

[STAT 4540] Exam-2

Michael Ghattas

4/3/2022

Problem 1

```
library(ltmr)

df <- load("/Users/Home/documents/Michael_Ghattas/School/CU_Boulder/2022/Spring 2022/STAT - 4540/Exams/2/Exam2dat
a.RData");

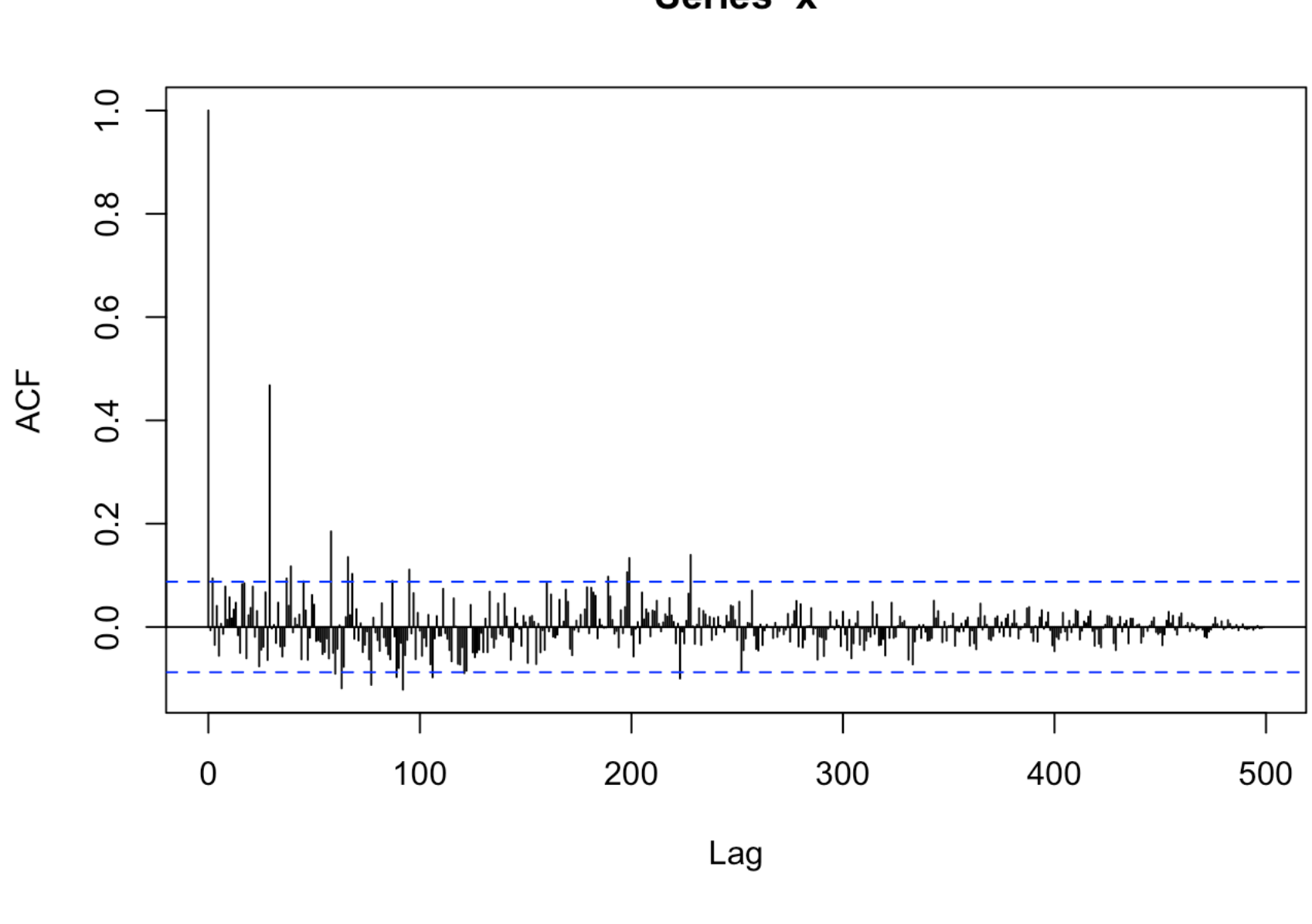
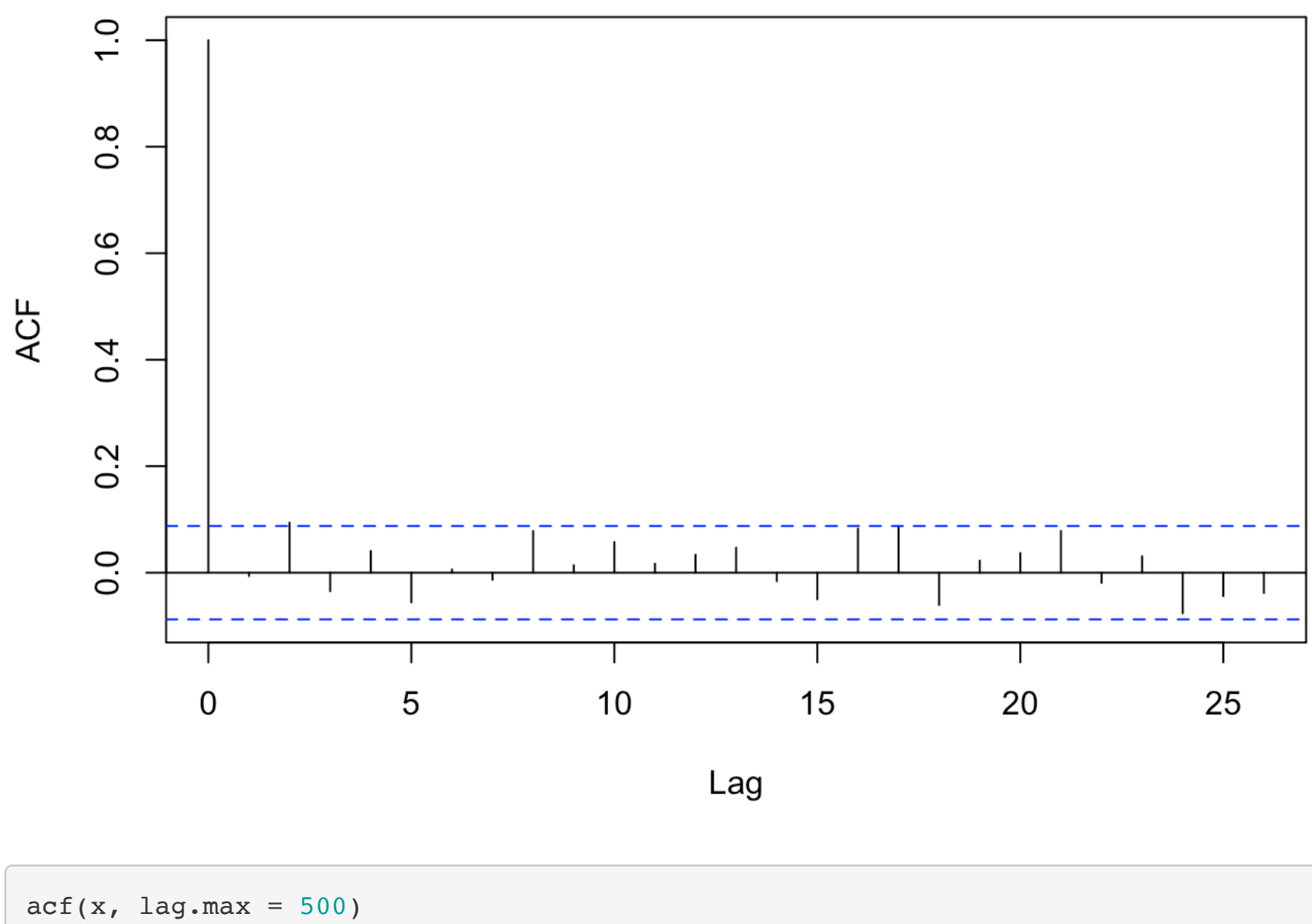
