

VarLinearExample

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Libraries

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

Data Generation

$$z_{1,t} = 0.8z_{1,t-1} + 0.6z_{2,t-1} + 0.1t + \epsilon_{1,t} + 0.12\epsilon_{1,t-1}$$

$$z_{2,t} = 0.2z_{1,t-1} + 0.3z_{2,t-1} + \epsilon_{2,t} + 0.1\epsilon_{1,t-1} + 0.025\epsilon_{2,t-1}$$

$$z_t = \begin{pmatrix} 0.1 \\ 0 \end{pmatrix} t + \begin{pmatrix} 0.8 & 0.6 \\ 0.2 & 0.3 \end{pmatrix} z_{t-1} + \epsilon_t + \begin{pmatrix} 0.12 & 0 \\ 0.1 & 0.025 \end{pmatrix} \epsilon_{t-1}$$

```
set.seed(6)
skip = 10
length = 100
testLength = 20
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] = 0.8*ts1[t-1] + 0.6*ts2[t-1] + 0.1*t + noise1[t] + 0.12*noise1[t-1]
  ts2[t] = 0.2*ts1[t-1] + 0.3*ts2[t-1] + noise2[t] + 0.1*noise1[t-1] + 0.025*noise2[t-1]
}
```

```

# 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)]

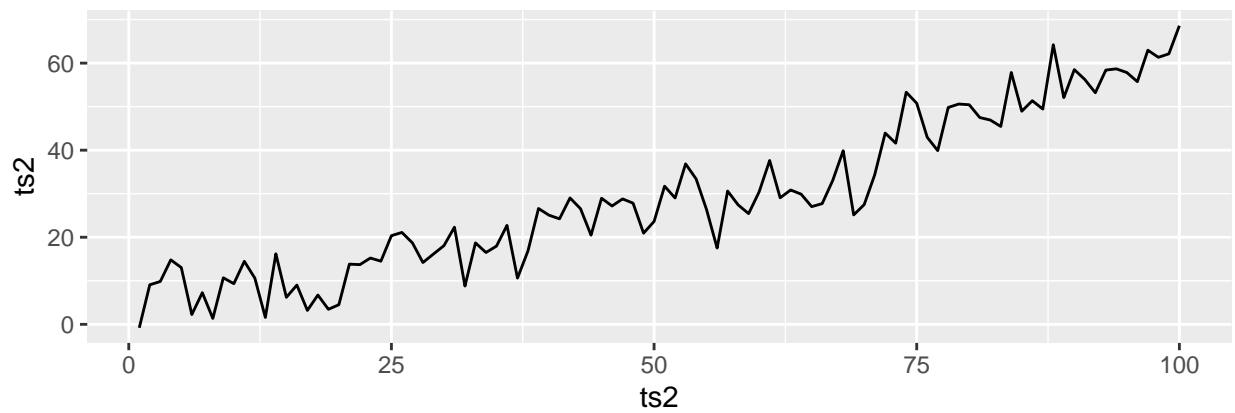
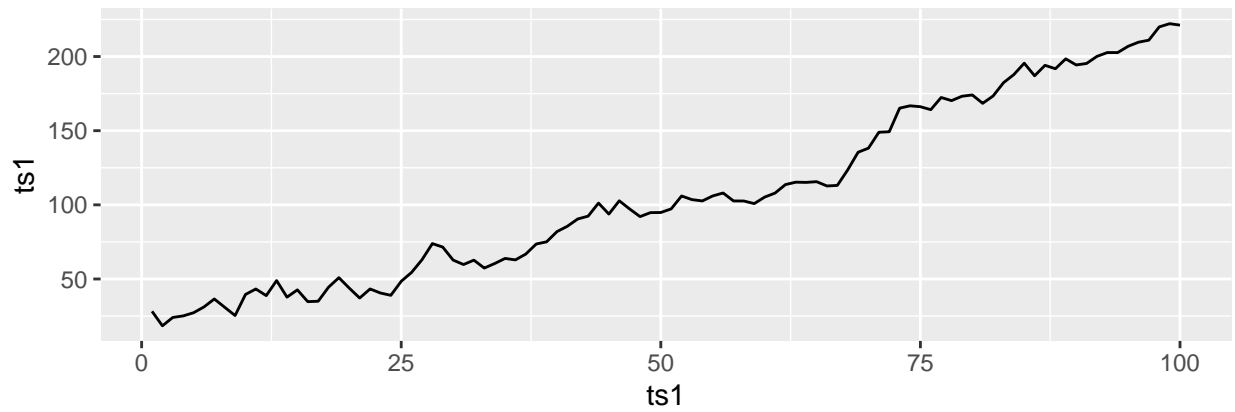
# Turns them into a time series object
ts = as_tibble(ts1)
ts = rename(ts, "ts1" = "value")
ts[,2] = ts2
ts = rename(ts, "ts2" = "...2")
ts[,3] = 1:length
ts = rename(ts, "index" = "...3")

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")

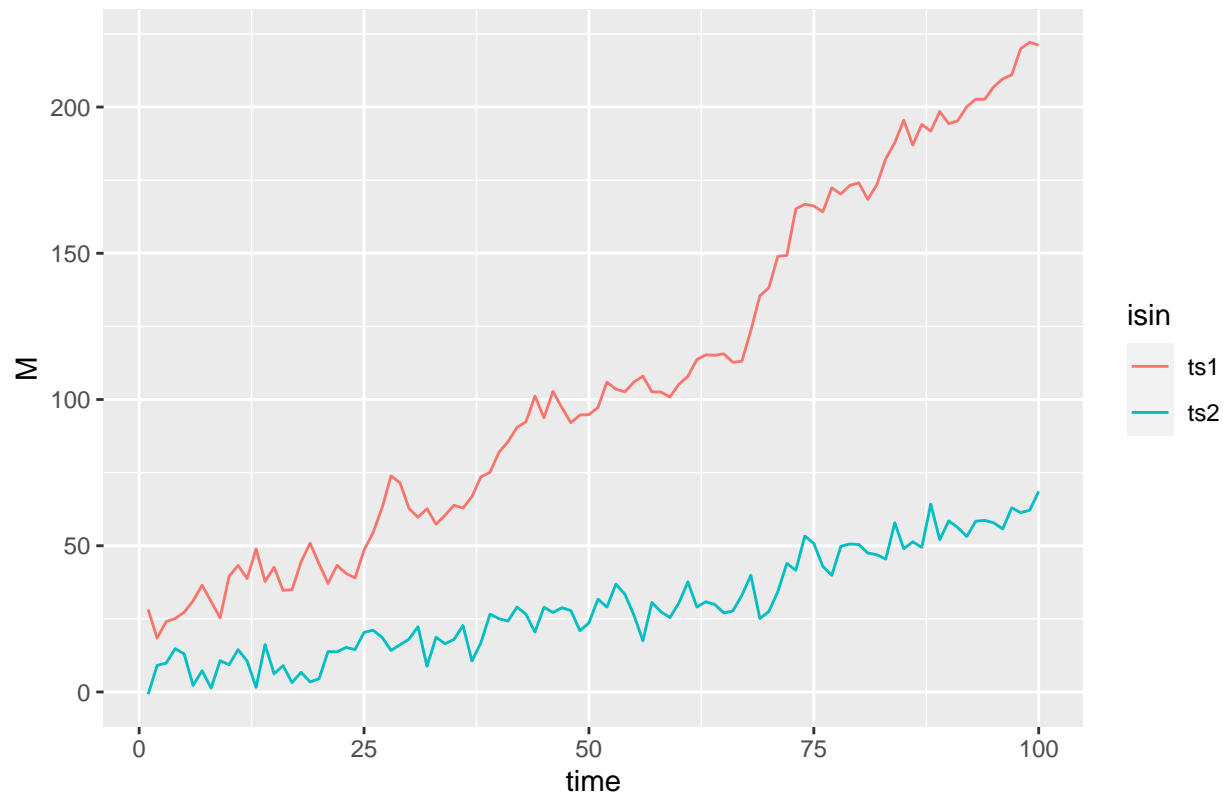
plot1 = ts %>% autoplot(ts1) + xlab("ts1")
plot2 = ts %>% autoplot(ts2) + xlab("ts2")
grid.arrange(plot1, plot2, nrow=2)

