

# VARComplexExample

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## Libraries

```
library(dplyr)
library(tsibble)
library(ggplot2)
library(feasts)
library(gridExtra)
library(MTS)
library(tseries)
library(forecast)
library(seastests)
```

## Data Generation

$$z_{1,t} = z_{2,t-1} + \epsilon_{1,t}$$

$$z_{2,t} = -1.01z_{1,t-1} + 0.2z_{2,t-1} + \epsilon_{2,t}$$

$$z_t = \begin{pmatrix} 0 & 1 \\ -1.01 & 0.2 \end{pmatrix} z_{t-1} + \epsilon_t$$

```
set.seed(6)
skip = 20
length = 240
testLength = 180
noiseSd = 5

dataLength = skip + length + testLength

# Make some noise!
noise1 = rnorm(dataLength, 0, noiseSd)
noise2 = rnorm(dataLength, 0, noiseSd)

# Sets the first data point
ts1 = vector("numeric", length)
ts2 = vector("numeric", length)
ts1[1] = noise1[1]
ts2[1] = noise2[1]

# Loops though, makes linear data
for(t in 2:dataLength) {
  ts1[t] = ts2[t-1] + noise1[t] + noise1[t]
  ts2[t] = -1.01*ts1[t-1] + 0.2*ts2[t-1] + noise2[t]
```

```

}

# Takes out the testing data
test1 = ts1[(length + skip + 1):(dataLength)]
ts1 = ts1[(skip + 1):(length+skip)]
test2 = ts2[(length + skip + 1):(dataLength)]
ts2 = ts2[(skip + 1):(length+skip)]

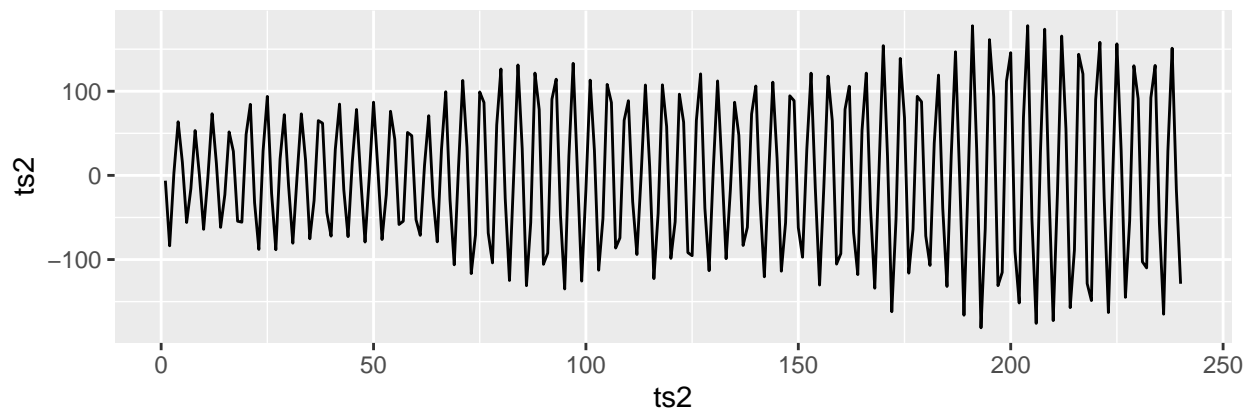
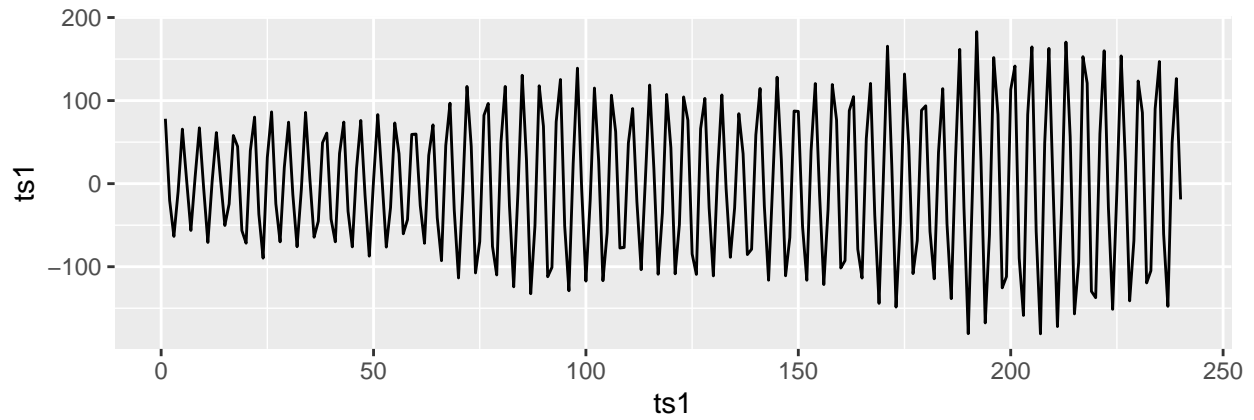
# Turns them into a time series object
ts = as_tibble(ts1)
ts = rename(ts, "ts1" = "value")
ts[,2] = ts2
ts = rename(ts, "ts2" = "...2")
ts[,3] = 1:length
ts = rename(ts, "index" = "...3")

tsTest = as_tibble(test1)
tsTest = rename(tsTest, "ts1" = "value")
tsTest[,2] = test2
tsTest = rename(tsTest, "ts2" = "...2")
tsTest[,3] = (length + 1):(length + testLength)
tsTest = rename(tsTest, "index" = "...3")
tsTest = tsTest %>% as_tsibble(index = "index")

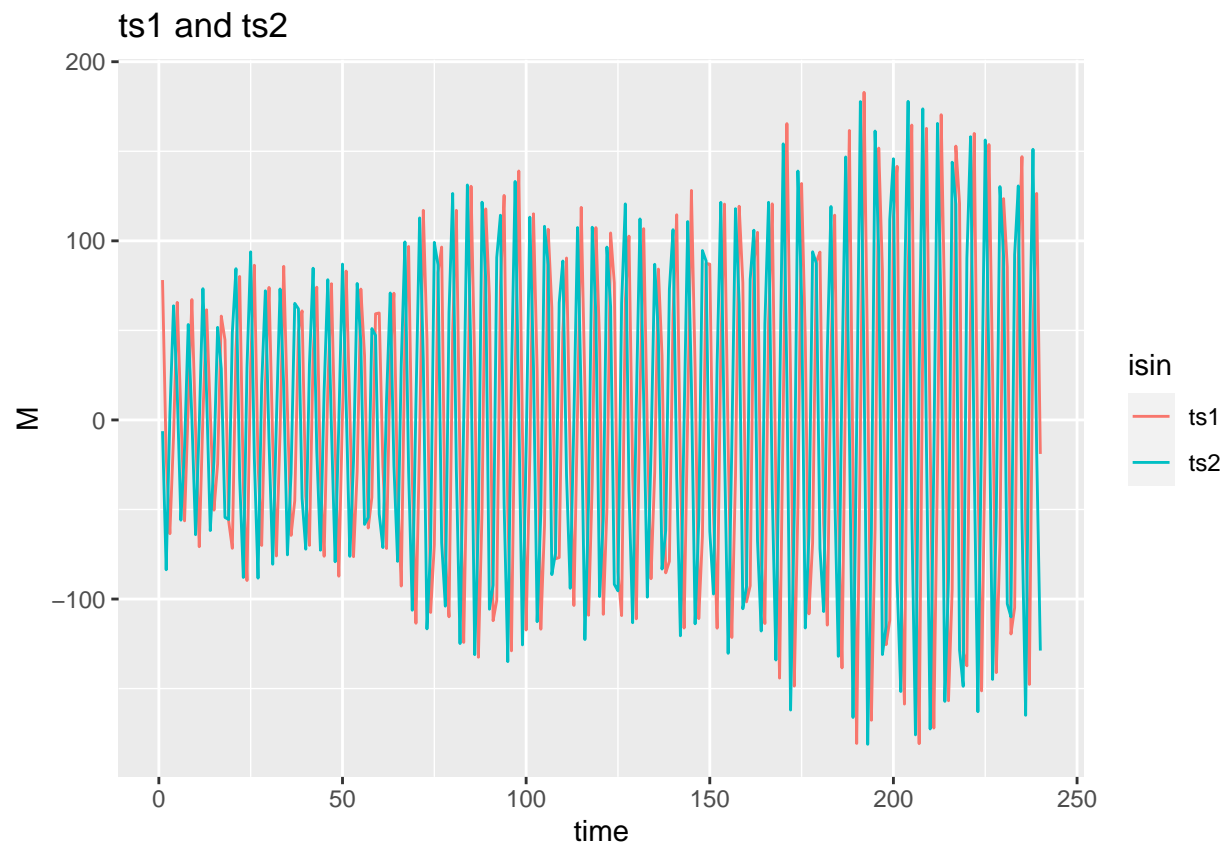
ts = ts %>% as_tsibble(index = "index")

plot1 = ts %>% autoplot(ts1) + xlab("ts1")
plot2 = ts %>% autoplot(ts2) + xlab("ts2")
grid.arrange(plot1, plot2, nrow=2)

