

# Assignment 4 - Time Series

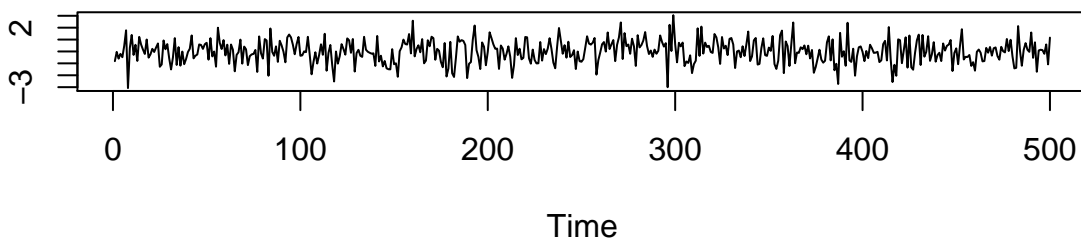
*Saha Debanshee Gopal*

*November 29, 2016*

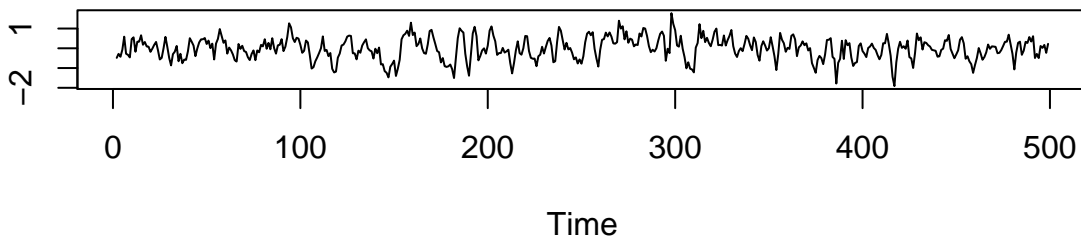
## Question 1.

```
#White noise and moving average plot for 500 observations:  
w = rnorm(500,0,1) #500 N(0,1) variates  
v = filter(w, sides=2, rep(1/3,3)) #moving average  
par(mfrow=c(2,1))  
plot.ts(w, main="White noise", ylab="")  
plot.ts(v, main="Moving average", ylab="")
```

**White noise**

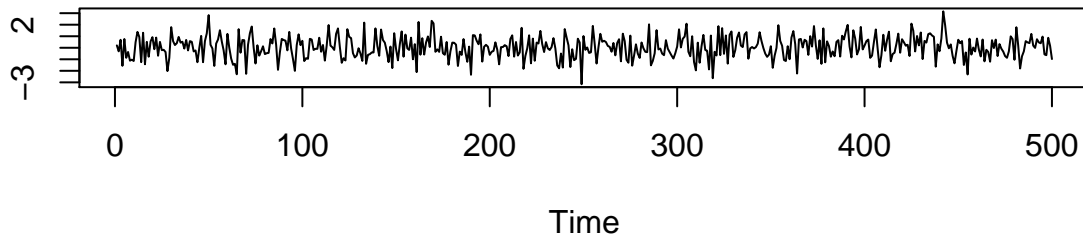


**Moving average**

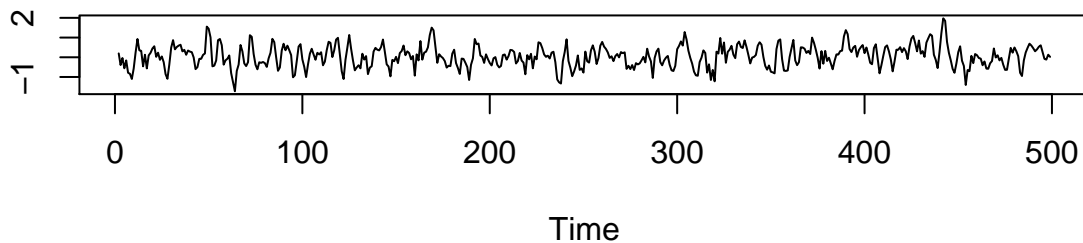


```
#White noise and moving average plot for 50 observations:  
w = rnorm(500,0,1) #500 N(0,1) variates  
v = filter(w, sides=2, rep(1/3,3)) #moving average  
par(mfrow=c(2,1))  
plot.ts(w, main="White noise", ylab="")  
plot.ts(v, main="Moving average", ylab="")
```