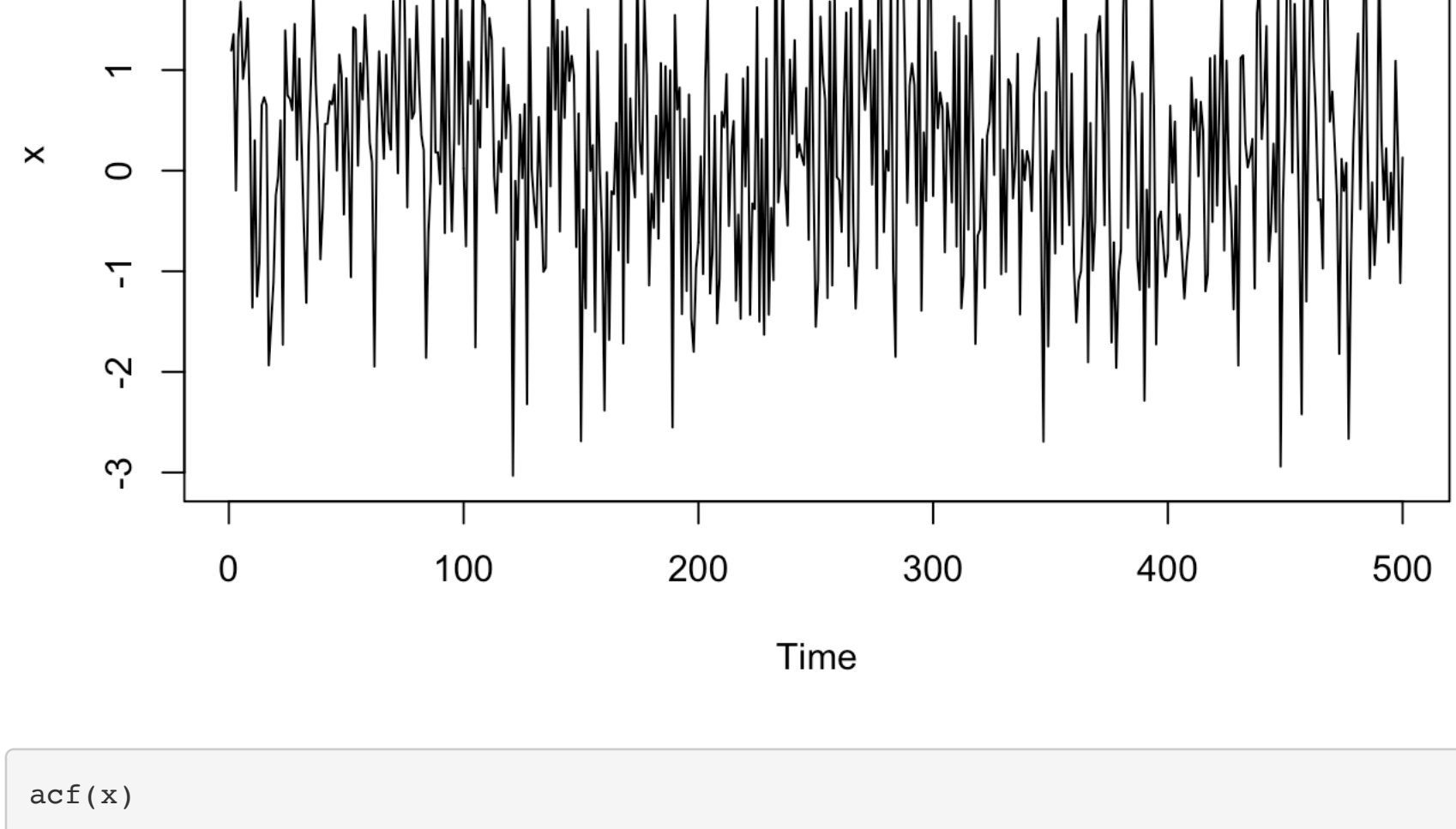
dat <- data.frame(x = x)
x = dat[, 1]
mean(x)

## [1] 0.2805136

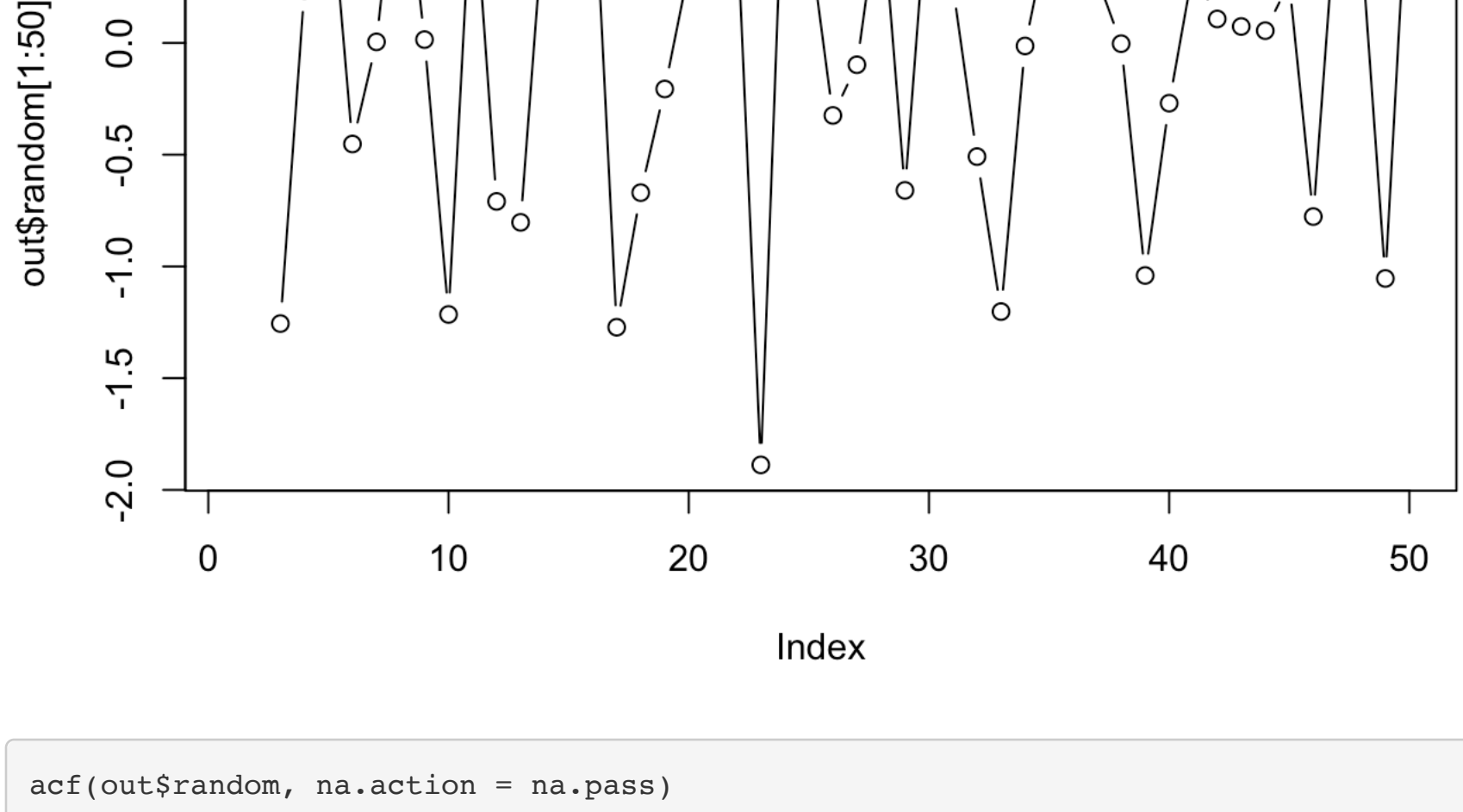
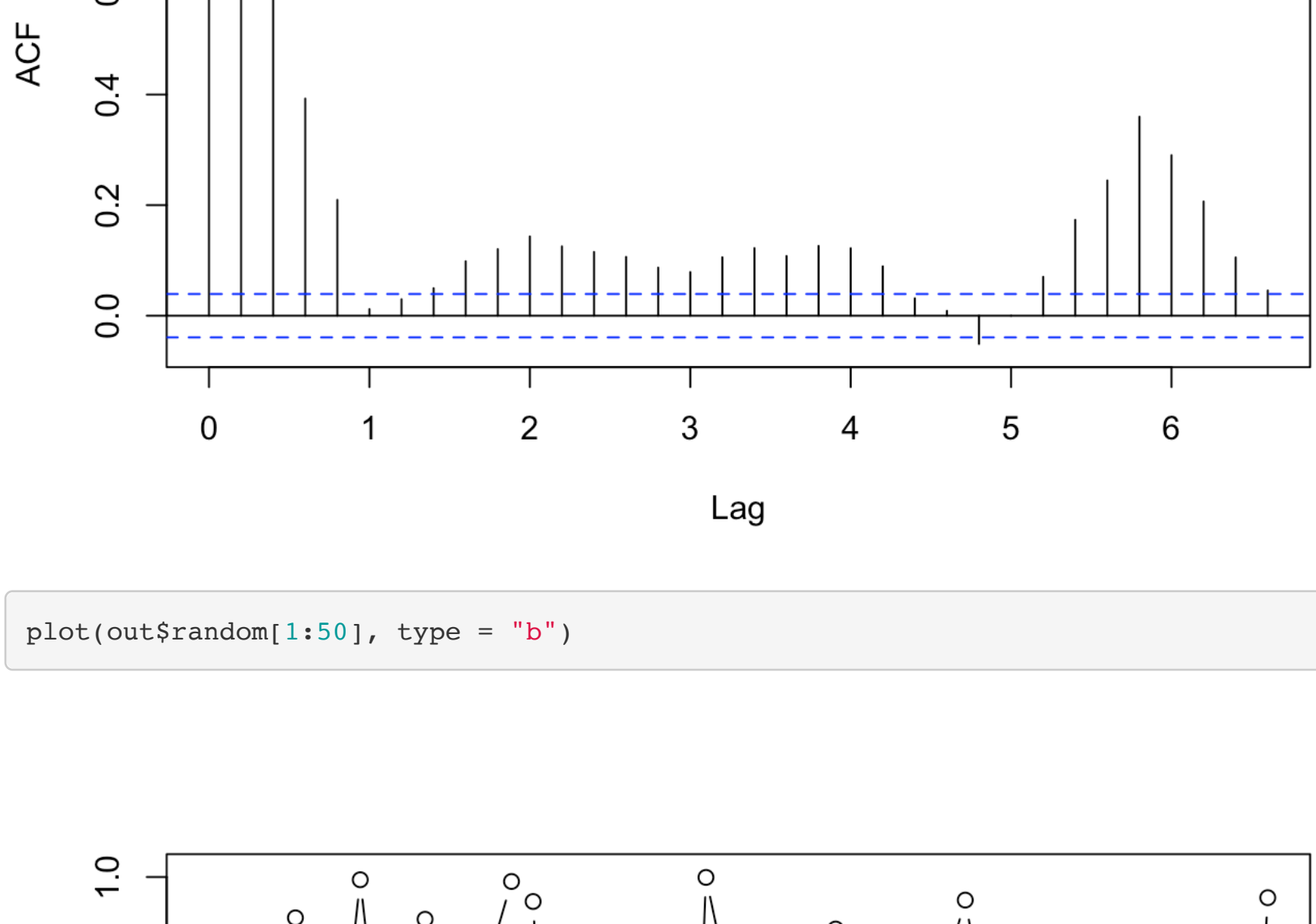
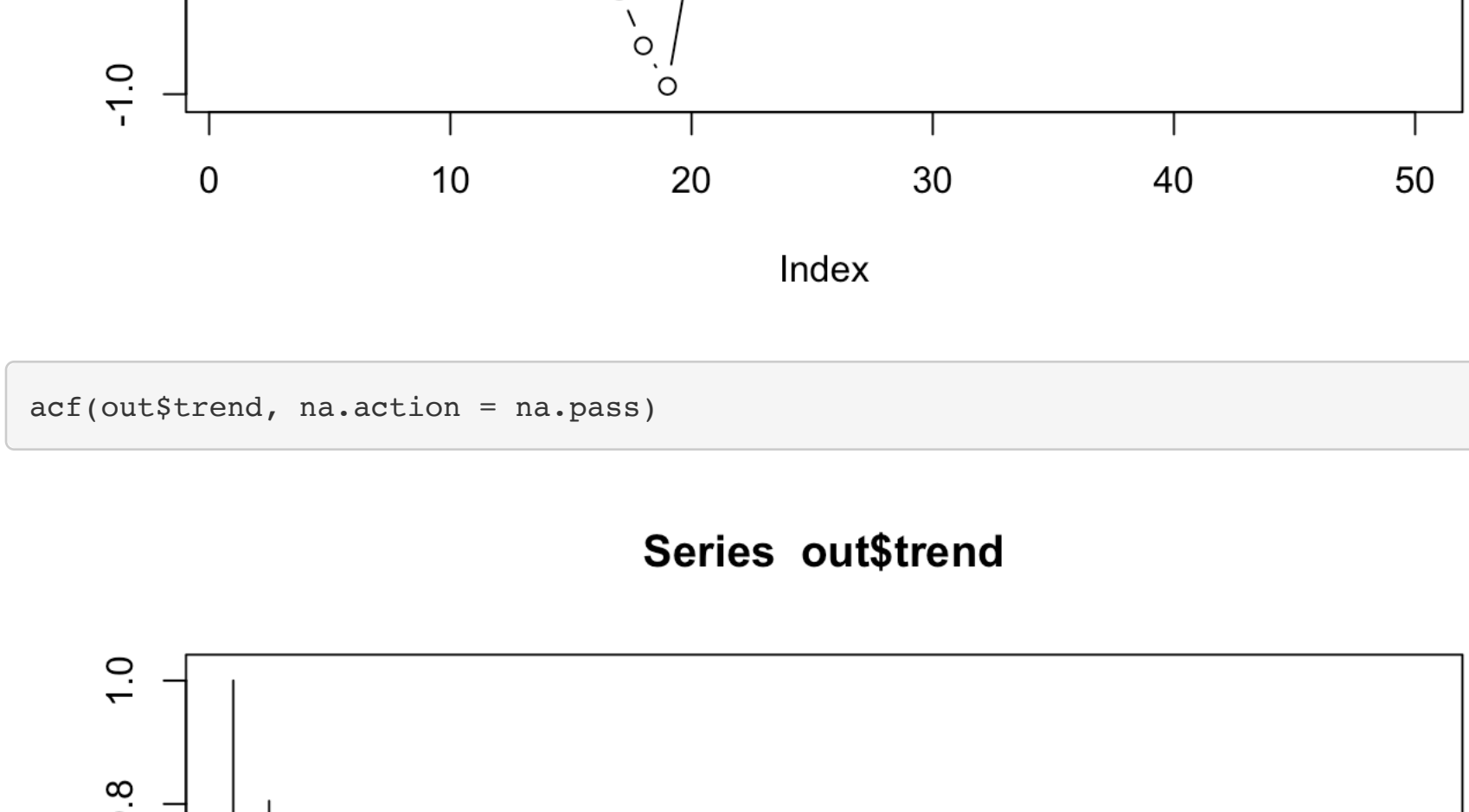
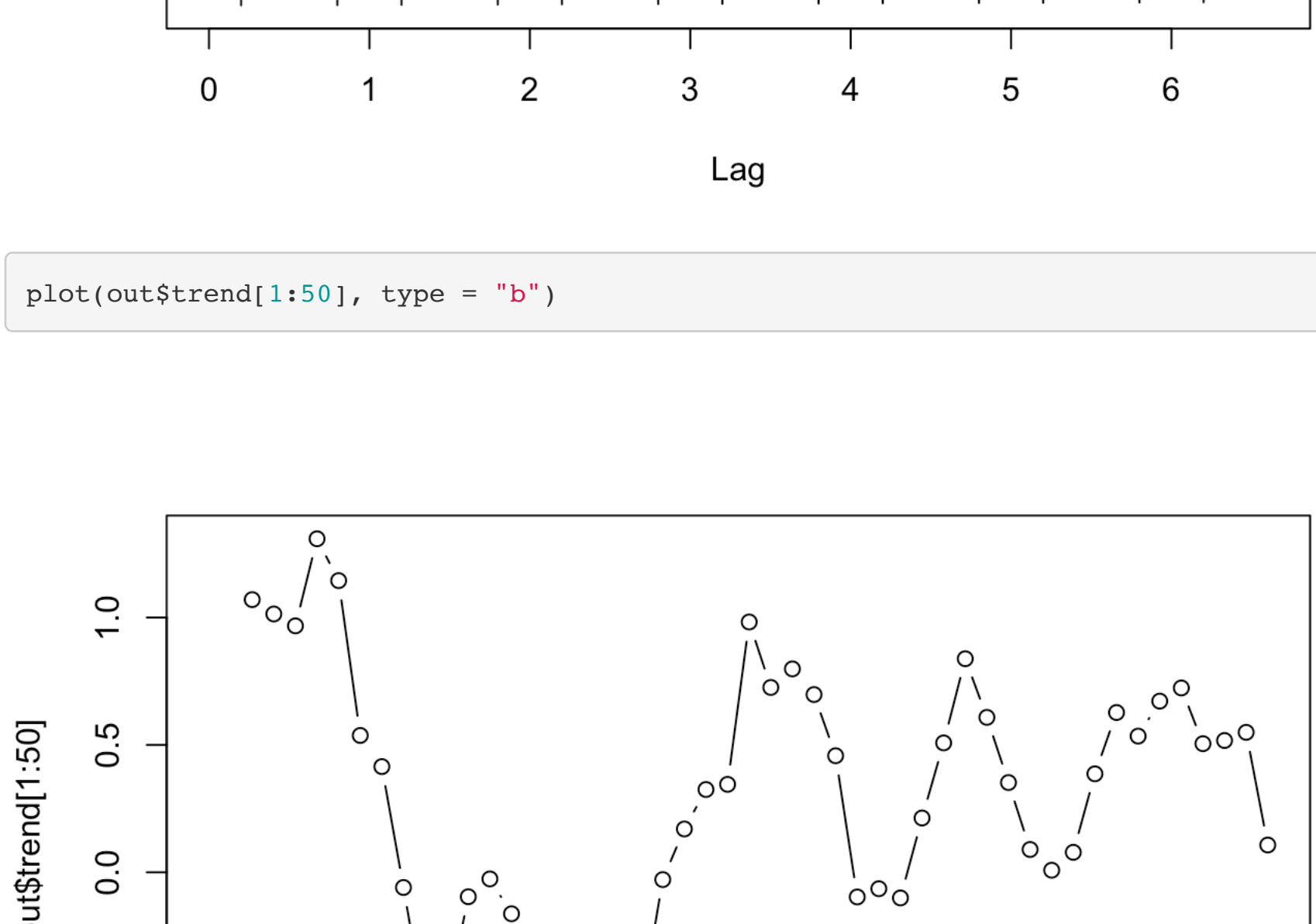
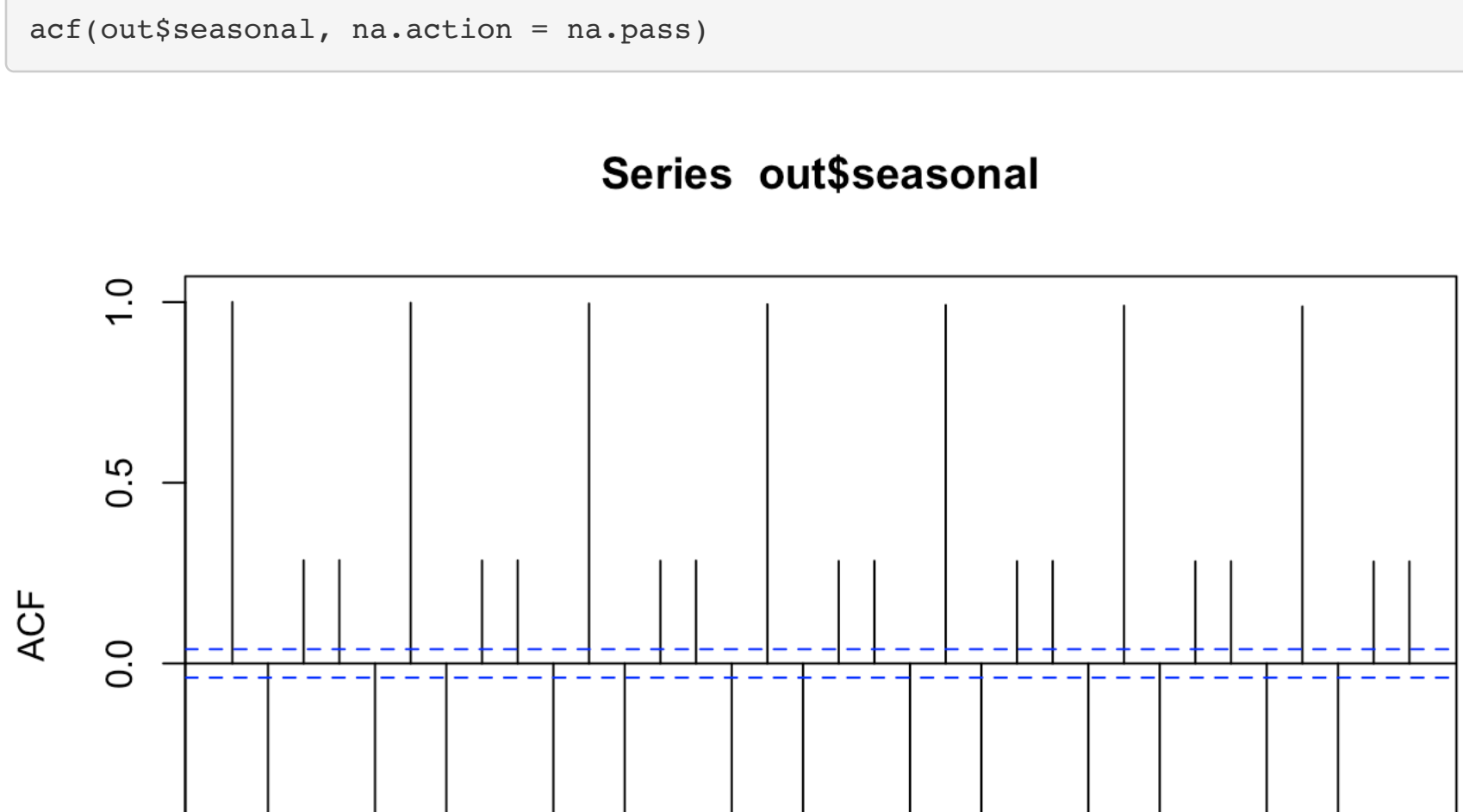
