

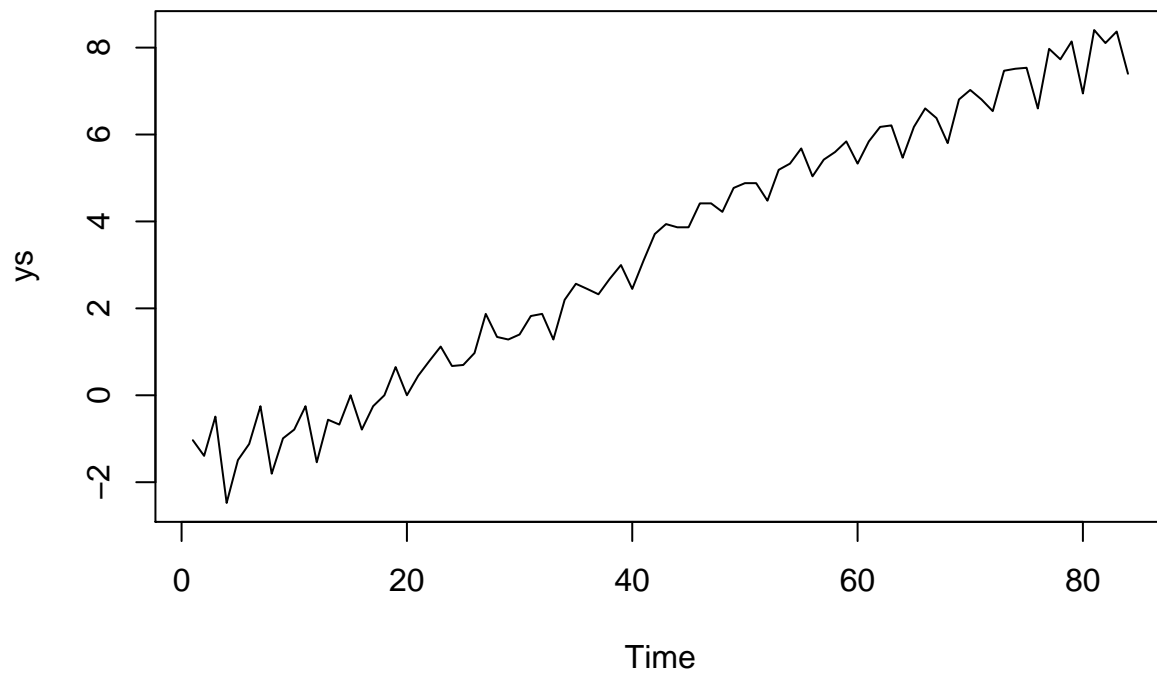
exam_part2.R

spinoza

2021-04-09

```
library(astsa)

# problem 1
# part (a)
tsdata <- ts(jj)
n <- length(tsdata)
ys <- exp((1/n)*sum(log(tsdata)))*log(tsdata)
plot(ys)
```



