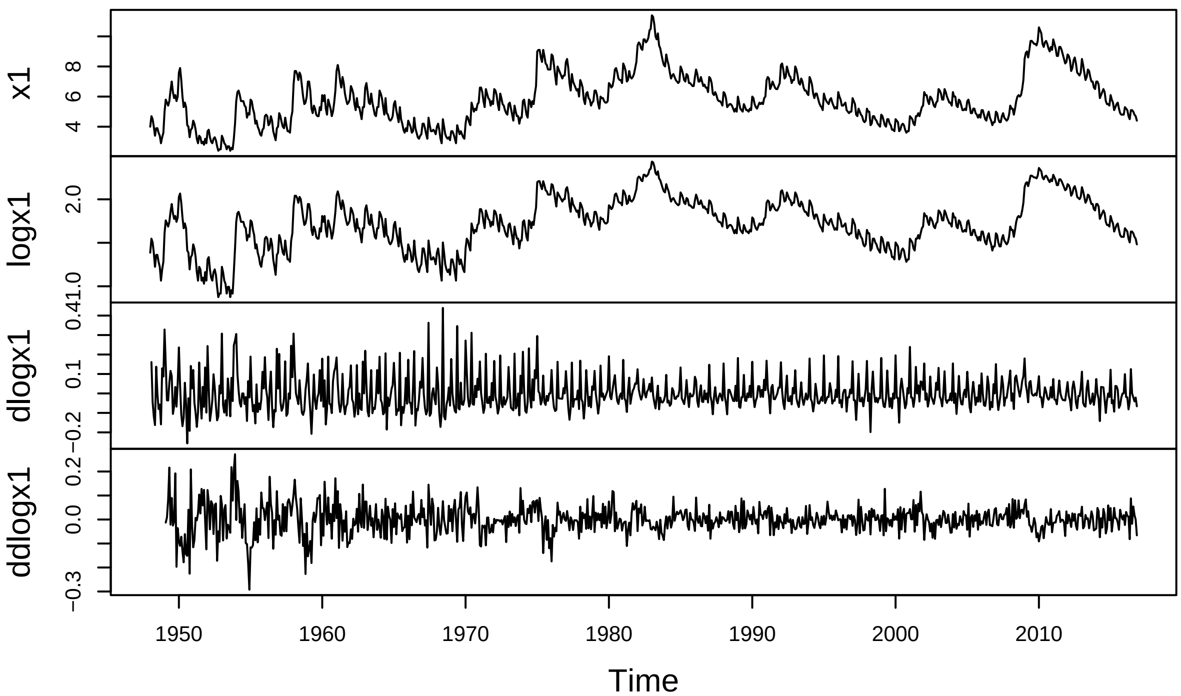
Homework 3

Alex Wako

2023-02-21

1

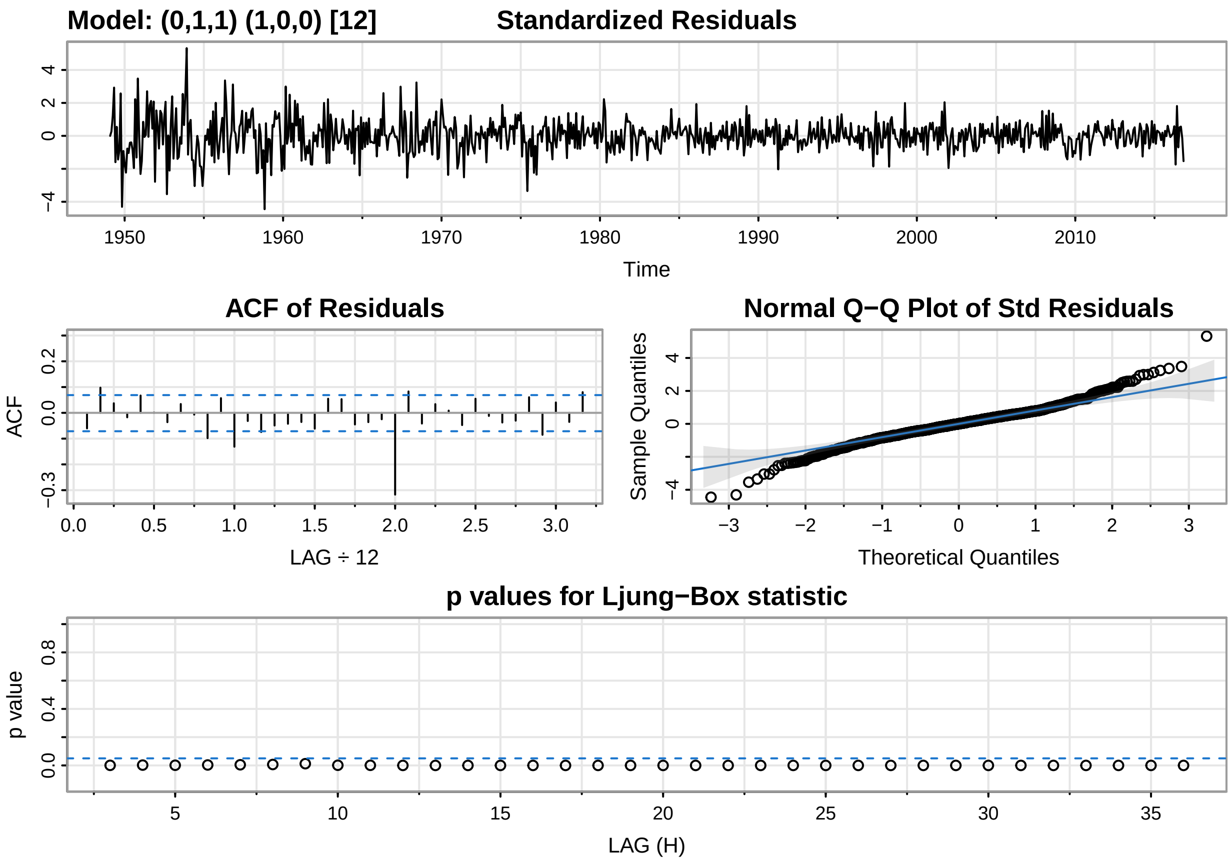
```
x1 = UnempRate
logx1 = log(x1)
dlogx1 = diff(logx1)
ddlogx1 = diff(dlogx1, 12)
plot.ts(cbind(x1, logx1, dlogx1, ddlogx1), main = "")
```




```
sarima(ddlogx1, 0, 1, 1, 1, 0, 0, 12)  # The Seasonal ARIMA model
```

```
## initial  value -2.558221
## iter   2 value -2.938052
## iter   3 value -2.963814
## iter   4 value -2.977279
## iter   5 value -2.977581
## iter   6 value -2.981767
## iter   7 value -2.983573
## iter   8 value -2.984825
## iter   9 value -2.985008
## iter  10 value -2.985039
## iter  11 value -2.985050
```

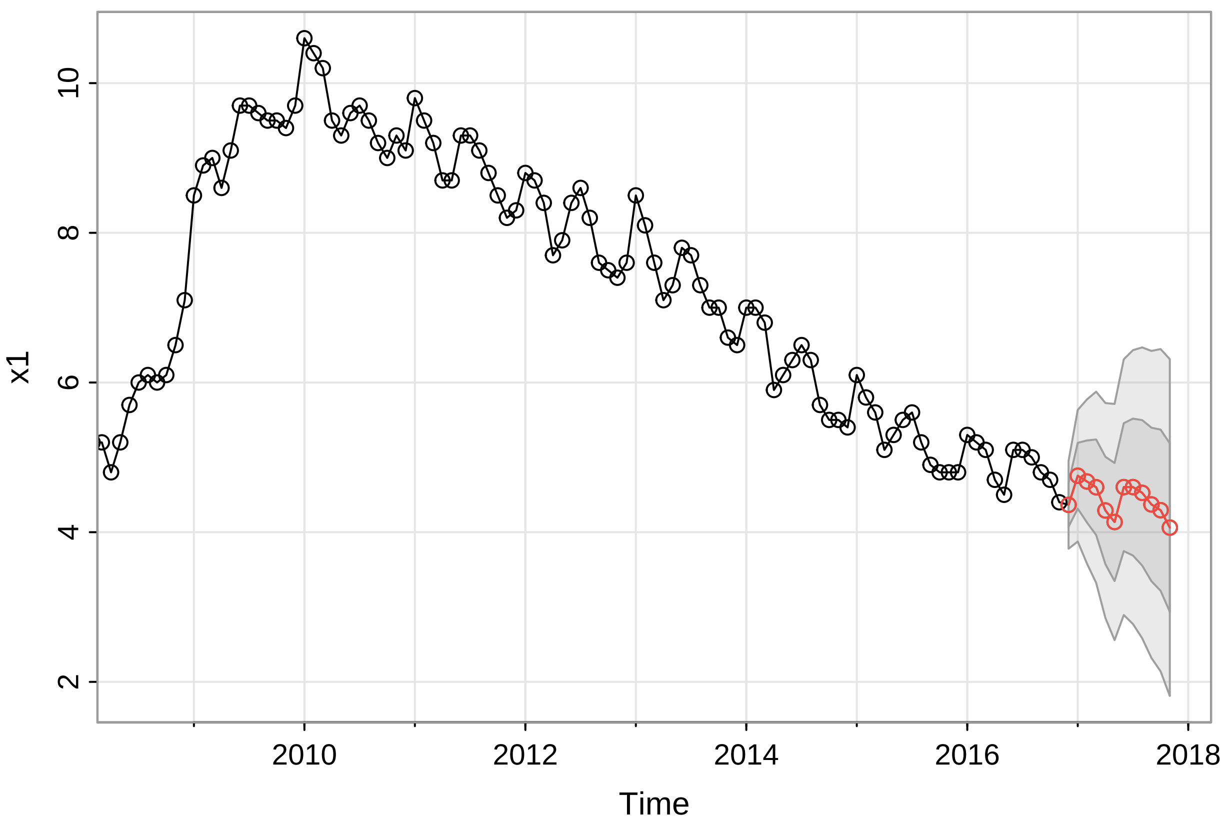
```
## iter  12 value -2.985050
## iter  12 value -2.985050
## iter  12 value -2.985050
## final  value -2.985050
## converged
## initial  value -2.957893
## iter   2 value -2.957980
## iter   3 value -2.958376
## iter   4 