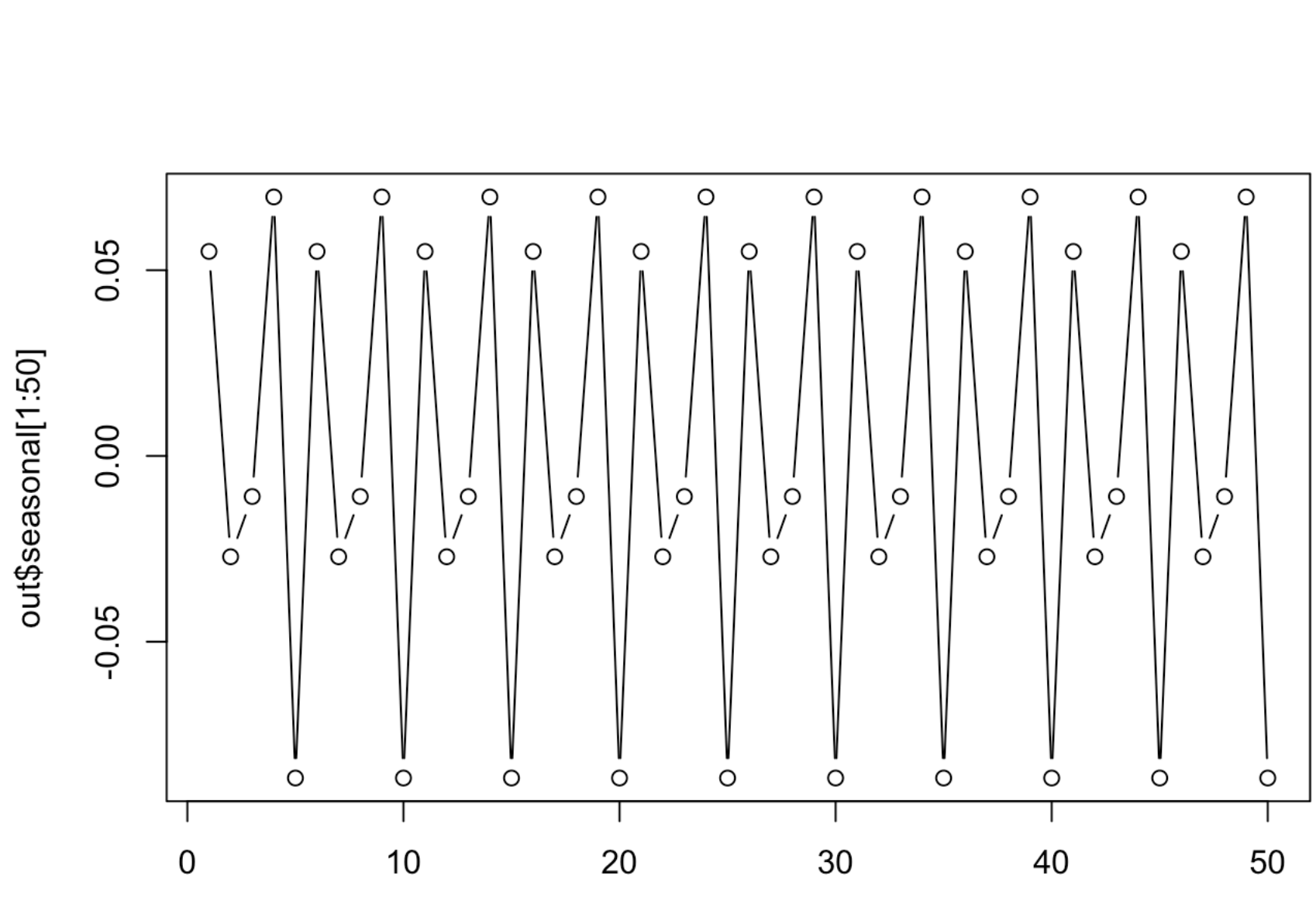
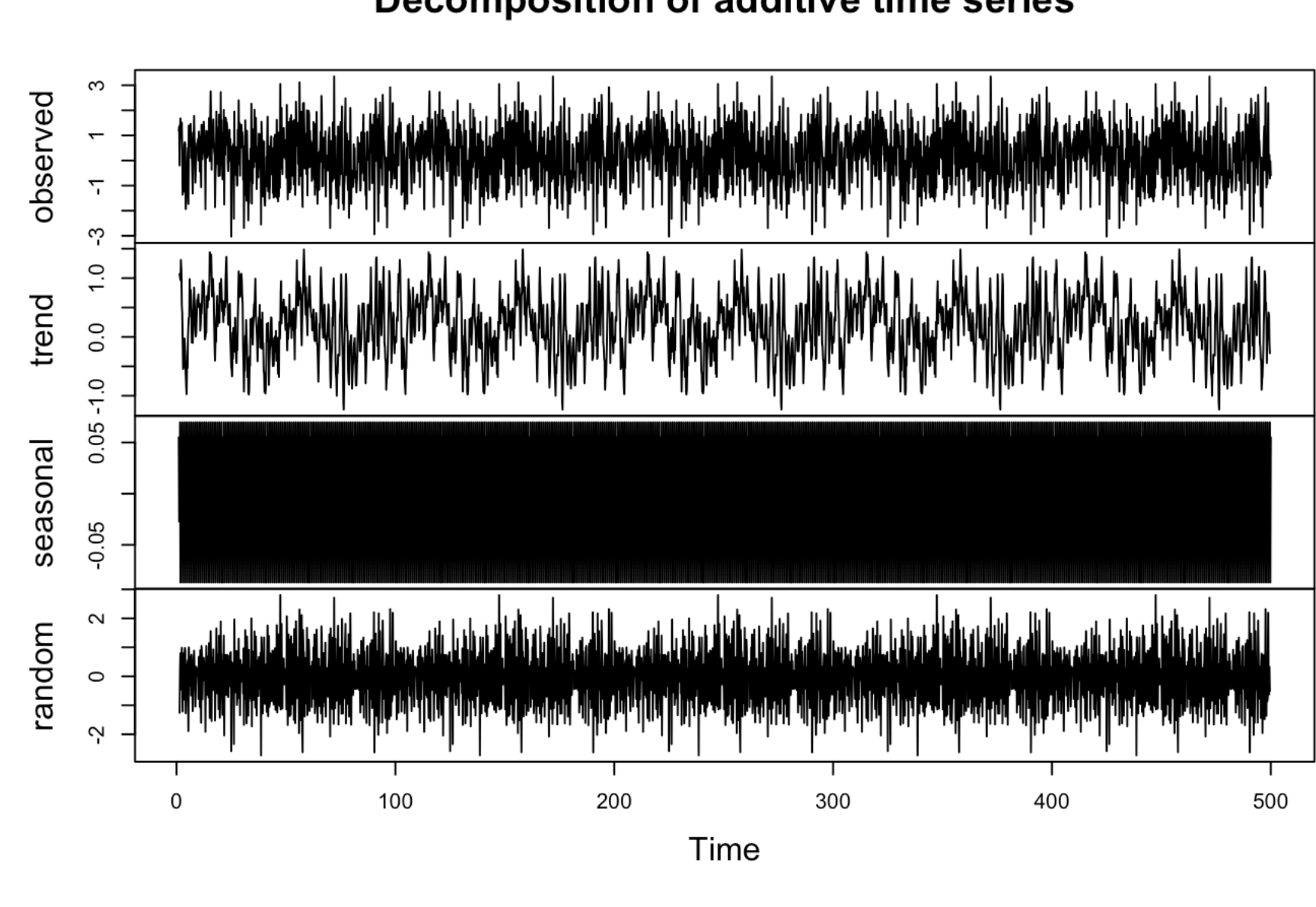
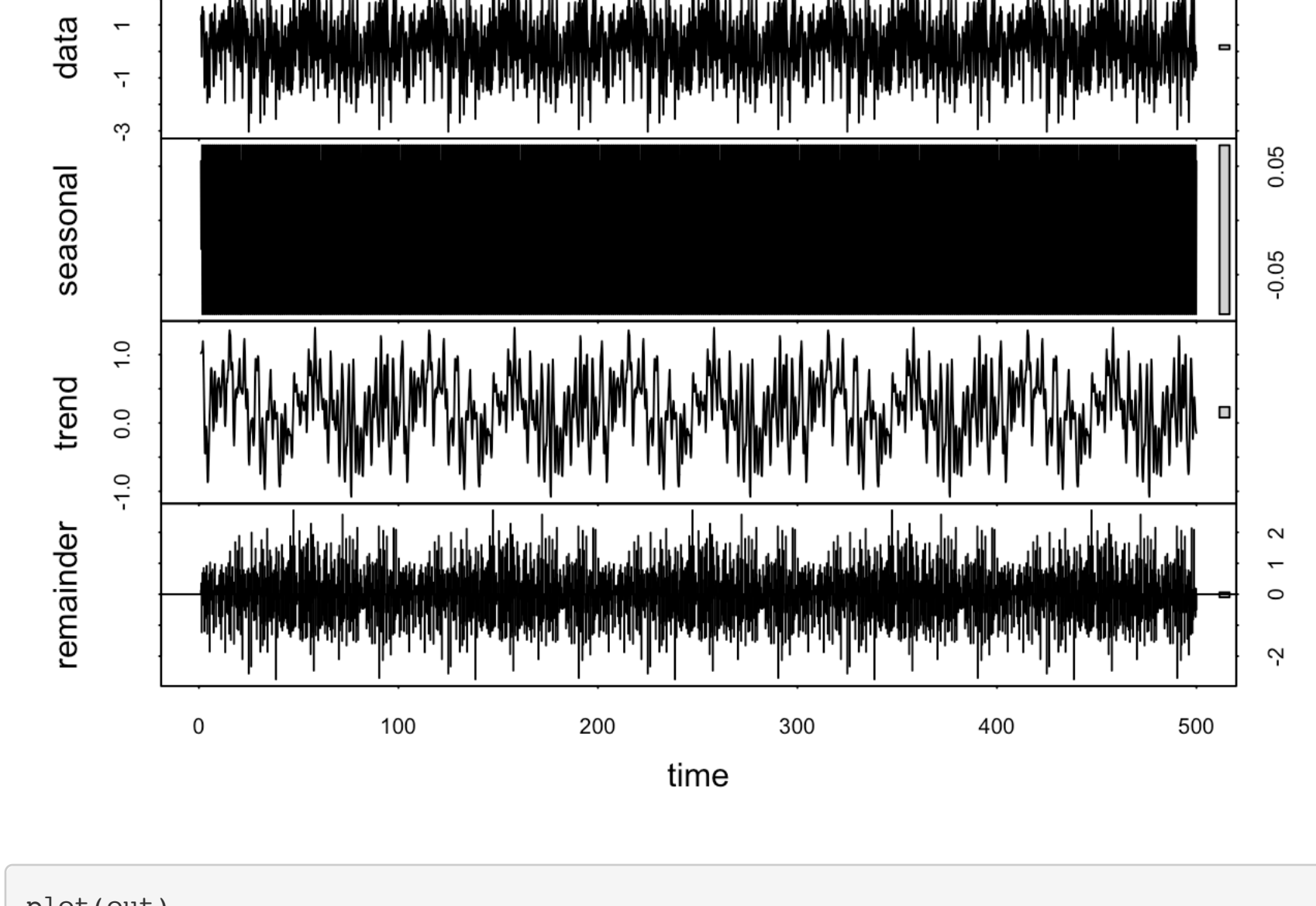
sd(x)

## [1] 1.13315

plot(x)
```



```
x <- ts(data = dat, start = c(1,1), end = c(500,1), frequency = 5)
out <- decompose(x = x, type = "additive")
decomposed <- stl(x, s.window = "periodic")
plot(decomposed)
```



```
x<- as.matrix(dat); dim(x)

## [1] 500 1

cos.c <- rep(cos(3 * pi * 1:500 / 500), 1)
c1 <- as.matrix(cos.c); dim(c1)

## [1] 500 1

sin.c <- rep(sin(3 * pi * 1:500 / 500), 1)
s1 <- as.matrix(sin.c); dim(s1)

## [1] 500 1

cos.c2 <- rep(cos(5 * pi * 1:500 / 500), 1)
c2 <- as.matrix(cos.c2); dim(c2)

## [1] 500 1

sin.c2 <- rep(sin(5 * pi * 1:500 / 500), 1)
s2 <- as.matrix(sin.c2); dim(s2)

## [1] 500 1

data <- data.frame(cbind(x, c1, s1, c2, s2))

fit <- lm(x ~ c1 + s1 + c2 + s2, data = data)
summary(fit)
```