```



```
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")
```

ts1 and ts2



Differencing

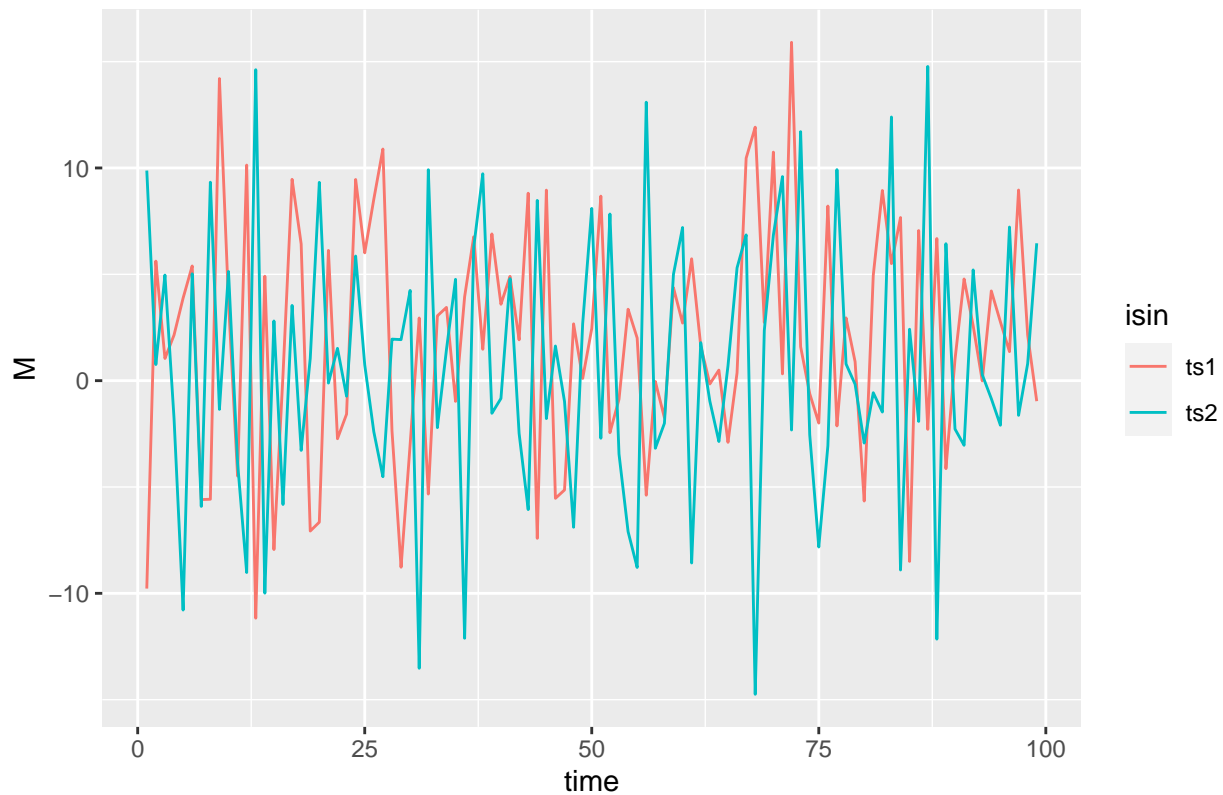
We are going to take the change between consecutive observations

$$y'_t = y_t - y_{t-1}$$

```
# Takes a lagged difference of 1
tsDiff = ts %>% diffM()
tsDiff[,3] = 1:(length-1)
tsDiff = tsDiff %>% as_tibble()
tsDiff = tsDiff %>% as_tsibble(index = "index")

df1 = data.frame(time = tsDiff$index, M = tsDiff$ts1, isin = "ts1")
df2 = data.frame(time = tsDiff$index, M = tsDiff$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



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

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

```
##
```

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

```
##
```

```
## data: tsDiff$ts1
```

```
## KPSS Level = 0.18727, Truncation lag parameter = 3, p-value = 0.1
```

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

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

```
##
```

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

```
##
```

```
## data: tsDiff$ts2
```

```
## KPSS Level = 0.049913, Truncation lag parameter = 3, p-value = 0.1
```

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

```
## selected order: aic = 5
```

```
## selected order: bic = 1
```

```
## selected order: hq = 2
```

```
## Summary table:
```

```
##      p    AIC    BIC    HQ    M(p) p-value
## [1,] 0 6.8313 6.8313 6.8313 0.0000 0.0000
## [2,] 1 6.6063 6.7112 6.6488 25.2281 0.0000
```

```
## [3,] 2 6.5534 6.7631 6.6382 10.7684 0.0293
## [4,] 3 6.5594 6.8739 6.6867 5.8722 0.2089
## [5,] 4 6.6225 7.0419 6.7921 1.3566 0.8517
## [6,] 5 6.5477 7.0719 6.7598 11.5914 0.0207
## [7,] 6 6.5624 7.1916 6.8170 4.7874 0.3098
## [8,] 7 6.6232 7.3572 6.9202 1.4128 0.8420
## [9,] 8 6.6631 7.5019 7.0025 2.8018 0.5915
## [10,] 9 6.6954 7.6391 7.0773 3.2241 0.5211
## [11,] 10 6.7526 7.8011 7.1768 1.5273 0.8218
## [12,] 11 6.6978 7.8512 7.1645 8.4738 0.0757
## [13,] 12 6.7360 7.9942 7.2451 2.5793 0.6305
## [14,] 13 6.7792 8.1422 7.3307 2.2016 0.6987
```

Fitting the model

$$z_t = \begin{pmatrix} 2.06 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 & 0.32 \\ 0.35 & -0.42 \end{pmatrix} z_{t-1} + \begin{pmatrix} -0.10 & 0 \\ 0 & -0.29 \end{pmatrix} z_{t-2} + a_t$$

```
# Does LS estimation of the model
```

```
m1 = VAR(tsDiff[, -3], 2)
```

```
## Constant term:
## Estimates: 2.025321 0.5879369
## Std.Error: 0.6184937 0.6496756
## AR coefficient matrix
## AR( 1 )-matrix
##      [,1] [,2]
## [1,] -0.0169 0.339
## [2,] 0.3315 -0.411
## standard error
##      [,1] [,2]
## [1,] 0.107 0.0972
## [2,] 0.112 0.1021
## AR( 2 )-matrix
##      [,1] [,2]
## [1,] -0.0882 0.0493
## [2,] -0.1230 -0.3291
## standard error
##      [,1] [,2]
## [1,] 0.104 0.0979
## [2,] 0.110 0.1029
##
## Residuals cov-mtx:
##      [,1] [,2]
## [1,] 26.084401 -7.081758
## [2,] -7.081758 28.780833
##
## det(SSE) = 700.5795
## AIC = 6.713524
## BIC = 6.923231
## HQ = 6.798372
```

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