## White noise

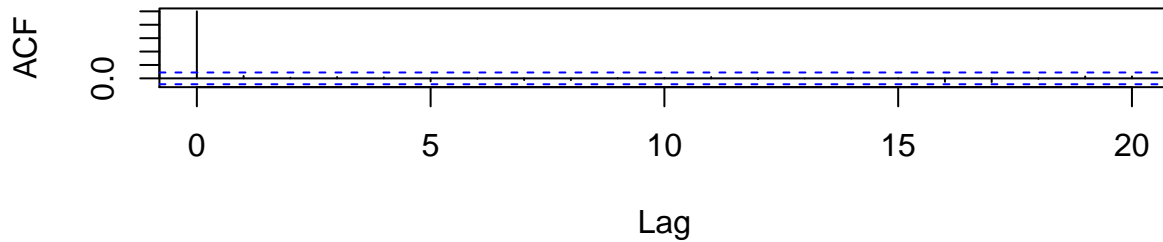


## Moving average

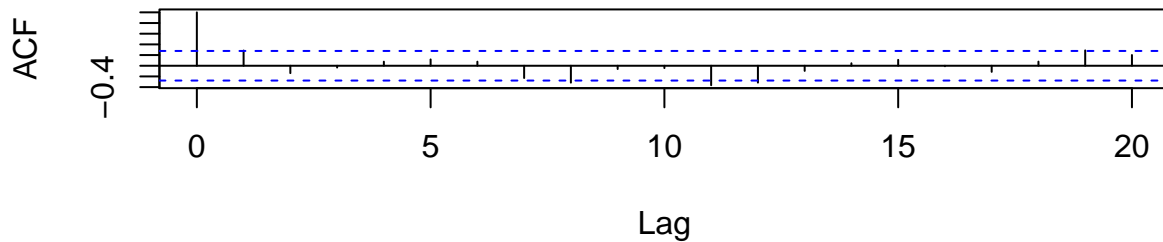


```
#Comparison
par(mfrow=c(2,1)) # Plot the graphs in 2 rows, 1 column
wa = rnorm(500, 0,1) # 500 white noise observations
acf(wa,20, # Plot and print the results for part a
    main = "Series of n=500 Gaussian White Noise Observations")
wb = rnorm(50, 0,1) # 50 white noise observations
acf(wb,20, # Plot and print the results for part a
    main = "Series of n=50 Gaussian White Noise Observations")
```

## Series of n=500 Gaussian White Noise Observations



## Series of n=50 Gaussian White Noise Observations



## The range of lag is bigger for smaller n.

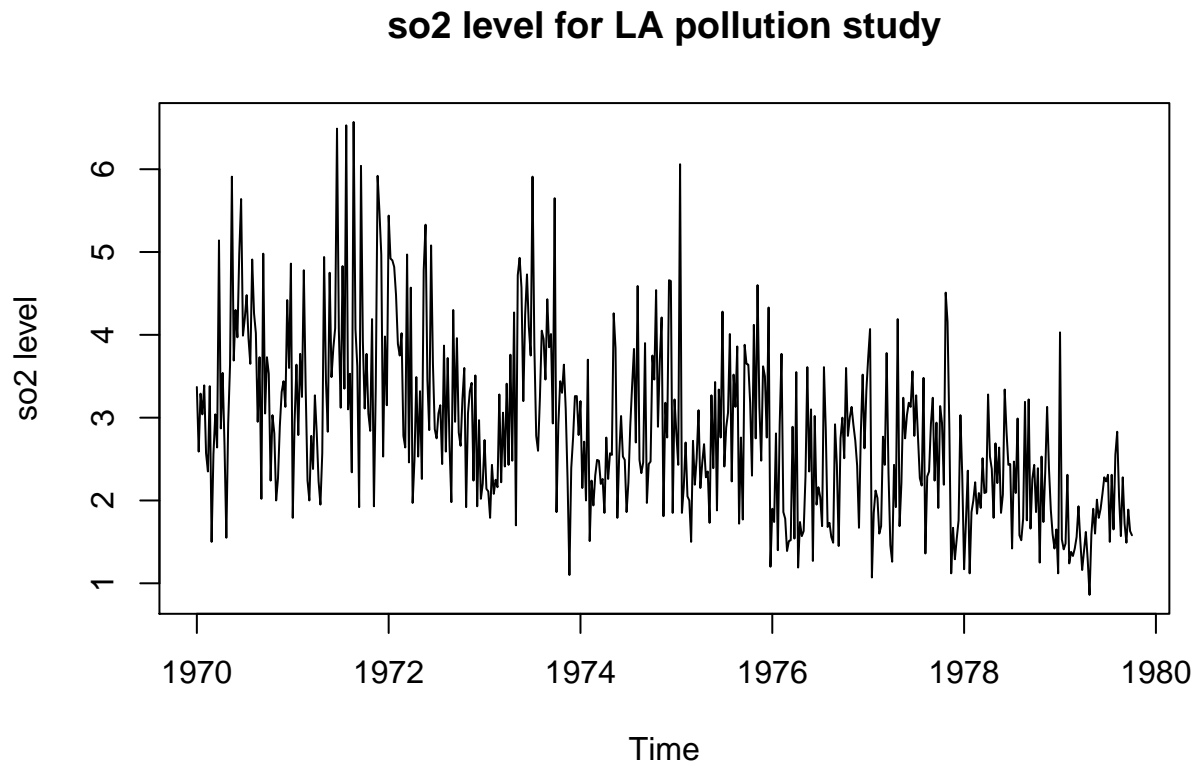
## Question 2.

```
library(astsa)
data()
so2
```