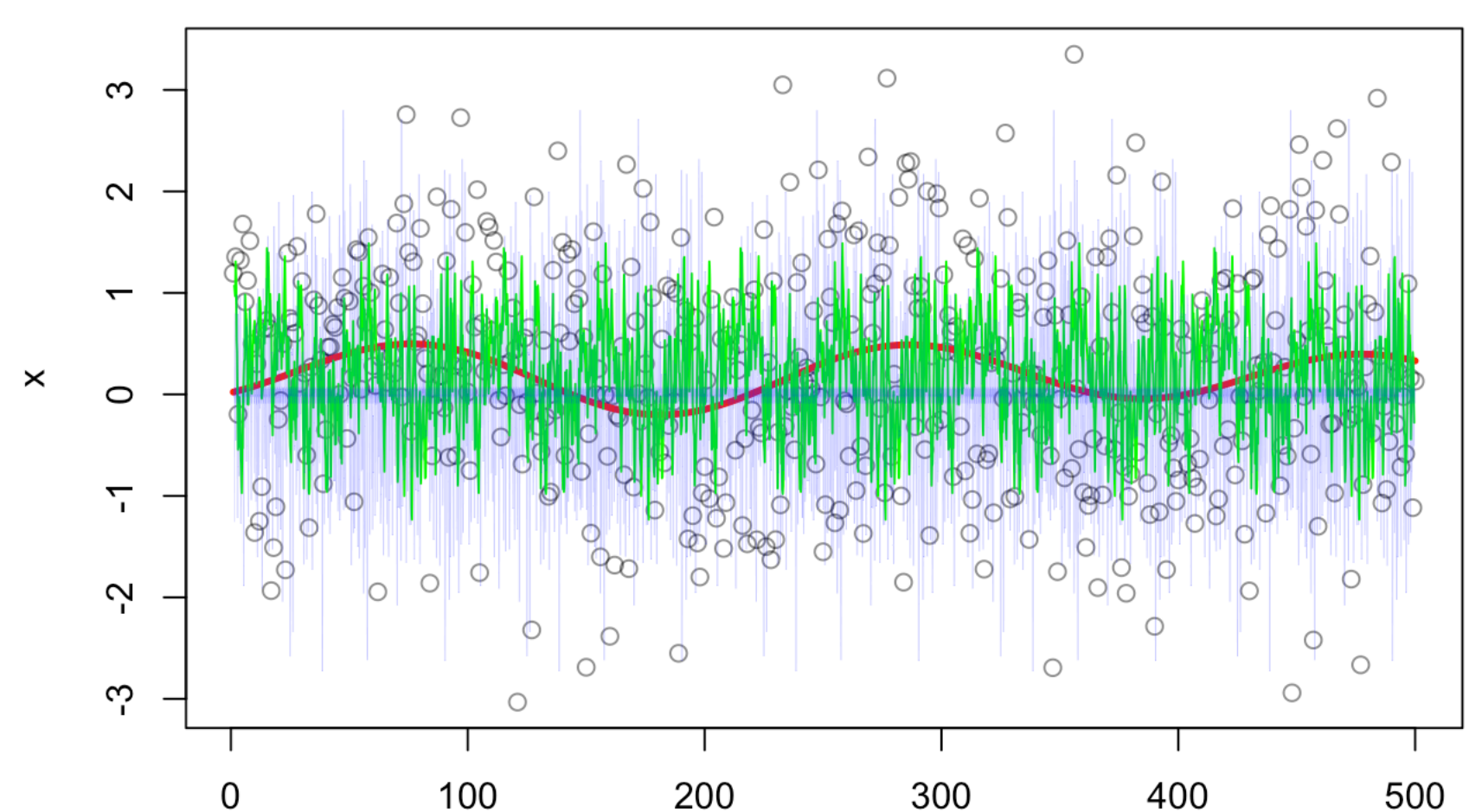
```
##
## Call:
## lm(formula = x ~ c1 + s1 + c2 + s2, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.2632 -0.7736 -0.0321  0.8161  3.2930
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.17386    0.05336   3.258 0.001199 **
## c1           0.08219    0.07069   1.163 0.245543
## s1           0.02752    0.07423   0.371 0.711028
## c2          -0.23885    0.07069  -3.379 0.000786 ***
## s2           0.16104    0.07199   2.237 0.025727 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Residual standard error: 1.118 on 495 degrees of freedom
## Multiple R-squared:  0.03475,    Adjusted R-squared:  0.02695
## F-statistic: 4.456 on 4 and 495 DF,    p-value: 0.001514
```

