Final Part 1

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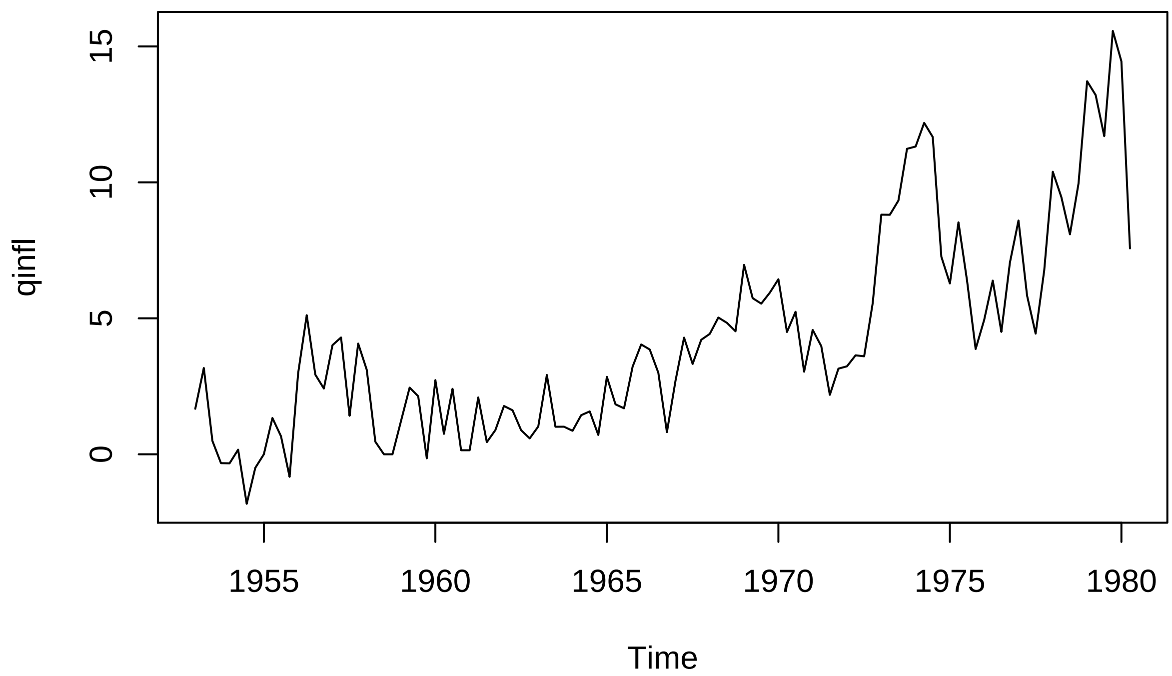
```r
# Liam Fruzyna
# MATH 4760
# Final Exam Part 1

library(astsa)
```

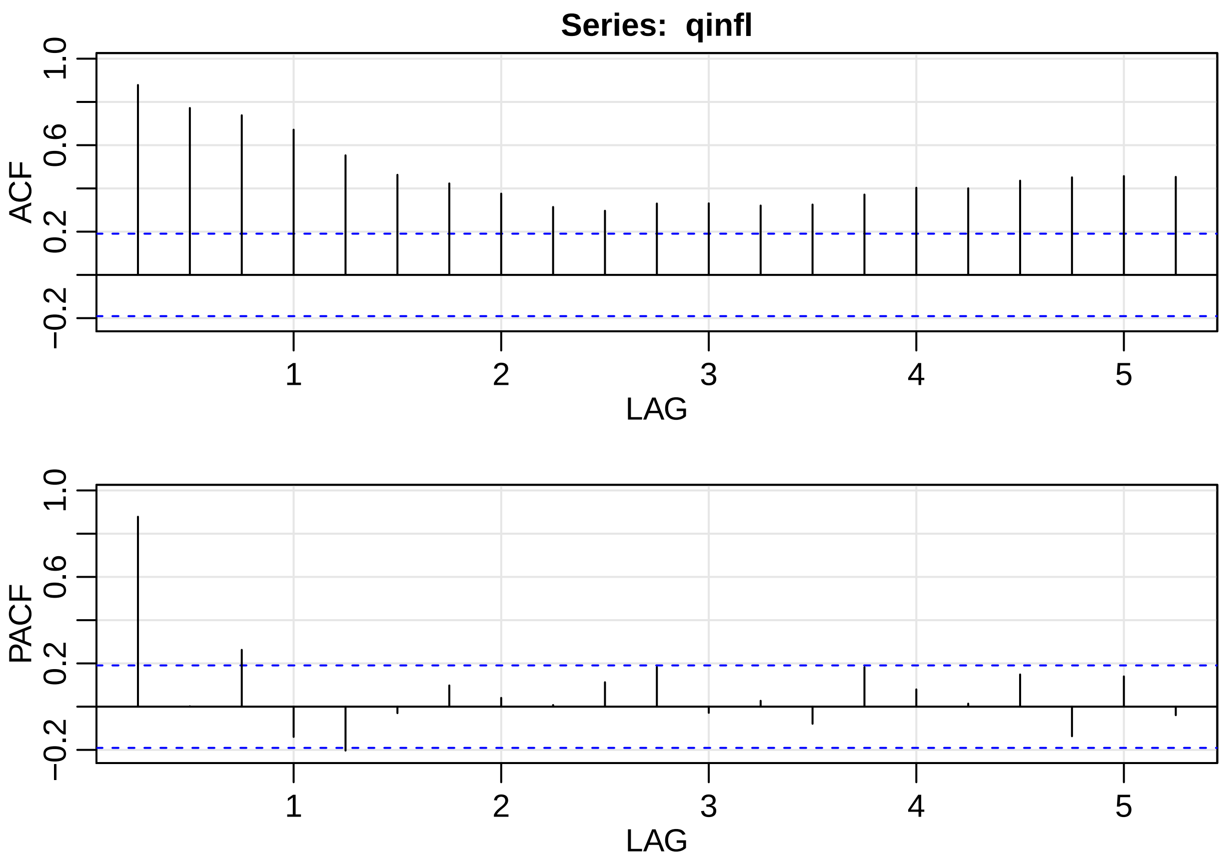
Consider the quarterly inflation data "qinfl"

1) For ARIMA model forecast next the 12 quarters' inflations with graph sowing the forecast values with its 95% confidence intervals.

```r
plot.ts(qinfl)
```

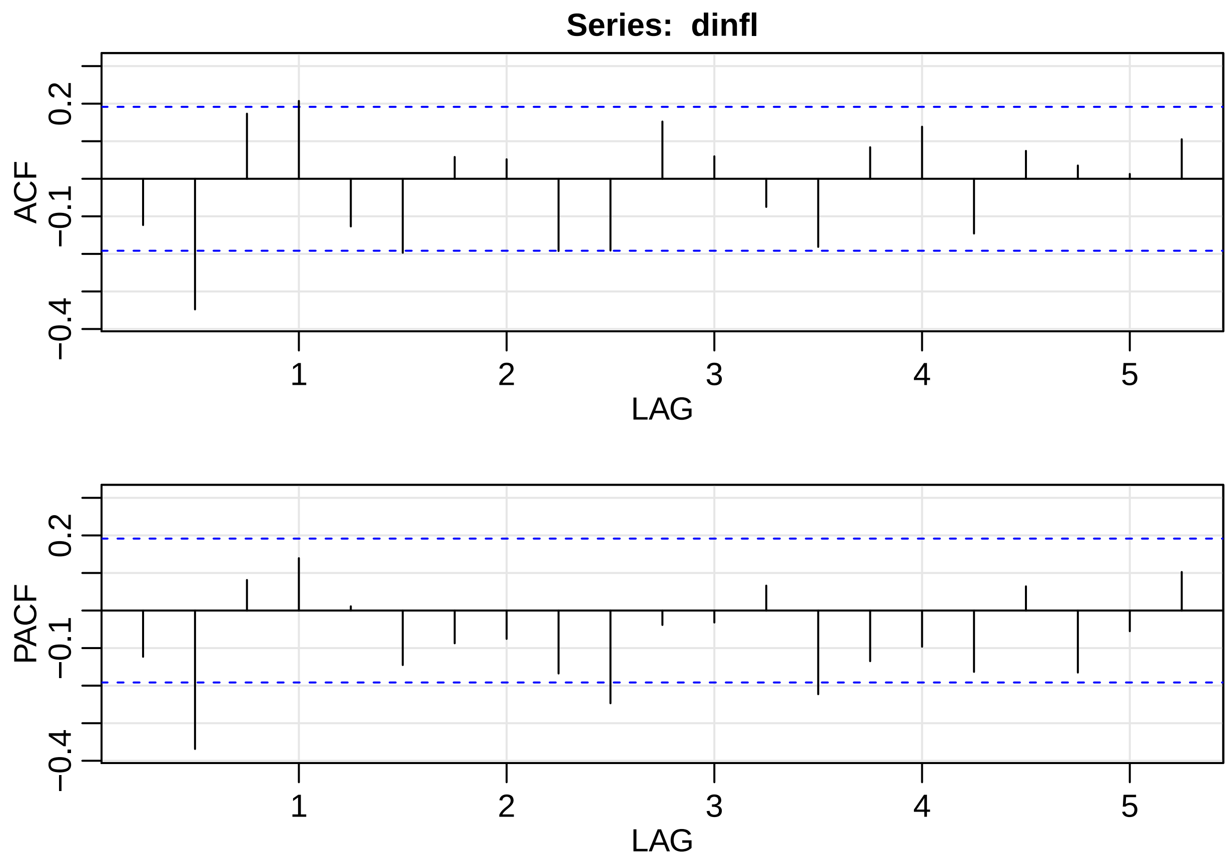



```r
acf2(qinfl) # Needs to be differenced
```




```
##        ACF  PACF
##  [1,] 0.88  0.88
##  [2,] 0.77  0.00
##  [3,] 0.74  0.26
##  [4,] 0.67 -0.14
##  [5,] 0.55 -0.20
##  [6,] 0.46 -0.03
##  [7,] 0.42  0.10
##  [8,] 0.38  0.04
##  [9,] 0.31  0.01
## [10,] 0.30  0.11
## [11,] 0.33  0.18
## [12,] 0.33 -0.03
## [13,] 0.32  0.03
## [14,] 0.33 -0.08
## [15,] 0.37  0.18
## [16,] 0.40  0.08
## [17,] 0.40  0.01
## [18,] 0.44  0.15
## [19,] 0.45 -0.14
## [20,] 0.46  0.14
## [21,] 0.45 -0.04
```