```



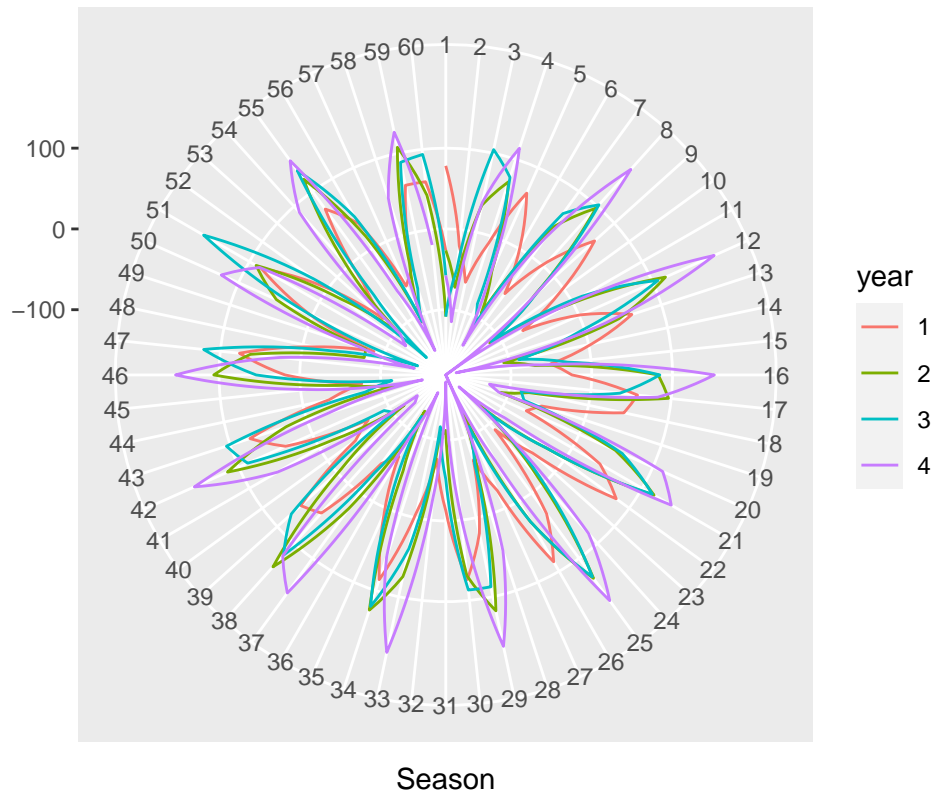
```
df1 = data.frame(time = ts$index, M = ts$ts1, isin = "ts1")
df2 = data.frame(time = ts$index, M = ts$ts2, isin = "ts2")
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("ts1 and ts2")
```



## Difference

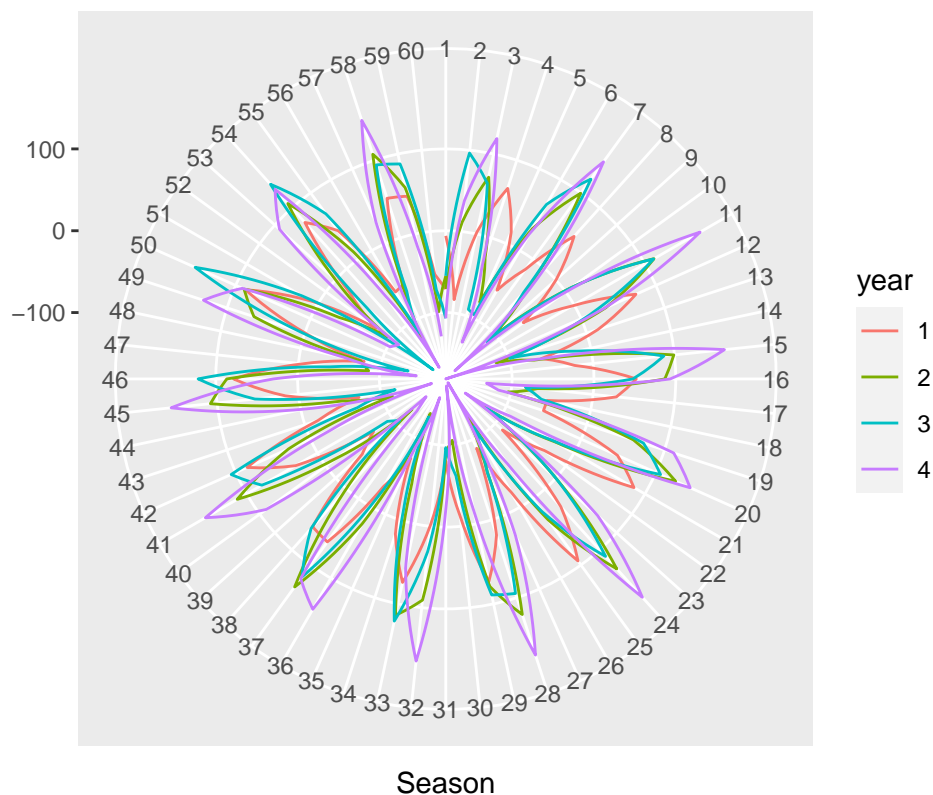
```
tsSeasonalPlot = ts %>% as.ts(start = c(1969, 2), frequency = 60)
ggseasonplot(tsSeasonalPlot[,1], polar = T ) + ggtitle("Seasonal Plot: ts1")
```

Seasonal Plot: ts1



```
ggseasonplot(tsSeasonalPlot[,2], polar = T ) + ggtitle("Seasonal Plot: ts2")
```