value -2.958406
## iter   5 value -2.958425
## iter   5 value -2.958425
## iter   5 value -2.958425
## final  value -2.958425
## converged
```




```
## $fit
##
## Call:
## arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),
##     xreg = constant, transform.pars = trans, fixed = fixed, optim.control = list(trace = trc,
##         REPORT = 1, reltol = tol))
##
## Coefficients:
##           ma1     sar1  constant
##       -0.8445  -0.5054     0e+00
## s.e.   0.0248   0.0313     2e-04
##
```

```
## sigma^2 estimated as 0.002677:  log likelihood = 1251.6,  aic = -2495.21
##
## $degrees_of_freedom
## [1] 810
##
## $ttable
##          Estimate     SE  t.value p.value
## ma1       -0.8445 0.0248 -34.0281  0.0000
## sar1      -0.5054 0.0313 -16.1380  0.0000
## constant   0.0000 0.0002   0.1068  0.9149
##
## $AIC
## [1] -3.069134
##
## $AICc
## [1] -3.069097
##
## $BIC
## [1] -3.046006
```

```
prediction1 <- sarima.for(x1, 12, 0, 1, 1, 1, 0, 0, 12)  # Forecast of the next 12 months
```



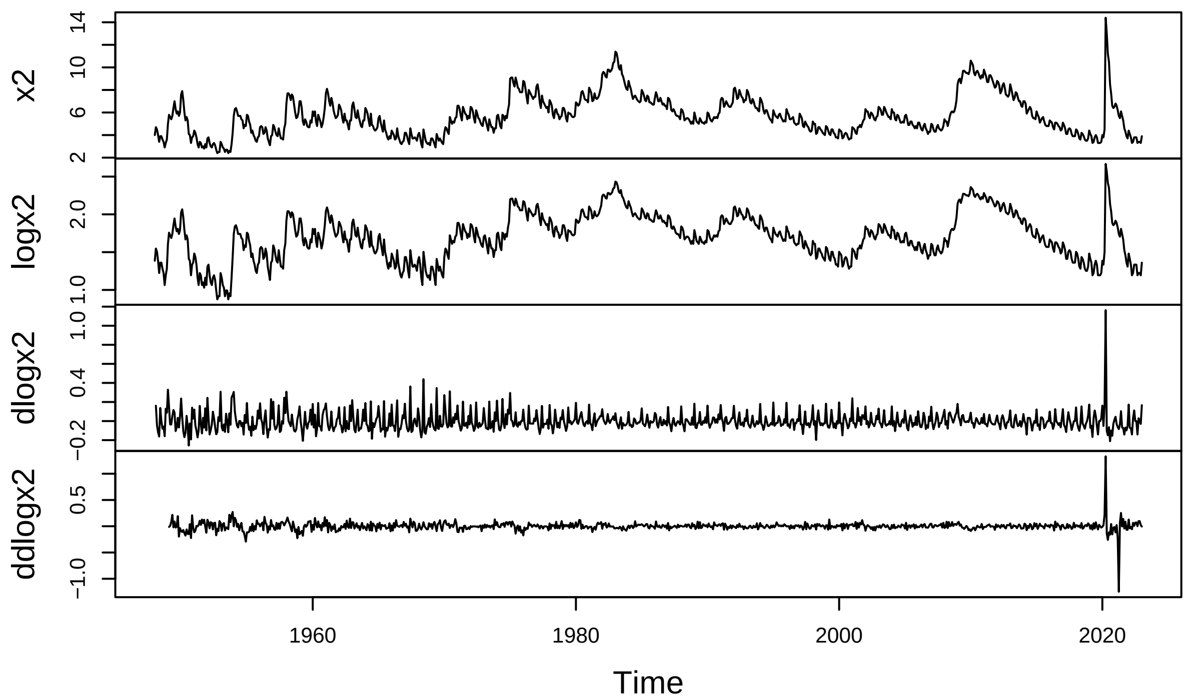

```
prediction1$pred
```

```
##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 2016
## 2017 4.754517 4.677452 4.600386 4.290383 4.135672 4.602128 4.602708 4.525643
##           Sep      Oct      Nov      Dec
## 2016                            4.365707
```

```
## 2017 4.370931 4.293866 4.061509
```

2

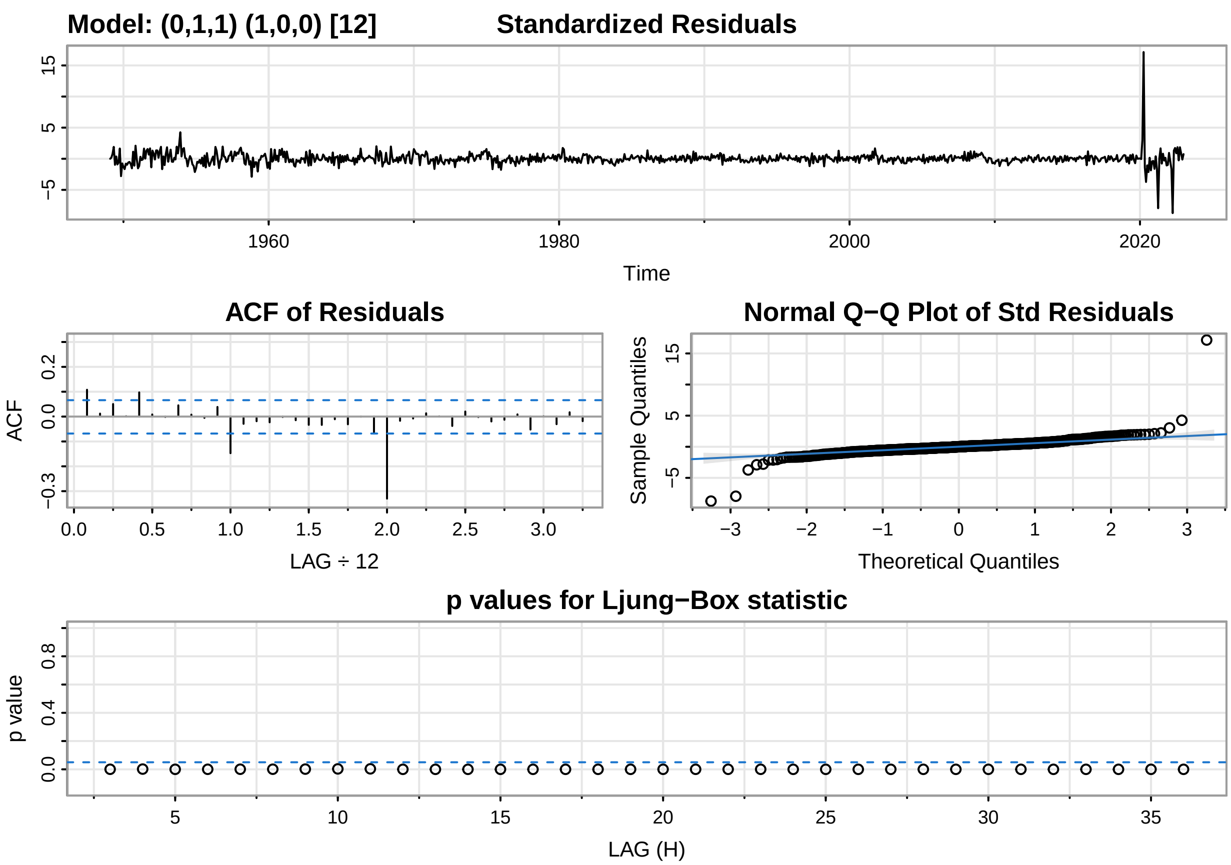
```r
temp <- read.table("Problem2.txt", header = T, sep = ",")
x2 <- ts(temp$Value, start = c(1948, 1), frequency = 12)
logx2 = log(x2)
dlogx2 = diff(logx2)
ddlogx2 = diff(dlogx2, 12)
plot.ts(cbind(x2, logx2, dlogx2, ddlogx2), main = "")
```




```r
sarima(ddlogx2, 0, 1, 1, 1, 0, 0, 12)  # The Seasonal ARIMA model
```

```