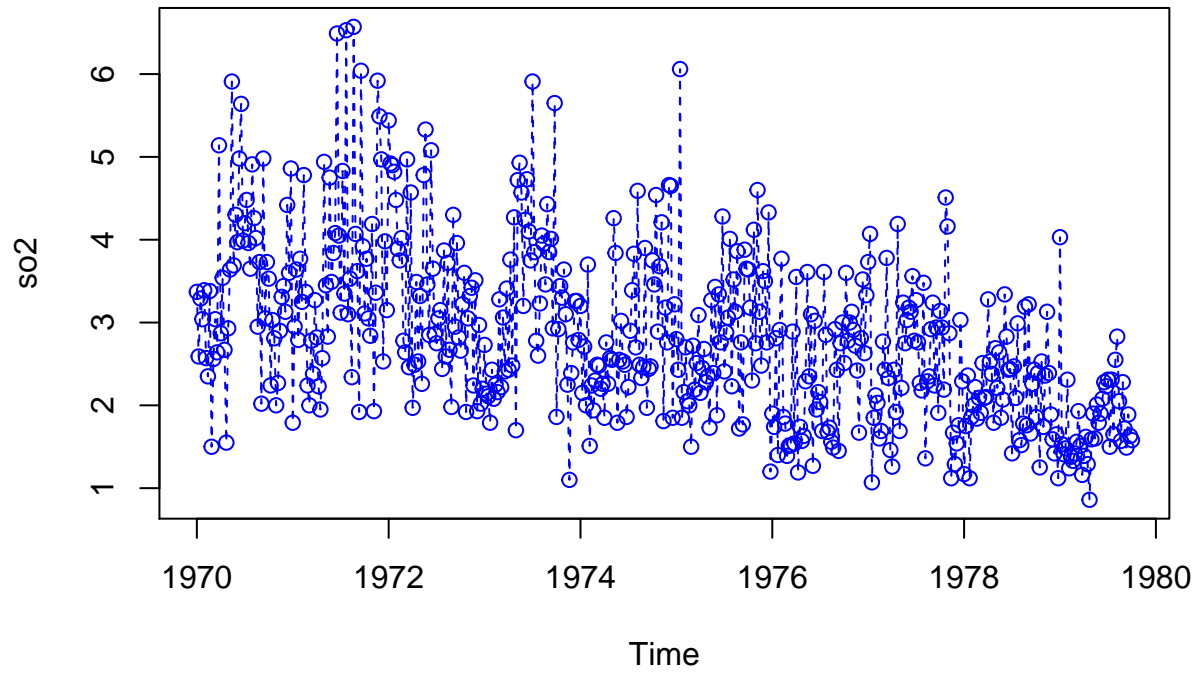
```
## Time Series:
## Start = c(1970, 1)
## End = c(1979, 40)
## Frequency = 52
## [1] 3.37 2.59 3.29 3.04 3.39 2.57 2.35 3.38 1.50 2.56 3.04 2.64 5.14 2.87
## [15] 3.54 2.67 1.55 2.93 3.64 5.91 3.69 4.30 3.97 4.98 5.64 3.99 4.20 4.48
## [29] 3.96 3.65 4.91 4.26 4.02 2.95 3.73 2.02 4.98 3.05 3.73 3.53 2.24 3.03
## [43] 2.81 2.00 2.27 2.90 3.31 3.44 3.13 4.42 3.60 4.86 1.79 2.95 3.64 2.79
## [57] 3.77 3.25 4.78 3.37 2.24 2.00 2.78 2.38 3.27 2.82 2.23 1.95 2.57 4.94
## [71] 3.45 2.83 4.75 3.49 3.84 4.08 6.49 4.05 3.12 4.83 3.35 6.53 3.10 3.53
## [85] 2.34 6.57 4.07 3.62 1.92 6.04 3.92 3.11 3.77 3.05 2.84 4.19 1.93 3.36
## [99] 5.92 5.49 4.97 2.53 3.98 3.15 5.44 4.92 4.90 4.82 4.48 3.89 3.75 4.02
## [113] 2.78 2.64 4.97 2.46 4.57 1.97 2.49 3.49 2.53 3.32 2.26 4.78 5.33 3.46
## [127] 2.85 5.08 3.65 2.86 2.75 3.05 3.15 2.44 3.87 2.59 3.72 2.67 1.98 4.30
## [141] 2.95 3.96 2.82 2.66 3.22 3.60 1.92 3.05 3.32 3.42 2.24 3.51 1.93 2.97
## [155] 2.02 2.20 2.73 2.14 2.11 1.79 2.43 2.08 2.25 2.16 3.28 2.22 3.06 2.41
## [169] 3.41 2.43 3.76 2.48 4.27 1.70 4.72 4.93 4.57 3.20 4.24 4.73 4.10 3.75
```

```
## [183] 5.91 3.85 2.78 2.60 3.23 4.05 3.95 3.46 4.43 3.85 4.01 2.93 5.65 1.86
## [197] 2.92 3.44 3.30 3.64 3.10 2.25 1.10 2.39 2.76 3.26 3.26 2.79 3.20 2.15
## [211] 2.71 2.00 3.70 1.51 2.24 1.94 2.30 2.49 2.48 2.20 2.26 1.85 2.76 2.26
## [225] 2.57 2.55 4.26 3.84 1.79 2.55 3.02 2.53 2.49 1.86 2.22 2.90 3.39 3.83
## [239] 2.70 4.59 2.49 2.33 2.46 3.90 1.97 2.44 2.47 3.75 3.46 4.54 2.89 3.68
## [253] 4.21 1.81 3.18 2.76 4.66 4.65 1.85 3.22 2.80 2.43 6.06 1.85 2.16 2.70
## [267] 2.05 2.00 1.50 2.72 2.19 2.51 3.09 2.15 2.45 2.68 2.28 2.35 1.73 3.27
## [281] 2.39 3.43 1.88 3.34 2.76 4.28 2.41 2.88 3.06 4.01 2.23 3.52 3.13 3.86
## [295] 1.72 2.76 1.77 3.88 3.65 3.64 3.18 2.30 4.12 2.75 4.60 3.13 2.48 3.62
## [309] 3.50 2.76 4.33 1.20 1.90 1.74 2.81 1.40 2.91 3.77 1.86 1.78 1.39 1.51
## [323] 1.52 2.89 1.54 3.55 1.19 1.74 1.57 1.63 2.29 3.61 2.35 3.10 1.27 3.02
## [337] 1.95 2.16 2.04 1.69 3.61 2.85 1.68 1.73 1.56 1.49 2.92 2.43 1.45 2.75
## [351] 3.00 2.51 3.60 2.78 3.00 3.13 2.91 2.72 2.42 1.67 2.81 3.52 2.63 3.33
## [365] 3.73 4.07 1.07 1.85 2.12 2.03 1.60 1.69 2.77 2.43 3.78 2.33 1.46 1.26
## [379] 2.43 1.92 4.19 1.69 2.21 3.24 2.75 3.03 3.18 3.13 3.56 2.78 3.27 2.76
## [393] 2.27 2.18 3.48 1.36 2.29 2.35 2.92 3.24 2.24 2.94 1.91 3.14 2.94 2.19
## [407] 4.51 4.16 2.87 1.12 1.67 1.29 1.54 1.76 3.03 2.29 1.17 1.75 2.36 1.12
## [421] 1.86 2.00 2.22 1.84 2.09 1.91 2.51 2.09 2.10 3.28 2.53 2.38 1.79 2.69
## [435] 2.21 2.64 1.85 2.07 3.34 2.83 2.43 2.44 1.42 2.47 2.09 2.99 1.58 1.52
## [449] 1.78 3.19 1.76 3.22 1.66 2.26 2.43 1.86 2.39 1.25 2.53 1.74 2.36 3.13
## [463] 2.39 1.89 1.59 1.42 1.65 1.12 4.03 1.53 1.41 1.48 2.31 1.24 1.38 1.33
## [477] 1.42 1.56 1.93 1.51 1.16 1.39 1.62 1.29 0.86 1.59 1.90 1.60 2.01 1.79
## [491] 1.90 2.08 2.28 2.23 2.31 1.50 2.31 1.65 2.55 2.83 2.05 1.57 2.28 1.72
## [505] 1.49 1.89 1.63 1.58
```

```
plot(so2, ylab="so2 level", main="so2 level for LA pollution study")
```