## Seasonal Plot: ts2

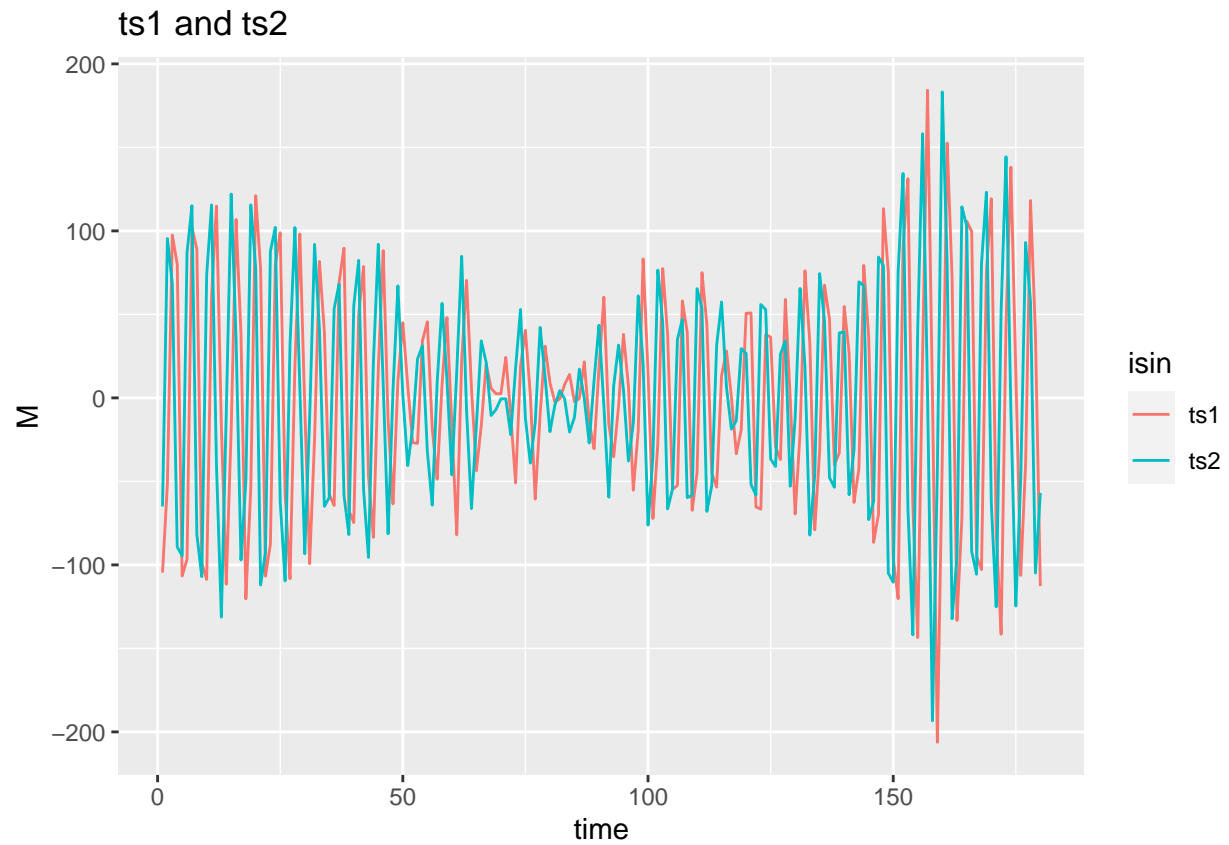


## Taking the seasonal difference

$$y'_t = y_t - y_{t-60}$$

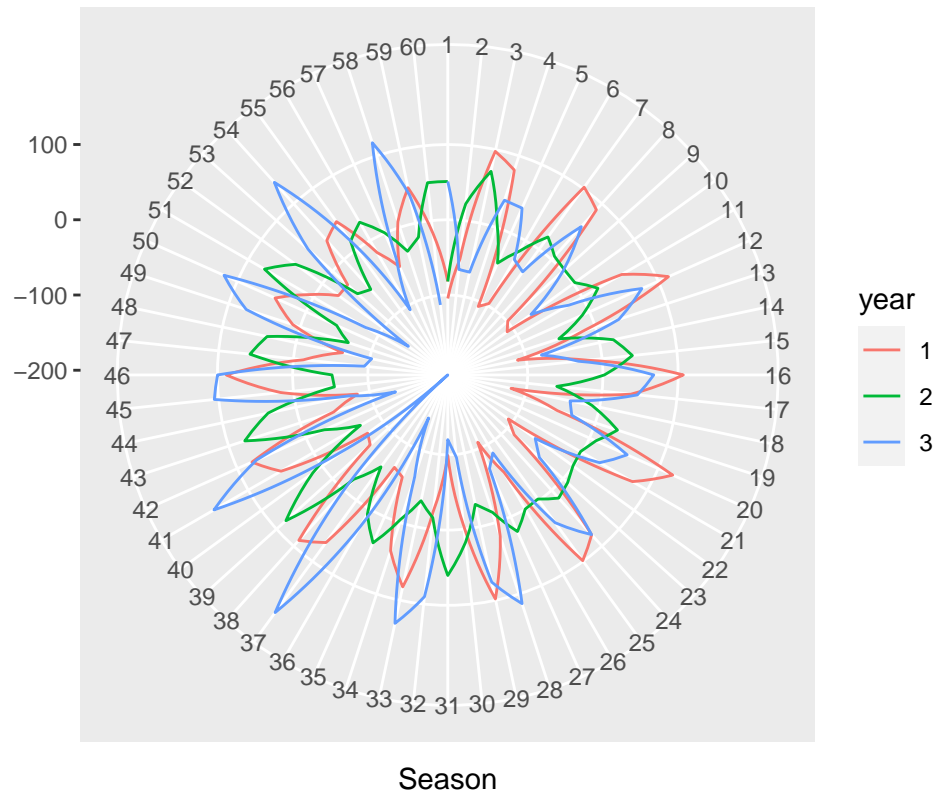
```
tsSeasonal = ts %>% diffM(d = 60)
tsSeasonal = tsSeasonal %>% as_tibble()
tsSeasonal[,3] = 1:(length - 60)
tsSeasonal = tsSeasonal %>% as_tsibble(index = "index")

df1 = data.frame(time = tsSeasonal$index, M = tsSeasonal$ts1, isin = "ts1")
df2 = data.frame(time = tsSeasonal$index, M = tsSeasonal$ts2, isin = "ts2")
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("ts1 and ts2")
```



```
tsSeasonalPlot = tsSeasonal %>% as.ts(start = c(1969, 2), frequency = 60)
ggseasonplot(tsSeasonalPlot[,1], polar = T ) + ggtitle("Seasonal Plot: ts1 with seasonal difference")
```

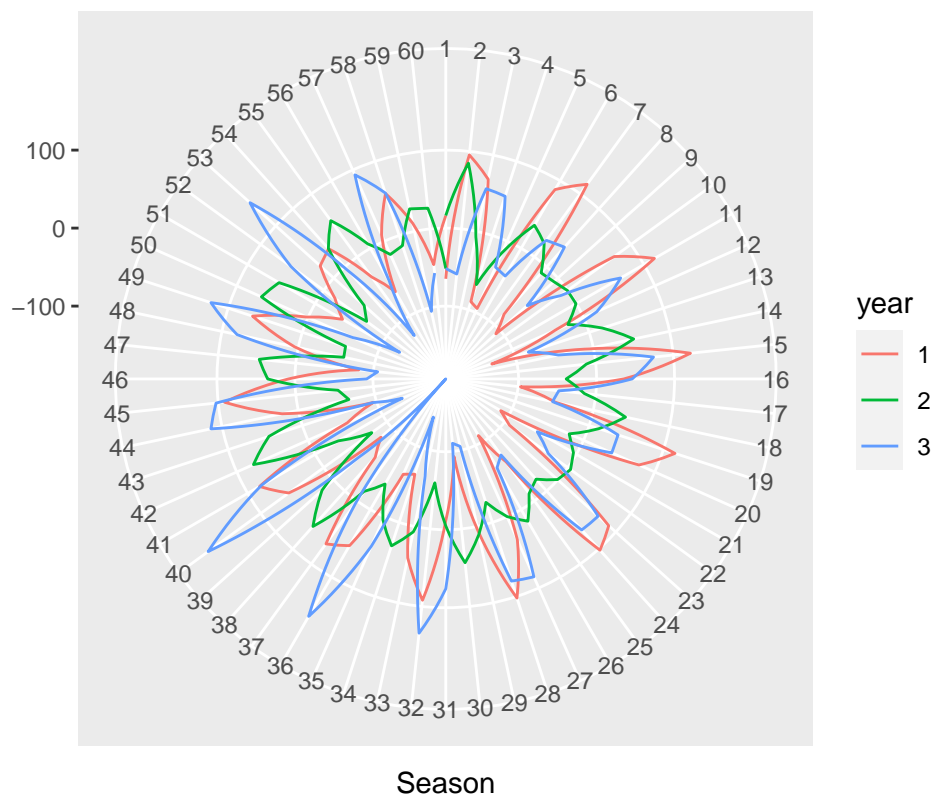
Seasonal Plot: ts1 with seasonal difference



```
ggseasonplot(tsSeasonalPlot[,2], polar = T ) + ggtitle("Seasonal Plot: ts2 with seasonal difference")
```



