HW: Week 10

36-350 – Statistical Computing

Week 10 – Spring 2022

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You must submit **your own** HW as a knitted PDF file on Gradescope.

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
suppressWarnings(library(tidyverse))
```

HW Length Cap Instructions

- If the question requires you to print a data frame in your solution e.g. `q1_out_df`, you must first apply **head(q1__out__df, 30)** and **dim(q1__out__df)** in the final knitted pdf output for such a data frame.
- Please note that this only applies if you are knitting the `Rmd` to a `pdf`, for Gradescope submission purposes.
- If you are using the data frame output for visualization purposes (for example), use the entire data frame in your exploration
- The **maximum allowable length** of knitted pdf HW submission is **30 pages**. Submissions exceeding this length *will not be graded* by the TAs. All pages must be tagged as usual for the required questions per the usual policy
- For any concerns about HW length for submission, please reach out on Piazza during office hours

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Question 1

(20 points)

How old (in days) were sprinters on the days they achieved fast times? Below, we read in `sprint.lines`. Your goal: examine `sprint.lines`, extract the birthdays and the sprint days for each line, and determine the difference. Histogram your result. (Change the x-axis label to “Sprinter Age (Days)”. You should observe a skew distribution that peaks between 8,000 and 9,000 days.

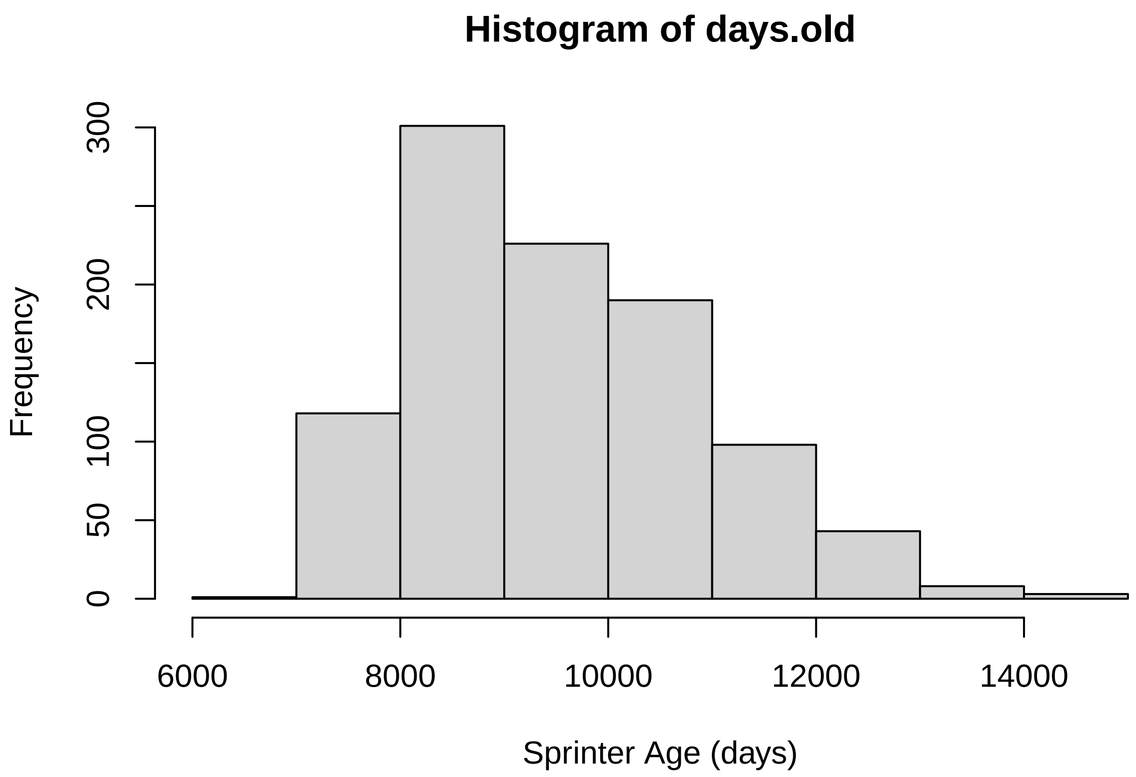
```r
sprint.lines = readLines("http://www.stat.cmu.edu/~mfarag/350/men_100m.html")
data.lines = grep(" +(9|10)\\.",sprint.lines)
sprint.lines = sprint.lines[min(data.lines):max(data.lines)]
sprint.lines[1] = substr(sprint.lines[1],10,nchar(sprint.lines[1]))

