hw1_zejie8913006

2023-10-11

1. Deterministic and stochastic trends. Stationarity.

```r
cat("Answer : A\n")
```

```
## Answer : A
```

```r
cat("Explanation:\nI is true because deterministic trend is a function estimated
    by regression, and it changes slowly, making it extrapolated.\nII is false
    because linear models include trends, which violate the rule of a constant
    mean required for stantionary time series.\nIII is fasle because the
    autocovariance function can have values greater than 1 in magnitude. ")
```

```
## Explanation:
## I is true because deterministic trend is a function estimated
##     by regression, and it changes slowly, making it extrapolated.
## II is false
##     because linear models include trends, which violate the rule of a constant
##     mean required for stantionary time series.
## III is fasle because the
##     autocovariance function can have values greater than 1 in magnitude.
```

2. Random walk and stationarity

```r
# answer on below
```

3. Calculation of sample acf.

```r
# Create a data frame with a stock prices during each day
Xt <- data.frame(
    Number = 1:10,
    price = c(538, 548, 528, 608, 598, 589, 548, 514, 501, 498)
)

# Calculate the mean of the "Value" column
mean_Xt <- mean(Xt$price);mean_Xt
```

```
## [1] 547
```

```r
## To estimate autocorrelation at lag 3
lag <- 3
n <- 10

# To compute the covariance of Xt and X(t+3)
autocov_3 <- sum((Xt$price[1:(n - lag)] - mean_Xt) * (Xt$price[(lag + 1):n] - mean_Xt)) ;autocov_3
```

```
## [1] -4899
```

```r
# To compute the variance of Xt
variance <- sum((Xt$price - mean_Xt)^2) ;variance
```

```
## [1] 14136
```

```r
# Computing autocorrelation by dividing covariance with variance
autocorr_3 <- autocov_3 / variance
cat("autocorr_3 :", autocorr_3, "\n")
```

```
## autocorr_3 : -0.346562
```

```r
# answer on below
```

4. Polyroot command in R.

```r
root_of_f <- polyroot(c(1, -5))
cat("Root of f(z): ")
```

```
## Root of f(z):
```

```r
cat(root_of_f, sep=", ")
```

```
## 0.2+0i
```

```r
root_of_g <- polyroot(c(1, -0.75, 0.125))
cat("\nRoot of g(z): ")
```

```
##
## Root of g(z):
```

```r
cat(root_of_g, sep=", ")
```

```
## 2+0i, 4-0i
```

```r
# answer on below
```

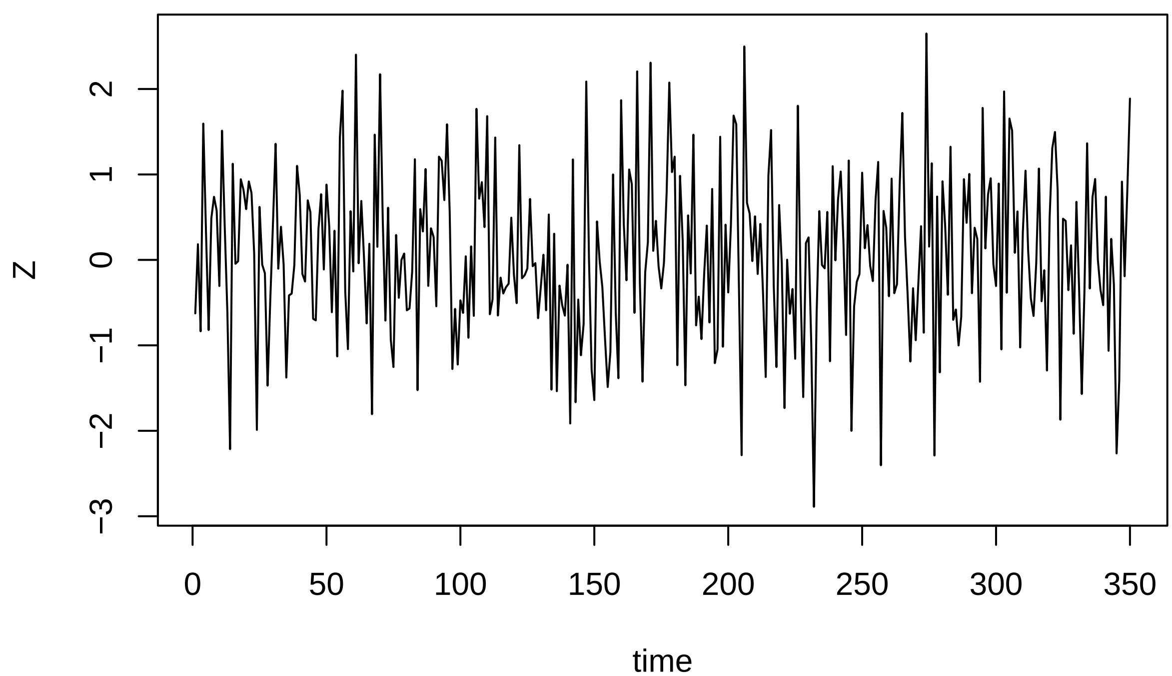
5. Model identification.

```r
# answer on below
```