```
## Constant term:
## Estimates: 2.05642 0
```

```
## Std.Error: 0.5594857 0
## AR coefficient matrix
## AR( 1 )-matrix
##      [,1] [,2]
## [1,] 0.00 0.328
## [2,] 0.35 -0.422
## standard error
##      [,1] [,2]
## [1,] 0.000 0.0881
## [2,] 0.104 0.0973
## AR( 2 )-matrix
##      [,1] [,2]
## [1,] -0.103 0.000
## [2,] 0.000 -0.294
## standard error
##      [,1] [,2]
## [1,] 0.0993 0.0000
## [2,] 0.0000 0.0984
##
## Residuals cov-mtx:
##      [,1] [,2]
## [1,] 26.156572 -7.129567
## [2,] -7.129567 29.275139
##
## det(SSE) = 714.9066
## AIC = 6.673162
## BIC = 6.804229
## HQ = 6.726192
```

Model Checking

Multivariate Portmanteau Statistics

Let R_ℓ be the theoretical lag ℓ cross-correlation matrix of innovation a_t

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

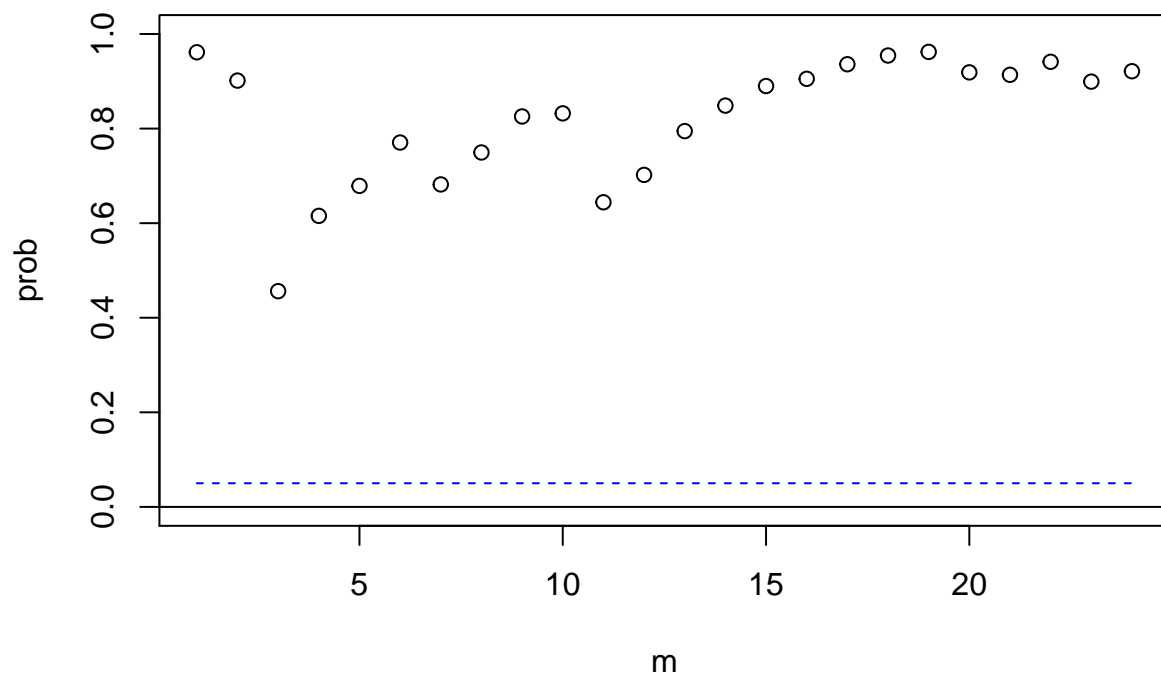
$H_A: R_j \neq 0$ for some $1 \leq j \leq m$

```
mq(m1R$residuals)
```

```
## Ljung-Box Statistics:
##      m      Q(m)    df    p-value
## [1,] 1.000    0.615   4.000    0.96
## [2,] 2.000    3.470   8.000    0.90
## [3,] 3.000   11.869  12.000    0.46
## [4,] 4.000   13.775  16.000    0.62
## [5,] 5.000   16.598  20.000    0.68
## [6,] 6.000   18.647  24.000    0.77
## [7,] 7.000   23.993  28.000    0.68
## [8,] 8.000   26.316  32.000    0.75
## [9,] 9.000   28.043  36.000    0.83
## [10,] 10.000  31.412  40.000    0.83
## [11,] 11.000  39.988  44.000    0.64
## [12,] 12.000  42.365  48.000    0.70
## [13,] 13.000  43.451  52.000    0.79
```

##	[14,]	14.000	45.201	56.000	0.85
##	[15,]	15.000	46.968	60.000	0.89
##	[16,]	16.000	49.704	64.000	0.91
##	[17,]	17.000	51.191	68.000	0.94
##	[18,]	18.000	53.017	72.000	0.95
##	[19,]	19.000	55.592	76.000	0.96
##	[20,]	20.000	63.017	80.000	0.92
##	[21,]	21.000	66.953	84.000	0.91
##	[22,]	22.000	68.259	88.000	0.94
##	[23,]	23.000	75.149	92.000	0.90
##	[24,]	24.000	77.132	96.000	0.92

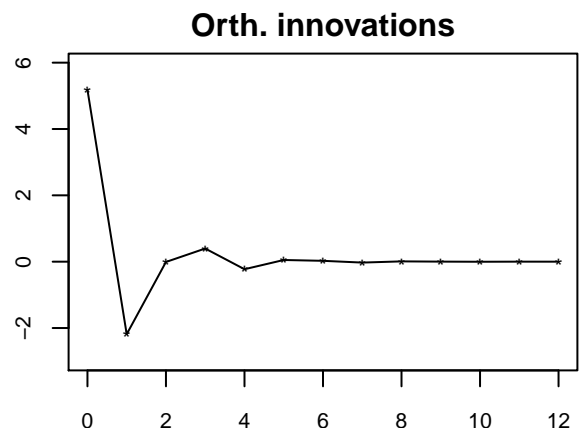
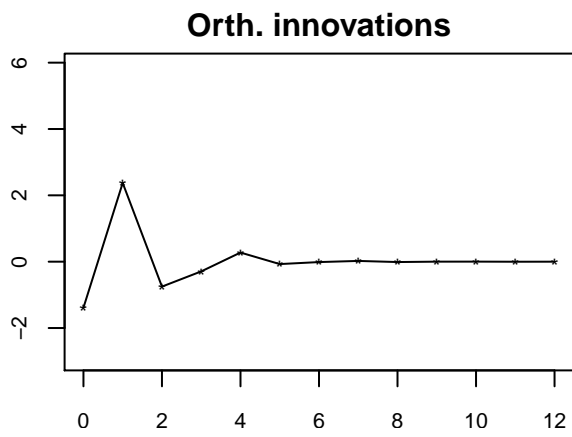
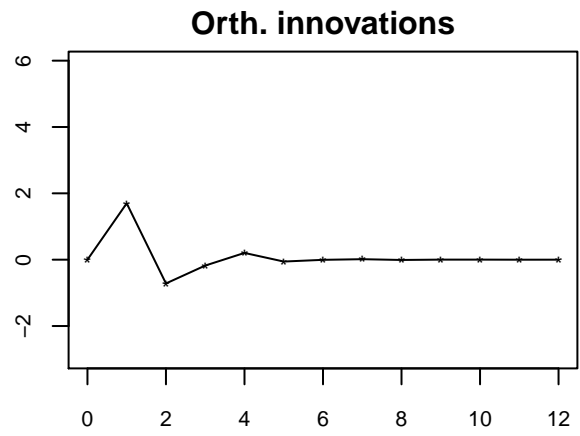
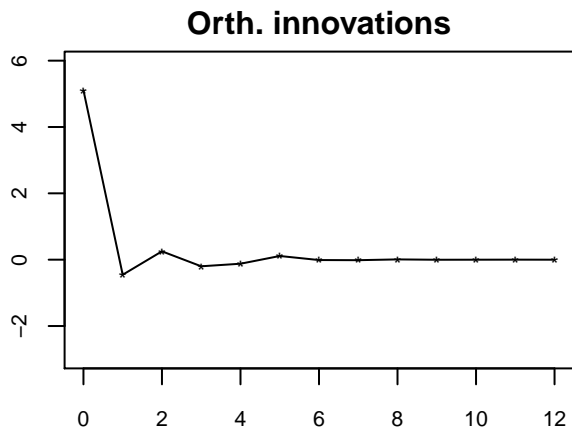
p-values of Ljung-Box statistics



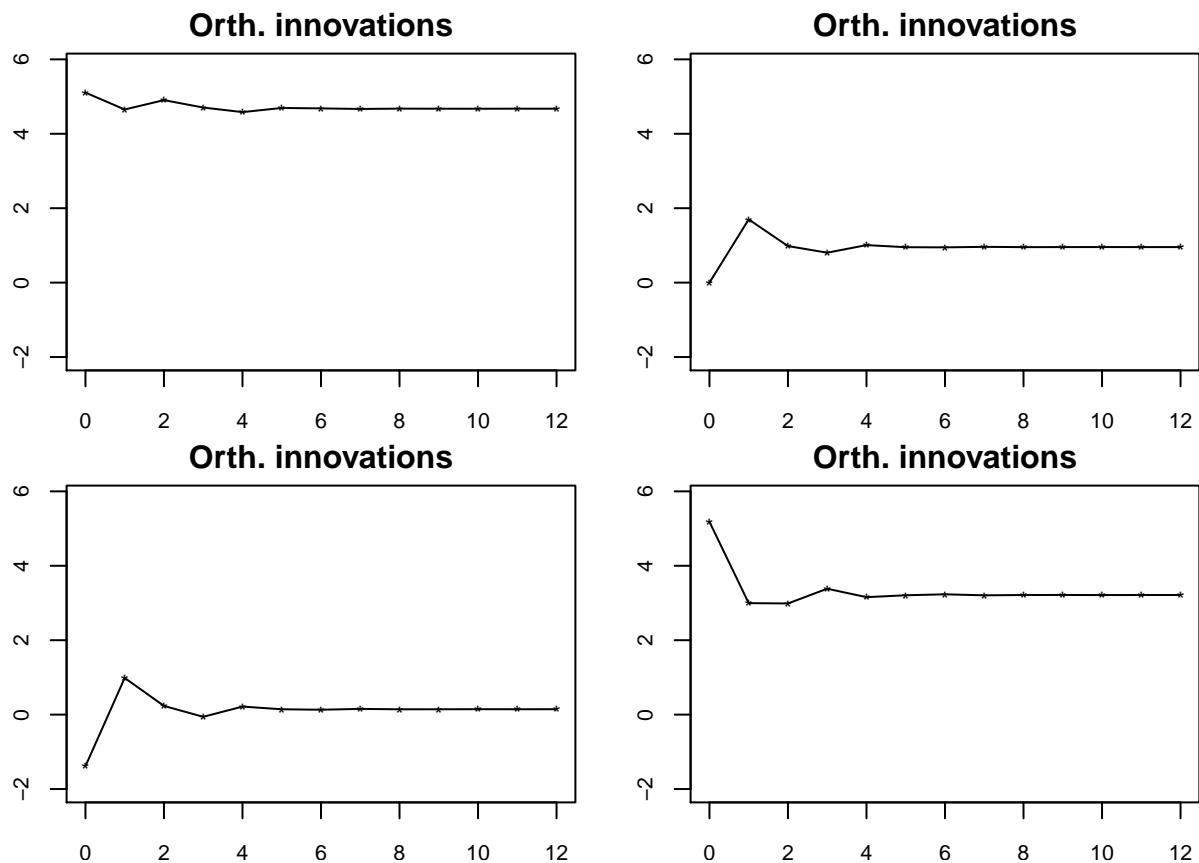
Impulse

The first graph is the impulse response, while the second is accumulated response.

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

Press return to continue



Model Forecasting