# FILL ME IN
pattern = "[0-9]{2}\\.[0-9]{2}\\.[0-9]{4}"
reg.exp = regexpr(pattern, sprint.lines, useBytes = TRUE)
sprint.dates = regmatches(sprint.lines, reg.exp)

pattern2 = "[0-9]{2}\\.[0-9]{2}\\.[0-9]{2}"
reg.exp2 = regexpr(pattern2, sprint.lines, useBytes = TRUE)
birth.dates = regmatches(sprint.lines, reg.exp2)

sprint.dates = apply(data.frame(sprint.dates), 1, as.Date, format="%d.%m.%Y")
birth.dates = apply(data.frame(birth.dates), 1, function(x) {sub("(..)$", "19\\1", x)}) %>%
  data.frame(.) %>%
  apply(., MARGIN = 1, as.Date, format="%d.%m.%Y")

days.old = sprint.dates - birth.dates
hist(days.old, xlab ="Sprinter Age (days)")
```



Here we read in data containing the dates that objects were loaned by the CMU libraries in April 2019:

```
load(url("http://www.stat.cmu.edu/~mfarag/350/HW_10_Q2.Rdata"))
```

The variable that is loaded is `loan.dates`.

Question 2

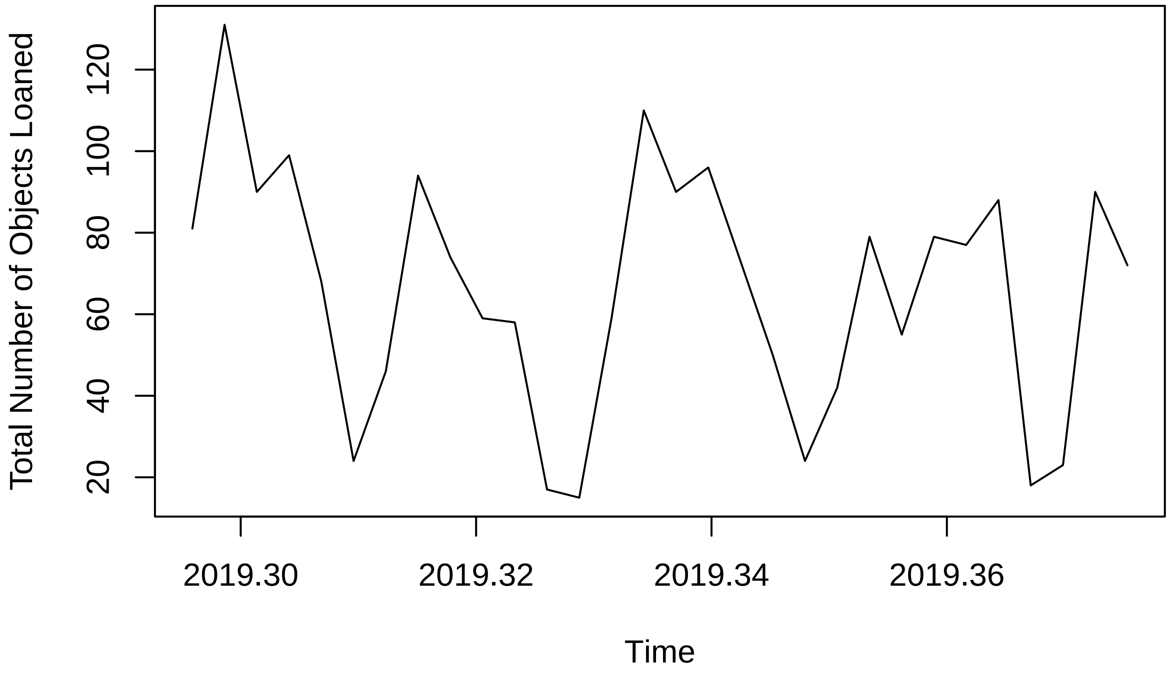
(20 points)

From these data, create an object of the `ts` class that shows the total number of objects loaned each day. Note that to define a daily time series, the variable passed as `start` has to include the year (2019) and then the day of the year (e.g., January 1st is 1, February 1st is 32, etc.), and `frequency` should be set to 365. To get the day of the year: see `format()`: if you pass in the first day of the month and the argument `"%j"`, you will get out the day of the year. (Cast this to `numeric`, though!) Plot your result. The x-axis will show decimals indicating the fraction of the way through the year, so seeing, e.g., "2019.26" is OK. Change your y-axis label to something more appropriate than a variable name. (Hint: you'll want to make sure your dates `sort()` correctly when using `table()` to determine the number of loans per day. In other words, 4/10 should not immediately follow 4/1, but it might. If you convert to `Date` format first, sorting should work out OK.)