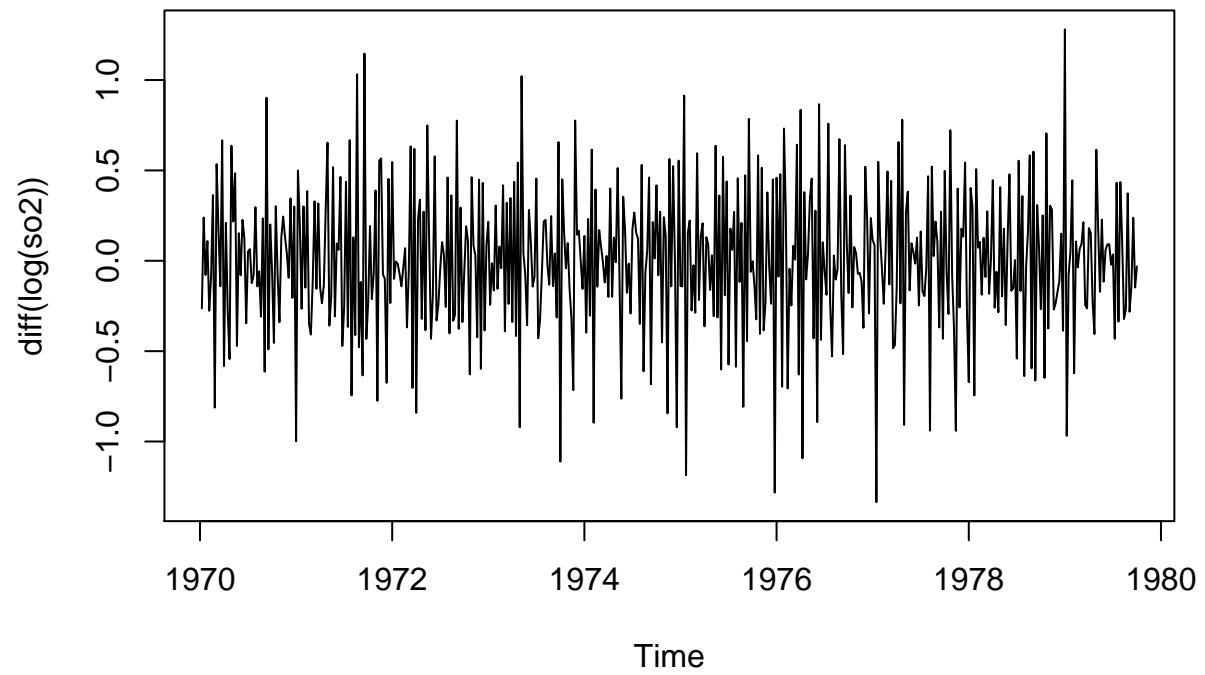


```
plot(so2, type="o", col="blue", lty="dashed")
```