```
pred = VARpred(m1R, h = testLength)
```

```
## orig 99
## Forecasts at origin: 99
##      ts1      ts2
## [1,] 3.952 -3.298648
## [2,] 1.074  0.873148
## [3,] 1.936  0.978617
## [4,] 2.267  0.007245
## [5,] 1.859  0.501876
## [6,] 1.988  0.436695
## [7,] 2.008  0.363385
## [8,] 1.971  0.420701
## [9,] 1.988  0.405076
## [10,] 1.986  0.400628
## [11,] 1.983  0.406654
## [12,] 1.985  0.404310
## [13,] 1.985  0.404263
## [14,] 1.984  0.404818
## [15,] 1.985  0.404516
## [16,] 1.985  0.404560
## [17,] 1.985  0.404604
## [18,] 1.985  0.404569
## [19,] 1.985  0.404579
```

```

## [20,] 1.985 0.404581
## Standard Errors of predictions:
##      [,1] [,2]
## [1,] 5.114 5.411
## [2,] 5.413 6.308
## [3,] 5.467 6.353
## [4,] 5.474 6.372
## [5,] 5.479 6.383
## [6,] 5.480 6.383
## [7,] 5.480 6.383
## [8,] 5.480 6.383
## [9,] 5.480 6.383
## [10,] 5.480 6.383
## [11,] 5.480 6.383
## [12,] 5.480 6.383
## [13,] 5.480 6.383
## [14,] 5.480 6.383
## [15,] 5.480 6.383
## [16,] 5.480 6.383
## [17,] 5.480 6.383
## [18,] 5.480 6.383
## [19,] 5.480 6.383
## [20,] 5.480 6.383
## Root mean square errors of predictions:
##      [,1] [,2]
## [1,] 5.242 5.546
## [2,] 5.835 7.462
## [3,] 5.547 6.420
## [4,] 5.484 6.402
## [5,] 5.487 6.398
## [6,] 5.482 6.384
## [7,] 5.480 6.383
## [8,] 5.480 6.383
## [9,] 5.480 6.383
## [10,] 5.480 6.383
## [11,] 5.480 6.383
## [12,] 5.480 6.383
## [13,] 5.480 6.383
## [14,] 5.480 6.383
## [15,] 5.480 6.383
## [16,] 5.480 6.383
## [17,] 5.480 6.383
## [18,] 5.480 6.383
## [19,] 5.480 6.383
## [20,] 5.480 6.383

# Calculates the confidence interval
upperConfDiff = pred$pred + 1.96 * pred$se.err
lowerConfDiff = pred$pred - 1.96 * pred$se.err

testDiff = tsTest %>% diffM()
testDiff[,3] = 1:(testLength-1)
testDiff = testDiff %>% as_tibble()
testDiff = testDiff %>% as_tsibble(index = "index")

```

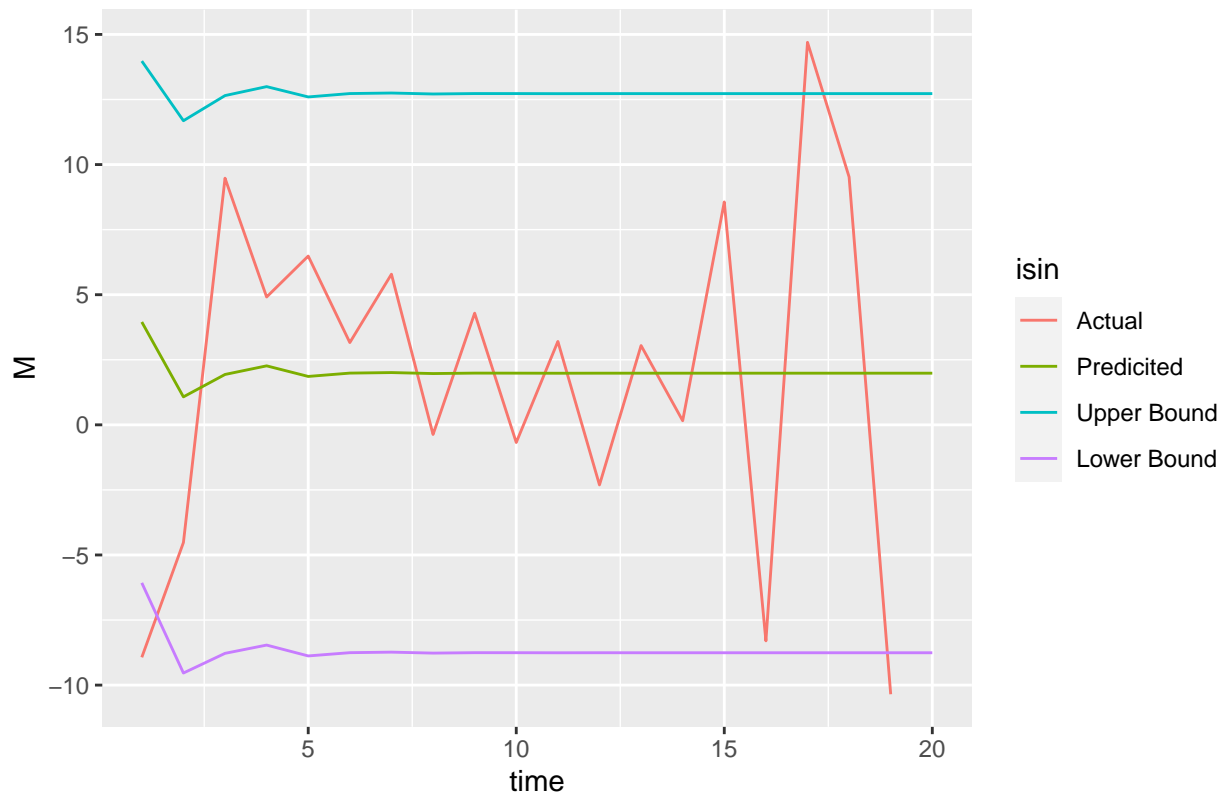
```