```r
dates = apply(data.frame(loan.dates), 1, function(x){as.Date(x, format="%m/%d/%y")})
start = as.numeric(format(as.Date(min(dates), origin="01-01-1970"), format="%j"))

count.table = table(dates)
sorted = names(count.table)
dates.ts = ts(count.table, start = c(2019, start), frequency = 365)

plot(dates.ts, xlab="Time", ylab="Total Number of Objects Loaned")
```

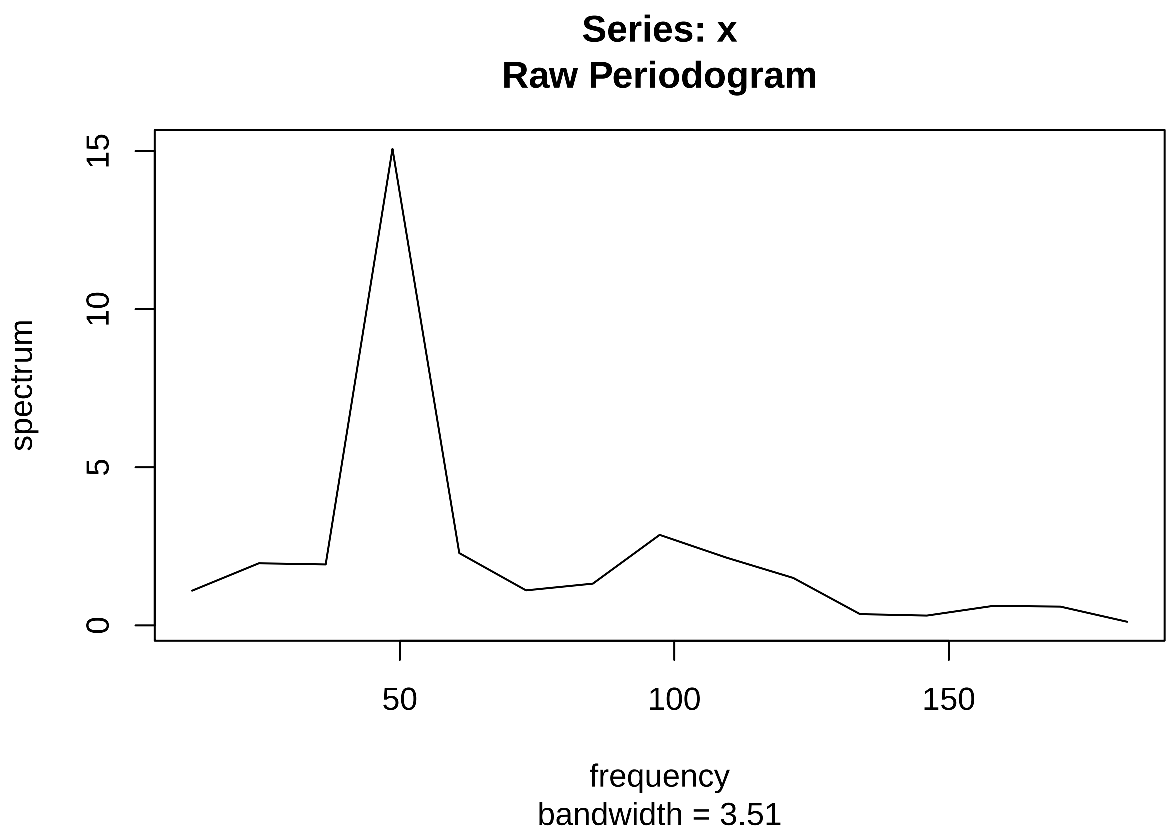


Question 3

(20 points)

Construct a periodogram for the time-series data in Q2. Determine how many cycles correspond to the maximum spectral value by dividing the maximum `frequency` value by the `frequency` value associated with the maximum `spectrum` value. Interpret that number of cycles.

