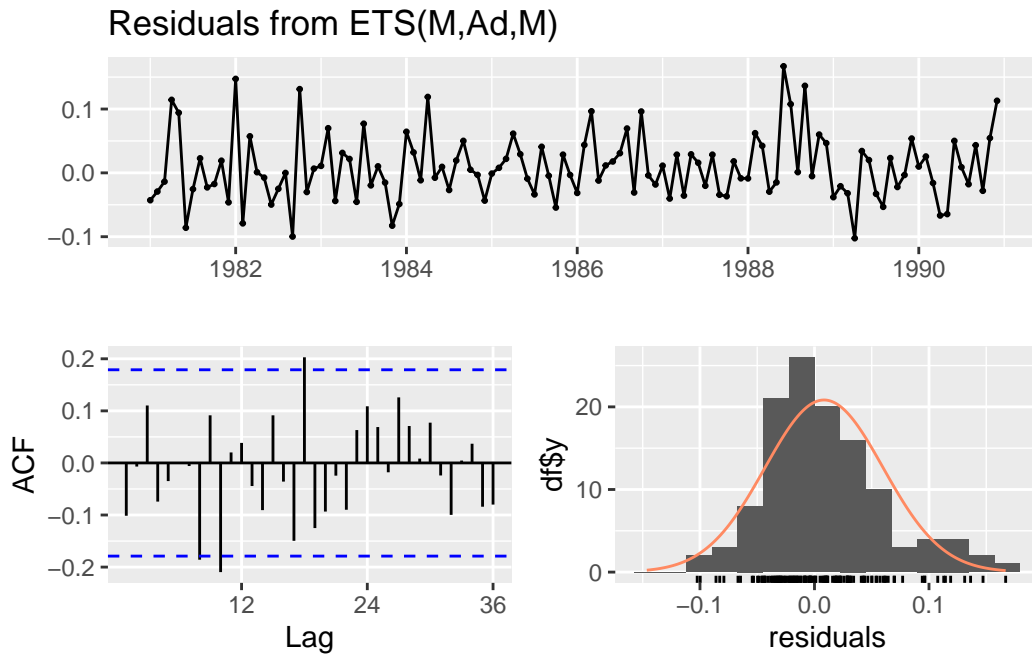
```
checkresiduals(fit_K_ets1)
```



```
##
## Ljung-Box test
##
## data: Residuals from ETS(A,Ad,A)
## Q* = 36.158, df = 7, p-value = 6.769e-06
##
## Model df: 17. Total lags used: 24
```

```
ETS(M,Ad,M)  fit_K_ets2      .
```

```
checkresiduals(fit_K_ets2)
```



```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,Ad,M)
## Q* = 34.451, df = 7, p-value = 1.418e-05
##
## Model df: 17.   Total lags used: 24
```

```
test data      .
```

```
fc_K <- forecast(fit_K)
accuracy(fc_K, test_K)
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -117.8446 8079.833 5752.686 -0.1325567 3.815935 0.3223641
## Test set    -33473.2740 45118.350 37348.980 -12.4581745 13.967241 2.0929303
##              ACF1 Theil's U
## Training set 0.1387895      NA
## Test set    0.6467465  1.67741
```

```

fc_K_ets1 <- forecast(fit_K_ets1)
accuracy(fc_K_ets1, test_K)
##               ME          RMSE          MAE          MPE          MAPE          MASE
## Training set  1116.089  8322.678  5764.589  0.4909287  3.788076  0.3230311
## Test set     -26763.496 38813.714 33571.599 -9.9007782 12.507782 1.8812566
##               ACF1 Theil's U
## Training set  0.09314822      NA
## Test set     0.55156580  1.469369

```

```

fc_K_ets2 <- forecast(fit_K_ets2)
accuracy(fc_K_ets2, test_K)
##               ME          RMSE          MAE          MPE          MAPE          MASE
## Training set  1147.204  8155.819  5774.677  0.5763675  3.839131  0.3235964
## Test set     -25539.311 37954.952 32640.675 -9.4299420 12.153867 1.8290903
##               ACF1 Theil's U
## Training set  0.02357097      NA
## Test set     0.54315176  1.439223

```

ETS(M,Ad,M) fit_K_ets2 . ARIMA ETS(M,Ad,M)

Figure 26 .

```

p1 <- autoplot(fc_K, include = 24) +
  autolayer(test_K, color = "red", size = .8) +
  ylab(NULL)

p2 <- autoplot(fc_K_ets2, include = 24) +
  autolayer(test_K, color = "red", size = .8) +
  ylab(NULL)
p1 / p2