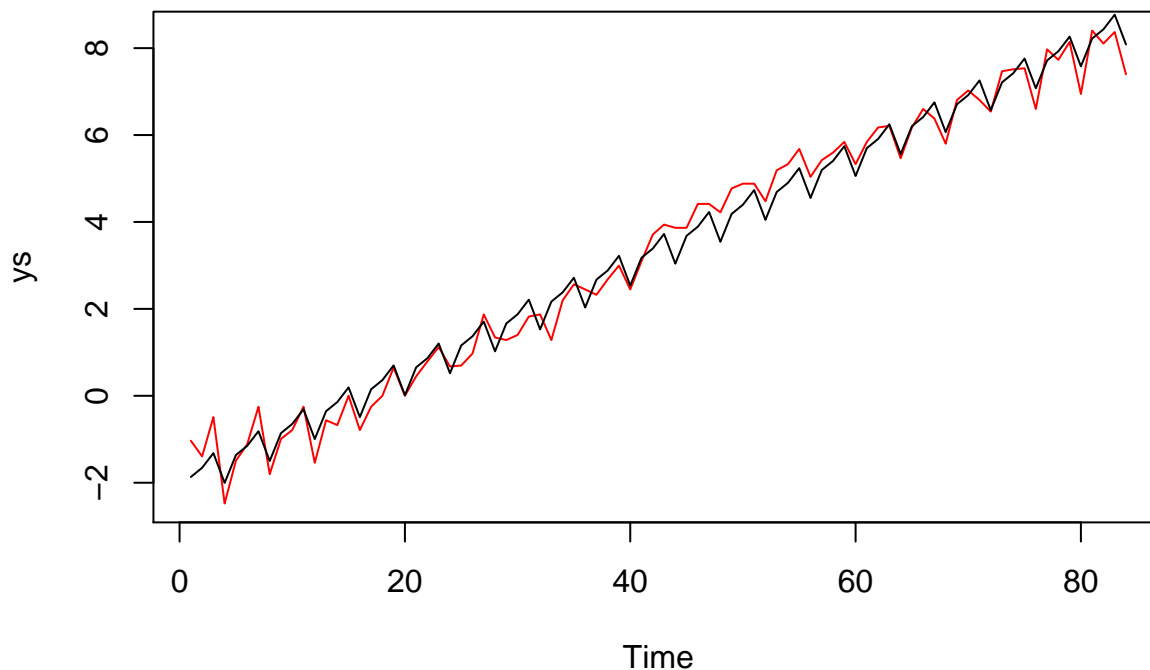
```
# part (b)
t <- 1:84
qt <- as.factor(rep(1:4,21))
q1 <- qt==1
q2 <- qt==2
q3 <- qt==3
m <- cbind(t,q1,q2,q3,ys)

# fit regression model to data
fit <- lm(ys~t+q1+q2+q3, data=m)

summary(fit)
```

```
##
## Call:
## lm(formula = ys ~ t + q1 + q2 + q3, data = m)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.8847 -0.2735 -0.0356  0.2553  0.8342
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.508319   0.111529  -22.490 < 2e-16 ***
## t             0.126112   0.001704   73.999 < 2e-16 ***
## q1            0.514570   0.116866   4.403 3.31e-05 ***
## q2            0.599431   0.116803   5.132 2.01e-06 ***
## q3            0.810985   0.116766   6.945 9.50e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3783 on 79 degrees of freedom
## Multiple R-squared:  0.9859, Adjusted R-squared:  0.9852
## F-statistic: 1379 on 4 and 79 DF,  p-value: < 2.2e-16
```

```
plot(ys,col="red")
lines(fitted.values(fit),type="l")
```