## initial  value -2.158985
## iter   2 value -2.463714
## iter   3 value -2.537353
## iter   4 value -2.539319
## iter   5 value -2.553933
## iter   6 value -2.561164
## iter   7 value -2.563693
## iter   8 value -2.565696
## iter   9 value -2.566640
## iter  10 value -2.567212
## iter  11 value -2.567329
## iter  12 value -2.567357
## iter  13 value -2.567357
## iter  14 value -2.567357
## iter  14 value -2.567357
## iter  14 value -2.567357
## final  value -2.567357
## converged
```

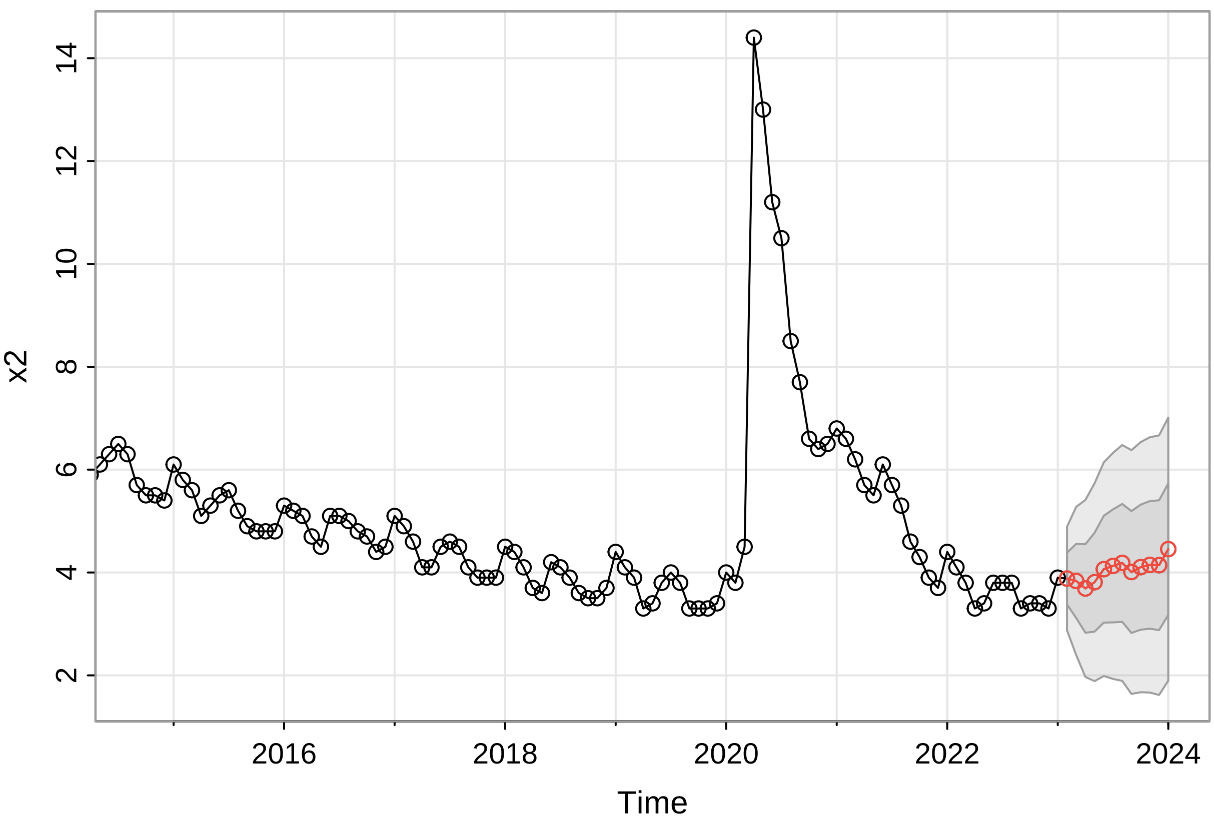
```
## initial  value -2.561744
## iter   2 value -2.561903
## iter   3 value -2.567387
## iter   4 value -2.567734
## iter   5 value -2.568936
## iter   6 value -2.569614
## iter   7 value -2.571693
## iter   8 value -2.572800
## iter   9 value -2.574053
## iter  10 value -2.574211
## iter  11 value -2.574600
## iter  12 value -2.574792
## iter  13 value -2.574979
## iter  14 value -2.575121
## iter  15 value -2.575122
## iter  15 value -2.575122
## iter  15 value -2.575122
## final  value -2.575122
## converged
```