```r
dinfl = diff(qinfl)
acf2(dinfl)
```

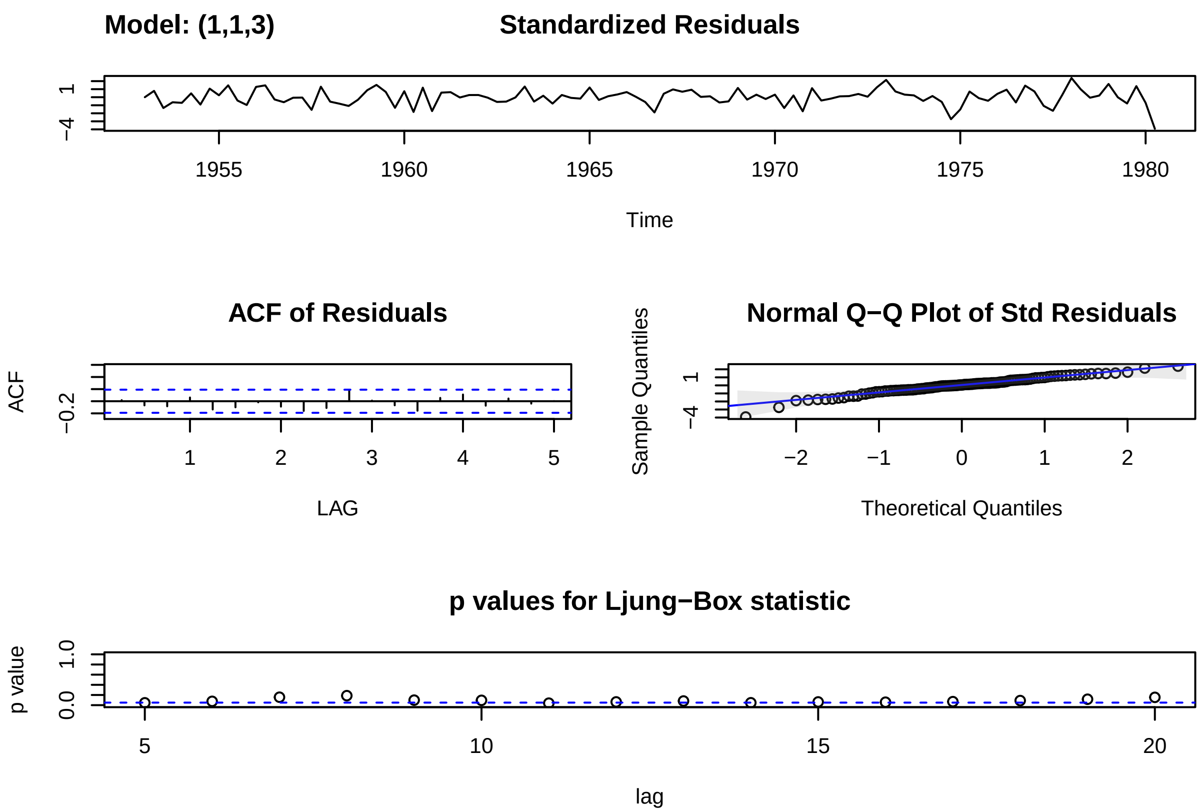



```
##          ACF  PACF
##  [1,] -0.12 -0.12
##  [2,] -0.35 -0.37
##  [3,]  0.17  0.08
##  [4,]  0.21  0.14
##  [5,] -0.13  0.01
##  [6,] -0.20 -0.15
##  [7,]  0.06 -0.09
##  [8,]  0.05 -0.08
##  [9,] -0.19 -0.17
## [10,] -0.19 -0.25
## [11,]  0.15 -0.04
## [12,]  0.06 -0.03
## [13,] -0.07  0.07
## [14,] -0.18 -0.22
## [15,]  0.08 -0.13
## [16,]  0.14 -0.10
## [17,] -0.15 -0.16
## [18,]  0.07  0.06
## [19,]  0.04 -0.17
## [20,]  0.01 -0.06
## [21,]  0.11  0.10
```

```
sarima(qinfl, 1, 1, 3)
```

```
## initial  value 0.582475
## iter   2 value 0.501726
```

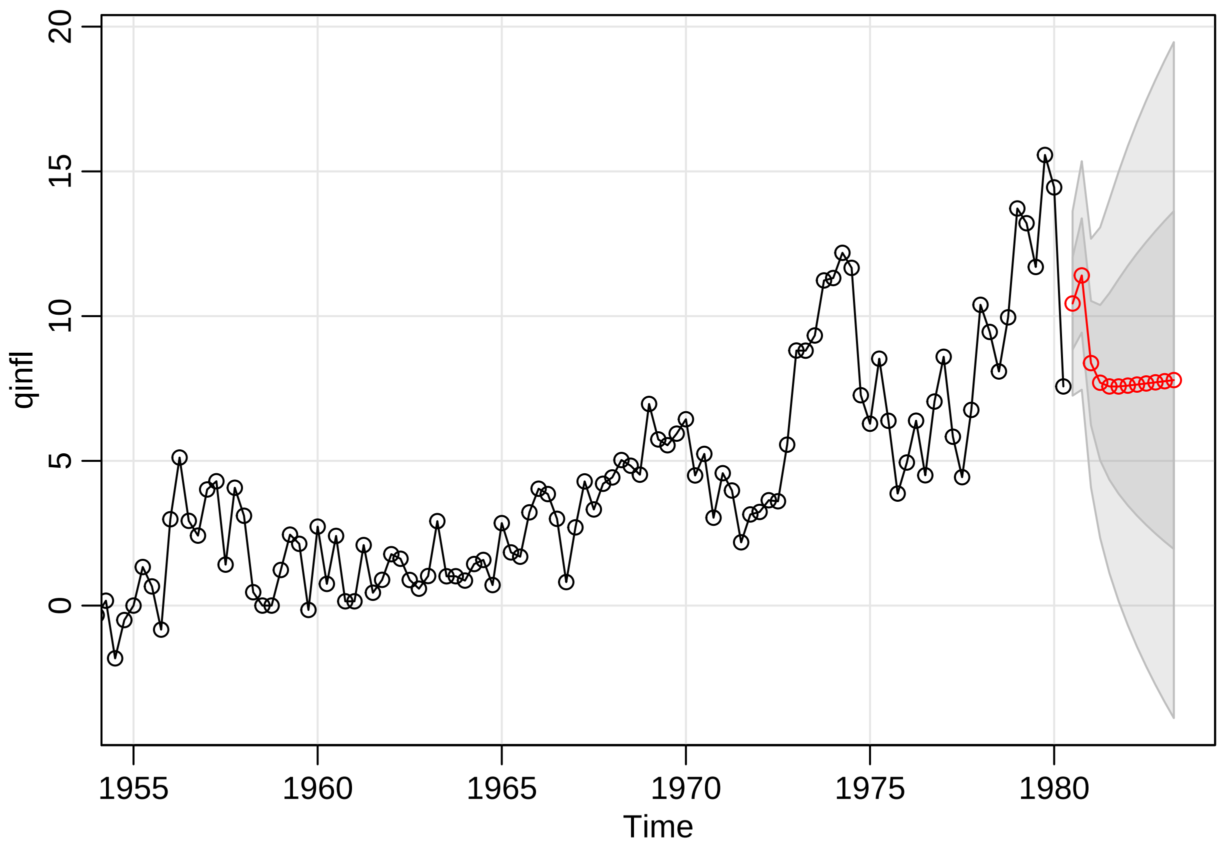
```
## iter   3 value 0.497030
## iter   4 value 0.492511
## iter   5 value 0.490477
## iter   6 value 0.488598
## iter   7 value 0.485779
## iter   8 value 0.483377
## iter   9 value 0.481541
## iter  10 value 0.480906
## iter  11 value 