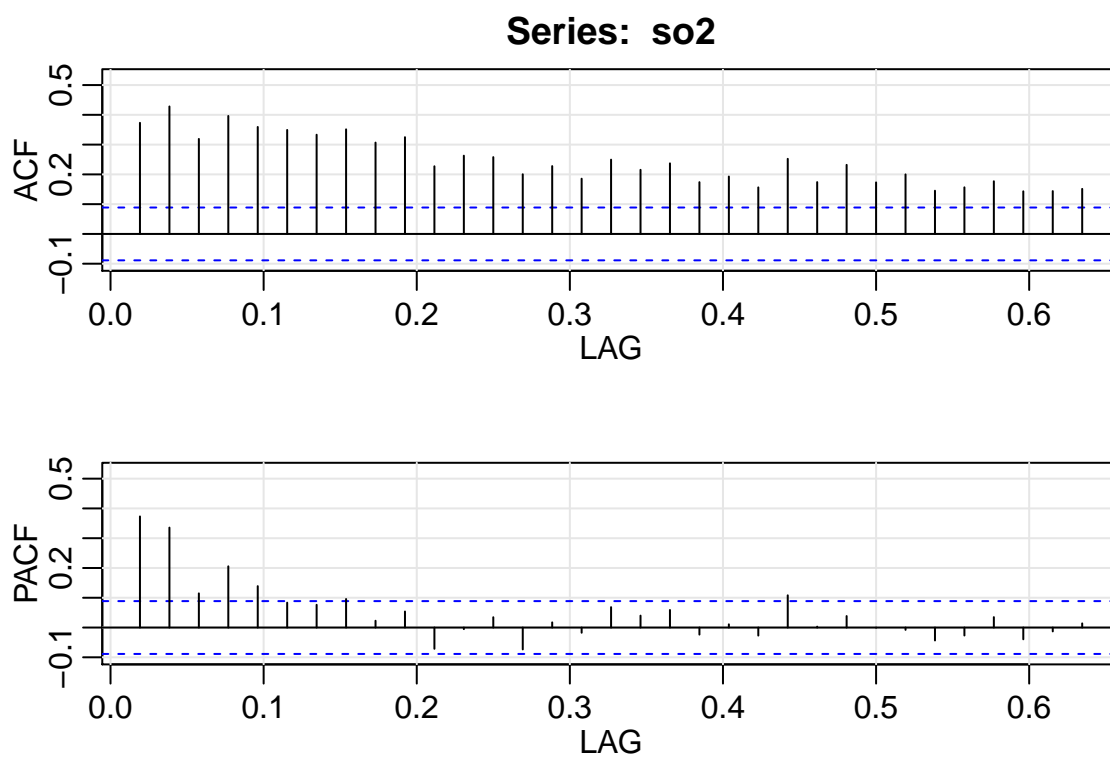


```
plot(diff(log(so2)), main="logged and diffed")
```