```
periodogram = spectrum(dates.ts,log="no")
```



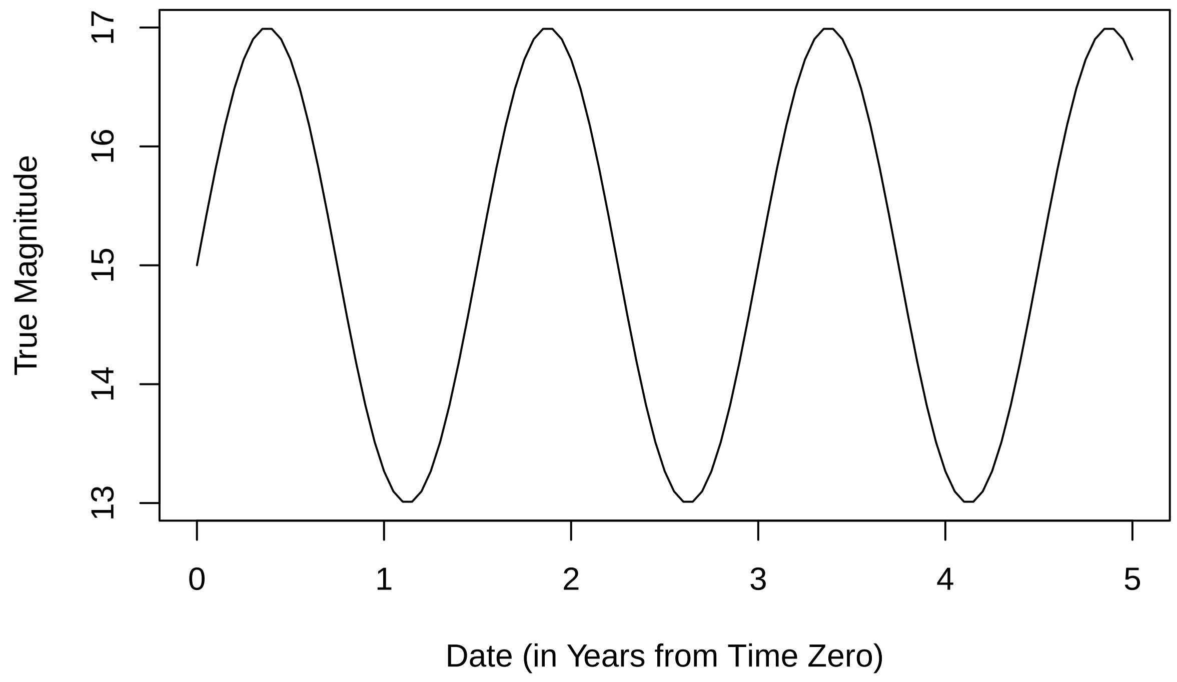
```
max(periodogram$freq)/periodogram$freq[which.max(periodogram$spec)]
```

```
## [1] 3.75
```

```
About every 3.75 cycles, you will see the maximal spectral value again. So in about 3 years and 9 month
```

Let's say you have a source of light whose magnitude (a logarithmic measure of brightness) varies sinusoidally:

```
t = seq(0,5,by=0.05)
y = 15 + 2*sin(2*pi*t/1.5)
plot(t,y,typ="l",xlab="Date (in Years from Time Zero)",ylab="True Magnitude")
```



Question 4

(20 points)

How well can you estimate the mean magnitude of this source if you observe it at n random times sampled uniformly over five years? (This isn't really about `Date` or `POSIXlt`, but a more general exercise that reminds you that features that you extract from any set of data—like a time series of measurements—are random variables. . . and that the more times you look, the better your estimate.) Write a function that generates n data given the model above. Assume each measurement has an additive uncertainty $\epsilon\ N(0,(0.2)^2)$. Call your function $k = 1000$ times, and save the mean of the magnitude observed with each call. Try $n = 10$, $n = 20$, and $n = 40$, and record (and display!) the sample standard deviations of the magnitude means. You should see that the sample standard deviation for $n = 40$ is roughly half that for $n = 10$. $\sqrt{n}$ n'at.