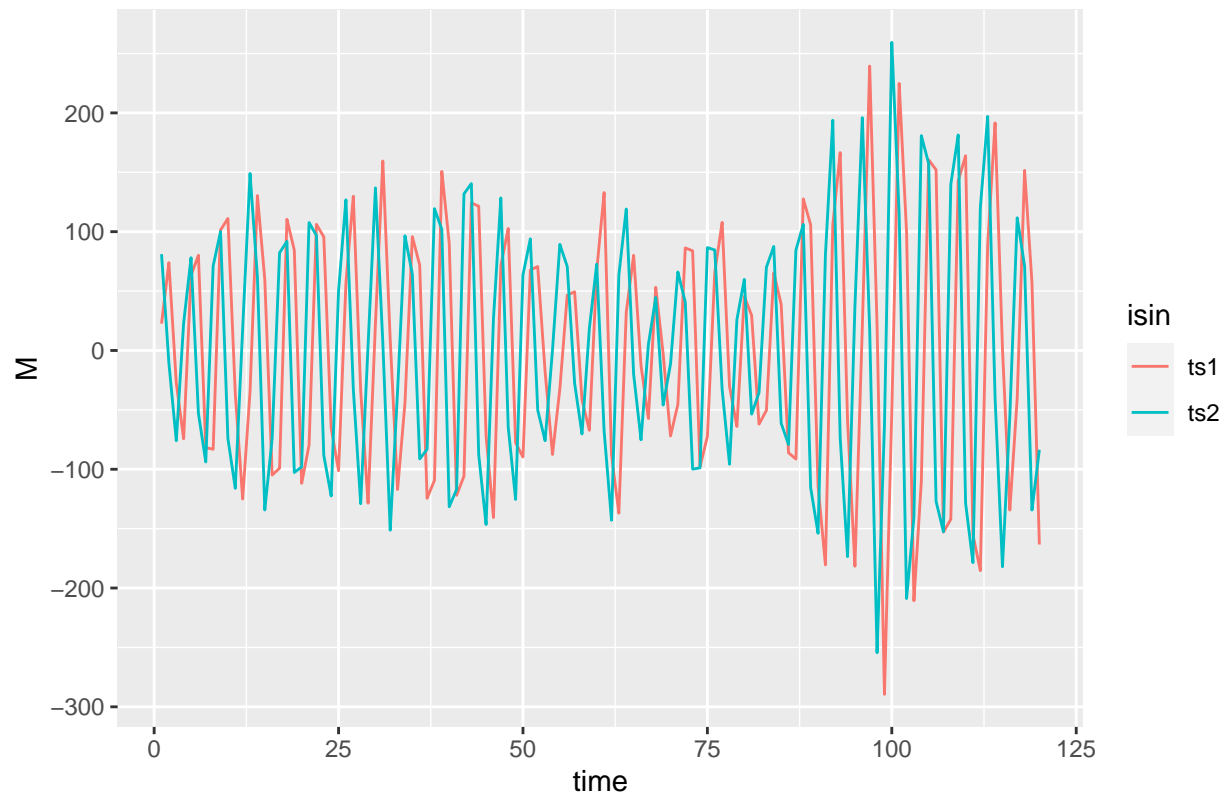
Seasonal Plot: ts2 with seasonal difference



```
tsSeasonal = tsSeasonal %>% diffM(d = 60)
tsSeasonal = tsSeasonal %>% as_tibble()
tsSeasonal[,3] = 1:(length - 120)
tsSeasonal = tsSeasonal %>% as_tsibble(index = "index")

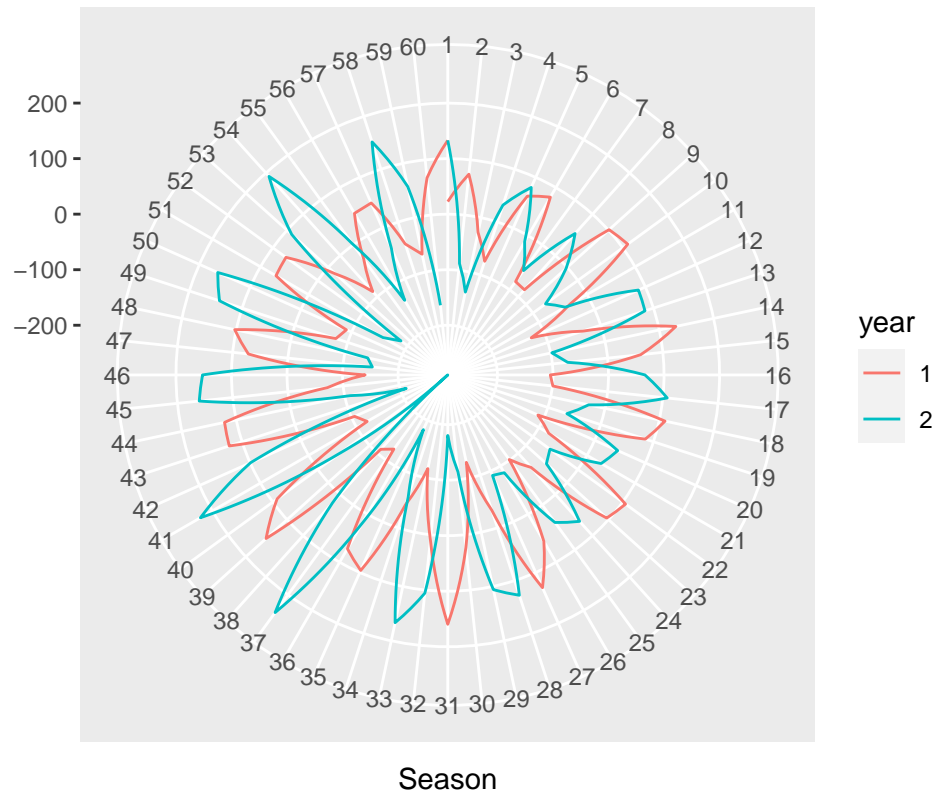
df1 = data.frame(time = tsSeasonal$index, M = tsSeasonal$ts1, isin = "ts1")
df2 = data.frame(time = tsSeasonal$index, M = tsSeasonal$ts2, isin = "ts2")
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("ts1 and ts2")
```

ts1 and ts2



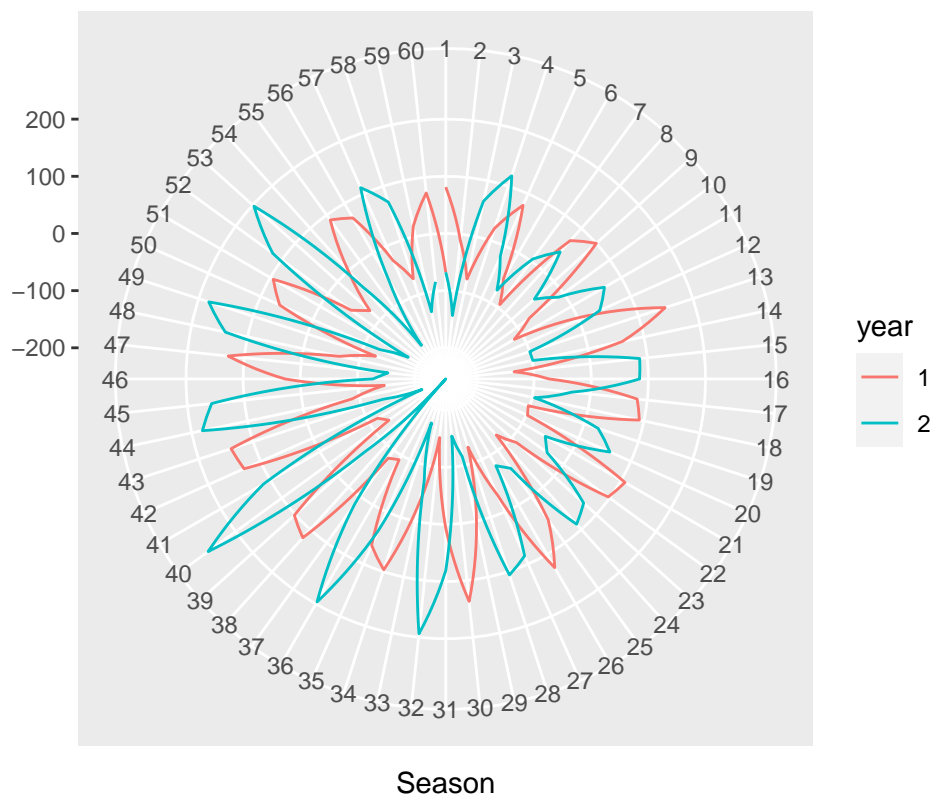
```
tsSeasonalPlot = tsSeasonal %>% as.ts(start = c(1969, 2), frequency = 60)
ggseasonplot(tsSeasonalPlot[,1], polar = T ) + ggtitle("Seasonal Plot: ts1 with 2nd seasonal difference")
```

Seasonal Plot: ts1 with 2nd seasonal difference



```
ggseasonplot(tsSeasonalPlot[,2], polar = T ) + ggtitle("Seasonal Plot: ts2 with 2nd seasonal difference")
```

## Seasonal Plot: ts2 with 2nd seasonal difference



## Webel-Ollech Test

```
kpss.test(tsSeasonal$ts1)
```

```
## Warning in kpss.test(tsSeasonal$ts1): p-value greater than printed p-value
```

```
##
```

```
## KPSS Test for Level Stationarity
```

```
##
```

```
## data: tsSeasonal$ts1
```

```
## KPSS Level = 0.065899, Truncation lag parameter = 4, p-value = 0.1
```

```
kpss.test(tsSeasonal$ts2)
```

```
## Warning in kpss.test(tsSeasonal$ts2): p-value greater than printed p-value
```

```
##
```

```
## KPSS Test for Level Stationarity
```

```
##
```

```
## data: tsSeasonal$ts2
```

```
## KPSS Level = 0.042954, Truncation lag parameter = 4, p-value = 0.1
```

## Fitting the model

```
VARorder(tsSeasonal[, -3])
```

```
## selected order: aic = 1
```

```
## selected order: bic = 1
## selected order: hq = 1
## Summary table:
##      p      AIC      BIC      HQ      M(p) p-value
## [1,] 0 18.7640 18.7640 18.7640 0.0000 0.0000
## [2,] 1 11.5006 11.5935 11.5383 758.6653 0.0000
## [3,] 2 11.5185 11.7044 11.5940 4.9453 0.2930
## [4,] 3 11.5101 11.7888 11.6233 7.4755 0.1128
## [5,] 4 11.5036 11.8752 11.6545 7.1352 0.1289
## [6,] 5 11.5354 12.0000 11.7241 3.3273 0.5046
## [7,] 6 11.5474 12.1049 11.7738 5.1099 0.2762
## [8,] 7 11.5567 12.2071 11.8209 5.2482 0.2628
## [9,] 8 11.6112 12.3545 11.9130 1.0927 0.8954
## [10,] 9 11.5820 12.4182 11.9216 8.3875 0.0784
## [11,] 10 11.6005 12.5296 11.9778 4.1206 0.3899
## [12,] 11 11.6294 12.6515 12.0445 3.1514 0.5328
## [13,] 12 11.6264 12.7414 12.0792 5.6769 0.2246
## [14,] 13 11.5554 12.7633 12.0459 10.9446 0.0272
```

$$z_t = \begin{pmatrix} 0 & 0.90 \\ -0.95 & 0.22 \end{pmatrix} z_{t-1} + a_t$$

```
m1 = VAR(tsSeasonal[, -3], p = 1)
```

```
## Constant term:
## Estimates: 0.4089481 -0.2947539
## Std.Error: 2.282573 1.127269
## AR coefficient matrix
## AR( 1 )-matrix
##      [,1] [,2]
## [1,] -0.023 0.977
## [2,] -1.002 0.177
## standard error
##      [,1] [,2]
## [1,] 0.0217 0.0215
## [2,] 0.0107 0.0106
##
## Residuals cov-mtx:
##      [,1] [,2]
## [1,] 604.23864 -17.95039
## [2,] -17.95039 147.37184
##
## det(SSE) = 88725.54
## AIC = 11.45997
## BIC = 11.55289
## HQ = 11.4977
```

```
m1R = refVAR(m1)
```

```
## Constant term:
## Estimates: 0 0
## Std.Error: 0 0
## AR coefficient matrix
## AR( 1 )-matrix
##      [,1] [,2]
## [1,] -0.023 0.977
```

```
## [2,] -1.002 0.177
## standard error
##      [,1]  [,2]
## [1,] 0.0216 0.0214
## [2,] 0.0107 0.0106
##
## Residuals cov-mtx:
##      [,1]  [,2]
## [1,] 604.4058 -18.0709
## [2,] -18.0709 147.4587
##
## det(SSE) = 88798.34
## AIC = 11.46079
## BIC = 11.55371
## HQ  = 11.49852
```