0.480606
## iter  12 value 0.480583
## iter  13 value 0.480574
## iter  14 value 0.480569
## iter  15 value 0.480569
## iter  16 value 0.480568
## iter  17 value 0.480568
## iter  18 value 0.480568
## iter  18 value 0.480568
## iter  18 value 0.480568
## final  value 0.480568
## converged
## initial  value 0.471653
## iter   2 value 0.471158
## iter   3 value 0.470831
## iter   4 value 0.470431
## iter   5 value 0.470256
## iter   6 value 0.470233
## iter   7 value 0.470233
## iter   8 value 0.470233
## iter   8 value 0.470233
## iter   8 value 0.470233
## final  value 0.470233
## converged
```




```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), xreg = constant, optim.control = list(trace = trc, REPORT = 1,
##     reltol = tol))
##
## Coefficients:
##          ar1      ma1      ma2     ma3  constant
##       0.2337  -0.5016  -0.1372  0.5252    0.0387
## s.e.  0.1666   0.1367   0.1086  0.0947    0.1751
##
## sigma^2 estimated as 2.535:  log likelihood = -205.92,  aic = 423.84
##
## $degrees_of_freedom
## [1] 104
##
## $ttable
##          Estimate     SE t.value p.value
## ar1        0.2337 0.1666  1.4026  0.1637
## ma1       -0.5016 0.1367 -3.6688  0.0004
## ma2       -0.1372 0.1086 -1.2628  0.2095
## ma3        0.5252 0.0947  5.5467  0.0000
## constant   0.0387 0.1751  0.2209  0.8256
##
## $AIC
```

```
## [1] 2.021012
##
## $AICc
## [1] 2.046608
##
## $BIC
## [1] 1.143761
```

```
sarima.for(qinfl, 12, 1, 1, 3)
```

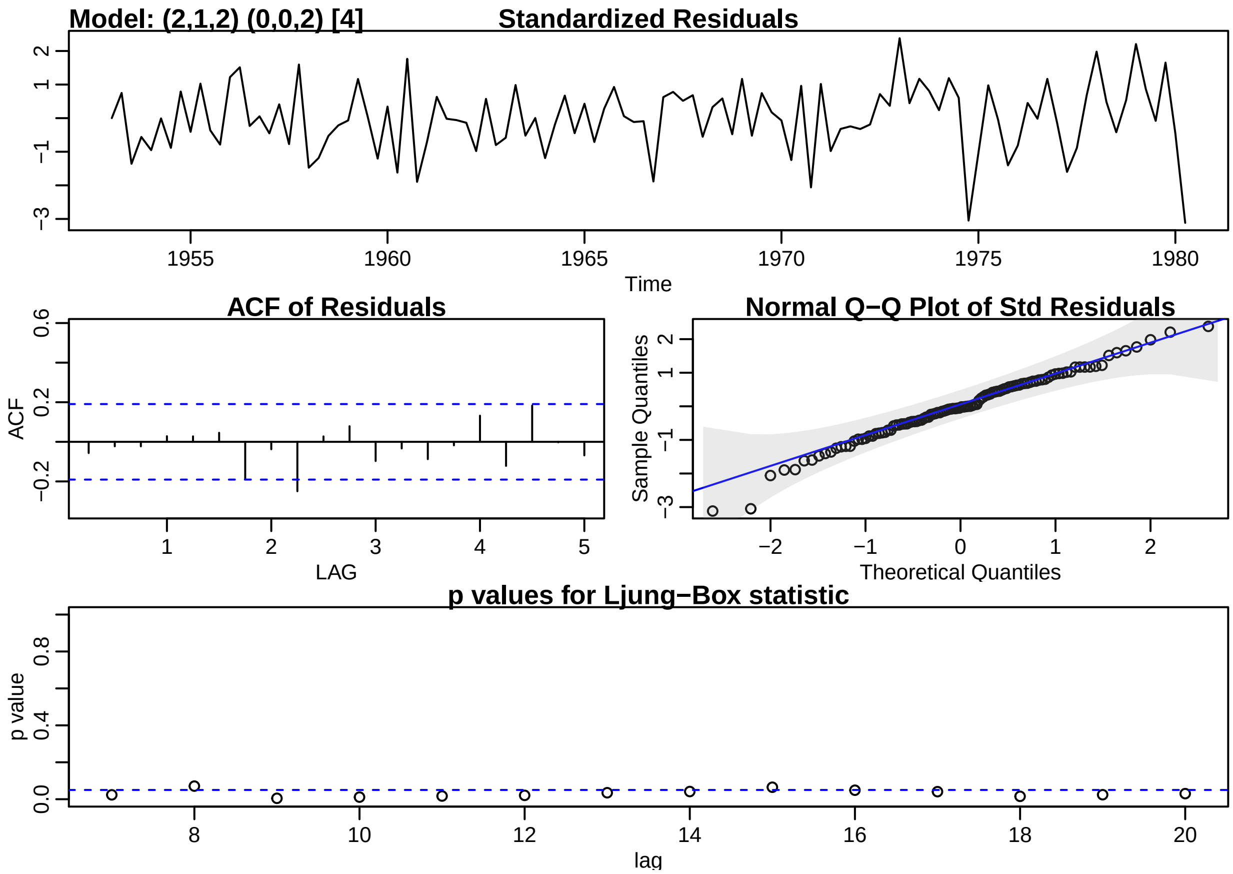



```
## $pred
##           Qtr1      Qtr2      Qtr3      Qtr4
## 1980                     10.436789 11.405921
## 1981  8.377481  7.699271  7.570387  7.569898
## 1982  7.599419  7.635955  7.674129  7.712687
## 1983  7.751335  7.790003
##
## $se
##          Qtr1     Qtr2     Qtr3     Qtr4
## 1980                   1.592096 1.973187
## 1981 2.147505 2.683615 3.224381 3.707019
## 1982 4.137998 4.529065 4.889150 5.224519
## 1983 5.539632 5.837763
```