tsPredDiff = as_tibble(pred$pred[,1])
tsPredDiff = rename(tsPredDiff, "ts1" = "value")
tsPredDiff[,2] = pred$pred[,2]
tsPredDiff = rename(tsPredDiff, "ts2" = "...2")
tsPredDiff[,3] = 1:testLength
tsPredDiff = rename(tsPredDiff, "index" = "...3")
tsPredDiff = tsPredDiff %>% as_tsibble(index = "index")

df1 = data.frame(time = testDiff$index, M = testDiff$ts1, isin = "Actual")
df2 = data.frame(time = tsPredDiff$index, M = tsPredDiff$ts1, isin = "Predicited")
df3 = data.frame(time = 1:testLength, M = upperConfDiff[,1], isin = "Upper Bound")
df4 = data.frame(time = 1:testLength, M = lowerConfDiff[,1], isin = "Lower Bound")
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicited of Differenced Values")

```

Predicited of Differenced Values for ts1

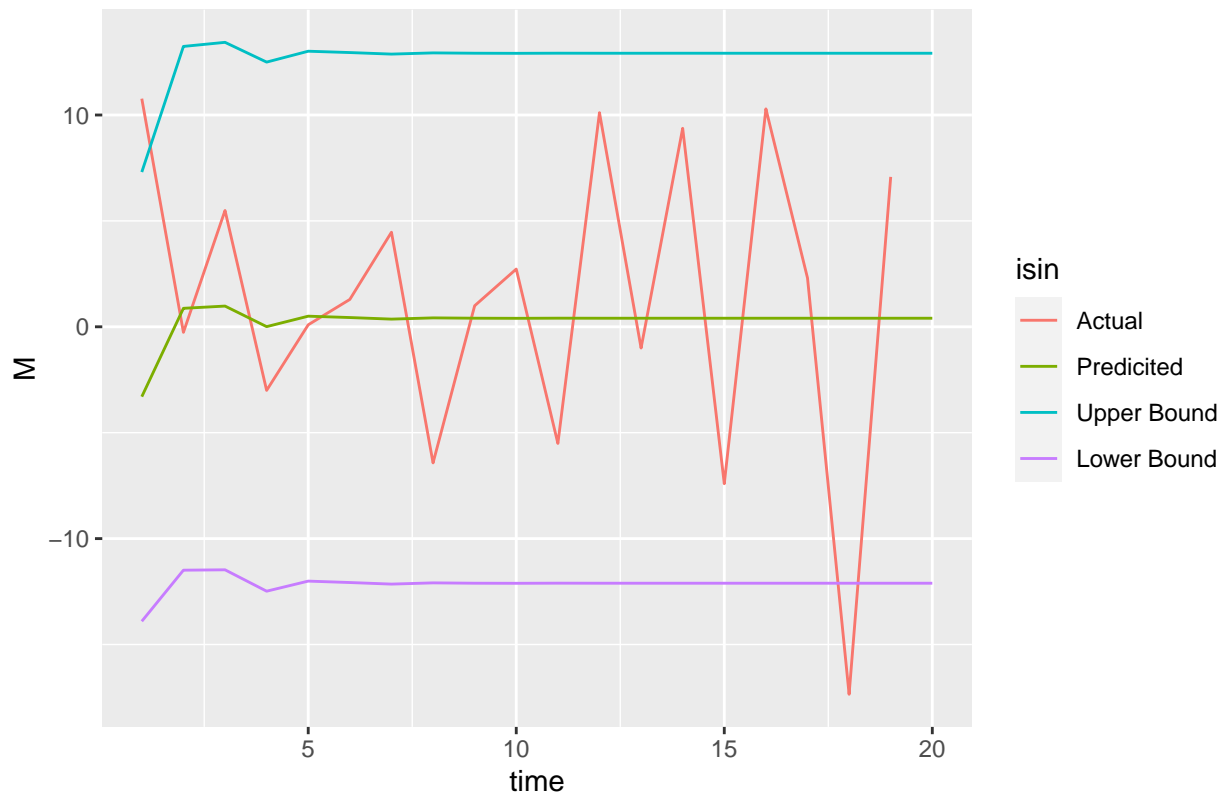


```

df1 = data.frame(time = testDiff$index, M = testDiff$ts2, isin = "Actual")
df2 = data.frame(time = tsPredDiff$index, M = tsPredDiff$ts2, isin = "Predicited")
df3 = data.frame(time = 1:testLength, M = upperConfDiff[,2], isin = "Upper Bound")
df4 = data.frame(time = 1:testLength, M = lowerConfDiff[,2], isin = "Lower Bound")
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicited of Differenced Values")

```

Predicted of Differenced Values for ts2



Inverting the Differencing

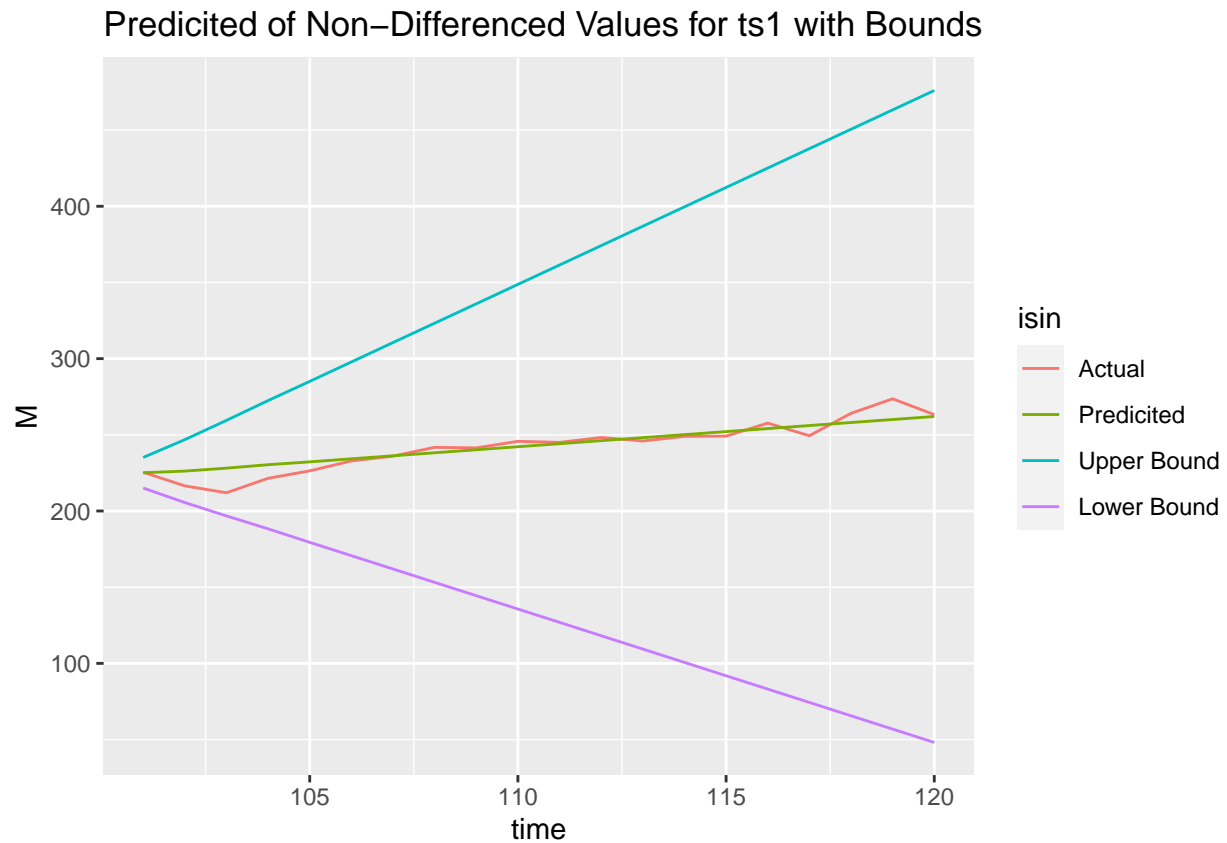
$$y_t = \sum_{i=1}^t y_i' + y_0$$