## Model Checking

### Multivariate Portmanteau Statistics

Let  $R_\ell$  be the theoretical lag  $\ell$  cross-correlation matrix of innovation  $a_t$

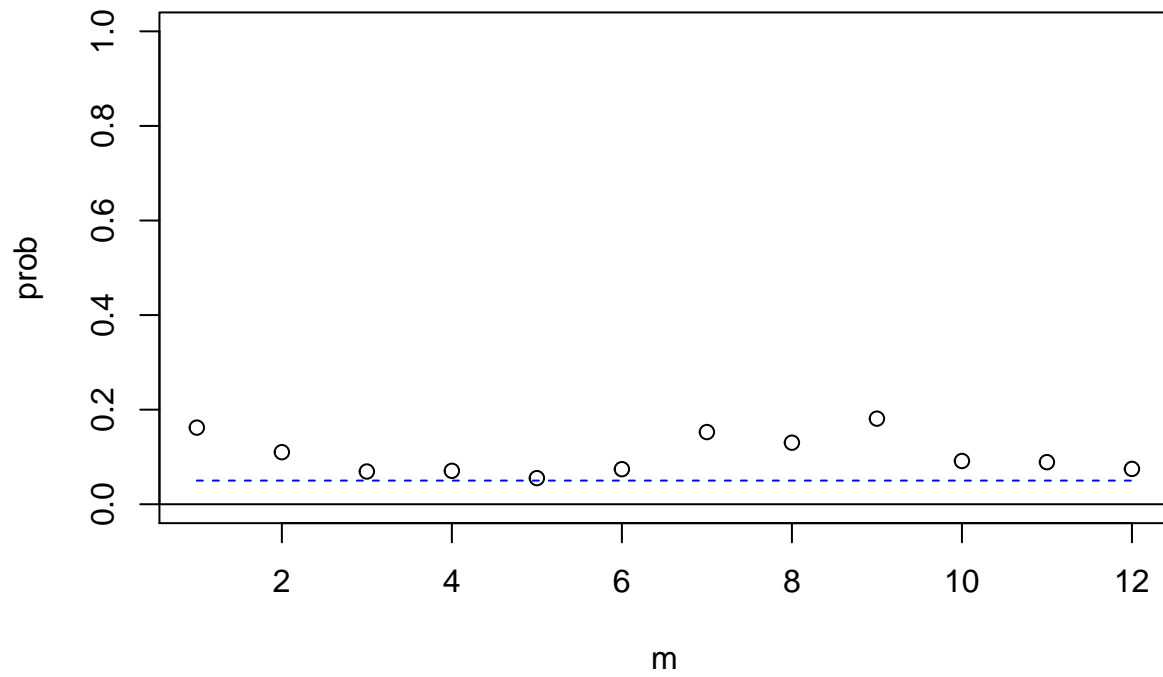
$H_0$ :  $R_1 = \dots = R_m = 0$

$H_A$ :  $R_j \neq 0$  for some  $1 \leq j \leq m$

```
mq(m1R$residuals, lag = 12)
```

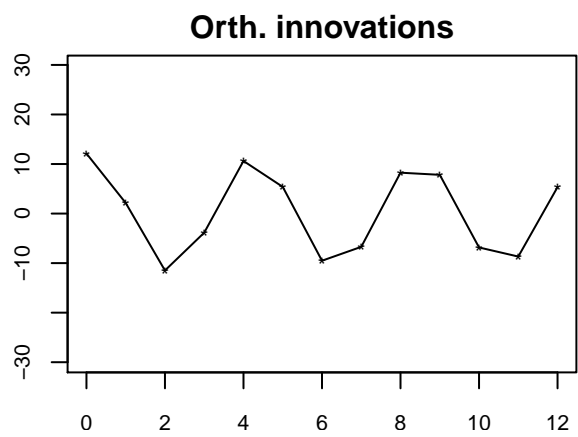
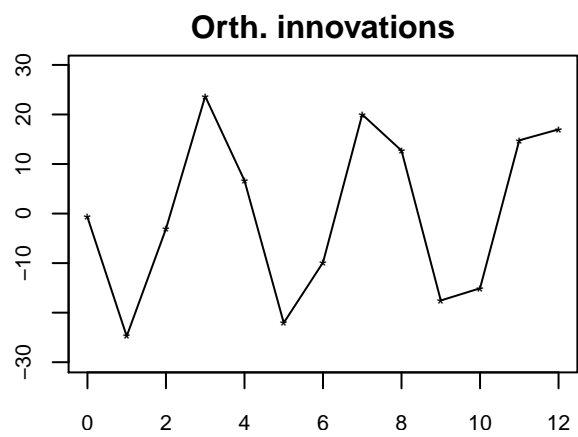
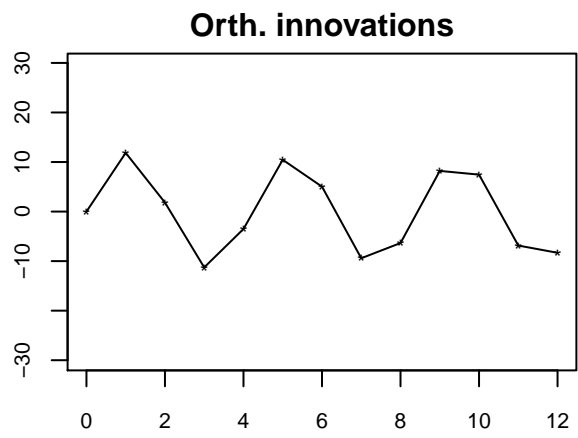
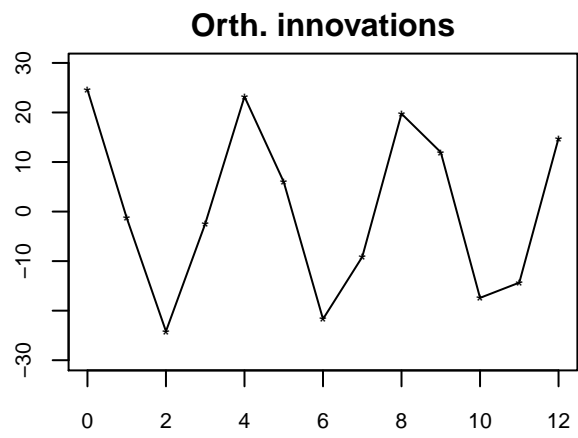
```
## Ljung-Box Statistics:
##      m      Q(m)    df    p-value
## [1,] 1.00     6.54    4.00     0.16
## [2,] 2.00    13.05    8.00     0.11
## [3,] 3.00    19.89   12.00     0.07
## [4,] 4.00    24.95   16.00     0.07
## [5,] 5.00    30.99   20.00     0.06
## [6,] 6.00    34.63   24.00     0.07
## [7,] 7.00    35.62   28.00     0.15
## [8,] 8.00    41.09   32.00     0.13
## [9,] 9.00    43.55   36.00     0.18
## [10,] 10.00   52.34   40.00     0.09
## [11,] 11.00   57.09   44.00     0.09
## [12,] 12.00   62.76   48.00     0.07
```