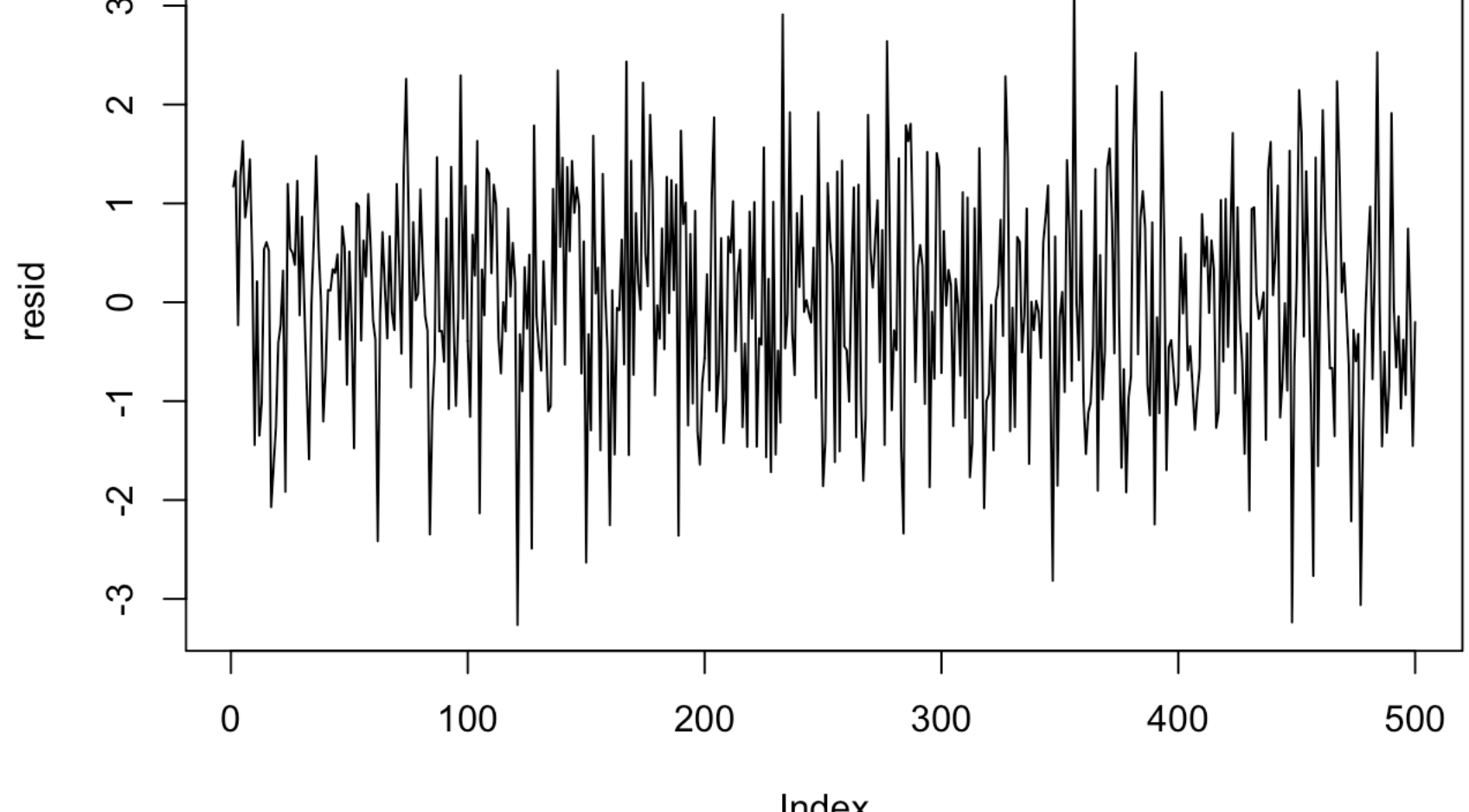
```
coef(fit)
```

```
## (Intercept)      c1      s1      c2      s2
## 0.17385832  0.08219102  0.02751739 -0.23884794  0.16104127
```

```
plot(x, type = "p", col = gray(0, .5))
lines(fit$fit, col = "red", lwd = 3)
lines(out$trend, col = "green", lwd = 1)
lines(out$seasonal, col = "blue", lwd = 0.1)
lines(out$random, col = "blue", lwd = 0.1)
```



```
resid <- fit$resid
plot(resid, type = "l")
```