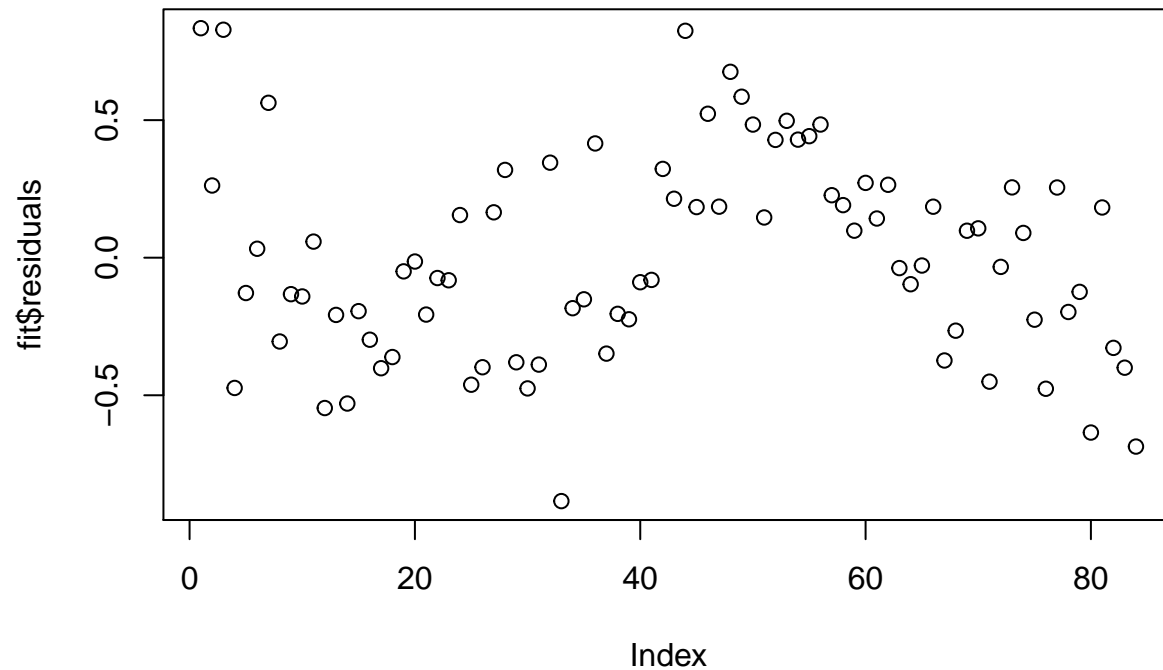


```
# part (c)
df <- 5
print("mse:")

## [1] "mse:"
print(summary(fit)$sigma^2)

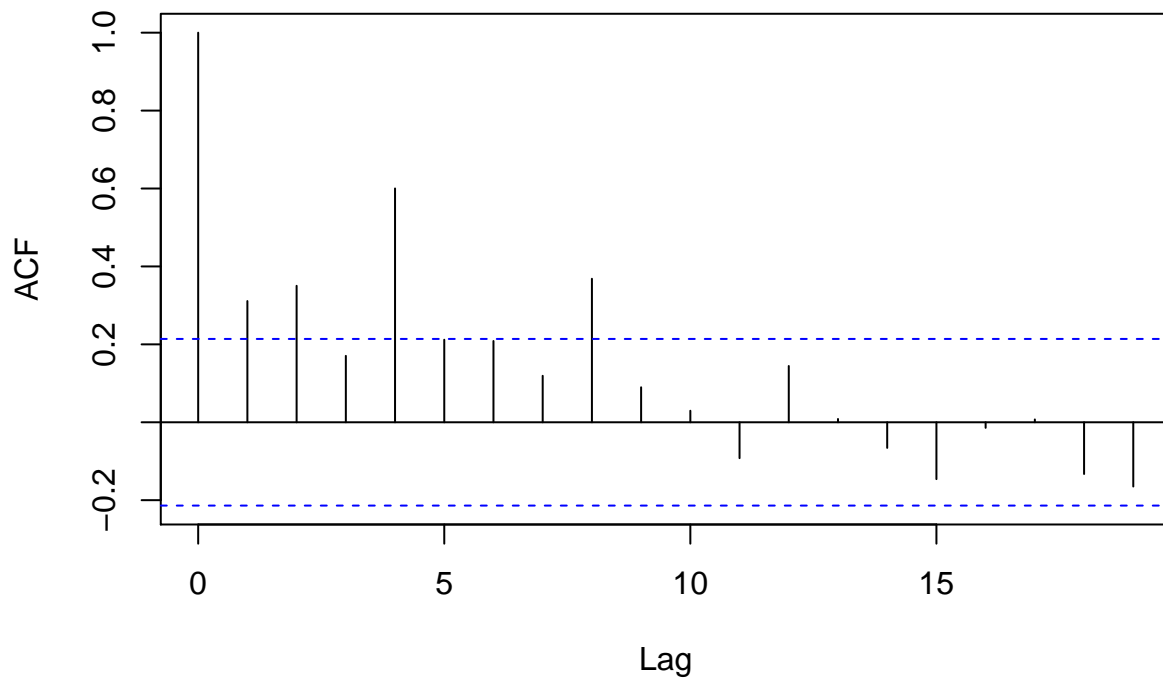
## [1] 0.14313
```

```
plot(fit$residuals)
```



```
acf(fit$residuals)
```