### logged and diffed



```
acf2(so2)
```



##		ACF	PACF
##	[1,]	0.37	0.37
##	[2,]	0.43	0.34
##	[3,]	0.32	0.11
##	[4,]	0.40	0.21
##	[5,]	0.36	0.14
##	[6,]	0.35	0.08
##	[7,]	0.33	0.08
##	[8,]	0.35	0.10
##	[9,]	0.31	0.02
##	[10,]	0.33	0.05
##	[11,]	0.23	-0.07
##	[12,]	0.26	-0.01
##	[13,]	0.26	0.03
##	[14,]	0.20	-0.07
##	[15,]	0.23	0.02
##	[16,]	0.19	-0.02
##	[17,]	0.25	0.07
##	[18,]	0.22	0.04
##	[19,]	0.24	0.06
##	[20,]	0.17	-0.02
##	[21,]	0.19	0.01
##	[22,]	0.16	-0.03
##	[23,]	0.25	0.11
##	[24,]	0.17	0.00
##	[25,]	0.23	0.04

```
## [26,] 0.17  0.00
## [27,] 0.20 -0.01
## [28,] 0.15 -0.04
## [29,] 0.16 -0.03
## [30,] 0.18  0.03
## [31,] 0.14 -0.04
## [32,] 0.14 -0.01
## [33,] 0.15  0.01
```

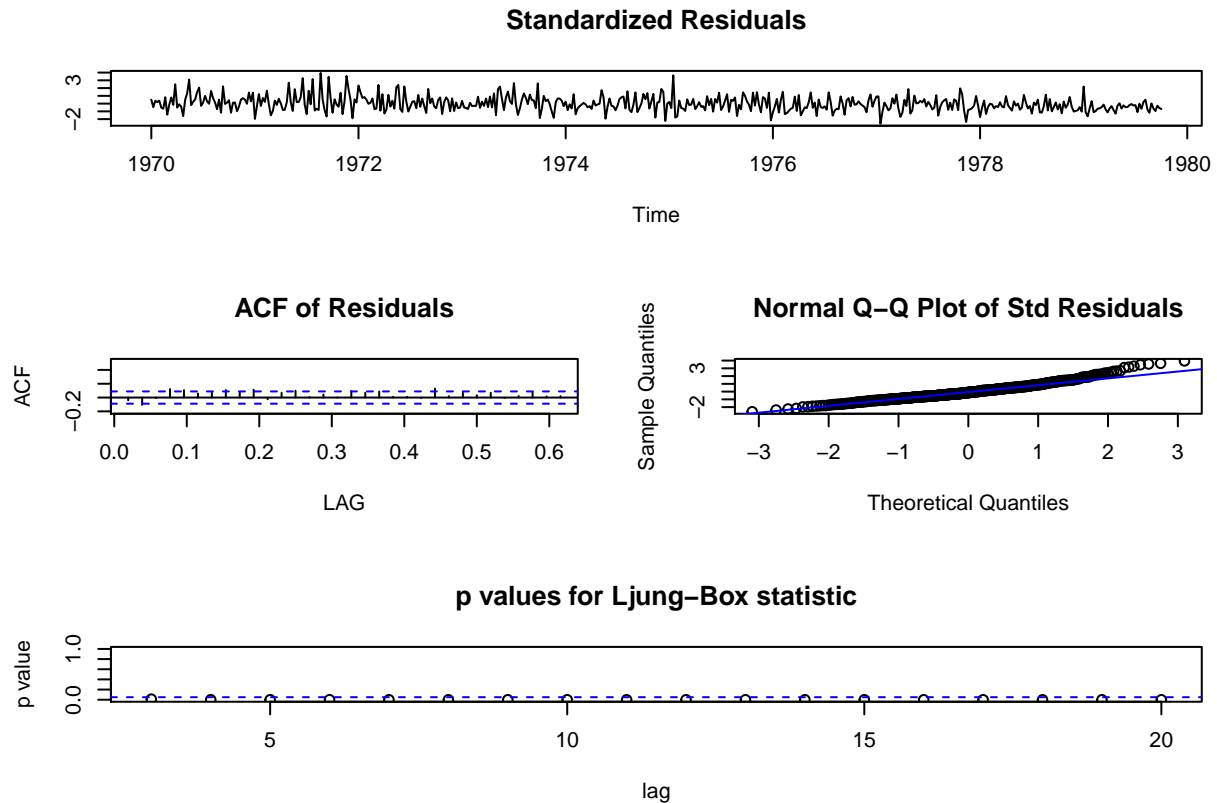
The data given is for everyday from year 1970 to 1980 while we need it to be monthly, Multiply the lag with 30 days makes it a month and acf and pacf values of the corresponding data show that the model is ARIMA(2,0,0)