```
## $fit
##
## Call:
## arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),
##     xreg = constant, transform.pars = trans, fixed = fixed, optim.control = list(trace = trc,
##         REPORT = 1, reltol = tol))
##
```

```
## Coefficients:
##           ma1     sar1  constant
##       -1.0000  -0.4851         0
## s.e.   0.0031   0.0295         0
##
## sigma^2 estimated as 0.005728:  log likelihood = 1025.53,  aic = -2043.07
##
## $degrees_of_freedom
## [1] 884
##
## $ttable
##          Estimate     SE   t.value p.value
## ma1       -1.0000 0.0031 -319.1882  0.0000
## sar1      -0.4851 0.0295  -16.4593  0.0000
## constant   0.0000 0.0000    0.0149  0.9882
##
## $AIC
## [1] -2.303348
##
## $AICc
## [1] -2.303317
##
## $BIC
## [1] -2.281757
```

```
prediction2 <- sarima.for(x2, 12, 1, 0, 1, 1, 0, 0, 12)  # Forecast of the next 12 months
```



```
prediction2$pred
```

```
##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 2023          3.882479 3.835774 3.689128 3.811265 4.064801 4.128280 4.186244
## 2024 4.454732
##           Sep      Oct      Nov      Dec
## 2023 4.009150 4.103485 4.147616 4.141909
## 2024
```

Comparing the two plots created by the Seasonal ARIMA(0, 1, 1) * (1, 0, 0), the forecast found in the first plot stays relatively similar to the actual data found in the second plot. A large number of unemployment occurred during the first quarter of 2020, likely due to the rise of COVID-19, and businesses needing to cut down on expenses, but by 2022, the time series plot went back down to follow the trend of the time series plot. From the forecast created from the second plot, a likely prediction is a small rising trend in unemployment for the next 12 months with the confidence intervals showing that to be more than likely that an even or rising trend will occur.