Series fit\$residuals



```
hist(fit$residuals)
```

*# The residuals do not look like white noise. according to the ACF, there
seems to be some correlation. Particularly, the periods seem to be correlated,*

```

# i.e., lags 4 and 8 are correlated.

# furthermore, when we plot the residuals, time units 40-65 seem to have a
# non-zero positive expectation. they should hover above and below more or
# less equally, but they seem to be above zero there.

# part (d)

# part (e)
library(forecast)

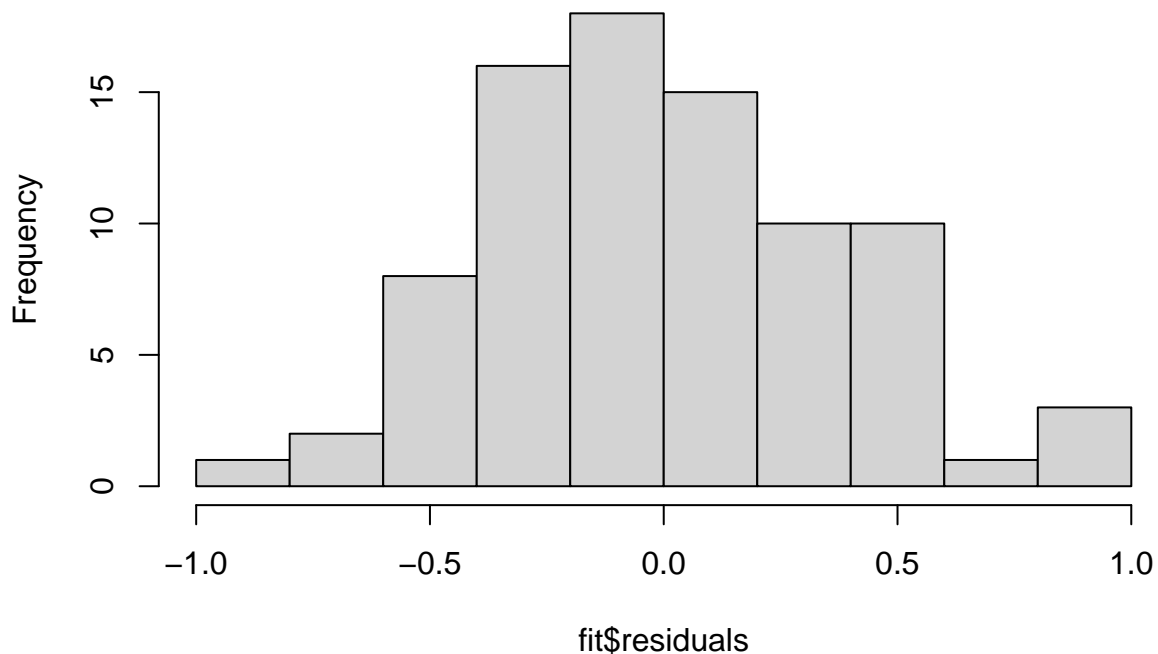
## Registered S3 method overwritten by 'quantmod':
##   method      from
## as.zoo.data.frame zoo

##
## Attaching package: 'forecast'

## The following object is masked from 'package:astsa':
##
##   gas