The AIC values support the hypothesis.

```
sarima(so2,2,0,0)
```

```
## initial  value 0.050063
## iter    2 value -0.065143
## iter    3 value -0.085047
## iter    4 value -0.085717
## iter    5 value -0.085720
## iter    6 value -0.085721
## iter    7 value -0.085721
## iter    8 value -0.085722
## iter    9 value -0.085723
## iter   10 value -0.085723
## iter   11 value -0.085723
## iter   12 value -0.085723
## iter   13 value -0.085723
## iter   13 value -0.085723
## iter   13 value -0.085723
## final   value -0.085723
## converged
## initial  value -0.086846
## iter    2 value -0.086847
## iter    3 value -0.086848
## iter    4 value -0.086848
## iter    5 value -0.086848
## iter    6 value -0.086848
## iter    7 value -0.086848
## iter    8 value -0.086848
## iter    9 value -0.086848
## iter   10 value -0.086848
## iter   10 value -0.086848
## iter   10 value -0.086848
## final   value -0.086848
## converged
```





```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), xreg = xmean, include.mean = FALSE, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##          ar1      ar2    xmean
##         0.2482  0.3367  2.8400
## s.e.   0.0417  0.0418  0.0976
##
## sigma^2 estimated as 0.8399:  log likelihood = -676.7,  aic = 1361.4
##
## $degrees_of_freedom
## [1] 505
##
## $ttable
##      Estimate      SE t.value p.value
## ar1      0.2482 0.0417  5.9507      0
## ar2      0.3367 0.0418  8.0650      0
## xmean     2.8400 0.0976 29.1133      0
##
## $AIC
## [1] 0.8373438
##
```