```
sarima(qinfl, 2, 1, 2, P=0, D=0, Q=2, S=4)
```

```
## initial  value 0.576204
## iter   2 value 0.541605
```

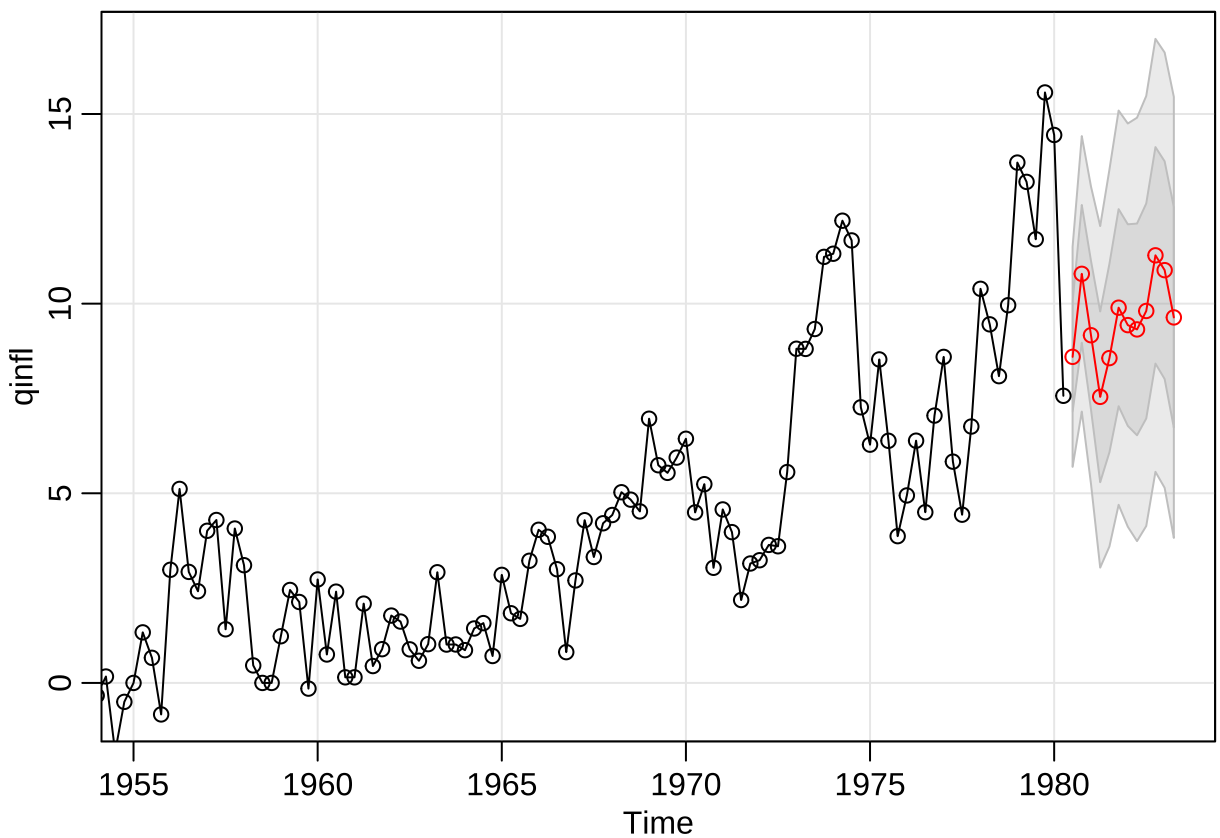
```
## iter   3 value 0.489909
## iter   4 value 0.481243
## iter   5 value 0.472145
## iter   6 value 0.470285
## iter   7 value 0.465362
## iter   8 value 0.461376
## iter   9 value 0.458618
## iter  10 value 0.457162
## iter  11 value 0.454645
## iter  12 value 0.447975
## iter  13 value 0.427464
## iter  14 value 0.422725
## iter  15 value 0.405948
## iter  16 value 0.395782
## iter  17 value 0.392902
## iter  18 value 0.391317
## iter  19 value 0.384954
## iter  20 value 0.383706
## iter  21 value 0.381471
## iter  22 value 0.381164
## iter  23 value 0.381118
## iter  24 value 0.381087
## iter  25 value 0.381084
## iter  26 value 0.381081
## iter  27 value 0.381081
## iter  27 value 0.381081
## iter  27 value 0.381081
## final  value 0.381081