```

Histogram of fit\$residuals



```

dEMA <- holt(ys,h=1,level=c(95),initial="simple")
summary(dEMA)

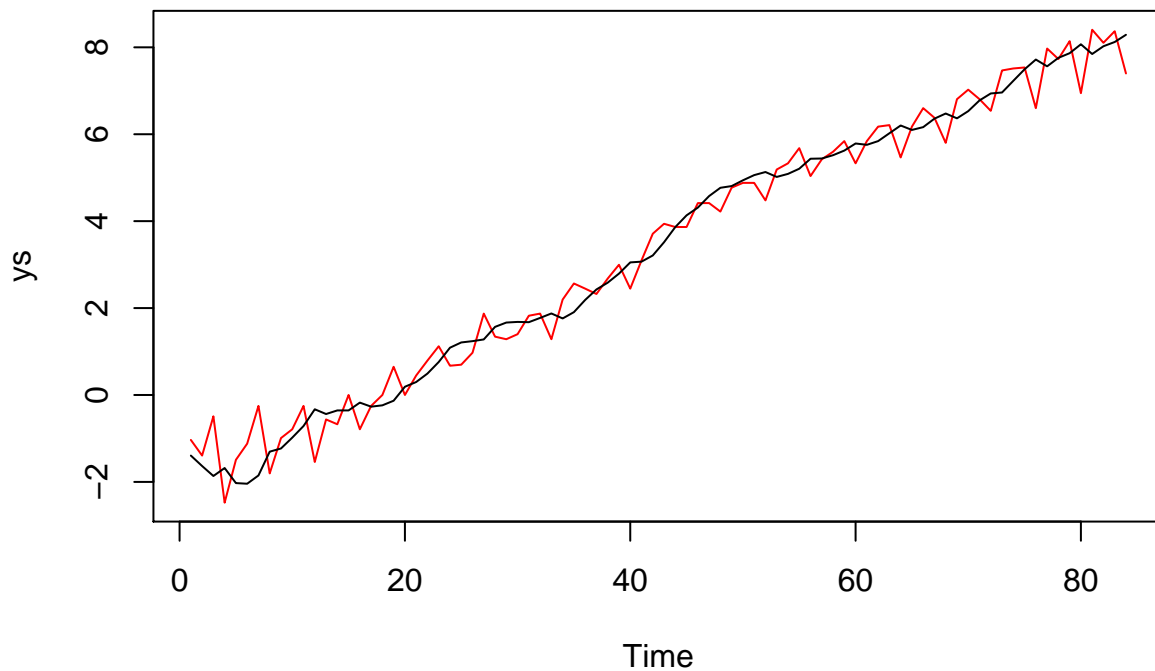
```

```

##
## Forecast method: Holt's method
##

```

```
## Model Information:
## Holt's method
##
## Call:
## holt(y = ys, h = 1, level = c(95), initial = "simple")
##
## Smoothing parameters:
##   alpha = 0.1922
##   beta  = 0.7383
##
## Initial states:
##   l = -1.0335
##   b = -0.3607
##
## sigma: 0.4987
## Error measures:
##           ME      RMSE      MAE MPE MAPE      MASE      ACF1
## Training set 0.02957531 0.4987013 0.3840707 NaN  Inf 0.7636477 -0.1033669
##
## Forecasts:
##   Point Forecast    Lo 95    Hi 95
## 85           8.108907 7.131471 9.086344
plot(ys,col="red")
lines(dEMA$fitted)
```



```
#plot(tsddata,col="red")
#lines(exp((1/alpha)*dEMA$fitted))

# part (g)

# from the summary output in party (a), the forecast using holt-winters double
# exponential method is: 8.108907 with a 95% prediction interval (7.131471 9.086344).
```

```
# problem 2
```

```
# part (b)
```

```
#  $Y(t) = -0.4 Y(t-1) + e(t)$ 
```

```
# AR(1), stationary and invertible
```

```
#  $\rho(k) = (-0.4)^k$ 
```

```
ARMAacf(ar=c(-.4),lag.max=12,pacf=F)
```

```
##           0           1           2           3           4
## 1.000000e+00 -4.000000e-01 1.600000e-01 -6.400000e-02 2.560000e-02
##           5           6           7           8           9
## -1.024000e-02 4.096000e-03 -1.638400e-03 6.553600e-04 -2.621440e-04
##          10          11          12
## 1.048576e-04 -4.194304e-05 1.677722e-05
```

```
#  $Y(t) = .9Y(t-1) + e(t) + .5e(t-1)$ 
```

```
# ARMA(1,1), stationary and invertible
```

```
#  $\rho(t) = .6984(.9)^t$ 
```

```
ARMAacf(ar=c(.9),ma=c(-.5),lag.max=12,pacf=F)
```

```
##           0           1           2           3           4           5           6           7
## 1.0000000 0.6285714 0.5657143 0.5091429 0.4582286 0.4124057 0.3711651 0.3340486
##           8           9          10          11          12
## 0.3006438 0.2705794 0.2435215 0.2191693 0.1972524
```

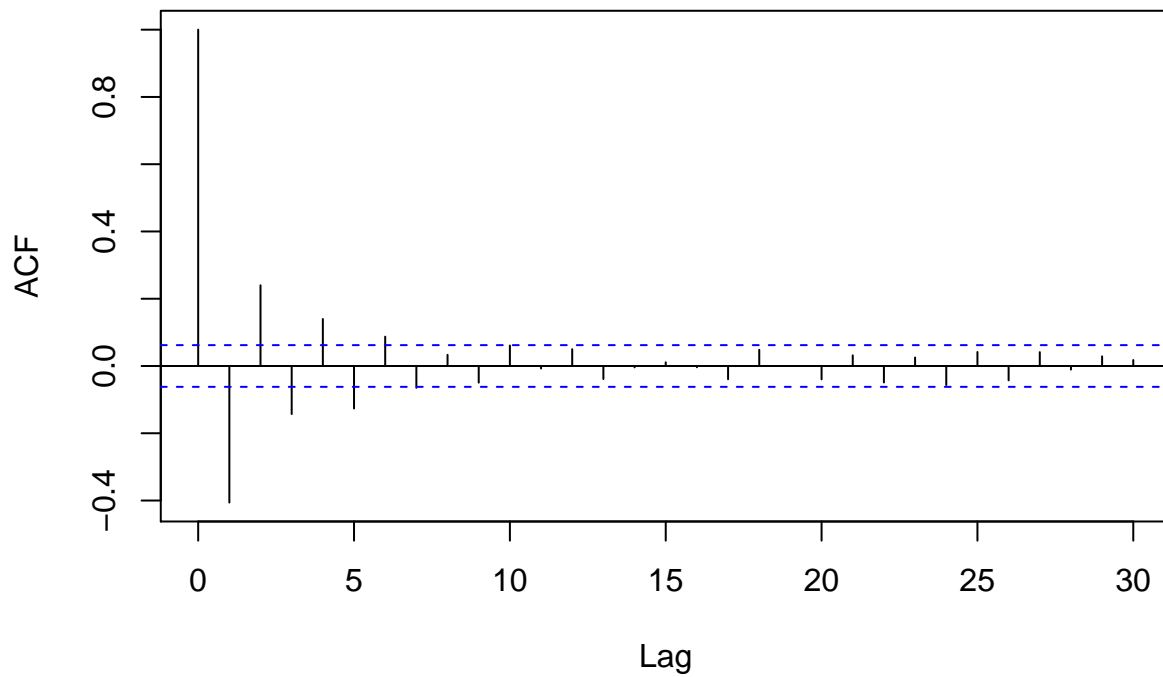
```
# part (c)
```

```
##(i)  $Y(t) = -0.4 Y(t-1) + e(t)$ 
```

```
ts1 <- arima.sim(n = 1000,
  list(ar = c(-0.4)),
  sd = 1)
```

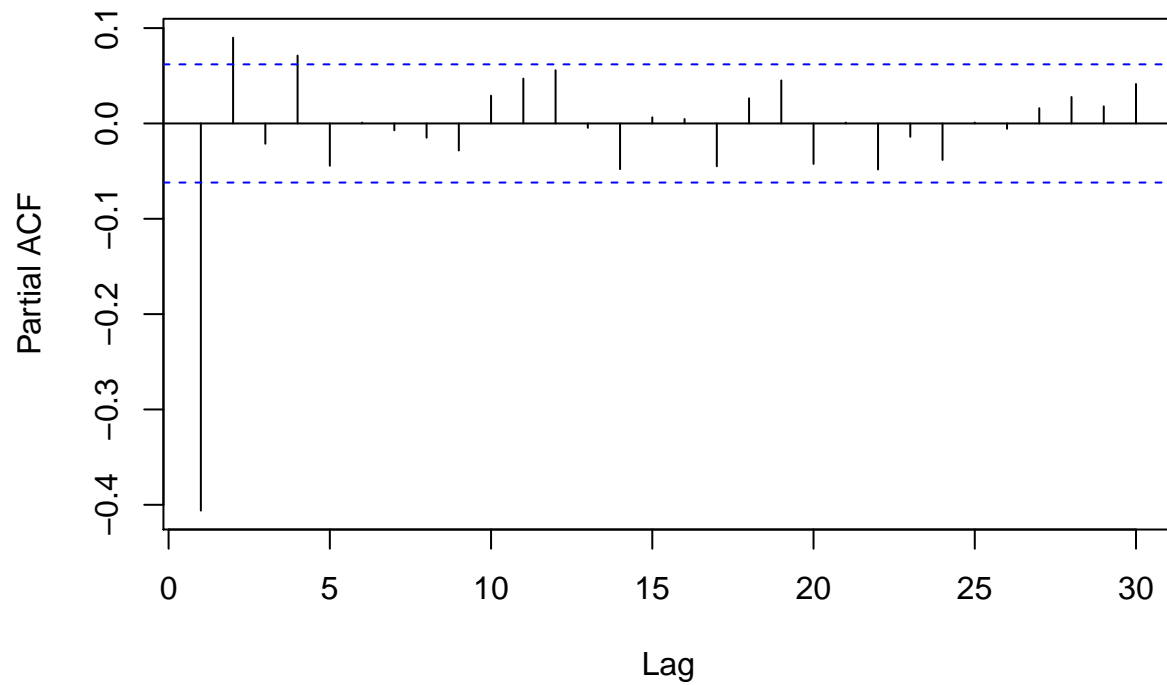
```
acf(ts1)
```

Series ts1



```
# we see that the ACF of AR(1) model:  
# (1) oscillates as expected since it has a negative coefficient -0.4.  
# (2) exponentially decays, as expected of an AR model  
  
pacf(ts1)
```

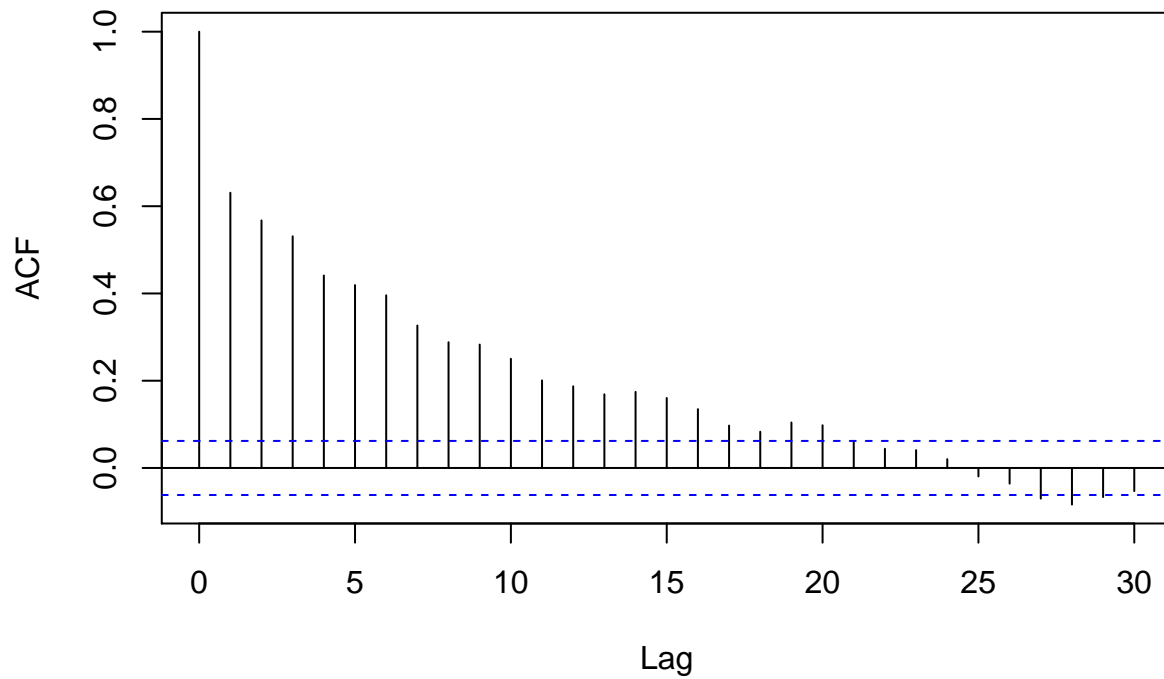
Series ts1



```
# the partial acf shows that only lag 1 is compatible with a non-zero value.  
# specifically, -0.4, as expected.
```