### p-values of Ljung-Box statistics



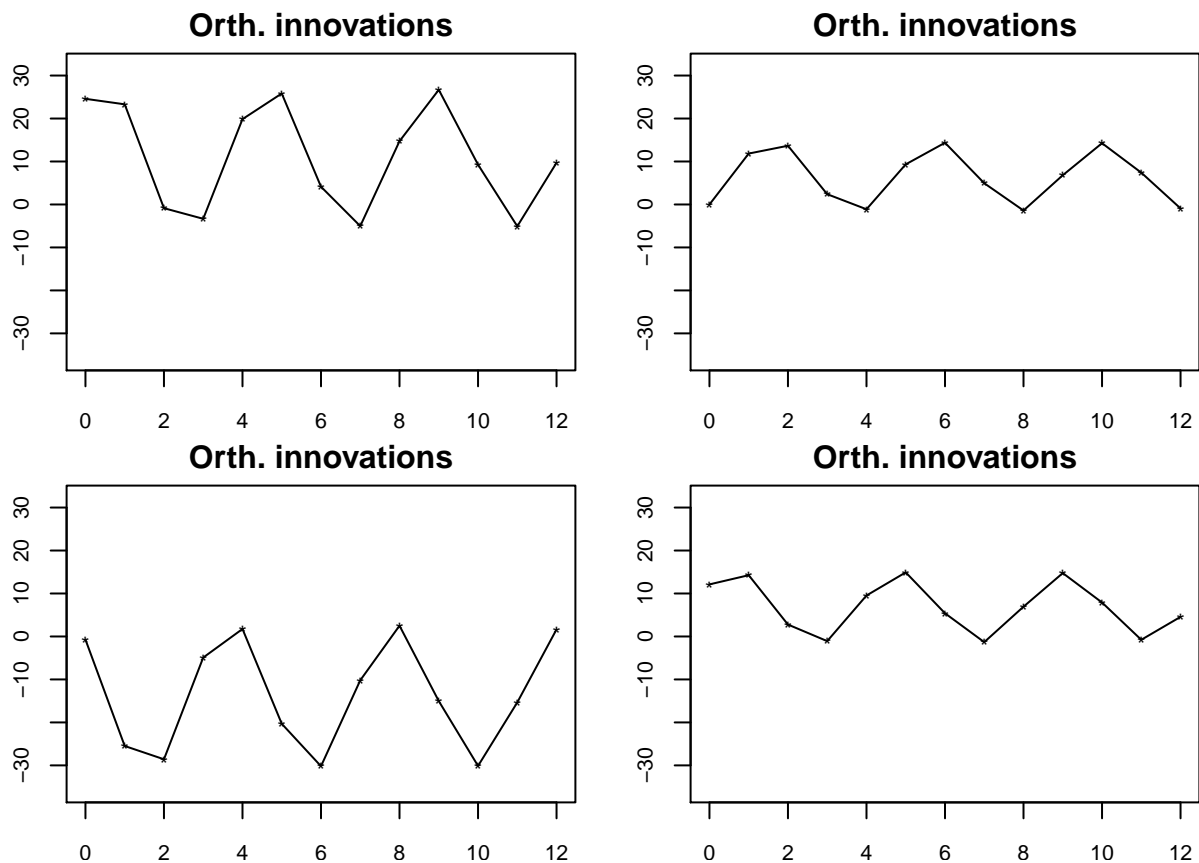
Impulse

```
VARirf(m1R$Phi, m1$Sigma)
```



## Press return to continue





## Model Forecasting

```
tsPredSeasonal = VARpred(m1R, h = testLength - 120)
```

```
## orig 120
## Forecasts at origin: 120
##          ts1      ts2
## [1,] -77.968 148.8950
## [2,] 147.324 104.4173
## [3,]  98.679 -129.1486
## [4,] -128.499 -121.6778
## [5,] -115.982 107.2392
## [6,] 107.481 135.1420
## [7,] 129.625 -83.8039
## [8,] -84.888 -144.6697
## [9,] -139.456  59.4857
## [10,]  61.344 150.2227
## [11,] 145.424 -34.9176
## [12,] -37.468 -151.8614
## [13,] -147.574  10.7073
## [14,]  13.853 149.7379
## [15,] 146.040  12.5756
## [16,]   8.939 -144.0882
## [17,] -141.041 -34.4121
## [18,] -30.398 135.2221
## [19,] 132.868  54.3438
```

```

## [20,] 50.067 -123.5122
## [21,] -121.874 -71.9807
## [22,] -67.558 109.3819
## [23,] 108.464 87.0079
## [24,] 82.554 -93.2924
## [25,] -93.082 -99.1888
## [26,] -94.813 75.7299
## [27,] 76.197 108.3677
## [28,] 104.173 -57.1923
## [29,] -58.293 -114.4693
## [30,] -110.548 38.1770
## [31,] 39.853 117.4964
## [32,] 113.930 -19.1683
## [33,] -21.351 -117.5265
## [34,] -114.384 0.6268
## [35,] 3.238 114.7057
## [36,] 112.043 17.0209
## [37,] 14.065 -109.2422
## [38,] -107.100 -33.3907
## [39,] -30.179 101.3980
## [40,] 99.802 48.1484
## [41,] 44.771 -91.4800
## [42,] -90.443 -61.0153
## [43,] -57.562 79.8304
## [44,] 79.350 71.7720
## [45,] 68.331 -66.8164
## [46,] -66.877 -80.2613
## [47,] -76.915 52.8205
## [48,] 53.394 86.3885
## [49,] 83.213 -38.2301
## [50,] -39.277 -90.1208
## [51,] -87.185 23.4282
## [52,] 24.901 91.4852
## [53,] 88.849 -8.7839
## [54,] -10.625 -90.5647
## [55,] -88.277 -5.3554
## [56,] -3.208 87.4936
## [57,] 85.592 18.6716
## [58,] 16.285 -82.4517
## [59,] -80.965 -30.8823
## [60,] -28.327 75.6581
## Standard Errors of predictions:
##      [,1] [,2]
## [1,] 24.58 12.14
## [2,] 27.32 27.66
## [3,] 36.52 30.11
## [4,] 38.30 38.49
## [5,] 44.92 40.48
## [6,] 46.50 46.42
## [7,] 51.56 48.40
## [8,] 53.21 52.80
## [9,] 57.11 54.93
## [10,] 58.93 58.19
## [11,] 61.90 60.50

```

```

## [12,] 63.91 62.89
## [13,] 66.12 65.36
## [14,] 68.31 67.06
## [15,] 69.92 69.64
## [16,] 72.23 70.84
## [17,] 73.37 73.44
## [18,] 75.73 74.29
## [19,] 76.54 76.84
## [20,] 78.88 77.48
## [21,] 79.48 79.90
## [22,] 81.72 80.43
## [23,] 82.22 82.66
## [24,] 84.30 83.19
## [25,] 84.78 85.16
## [26,] 86.64 85.76
## [27,] 87.18 87.45
## [28,] 88.79 88.15
## [29,] 89.42 89.55
## [30,] 90.76 90.38
## [31,] 91.52 91.50
## [32,] 92.60 92.46
## [33,] 93.47 93.32
## [34,] 94.30 94.39
## [35,] 95.29 95.02
## [36,] 95.91 96.17
## [37,] 96.97 96.63
## [38,] 97.42 97.82
## [39,] 98.53 98.16
## [40,] 98.86 99.34
## [41,] 99.97 99.61
## [42,] 100.23 100.74
## [43,] 101.30 100.99
## [44,] 101.53 102.03
## [45,] 102.53 102.31
## [46,] 102.78 103.24
## [47,] 103.67 103.56
## [48,] 103.96 104.35
## [49,] 104.73 104.74
## [50,] 105.08 105.40
## [51,] 105.72 105.86
## [52,] 106.14 106.38
## [53,] 106.65 106.91
## [54,] 107.14 107.31
## [55,] 107.53 107.89
## [56,] 108.07 108.19
## [57,] 108.37 108.82
## [58,] 108.95 109.03
## [59,] 109.17 109.67
## [60,] 109.77 109.84
## Root mean square errors of predictions:
##      [,1] [,2]
## [1,] 24.89 12.29
## [2,] 173.16 357.69
## [3,] 349.74 173.38

```

```
## [4,] 169.96 346.28
## [5,] 339.57 184.23
## [6,] 178.89 329.16
## [7,] 323.76 202.72
## [8,] 195.88 307.25
## [9,] 303.17 224.22
## [10,] 216.41 281.73
## [11,] 278.91 245.31
## [12,] 236.98 253.99
## [13,] 252.32 263.73
## [14,] 255.26 225.79
## [15,] 225.03 278.13
## [16,] 269.81 199.25
## [17,] 199.06 287.71
## [18,] 279.80 176.93
## [19,] 176.83 292.13
## [20,] 284.83 161.58
## [21,] 160.95 291.33
## [22,] 284.80 155.25
## [23,] 153.54 285.54
## [24,] 279.89 158.09
## [25,] 155.04 275.19
## [26,] 270.50 168.05
## [27,] 163.75 260.90
## [28,] 257.21 182.10
## [29,] 176.83 243.52
## [30,] 240.80 197.40
## [31,] 191.51 224.05
## [32,] 222.23 211.86
## [33,] 205.65 203.72
## [34,] 202.68 224.07
## [35,] 217.81 184.01
## [36,] 183.52 233.14
## [37,] 227.05 166.61
## [38,] 166.37 238.59
## [39,] 232.84 153.28
## [40,] 152.92 240.22
## [41,] 234.96 145.54
## [42,] 144.66 238.07
## [43,] 233.42 144.00
## [44,] 142.32 232.38
## [45,] 228.42 148.03
## [46,] 145.46 223.58
## [47,] 220.34 156.03
## [48,] 152.67 212.22
## [49,] 209.71 166.11
## [50,] 162.13 199.03
## [51,] 197.22 176.56
## [52,] 172.19 184.88
## [53,] 183.68 186.11
## [54,] 181.55 170.78
## [55,] 170.06 193.86
## [56,] 189.31 157.86
## [57,] 157.44 199.27
```

```
## [58,] 194.86 147.28
## [59,] 146.92 202.02
## [60,] 197.90 140.05
```

```
# Calculates the confidence interval
```

