# Week 1 exercises

# Daniel Alonso

November 18th, 2020

# Importing libraries

```
library(ggplot2)
library(foreach)
library(dplyr)
```

# Exercise 1

Simulating 100 trajectories of length n = 1000 for X and Y.

```
Traj_X <- data.frame()</pre>
Traj_Y <- data.frame()</pre>
for (k in 1:100) {
    X <- data.frame(x=1:1000, val=rep(0,1000), run=rep(k,1000))</pre>
    Y <- data.frame(x=1:1000, val=rep(0,1000), run=rep(k,1000))
    X_r \leftarrow rep(0,1000)
    Y_r \leftarrow rep(0,1000)
    for (i in 1:1000) {
         if (i > 1) {
             X_r[i] \leftarrow 0.5*X_r[i-1]+rnorm(1)
             Y_r[i] <- 2*Y_r[i-1]+rnorm(1)
    }
    X$val <- X_r
    Y$val <- Y_r
    Traj_X <- rbind(Traj_X, X)</pre>
    Traj_Y <- rbind(Traj_Y, Y)</pre>
}
```

#### a - Plotting simulated trajectories

#### Trajectories X

```
ggplot(data = Traj_X, aes(x=x, y=val)) +
   geom_line(aes(colour=run), show.legend=FALSE)
```

## Trajectories Y

The values of Y are too large for ggplot to show.

b - Use the simulated trajectories to estimate the mean and the covariance functions

```
mean_X = rep(0,100)
mean_Y = rep(0,100)
for (i in 1:100) {
    x = Traj_X %>% filter(run == i) %>% select(val)
    y = Traj_Y %>% filter(run == i) %>% select(val)
    mean_X[i] = mean(x$val)
    mean_Y[i] = mean(y$val)
}
```

The mean of all trajectories of X is the following:

```
mean(mean_X)
```

#### ## [1] 0.006358091

The mean of all trajectories of Y is the following:

```
mean(mean_Y)
```

#### ## [1] 7.706139e+296

The mean of the covariances of all combinations of trajectories is the following:

```
covs = rep(0,100*100)
cnt = 0
for (i in 1:100) {
    for (j in 1:100) {
        x = Traj_X %>% filter(run == i) %>% select(val)
        y = Traj_Y %>% filter(run == j) %>% select(val)
        cnt = cnt + 1
        covs[cnt] = cov(x,y)
    }
}
mean(covs)
```

c - Is the process stationary? Is it weakly stationary?

X is stationary but Y is not

d - If the process is weakly stationary, use the function acf to display the autocorrelation function and compare with your own estimate

```
acf(X[1,])
L=30
acfx=numeric(length=L)
```

```
for (i in 1:L){
   acfx[i]=mean(diag(gX[1:(n+1-i),(i+1):(n+1)]))
}
plot(1:L, acfx)
```

#### Exercise 2

```
I_0 = 5 \text{ and } S_0 = 1000
\alpha = 0.0005
\text{alpha} <-0.0001
\text{cases} <-c(5)
\text{s} <-1000
\text{i} <-5
\text{while (i > 0) } \{
\text{p} <-1 - (1 - \text{alpha})^{-}(\text{i})
\text{i} <-\text{rbinom}(1, \text{s}, \text{p})
\text{cases} <-c(\text{cases}, \text{i})
}
```

plot(cases)

```
ex1_report_files/figure-latex/unnamed-chunk-10-1.pdf
```

### Exercise 4

Given the transition matrix and initial distribution:

```
P <- c(0.1, 0.4, 0.2, 0.3,

0.6, 0, 0.2, 0.2,

0.1, 0.3, 0.3, 0.3,

0.5, 0.3, 0.1, 0.1)

P <- matrix(P,nrow=4,byrow=T)

alpha=rep(1/4,4) #uniform initial distribution
```

We define the following function to calculate matrix powers (thanks profe!):

```
matrixpower <- function(M,k) {
    # ARGUMENTS:
    # M: square matrix
    # k: exponent
    if(dim(M)[1]!=dim(M)[2]) return(print("Error: matrix M is not square"))
    if (k == 0) return(diag(dim(M)[1])) # if k=0 returns the identity matrix</pre>
```

```
if (k == 1) return(M)
  if (k > 1) return(M %*% matrixpower(M, k-1)) # if k>1 recursively apply the function
}
a - P(X_4 = 3|X_3 = 4)

P[4,3]
## [1] 0.1
b - P(X_4 = 3|X_2 = 4)

matrixpower(P,2)[4,3]
## [1] 0.2
c - P(X_1 = 1)
(t(alpha)%*%P)[1]
## [1] 0.325
d - E[X_2]
```