**Time Series Analysis: Homework 4** (20232863 Keywoong Bae)

1. (related with HW#3, prob. 4) Estimated the parameters of your identified model in HW#3, prob. 4. Also perform Ljung and Box test for the residuals.

You can see the detailed process in Rcode.

- Estimated parameters

| | AR1 | intercept |
| --- | --- | --- |
| | 0.4342 | 35.2418 |
| s.e. | 0.0719 | 0.9652 |

- Box-Ljung test.

X-squared = 10.754, df = 10, p-value = 0.3717

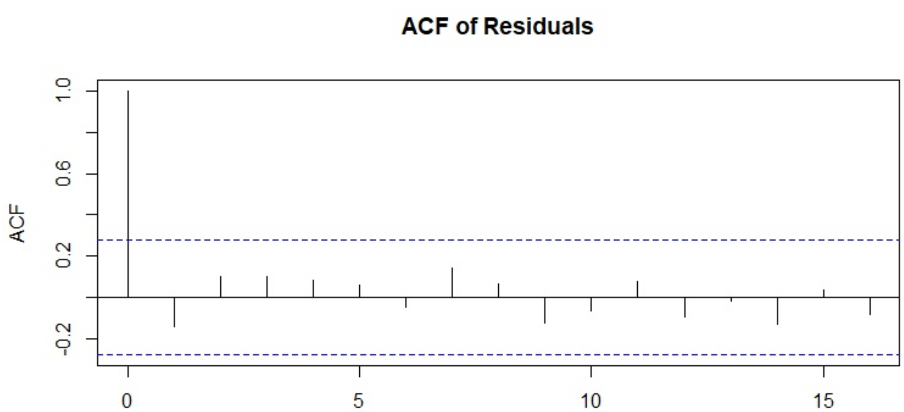
2. Identify the model for J08 series and estimate the related parameters. Perform diagnostic checking for the residuals.

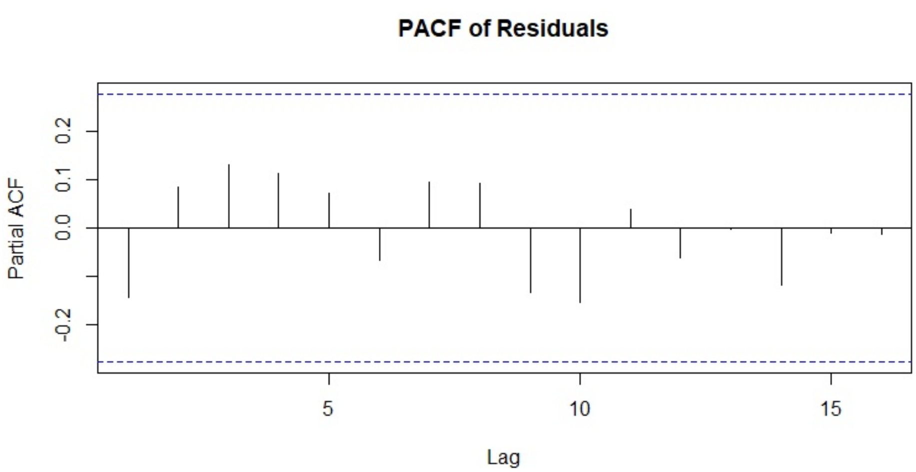
· AR(1) 모형.

| | ar1 | intercept |
|---|---|---|
| | 0.4433 | 18.7317 |
| s.e. | 0.1349 | 1.5904 |

· Diagnostic checking for residuals.

$\chi^2 = 5.7739$, $df = 10$, p-value $= 0.8339$.



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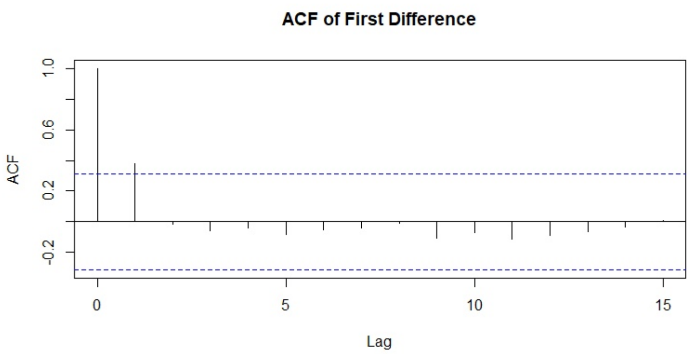
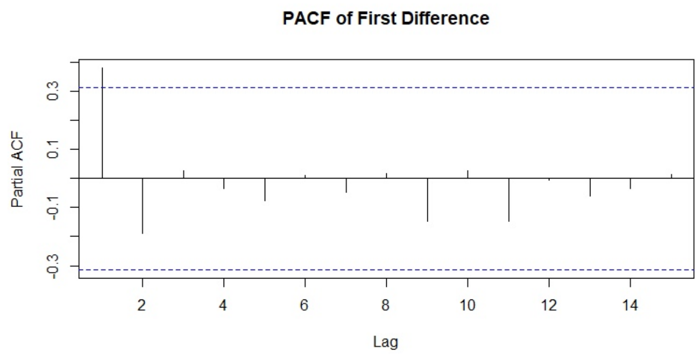
3. Consider J05 series.

(a) Obtain ACF and PACF of the first differenced series.

(b) Estimate the following three models and suggest the best model.