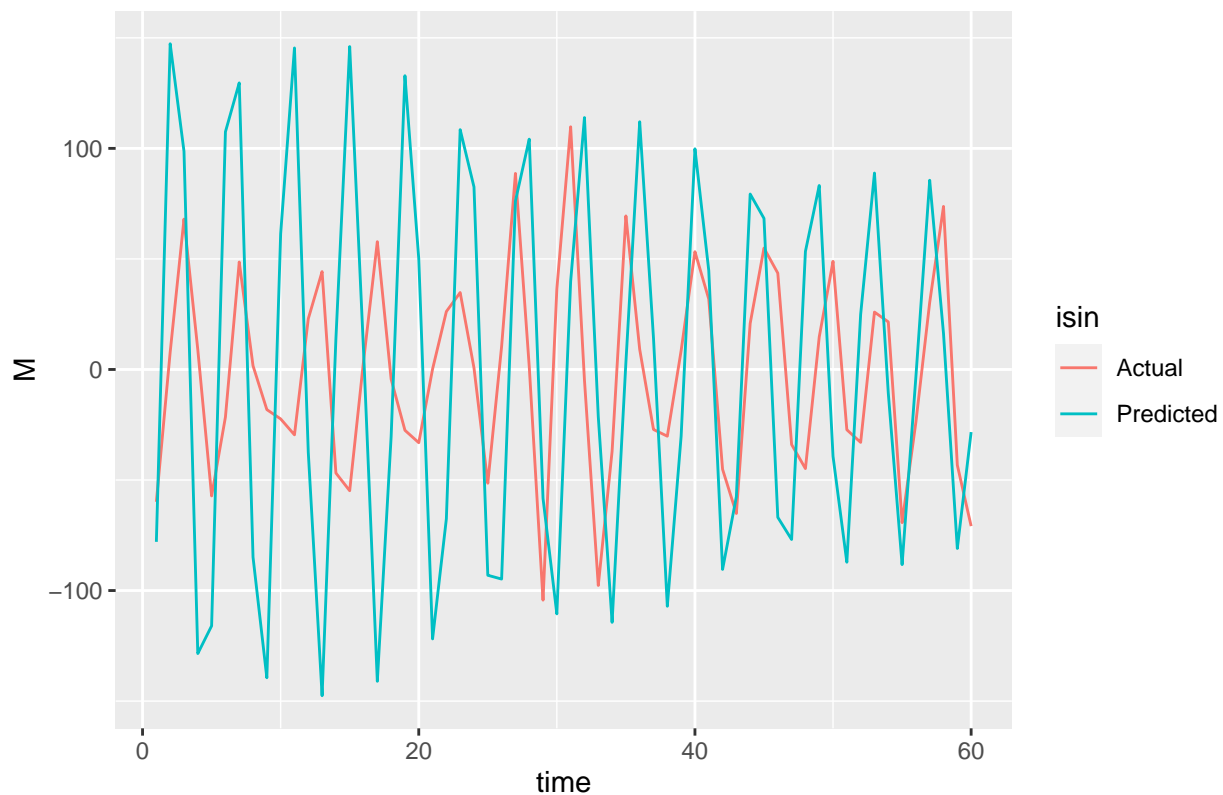
```
upperConf = tsPredSeasonal$pred + 1.96 * tsPredSeasonal$se.err
lowerConf = tsPredSeasonal$pred - 1.96 * tsPredSeasonal$se.err
```

```
tsTestSeasonal = tsTest %>% diffM(d = 60) %>% diffM(d = 60)
tsTestSeasonal = tsTestSeasonal %>% as_tibble()
tsTestSeasonal[,3] = 1:(testLength - 120)
tsTestSeasonal = tsTestSeasonal %>% as_tsibble(index = "index")
```

```
df1 = data.frame(time = tsTestSeasonal$index, M = tsTestSeasonal$ts1, isin = "Actual")
df2 = data.frame(time = tsTestSeasonal$index, M = tsPredSeasonal$pred[,1], isin = "Predicted")
df3 = data.frame(time = tsTestSeasonal$index, M = upperConf[,1], isin = "Upper Bound")
df4 = data.frame(time = tsTestSeasonal$index, M = lowerConf[,1], isin = "Lower Bound")
df = rbind(df1, df2)
```

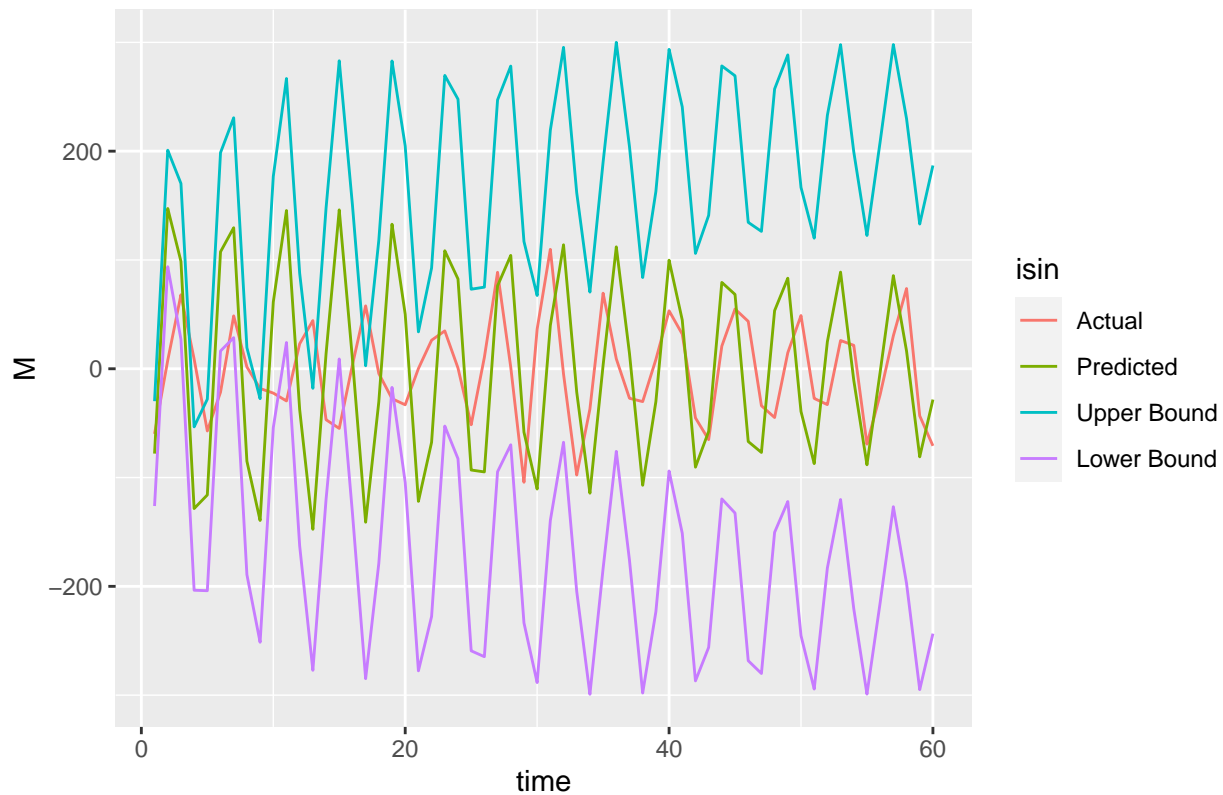
```
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted Values for ts1 without
```