```

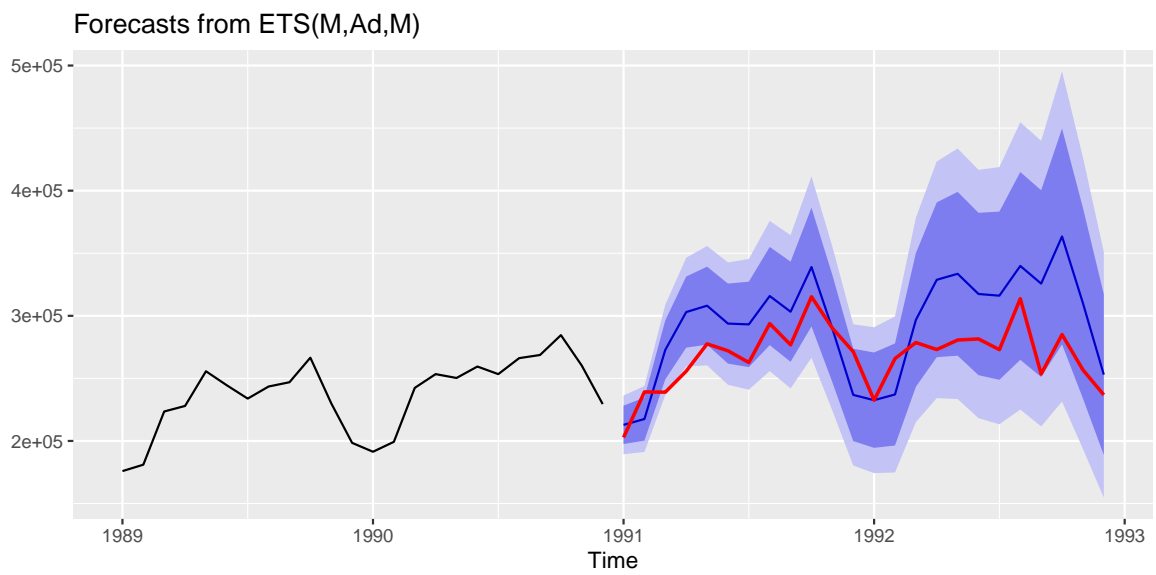
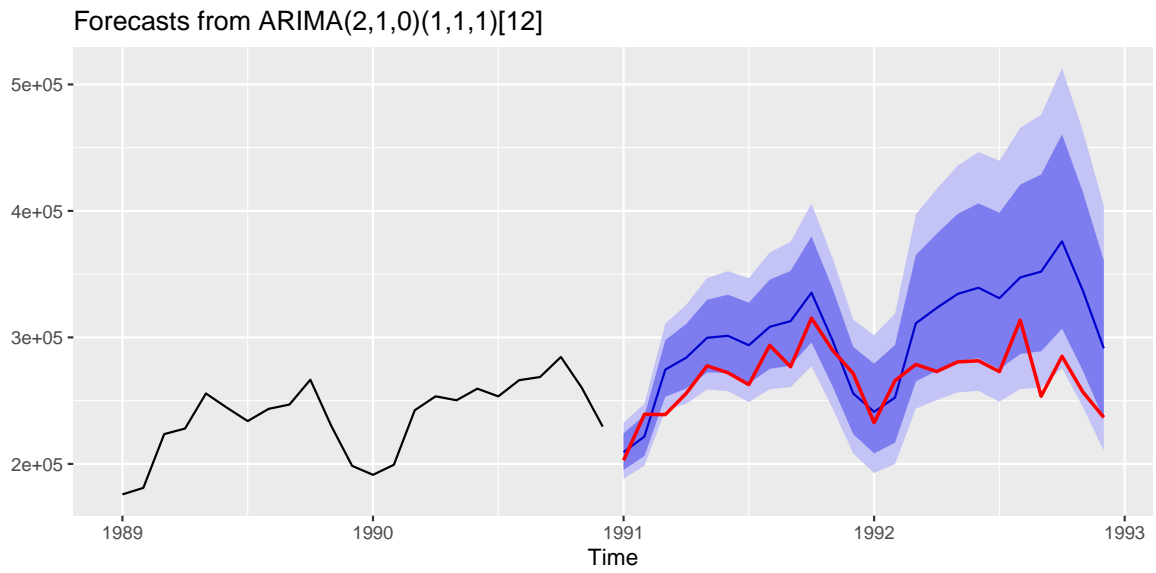


Figure 26: