

Assignment 01; STAT 626

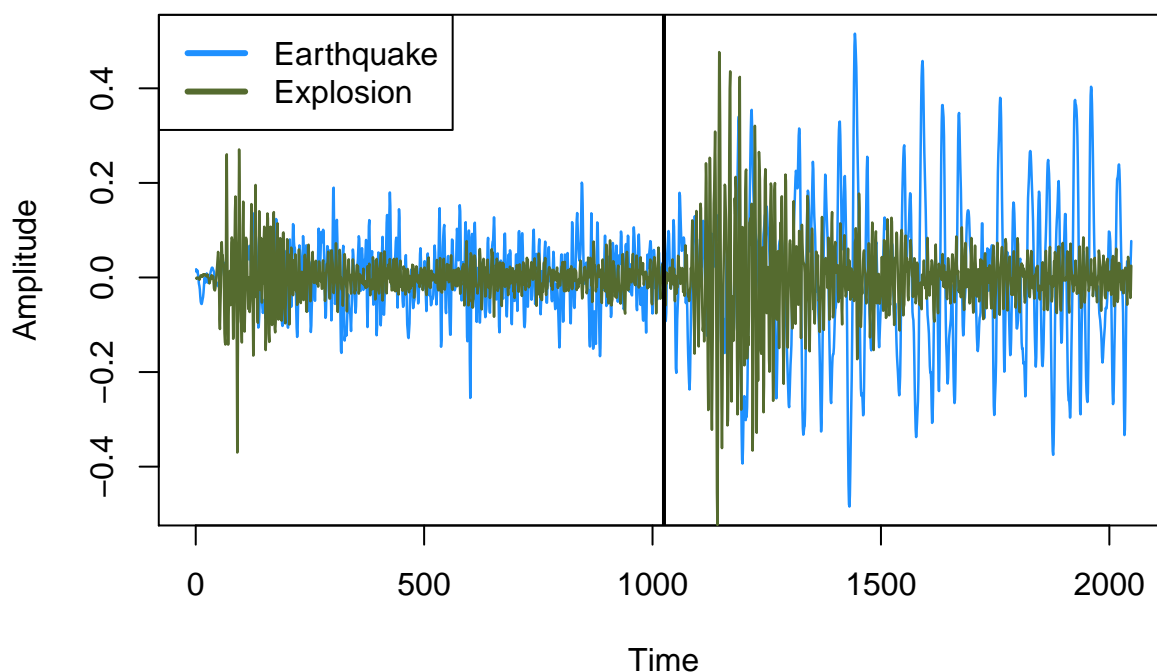
Philip Anderson; panders2@tamu.edu

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Question 1.1

```
plot.ts(EQ5, col="dodgerblue",
        , lwd=1.25
        , xlab="Time"
        , ylab="Amplitude"
        , main="EarthQuakes vs. Explosions")
lines(EXP6, col="darkolivegreen", lwd=1.25)
legend("topleft"
      , c("Earthquake", "Explosion")
      , lty=c(1,1)
      , lwd=c(3,3)
      , col=c("dodgerblue", "darkolivegreen")
      )
abline(v=1025, lwd=2)
```

EarthQuakes vs. Explosions



It appears from the plot that Earthquakes have a lower ratio of maximum amplitude in the first phase (where the black line breaks the graphic), to that of the second phase. We can check this below:

```
print("Earthquake ratio - max amplitude in phase 1 / max amplitude in phase 2")
```

```
## [1] "Earthquake ratio - max amplitude in phase 1 / max amplitude in phase 2"
```

```
max(abs(EQ5[1:1024])) / max(abs(EQ5[1025:2048]))
```

```
## [1] 0.494083
```

```
print("Explosion ratio - max amplitude in phase 1 / max amplitude in phase 2")
```

```
## [1] "Explosion ratio - max amplitude in phase 1 / max amplitude in phase 2"
```

```
max(abs(EXP6[1:1024])) / max(abs(EXP6[1025:2048]))
```

```
## [1] 0.707169
```

It also appears that in both phases, Earthquakes seem to be stationary (time-independent mean, time-independent variance), while Explosions do not - they have higher variance in the beginning of each phase, compared with the middle and end.

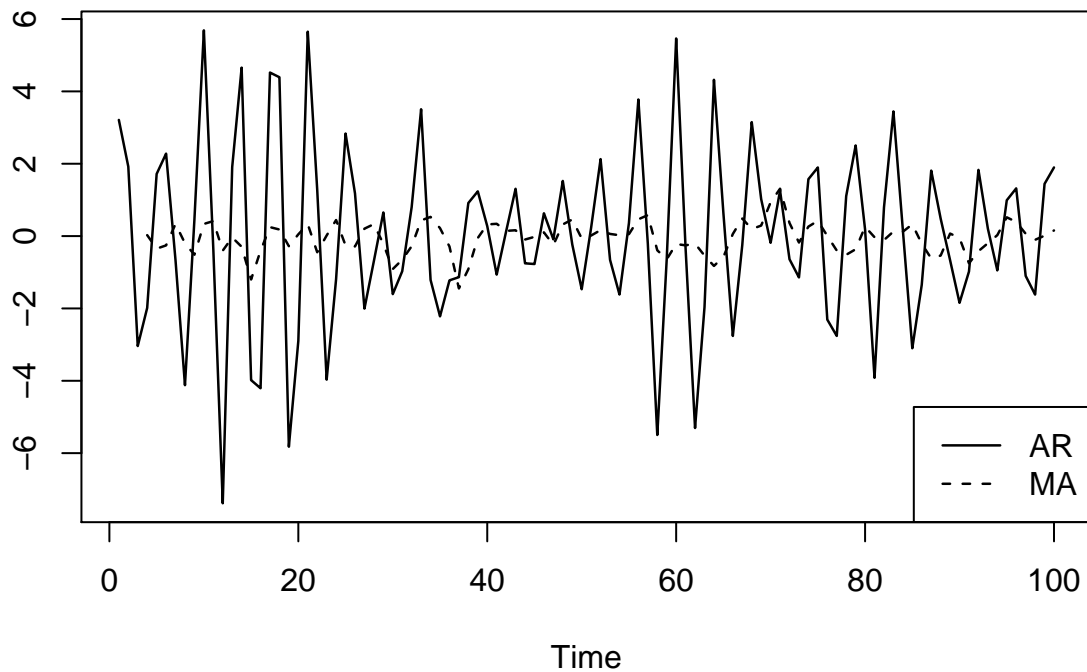
Question 1.3

Question 1.3A

```
set.seed(1739)
# generate random draws with variance 1
w <- rnorm(125, 0, 1) # white noise
# apply the autoregressive filter and throw out first 25 records as burn-in
# note that we are looking for no lag 1 effect, just lag 2
x <- filter(w, filter=c(0, -0.9), method="recursive")[-(1:25)]
# now apply the moving average filter to the autoregression
v <- filter(x, sides=1, filter=rep(1/4, 4))

plot.ts(x, main="Autoregression vs. Moving Average", ylab="", lwd=1.25)
lines(v, lty=2, lwd=1.25)
legend("bottomright", c("AR", "MA")
      , lty=c(1,2)
      , lwd=c(1.25, 1.25)
      )
```

Autoregression vs. Moving Average



The moving average filter sizeably reduces the amplitude of the time series; this implies that much of that effect may be noise.

Question 1.3B

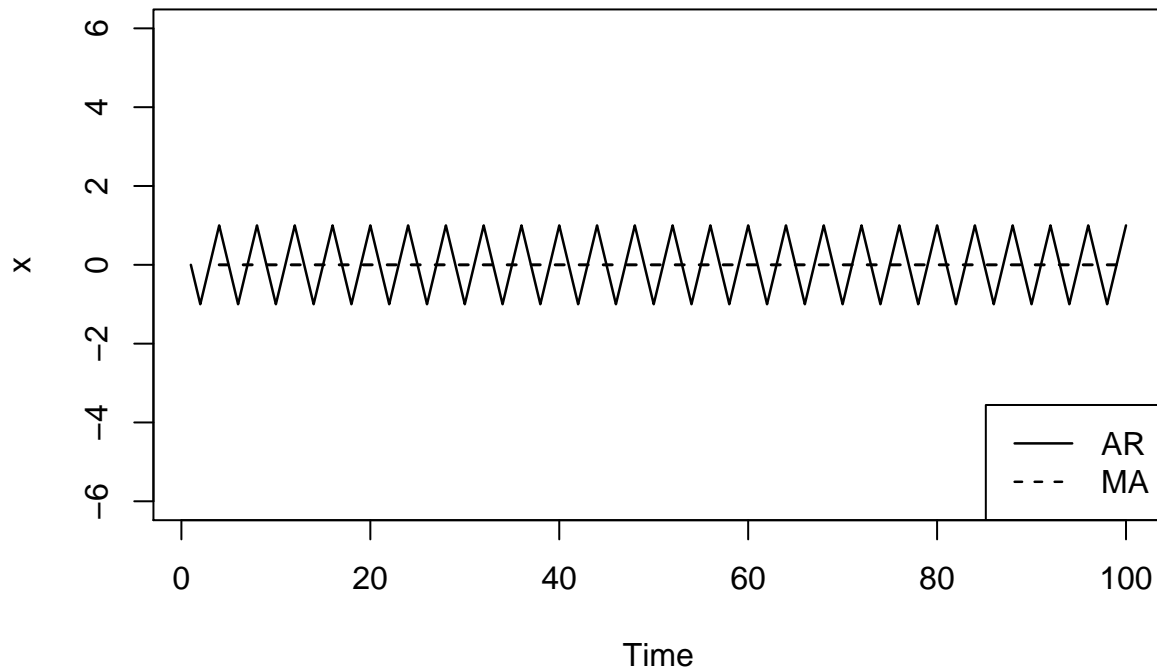
Generate a series but with no random component.

```
t <- seq(1, 100)
x <- cos(((2 * pi * t) / 4))
v <- filter(x, sides=1, filter=rep(1/4, 4))

plot.ts(x, lwd=1.25, main="Trend vs. Moving Average", ylim=c(-6, 6))
lines(v, lty=2, lwd=1.5)

legend("bottomright", c("AR", "MA")
      , lty=c(1,2)
      , lwd=c(1.25, 1.25)
      )
```

Trend vs. Moving Average



There is no noise to remove in the specified time series, so when we use the moving average filter with lag 4, a flat line is produced because the entire cycle of the trend is smoothed away.

Question 3C

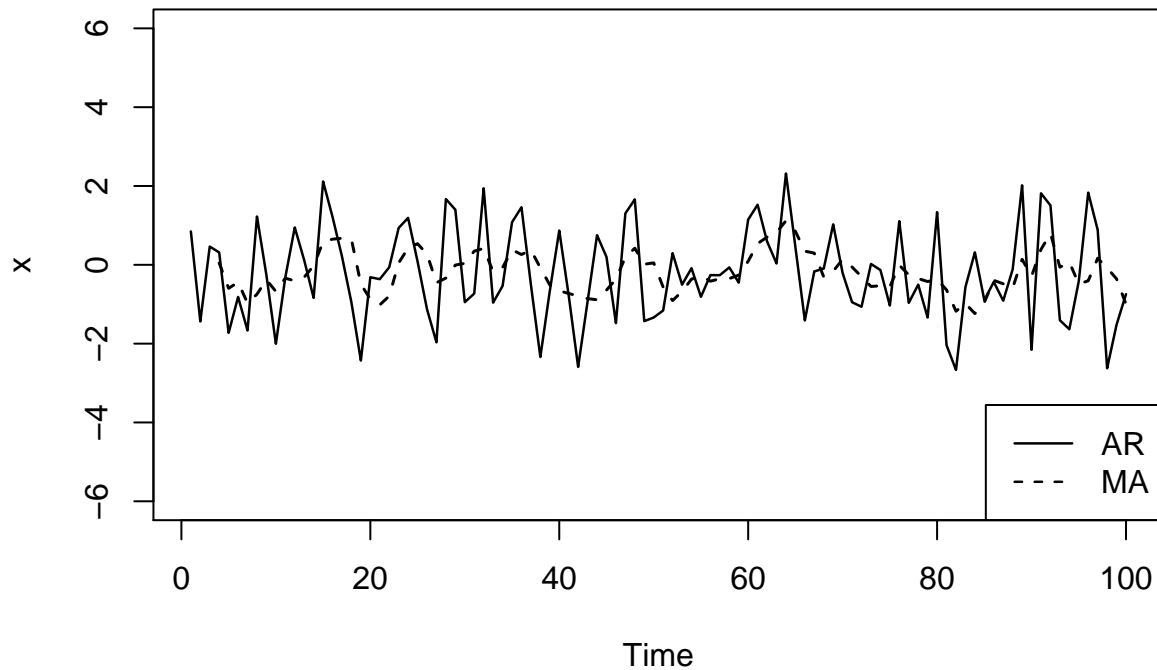
Repeat B but add white noise to the trend.

```
t <- seq(1, 100)
w <- rnorm(100, 0, 1)
x <- cos((2 * pi * t) / 4) + w

v <- filter(x, rep(1/4, 4), sides=1)
plot.ts(x, lwd=1.25, main="Trend with Noise vs. Moving Average", ylim=c(-6, 6))
lines(v, lty=2, lwd=1.5)

legend("bottomright", c("AR", "MA"),
      , lty=c(1,2)
      , lwd=c(1.25, 1.25)
      )
```

Trend with Noise vs. Moving Average



In theory, the moving average filter should be removing the noise we added in, leaving us with the cosine wave we produced in the previous problem. It produces a line with a clear periodicity, but it is not as clean as the pure trend I produced.

Question 3D

In all cases, the moving average removes a great deal of variance from the time series. If there is not a random component to the time series, the moving average filter can remove all of the variance to the extent that it produces a flat line (3B). The filter is not perfect, however - comparing the results of 1.3.B to 1.3.C shows that the filter does not leave the pure trend by trying to remove the added noise.