I do not believe the data is white noise, as we can see that there is correlation in the points once we set the max lag to 500. Additionally the data seems to indicate that there is a none stationary trend and seasonality imbedded within the random part of the data. Once the trend/seasonal elements have been removed, further examination of the residuals is needed.

problem 2:

- a) Assuming a stationary \mathcal{X} , \mathcal{Y}^{ACRF} we choose the criteria:
 $\min E_{loss}$, i.e. $L(x, y) = (x - y)^2$. If $X = x_{n+h}$ and $Y = x_1, \dots, x_n$,
 where the minimizer g of $E(x - g(y))^2$ is $g(Y) = E(X|Y)$, and
 $E[\bar{X}|\bar{Y}] = \bar{E}_X + \sum_{i=1}^n \sum_{j=1}^i (\bar{Y} - \bar{E}_X)$. We also concluded that the
 best linear predictor of x_{n+h} is $(P_n X_{n+h}) = a_0 + \sum_{j=1}^n a_j x_{n+1-j}$.
 With $P_n X_{n+h} = \bar{a}^T \bar{X}_n = \mathcal{P}_n(h) \mathcal{T}_n^T \bar{X}_n$. We looked at the Durbin-Levinson
 model, the Innovations algorithm, and the Infinite PAST approach, MLE, and XL.
 We also analyzed how $\tilde{P}_n X_{n+h} = \lim_{n \rightarrow \infty} P_{n,n} X_{n+h}$, where $P_{n,m} X_{n+h}$ is our BLE.

Problem 3:

$$\begin{aligned} a) \quad f(\lambda) &= \frac{1}{2\pi} \sum_{h=-2}^2 e^{-i\lambda h} \gamma(h) = \frac{1}{2\pi} (\gamma(2)e^{i2\lambda} + \gamma(1)e^{i\lambda} + \gamma(0) + \gamma(1)e^{-i\lambda} + \gamma(2)e^{-i2\lambda}) \\ &= \frac{1}{2\pi} [\gamma(0) + \gamma(1)(e^{i\lambda} + e^{-i\lambda}) + \gamma(2)(e^{i2\lambda} + e^{-i2\lambda})] \\ &= \boxed{\frac{1}{2\pi} [\gamma(0) + \gamma(1)\cos(\lambda) + \gamma(2)\cos(2\lambda)]} \end{aligned}$$

b)

i) • $\gamma_Z(t+h, t) = \text{cov}(Z_{t+h}, Z_t) = \text{cov}(X_{t+h} + Y_{t+h}, X_t + Y_t)$
 $= \text{cov}(X_{t+h}, X_t) + \text{cov}(X_{t+h}, Y_t) + \text{cov}(Y_{t+h}, X_t) + \text{cov}(Y_{t+h}, Y_t)$
 $= \text{cov}(X_{t+h}, X_t) + \text{cov}(Y_{t+h}, Y_t) = \gamma_X(t+h, t) + \gamma_Y(t+h, t)$
 • $\gamma_Z(h) = \gamma_X(h) + \gamma_Y(h)$

ii) • $\gamma_Z(h) = \gamma_X(h) + \gamma_Y(h)$
 • $\gamma_Z(h) = \int_{-\pi}^{\pi} e^{ikh\lambda} dF_Z(\lambda)$
 $\gamma_Z(h) = \int_{-\pi}^{\pi} e^{ikh\lambda} dF_X(\lambda) + \int_{-\pi}^{\pi} e^{ikh\lambda} dF_Y(\lambda)$
 $= \int_{-\pi}^{\pi} e^{ikh\lambda} (dF_X(\lambda) + dF_Y(\lambda))$
 • $dF_Z(\lambda) = dF_X(\lambda) + dF_Y(\lambda)$
 • $F_Z(\lambda) = \int_{-\pi}^{\lambda} dF_Z(v) = \int_{-\pi}^{\lambda} (dF_X(v) + dF_Y(v))$
 $= F_X(\lambda) + F_Y(\lambda)$

iii) Yes! As now we have to consider Y_{t-1} instead of Y_t .