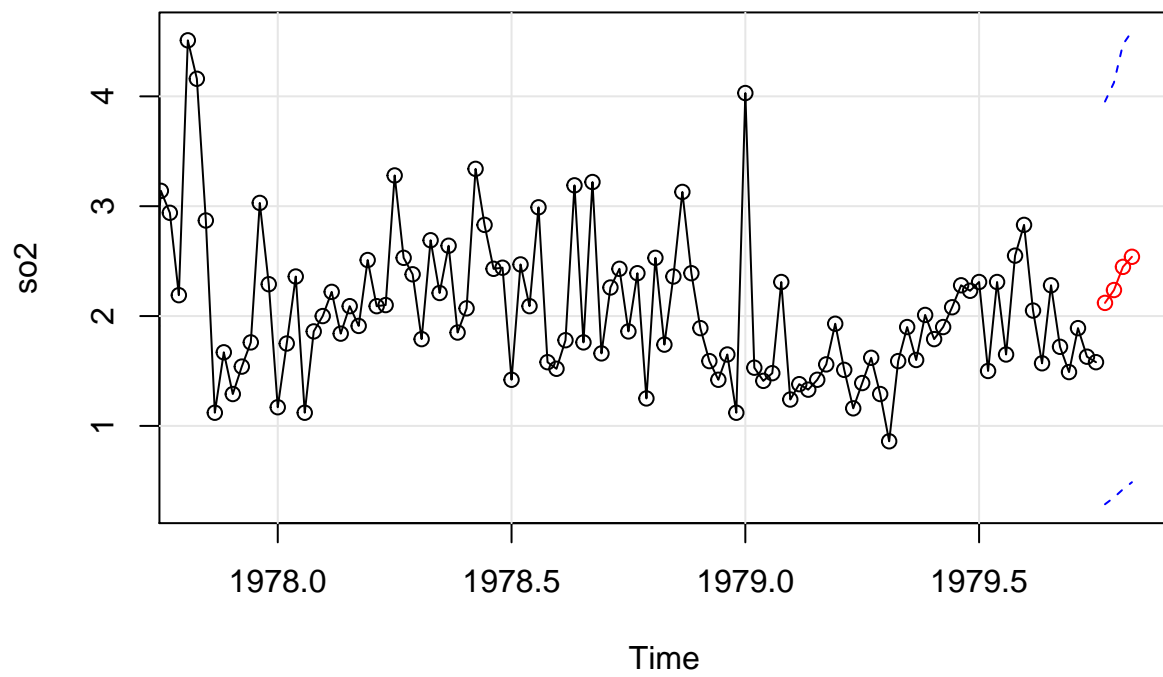
```

## $AICc
## [1] 0.8414373
##
## $BIC
## [1] -0.1376731
sarima.for(so2, 4, 2, 0, 0)

## $pred
## Time Series:
## Start = c(1979, 41)
## End = c(1979, 44)
## Frequency = 52
## [1] 2.119781 2.236927 2.447776 2.539562
##
## $se
## Time Series:
## Start = c(1979, 41)
## End = c(1979, 44)
## Frequency = 52
## [1] 0.916463 0.944274 1.012393 1.026111
library(forecast)

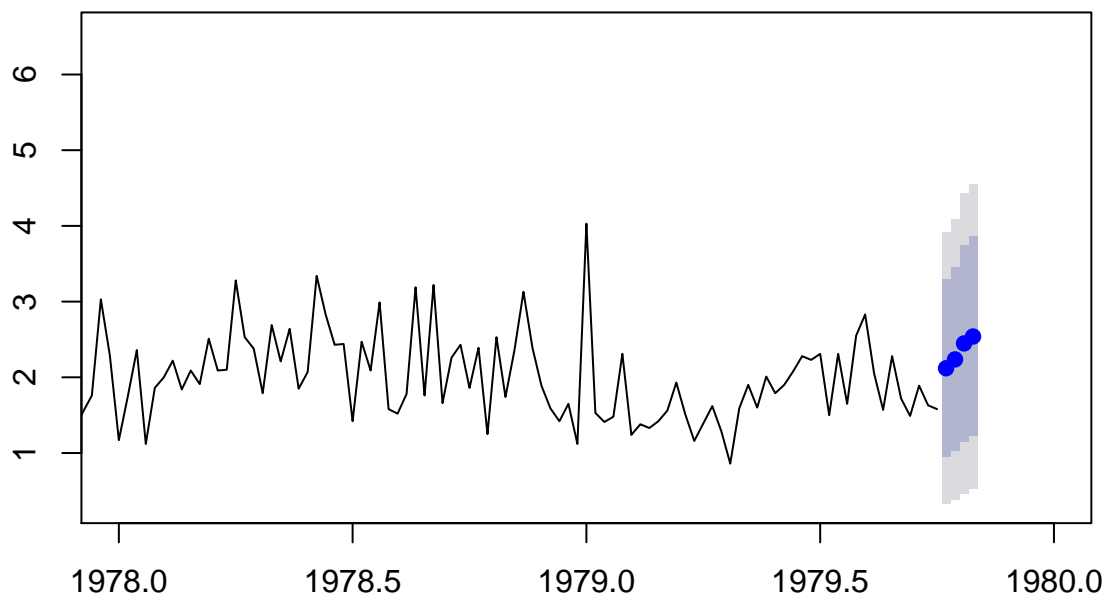
## Loading required package: zoo
##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric
## Loading required package: timeDate
## This is forecast 7.3
##
## Attaching package: 'forecast'
##
## The following object is masked from 'package:astsa':
##
##      gas

```



```
fit <- arima(so2,c(2,0,0))  
forecast_preds <- forecast.Arima(fit, h = 4)  
plot(forecast_preds, xlim = c(1978,1980))
```

Forecasts from ARIMA(2,0,0) with non-zero mean



forecast\_preds

##	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
##	1979.769	2.119781	0.945286	3.294275	0.3235462	3.916015
##	1979.788	2.236927	1.026791	3.447063	0.3861842	4.087670
##	1979.808	2.447776	1.150342	3.745210	0.4635220	4.432030
##	1979.827	2.539562	1.224547	3.854576	0.5284207	4.550703