```
set.seed(808)
my.fun = function(x){
  sample = sample(y, x, replace = TRUE)
  epsilon = rnorm(x, 0, 0.2)
  mean(sample + epsilon)
}

data = matrix(rep(10, 1000), ncol=1)
math.vector1 = apply(data,1,my.fun)
```

```
data = matrix(rep(20, 1000), ncol=1)
math.vector2 = apply(data,1,my.fun)

data = matrix(rep(40, 1000), ncol=1)
math.vector3 = apply(data,1,my.fun)

sd(math.vector1)
```

```
## [1] 0.4431335
```

```
sd(math.vector2)
```

```
## [1] 0.3088093
```

```
sd(math.vector3)
```

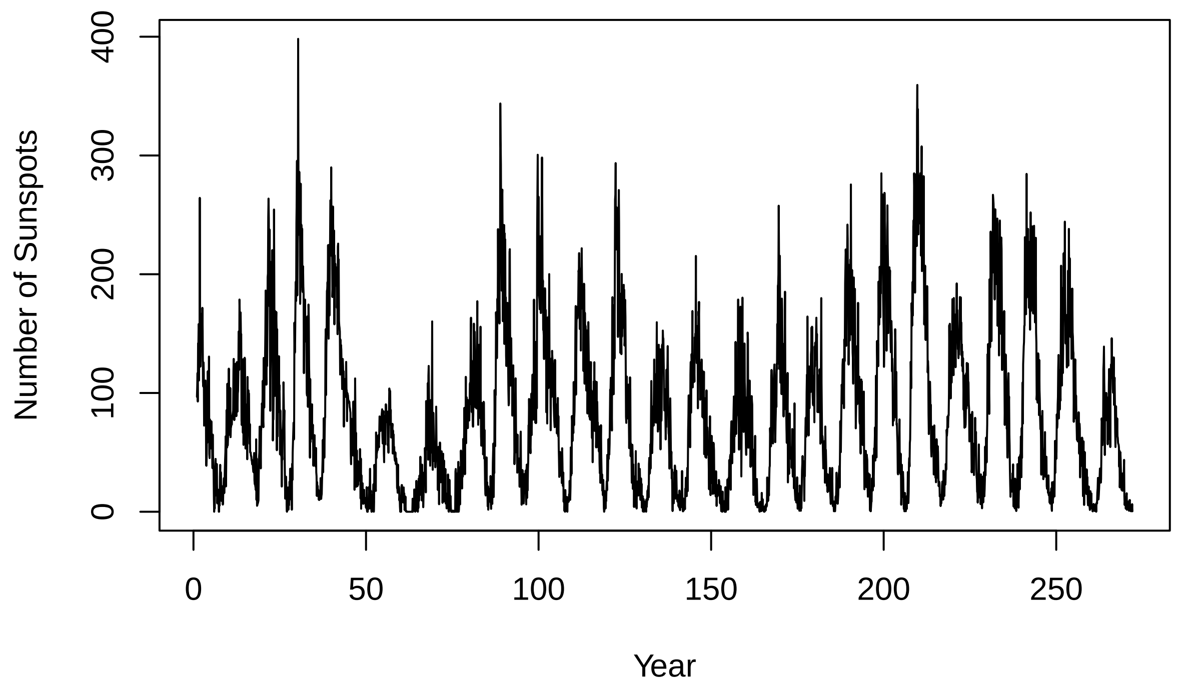
```
## [1] 0.2268912
```

Question 5

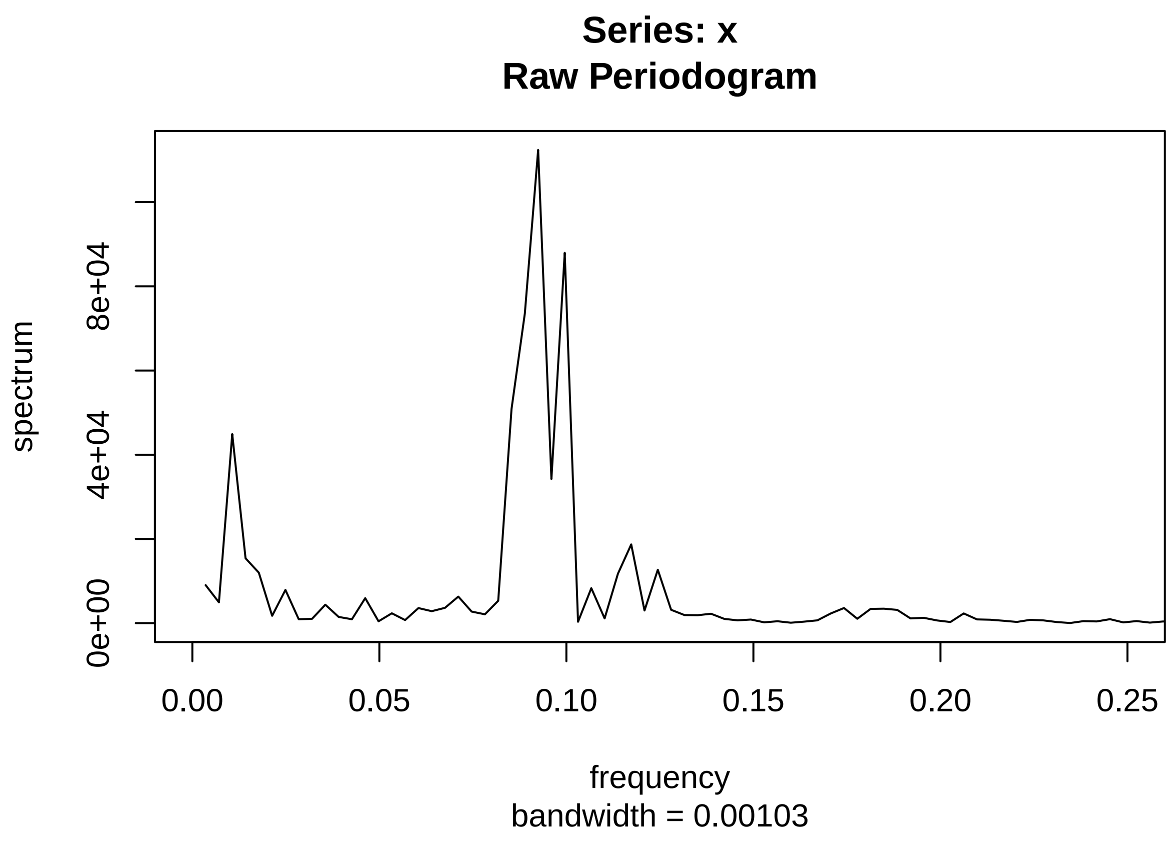
(20 points)

Data on monthly sunspot number are contained in the file `http://www.stat.cmu.edu/~mfarag/350/SN_m_tot_V2.0.csv`. Examine the file and read it into `R`, then define a time-series object with the data of the fourth column. Plot the time series (change the x-axis label to "Year" and the y-axis label to "Number of Sunspots"), and then plot the periodogram. For the latter, change the limits along the x-axis so as to zoom in on the peak that you should see. Determine the time-scale associated with the highest peak (using code, not by hand: examine the captured output of `spectrum()`... you need to capture the output, as otherwise `spectrum()` operates with `invisible()` return). Interpret this time-scale, using Google if necessary. (Hint: since you are inputting a time-series object into `spectrum()`, a `frequency` of 1 corresponds to 1 year.)