```
# Accumulates all of the transformed values
tsPred = tsPredDiff[,-3] %>% cumsum() %>% as_tibble()
upperConf = matrix(nrow = testLength, ncol = 2)
upperConf[,1] = upperConfDiff[,1] %>% cumsum()
upperConf[,2] = upperConfDiff[,2] %>% cumsum()
lowerConf = matrix(nrow = testLength, ncol = 2)
lowerConf[,1] = lowerConfDiff[,1] %>% cumsum()
lowerConf[,2] = lowerConfDiff[,2] %>% cumsum()

# Adds the intercepts
tsPred$ts1 = tsPred$ts1 + ts$ts1[length]
tsPred$ts2 = tsPred$ts2 + ts$ts2[length]
tsPred[,3] = (length + 1):(length + testLength)
tsPred = rename(tsPred, "index" = "...3")
tsPred = tsPred %>% as_tibble(index = "index")
upperConf[,1] = upperConf[,1] + ts$ts1[length]
upperConf[,2] = upperConf[,2] + ts$ts2[length]
lowerConf[,1] = lowerConf[,1] + ts$ts1[length]
lowerConf[,2] = lowerConf[,2] + ts$ts2[length]

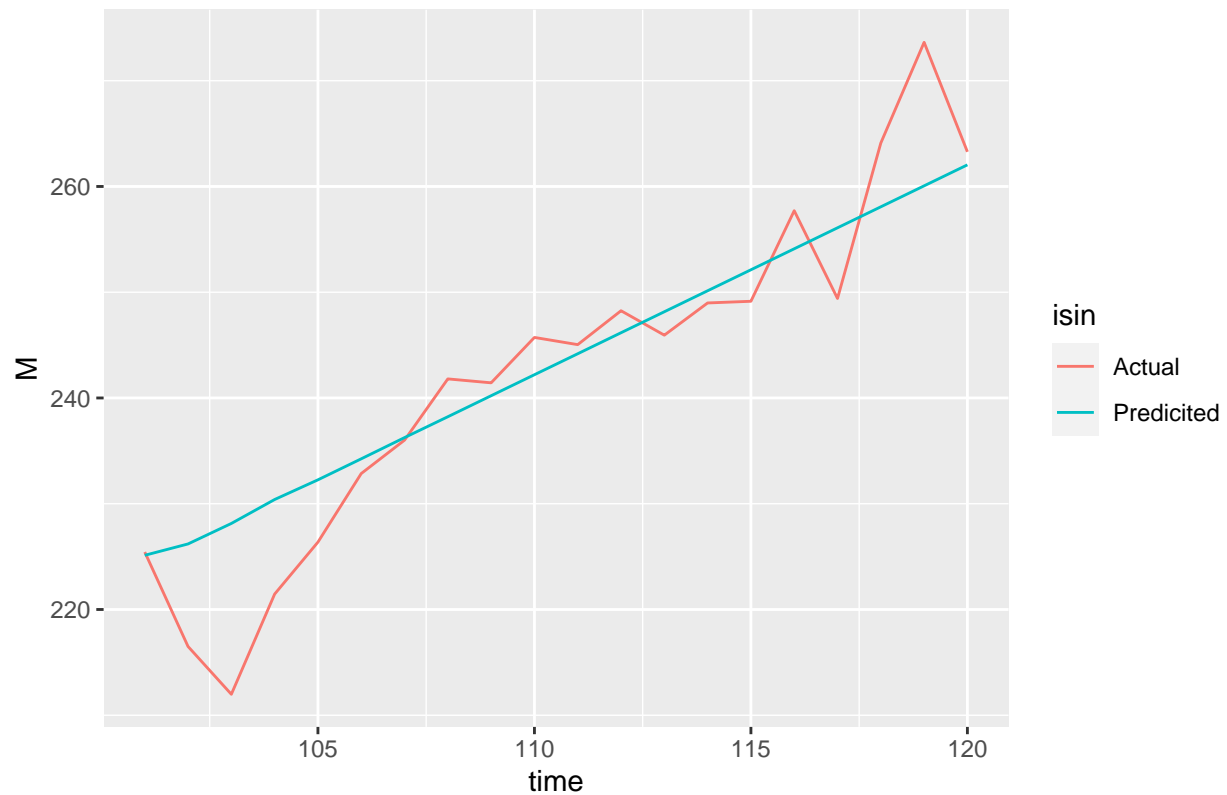
df1 = data.frame(time = tsTest$index, M = tsTest$ts1, isin = "Actual")
df2 = data.frame(time = tsPred$index, M = tsPred$ts1, isin = "Predicted")
```