Predicted Values for ts1 without Bounds



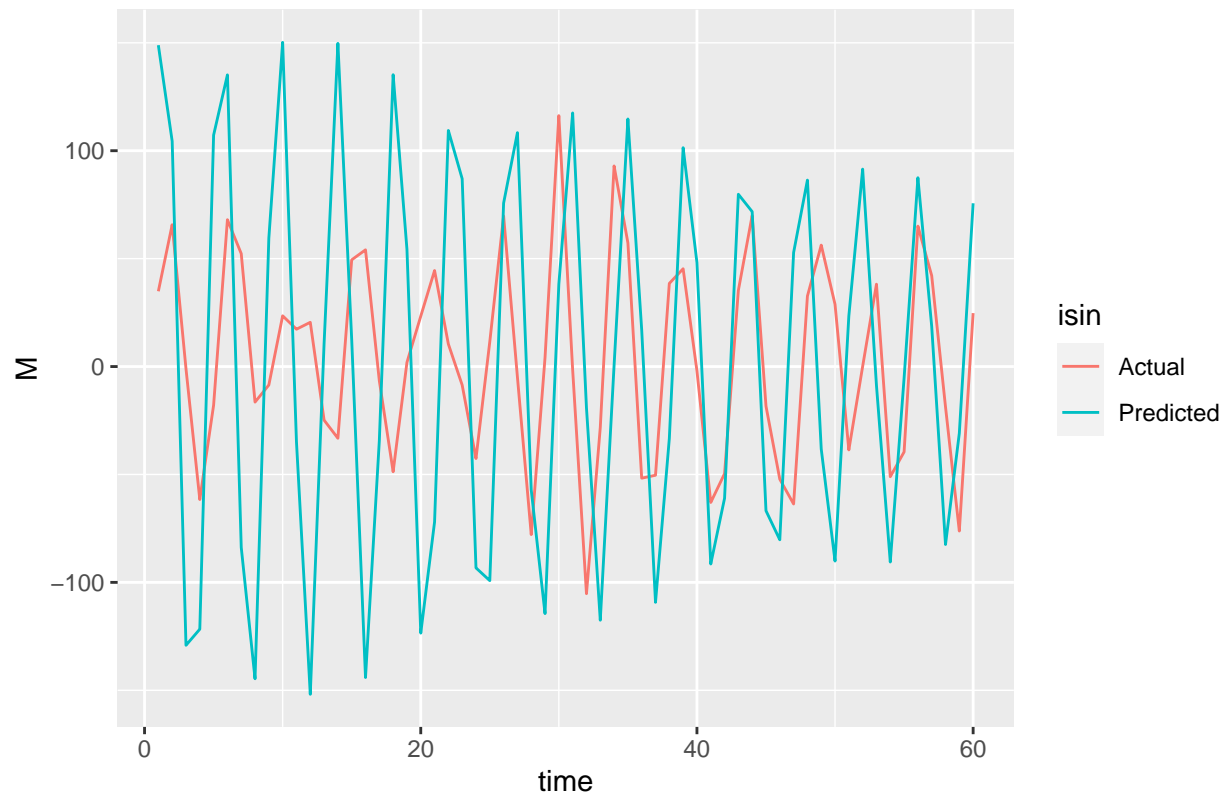
```
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted Values for ts1 with B
```

Predicted Values for ts1 with Bounds



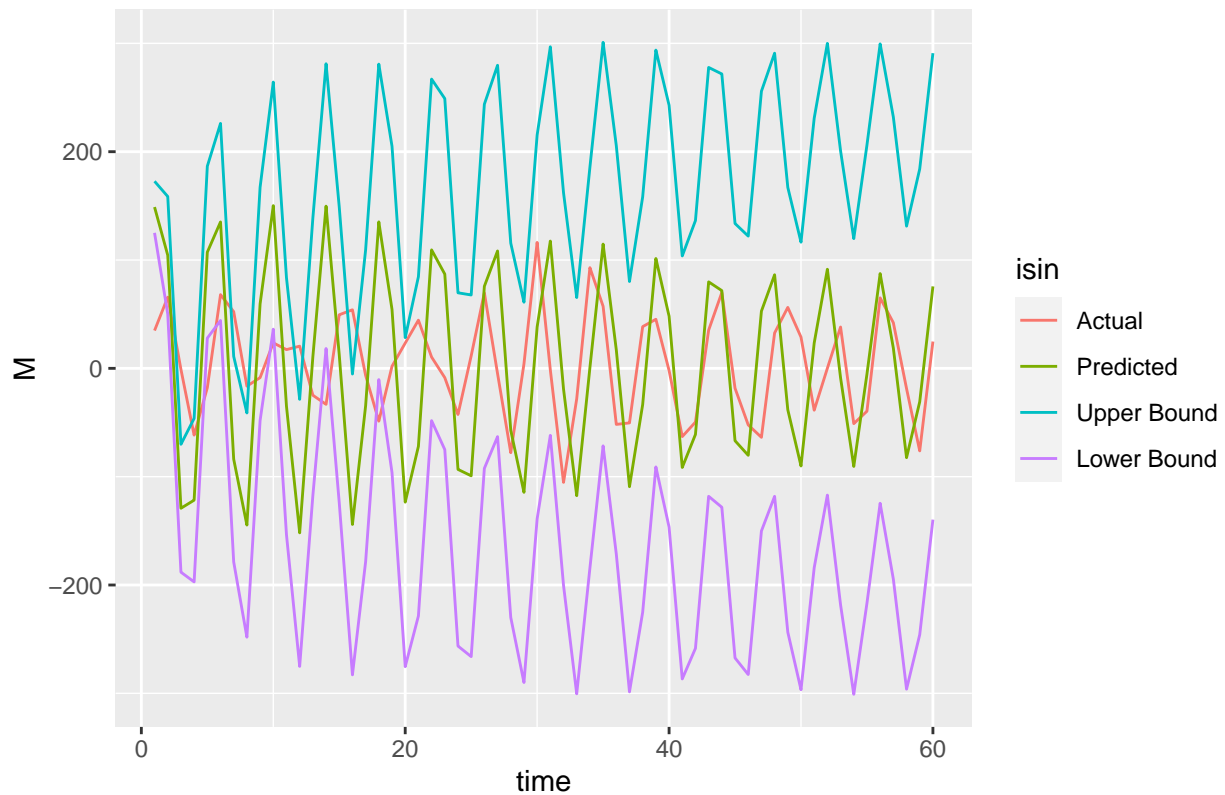
```
df1 = data.frame(time = tsTestSeasonal$index, M = tsTestSeasonal$ts2, isin = "Actual")
df2 = data.frame(time = tsTestSeasonal$index, M = tsPredSeasonal$pred[,2], isin = "Predicted")
df3 = data.frame(time = tsTestSeasonal$index, M = upperConf[,2], isin = "Upper Bound")
df4 = data.frame(time = tsTestSeasonal$index, M = lowerConf[,2], isin = "Lower Bound")
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted Values for ts2 without")
```

Predicted Values for ts2 without Bounds



```
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted Values for ts2 with B
```

Predicted Values for ts2 with Bounds



## Inverting the Difference

$$y_t = \sum_{i=0}^{t/60} y'_{t-60i} + y_0$$

```
# # Inverts
# tsPred = vector("numeric", testLength)
# for (t in 1:testLength) {
#   # Gets the current value
#   differenceSum = 0
#   for (i in 1:((t / 60) + 1)) {
#     differenceSum = differenceSum + tsPredSeasonal$pred[1 + 60*(i-1),1]
#   }
#   differenceSum = differenceSum + ts$ts1[length]
#   print(differenceSum)
# }
```

```
# drawStart = 1
#
```

```
# df1 = data.frame(time = seq(drawStart, length, length=length), M = ts$ts1, isin = "Train")
# df2 = data.frame(time = seq(length, length + testLength, length=testLength), M = tsTest$ts1, isin = "Test")
# df3 = data.frame(time = seq(length, length + testLength, length=testLength), M = pred$pred[,1], isin = "Predicted")
# df4 = data.frame(time = (length+1):(length+testLength), M = upperConf[,1], isin = "Upper Bound")
```



```

# df5 = data.frame(time = (length+1):(length + testLength), M = lowerConf[,1], isin = "Lower Bound")
# df = rbind(df1, df3)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts1 Bounds and")
# df = rbind(df1, df2, df3)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("without for ts1 Prediction Bounds")
# df = rbind(df1, df2, df3, df4, df5)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("without for ts1 with Bounds")
#
# df1 = data.frame(time = seq(drawStart, length, length=length), M = ts$ts2, isin = "Train")
# df2 = data.frame(time = seq(length, length + testLength, length=testLength), M = tsTest$ts2, isin = "Test")
# df3 = data.frame(time = seq(length, length + testLength, length=testLength), M = pred$pred[,2], isin = "Upper Bound")
# df4 = data.frame(time = (length+1):(length+testLength), M = upperConf[,2], isin = "Upper Bound")
# df5 = data.frame(time = (length+1):(length + testLength), M = lowerConf[,2], isin = "Lower Bound")
# df = rbind(df1, df3)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted for ts1 without Bounds")
# df = rbind(df1, df2, df3)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts1 without Bounds")
# df = rbind(df1, df2, df3, df4, df5)
# ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts1 with Bounds")

```

## MAE

```

# mean(abs(tsTest$ts1 - pred$pred[,1]))
# mean(abs(tsTest$ts2 - pred$pred[,2]))

```

## MSE

```

# mean((tsTest$ts1 - pred$pred[,1])*(tsTest$ts1 - pred$pred[,1]))
# mean((tsTest$ts2 - pred$pred[,2])*(tsTest$ts2 - pred$pred[,2]))

```