```
file = read.csv("http://www.stat.cmu.edu/~mfarag/350/SN_m_tot_V2.0.csv", sep=";", header=FALSE)
# file = read.csv
sunspot.ts = ts(file[,4], frequency = 12)
plot(sunspot.ts, xlab="Year", ylab="Number of Sunspots")
```



```
p = spectrum(sunspot.ts, xlim=c(0,0.25),log="no")
```



```
1/p$freq[which.max(p$spec)]
```

```
## [1] 10.81731
```

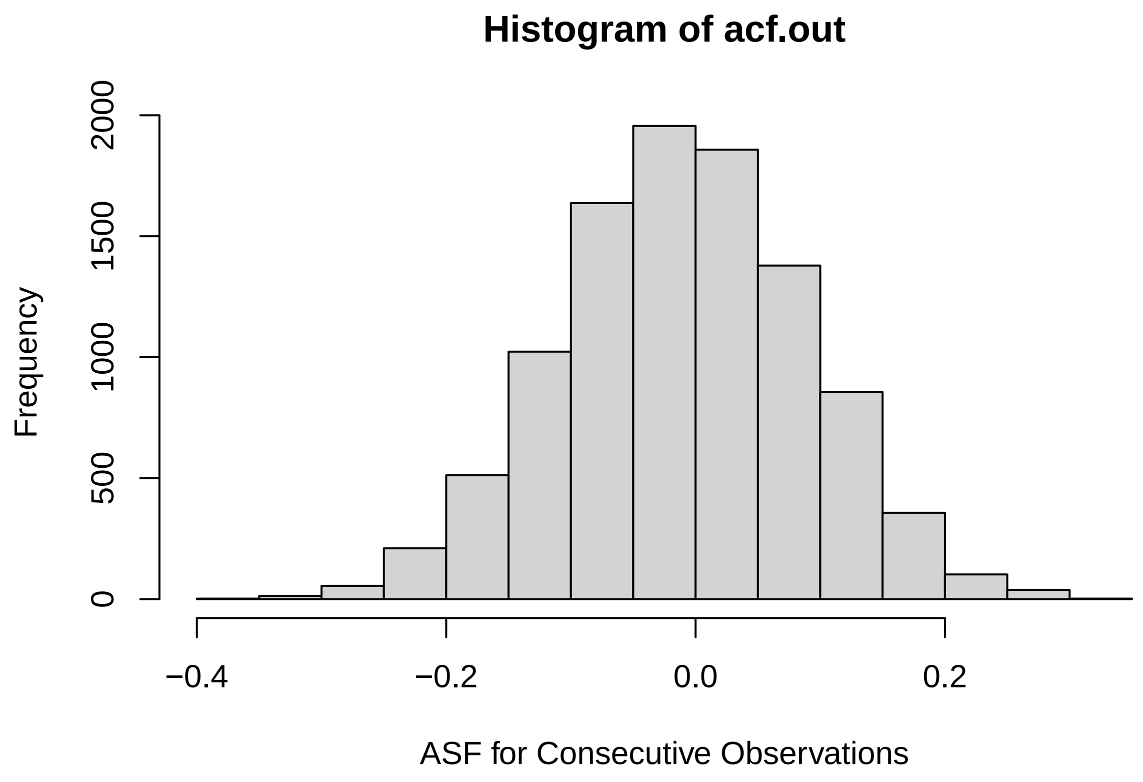
```
It takes about 10.8 cycles, aka 10.8 years, for sunspot activity to reach it’s peak. https://www2.hao.u
```

Question 6

(20 points)

What is observed correlation between two consecutive measurements in a white-noise time series? (The population value is zero.) Simulate 10,000 separate sequences that each contain 100 samples from a standard normal, input each sequence into `acf()`, and from the captured output, determine the acf value for consecutive data. (Note: for computational efficiency, pass the argument `plot=FALSE` to `acf()`.) Histogram your output. Last, determine the proportion of data that lie outside the confidence band given by $-1/n \pm 2/\sqrt{n}$... one would hope that this value is near 0.05. (It need not be exactly that.)

```
set.seed(707)
white.noise = matrix(rnorm(10000*100), ncol=100)
acf.out = apply(white.noise, 1, function(x){acf(x, plot=FALSE)$acf[2]})
hist(acf.out, xlab="ASF for Consecutive Observations")
```



```r
above = sum(acf.out > (-1/100 + 2/sqrt(100)))
below = sum(acf.out < (-1/100 - 2/sqrt(100)))
(above + below)/10000
```

```
## [1] 0.0398
```