```
df3 = data.frame(time = (length+1):(length+testLength), M = upperConf[,1], isin = "Upper Bound")
df4 = data.frame(time = (length+1):(length + testLength), M = lowerConf[,1], isin = "Lower Bound")
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicited of Non-Differenced V
```



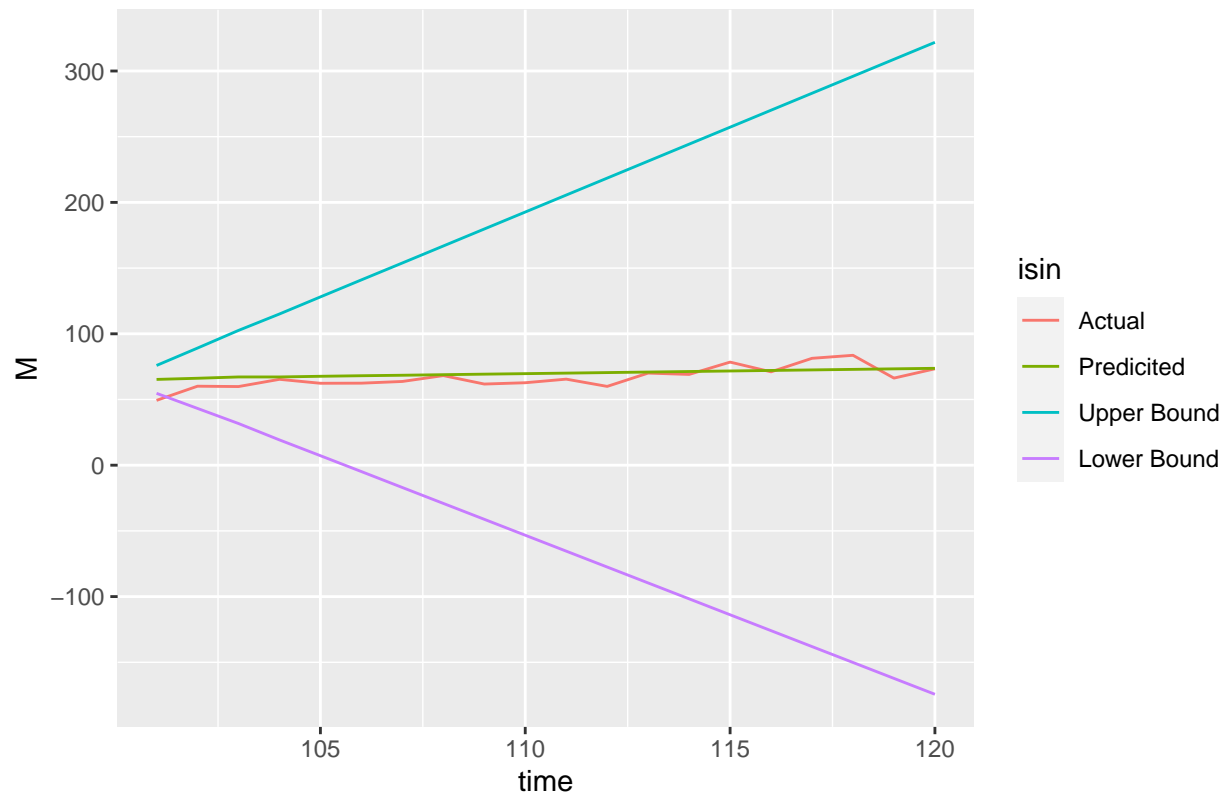
```
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicited of Non-Differenced V
```

Predicited of Non-Differenced Values for ts1 without Bounds



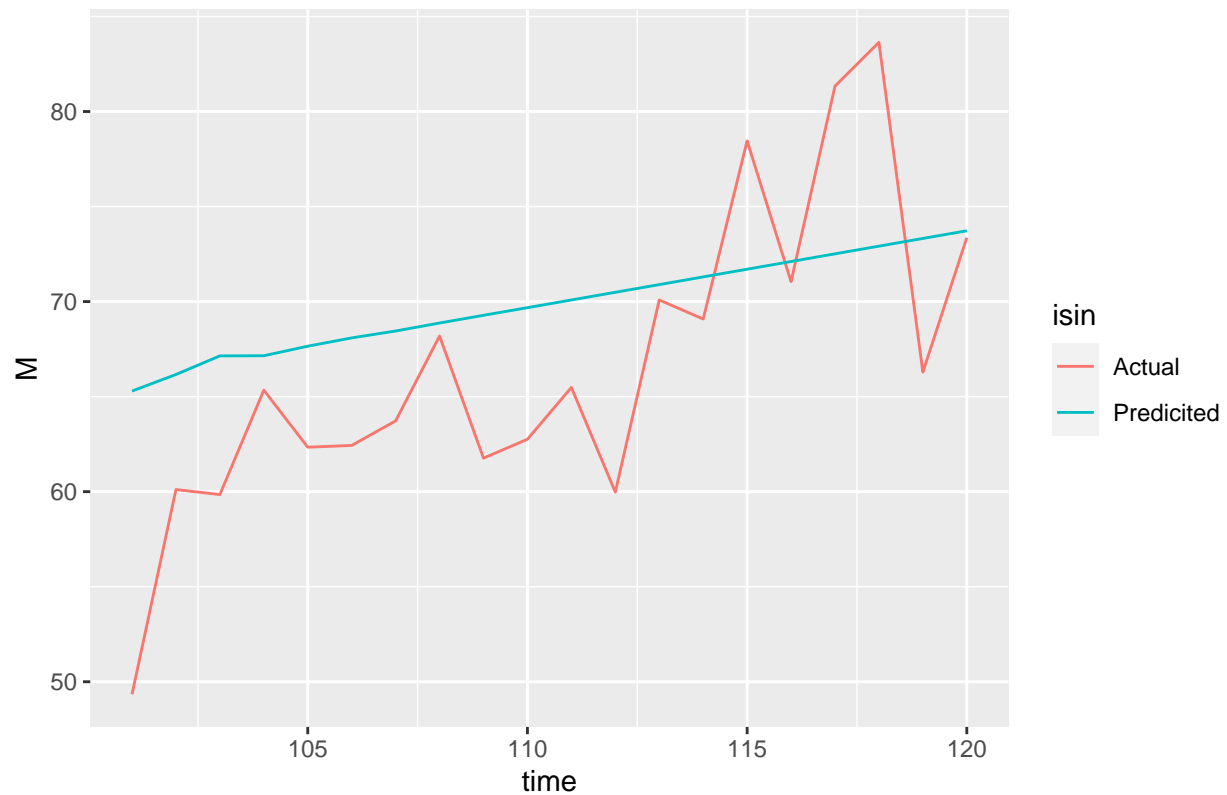
```
df1 = data.frame(time = tsTest$index, M = tsTest$ts2, isin = "Actual")
df2 = data.frame(time = tsPred$index, M = tsPred$ts2, isin = "Predicted")
df3 = data.frame(time = (length+1):(length+testLength), M = upperConf[,2], isin = "Upper Bound")
df4 = data.frame(time = (length+1):(length + testLength), M = lowerConf[,2], isin = "Lower Bound")
df = rbind(df1, df2, df3, df4)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicited of Non-Differenced V
```

Predicted of Non-Differenced Values for ts2 with Bounds



```
df = rbind(df1, df2)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Predicted of Non-Differenced V
```

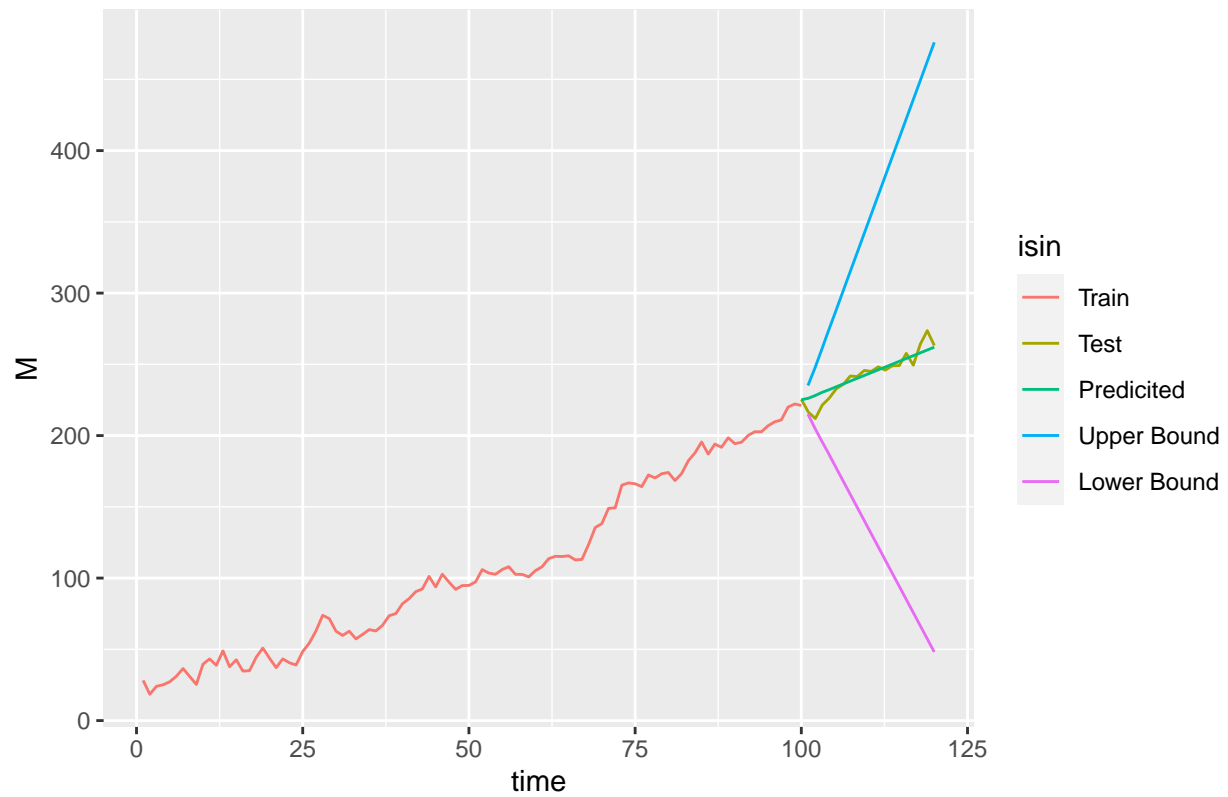

Predicted of Non-Differenced Values for ts2 without Bounds