## converged
## initial  value 0.397715
## iter   2 value 0.396544
## iter   3 value 0.394809
## iter   4 value 0.393995
## iter   5 value 0.392447
## iter   6 value 0.391521
## iter   7 value 0.390894
## iter   8 value 0.389284
## iter   9 value 0.388009
## iter  10 value 0.387326
## iter  11 value 0.387304
## iter  12 value 0.387303
## iter  13 value 0.387303
## iter  13 value 0.387303
## iter  13 value 0.387303
## final  value 0.387303
## converged
```




```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), xreg = constant, optim.control = list(trace = trc, REPORT = 1,
##     reltol = tol))
##
## Coefficients:
##           ar1      ar2      ma1     ma2     sma1     sma2  constant
##       -0.0574  -0.9802  -0.1891  0.7206  -0.2654  -0.3726    0.0833
## s.e.   0.0329   0.0215   0.0742  0.1165   0.0985   0.0910    0.0425
##
## sigma^2 estimated as 2.103:  log likelihood = -196.88,  aic = 409.76
##
## $degrees_of_freedom
## [1] 102
##
## $ttable
##          Estimate     SE  t.value p.value
## ar1       -0.0574 0.0329  -1.7422  0.0845
## ar2       -0.9802 0.0215 -45.5347  0.0000
## ma1       -0.1891 0.0742  -2.5482  0.0123
## ma2        0.7206 0.1165   6.1848  0.0000
## sma1      -0.2654 0.0985  -2.6937  0.0083
## sma2      -0.3726 0.0910  -4.0918  0.0001
## constant   0.0833 0.0425   1.9595  0.0528
```

```
##
## $AIC
## [1] 1.870722
##
## $AICc
## [1] 1.901865
##
## $BIC
## [1] 1.042571
```

```
sarima.for(qinfl, 12, 2, 1, 2, P=0, D=0, Q=2, S=4)
```




```
## $pred
##           Qtr1      Qtr2      Qtr3      Qtr4
## 1980                     8.597449 10.785500
## 1981  9.167564  7.542778  8.563805  9.893477
## 1982  9.433639  9.320403  9.806900 11.273727
## 1983 10.882496  9.636988
##
## $se
##          Qtr1     Qtr2     Qtr3     Qtr4
## 1980                   1.450234 1.815823
## 1981 1.959615 2.250994 2.483964 2.598478
## 1982 2.657761 2.790880 2.834463 2.853629
## 1983 2.869329 2.906474
```

2) Fit the state-space model $x_t = \Phi x_{t-1} + z_t$ $y_t = x_t + v_t$ $i = 1, 2, ..., n$ where z_t and v_t are independent white noise with variances σ^2 and σ_v^2. assume that x_0 $N(\mu_0, \Sigma_0)$

a) Fit the smoothed x_t^n with figure showing the plot of msooth qinfl and its 95% confidence intervals.

b) Forecast the next 12 quarters' inflations with a graph showing the forecast values with its 95% confidence intervals.

3) Compare the results of the ARIMA and state-space models giving their pros and cons.

Any ARIMA model can be represented in a state-space form, however, only simple state-space models can be represented in ARIMA form. ARIMA is good for approximations, it is never the exact model. State-space requires writing down an actual model. State-space allows for a greater variety of formulations, but models can get complicated. State-space allows exact modelling but that can cause instability.