AR(1), MA(1), ARMA(1,1)




```
> print(summary(ar1_model))

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

Coefficients:
         ar1  intercept
      0.3762    28.2201
s.e.  0.1465    26.9828

sigma^2 estimated as 11386:  log likelihood = -237.55,  aic = 481.1

Training set error measures:
                     ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set -0.9571547 106.7072 71.45644 700.6397 867.1336 0.8344099 0.07266774
```

```
> print(summary(ma1_model))

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

Coefficients:
         ma1  intercept
      0.4554    25.6357
s.e.  0.1474    24.2741

sigma^2 estimated as 10985:  log likelihood = -236.89,  aic = 479.78

Training set error measures:
                    ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 0.4376077 104.8076 68.65417 635.1649 827.1112 0.8016872 0.003665733
```

```
> print(summary(arma11_model))

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

Coefficients:
         ar1     ma1  intercept
      0.0083  0.4487    25.6524
s.e.  0.3356  0.3109    24.3797

sigma^2 estimated as 10984:  log likelihood = -236.89,  aic = 481.77

Training set error measures:
                    ME    RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 0.4250506 104.807 68.65703 635.6779 827.3483 0.8017206 0.002079242
```

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4. Consider an ARMA(1,3) model.

(a) Calculate one-step-ahead forecast at time n.

(b) Compute its variance of forecast error in (a).

(c) Derive an updating formula for the one-step-ahead forecast using minimum information.

(a)

```
> print(summary(arma13_model))

Call:
arima(x = timeseries, order = c(1, 0, 3))

Coefficients:
         ar1     ma1     ma2      ma3  intercept
      0.9301  0.5443  0.0422  -0.0374   656.6192
s.e.  0.0646  0.1777  0.2090   0.1805   284.5703

sigma^2 estimated as 10911:  log likelihood = -244.28,  aic = 500.57

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 11.22328 104.4566 68.48153 -1.222137 12.44121 0.8300507 -0.0363478
```

(b)

```
> print(forecast_n$pred)
Time Series:
Start = 41
End = 41
Frequency = 1
[1] 1206.545
```

(c)

```
> forecast_error_variance <- forecast_n$se^2
> print(forecast_error_variance)
Time Series:
Start = 41
End = 41
Frequency = 1
[1] 10911.17
```

5. Consider the series J14. Assume that it is identified as MA(2).
(a) Estimate the model using the first 200 observations.
(b) Obtain the one-step-ahead forecasts for the period thereafter and compare the actual values to compute forecast errors.
(c) Find the forecast performance measures, RMSE, MAD and MAPE for the forecasts in (b).

```
> ma2_model <- arima(timeseries[1:200], order = c(0, 0, 2))
> print(summary(ma2_model))

Call:
arima(x = timeseries[1:200], order = c(0, 0, 2))

Coefficients:
          ma1     ma2  intercept
      -0.6262  0.3637    -0.0490
s.e.   0.0631  0.0717     0.0341

sigma^2 estimated as 0.4279:  log likelihood = -199.15,  aic = 406.3

Training set error measures:
                     ME      RMSE       MAE      MPE     MAPE      MASE       ACF1
Training set 0.00205375 0.6541054 0.5275271 14.74782 417.3699 0.4778032 0.01010519
```

```
> # Obtain one-step-ahead forecasts for the period thereafter
> forecast_values <- predict(ma2_model, n.ahead = length(timeseries) - 200)$pred
> # Compare actual values to forecast values
> actual_values <- timeseries[201:length(timeseries)]
> forecast_errors <- actual_values - forecast_values
> actual_values
 [1]  0.06519868 -0.29935161  0.17358436  0.37036815  1.00027248 -2.24527957  0.19289826
 [8]  0.25045363 -0.31401811  0.67796408 -0.02159384 -0.56804637 -0.51660822  1.12140768
[15] -0.67298549  0.68307552  0.05529077  0.18348220  0.63844074  0.53522552 -0.15087304
[22]  0.06817626  0.92361101 -0.58433536  0.16357980 -0.54791505  0.48658575 -1.21916575
[29]  0.23942887 -0.39678418 -0.15273543  1.07147491 -2.75890970  1.57477204 -1.85797150
[36] -0.48410827 -0.56417613  1.42925889 -0.68869806  0.71376205 -1.19159542  1.89932158
[43] -0.44632788 -0.57541256  1.35933652  0.08133858 -0.20105248 -0.68060908  1.14239704
[50] -0.12708151
> forecast_errors
Time Series:
Start = 201
End = 250
Frequency = 1
 [1]  0.27468394 -0.28726983  0.22263324  0.41941703  1.04932136 -2.19623069  0.24194713
 [8]  0.29950251 -0.26496923  0.72701295  0.02745504 -0.51899749 -0.46755934  1.17045656
[15] -0.62393661  0.73212440  0.10433965  0.23253108  0.68748961  0.58427440 -0.10182416
[22]  0.11722514  0.97265989 -0.53528648  0.21262868 -0.49886618  0.53563463 -1.17011687
[29]  0.28847775 -0.34773530 -0.10368656  1.12052378 -2.70986083  1.62382092 -1.80892262
[36] -0.43505939 -0.51512725  1.47830777 -0.63964919  0.76281093 -1.14254654  1.94837046
[43] -0.39727900 -0.52636369  1.40838540  0.13038746 -0.15200360 -0.63156020  1.19144592
[50] -0.07803263
```

```
> # Compute Root Mean Squared Error (RMSE)
> RMSE <- sqrt(mean(forecast_errors^2))
> # Compute Mean Absolute Deviation (MAD)
> MAD <- mean(abs(forecast_errors))
> # Compute Mean Absolute Percentage Error (MAPE)
> MAPE <- mean(abs(forecast_errors / actual_values)) * 100
> # Print forecast performance measures
> cat("RMSE:", RMSE, "\n")
RMSE: 0.9128336
> cat("MAD:", MAD, "\n")
MAD: 0.694335
> cat("MAPE:", MAPE, "%\n")
MAPE: 110.9544 %
```

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