```
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 = tsPred$ts1, isin = "Prediction")
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, df2, df3, df4, df5)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts1 with Bounds")
```

Prediction for ts1 with Bounds

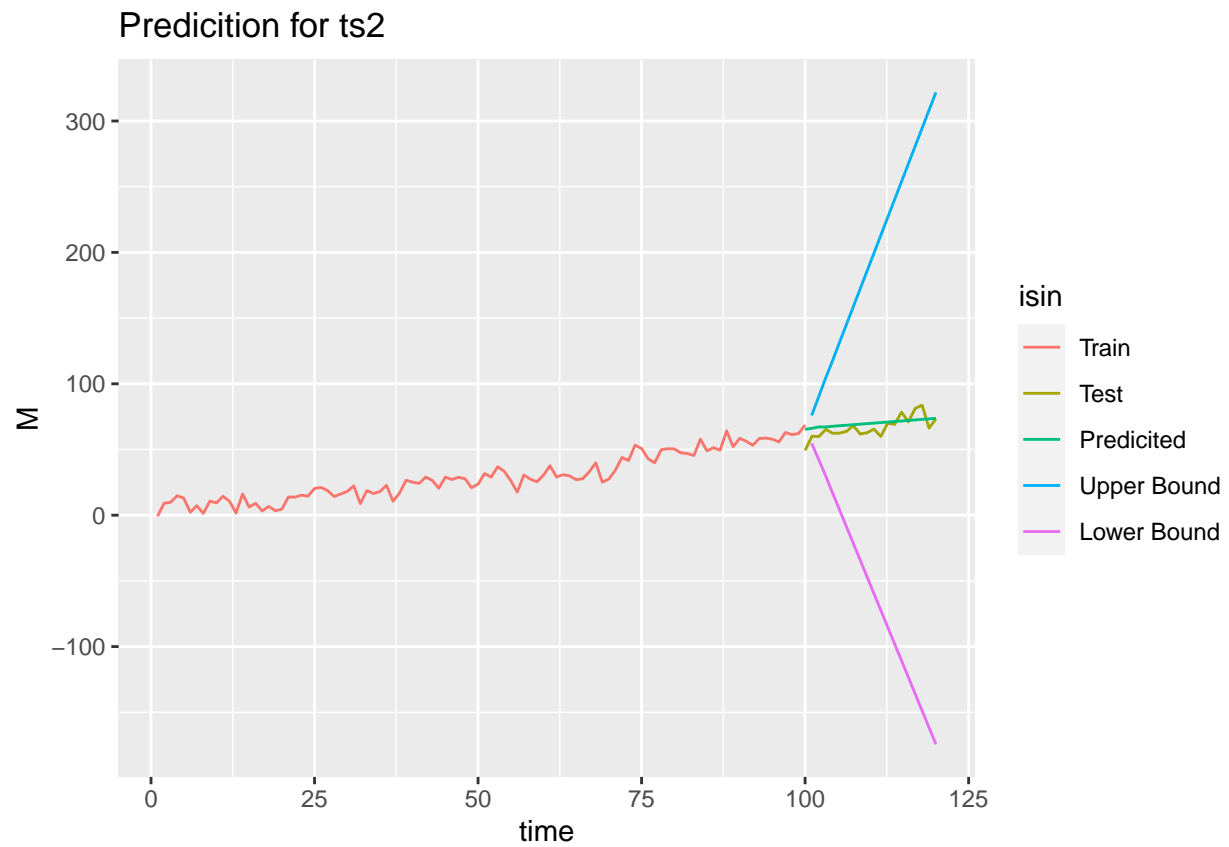


```
df = rbind(df1, df2, df3)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts1 without Bounds")
```

Prediction for ts1 witout Bounds

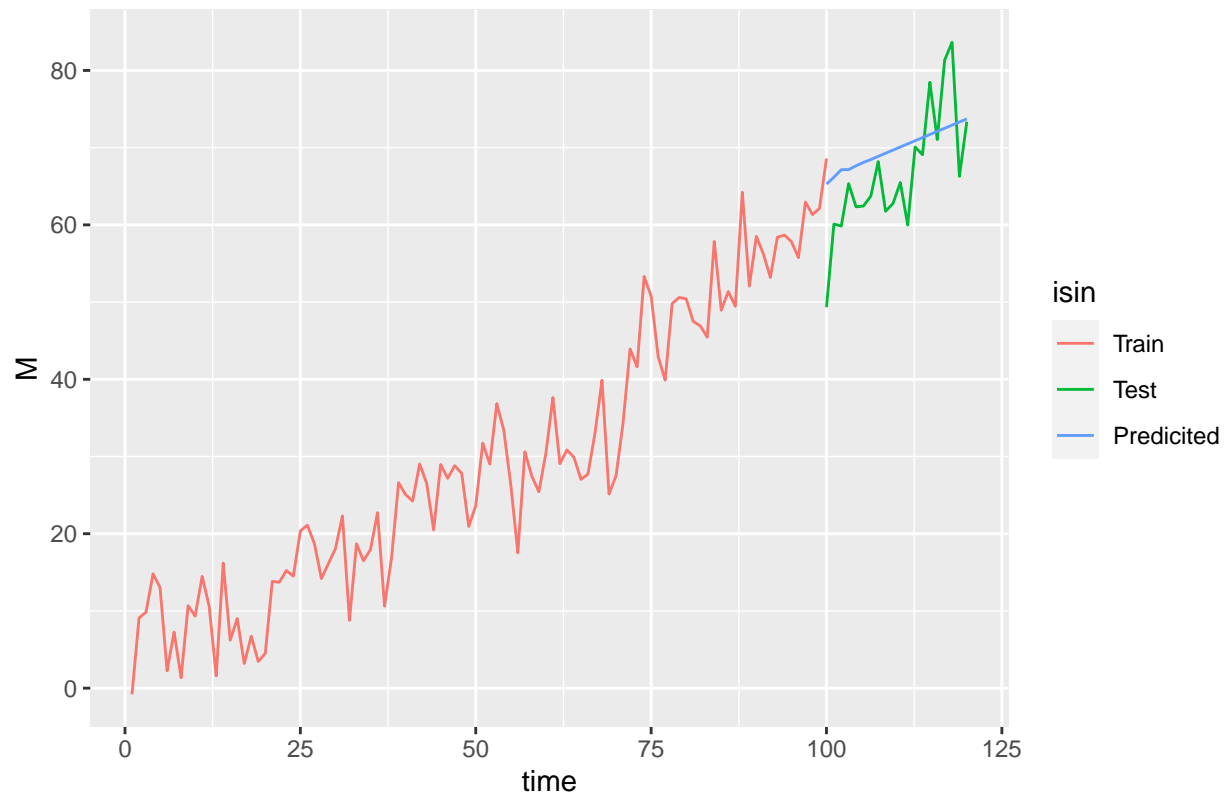


```
df1 = data.frame(time = seq(drawStart, length, length=length), M = ts$ts2, isin = "Train")
df2 = data.frame(time = seq(length, length + testLength, length=testLength), M = tsTest$ts2, isin = "Test")
df3 = data.frame(time = seq(length, length + testLength, length=testLength), M = tsPred$ts2, isin = "Predicted")
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, df2, df3, df4, df5)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts2")
```



```
df = rbind(df1, df2, df3)
ggplot(df, aes(x = time, y = M, color = isin)) + geom_line() + ggtitle("Prediction for ts2 without Bound")
```

Prediction for ts2 witout Bounds



MAE

```
mean(abs(tsTest$ts1 - tsPred$ts1))
```

```
## [1] 4.567337
```

```
mean(abs(tsTest$ts2 - tsPred$ts2))
```

```
## [1] 5.741117
```

MSE

```
mean((tsTest$ts1 - tsPred$ts1)*(tsTest$ts1 - tsPred$ts1))
```

```
## [1] 39.9089
```

```
mean((tsTest$ts2 - tsPred$ts2)*(tsTest$ts2 - tsPred$ts2))
```

```
## [1] 48.07554
```