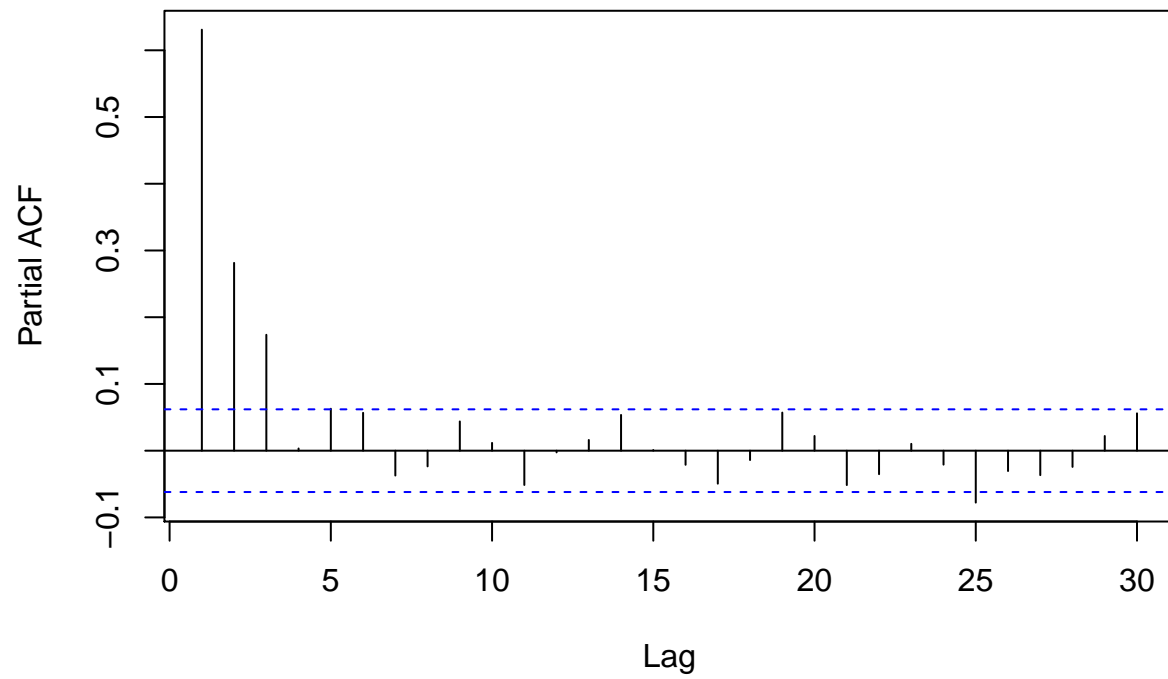
```
#  
##(iii)  $Y(t) = .9Y(t-1) + e(t) - (-.5)e(t-1)$   
# ARMA(1,1)  
ts2 <- arima.sim(n = 1000,  
                 list(ar = c(0.9),  
                     ma = c(-0.5)),  
                 sd = 1)  
  
acf(ts2)
```


Series ts2



```
# we see that the ACF of ARMA(2,2) model:  
#   (1) oscillates as expected since it has a negative coefficient -0.4.  
#   (2) exponentially decays, as expected of an AR model  
  
pacf(ts2)
```

Series ts2



*# the partial acf shows that only lag 1 is compatible with a non-zero value.
specifically, -0.4, as expected.*