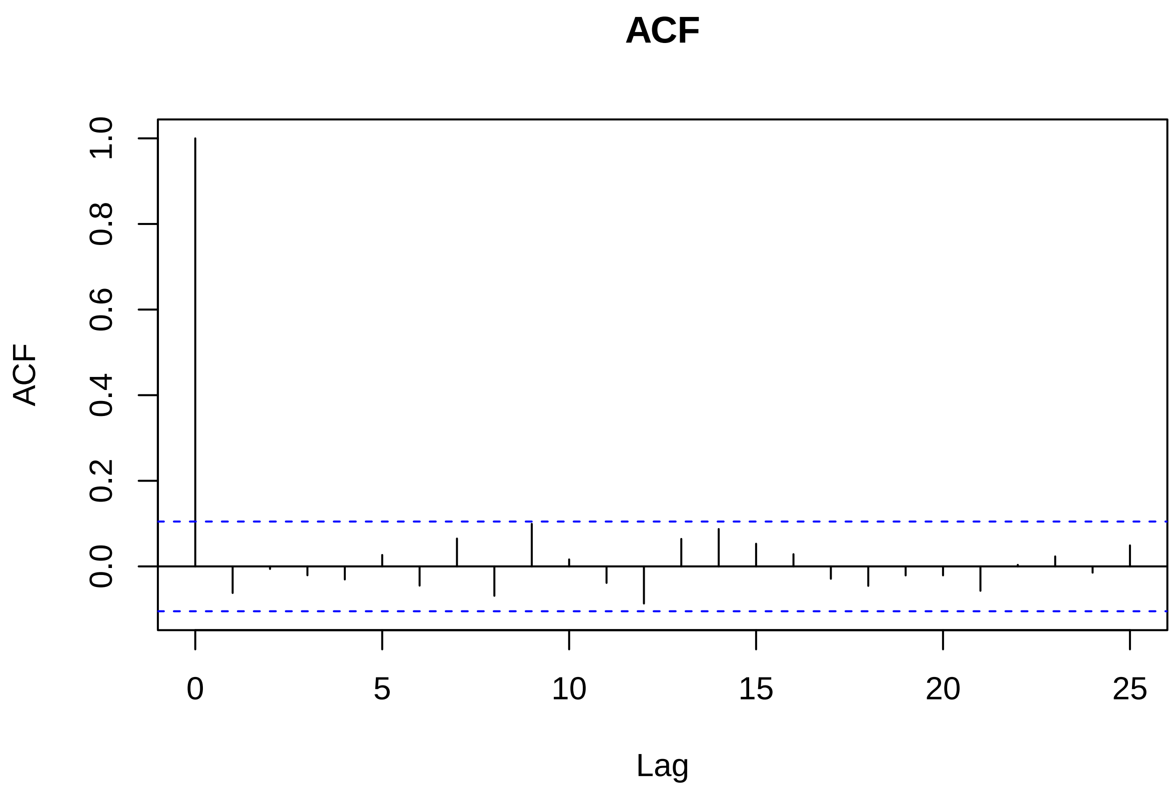
6. Please indicated True/False and explain briefly why.

(a) False Explanation: for (i), it is not necessary for white noise to have 0 mean as long as it is constant, (ii) is true, (iii) also have be satisfied for meeting the uncorrelated property.
(b) True additional proof on below ## 7. Gaussian White Noise and its square.
(c)

```r
set.seed(1)
# Generate 350 observations of the Gaussian white noise Z
Z <- rnorm(350)
plot.ts(Z, xlab = "time", ylab = "Z")
```

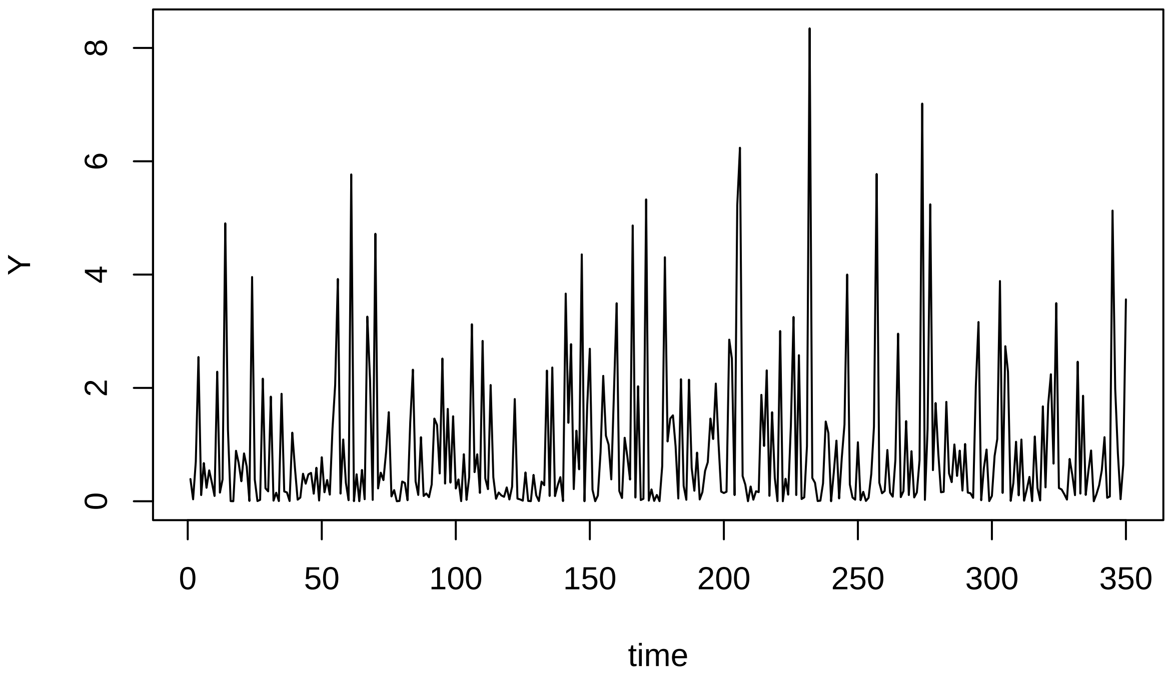



```r
acf(Z, main = "ACF")
```

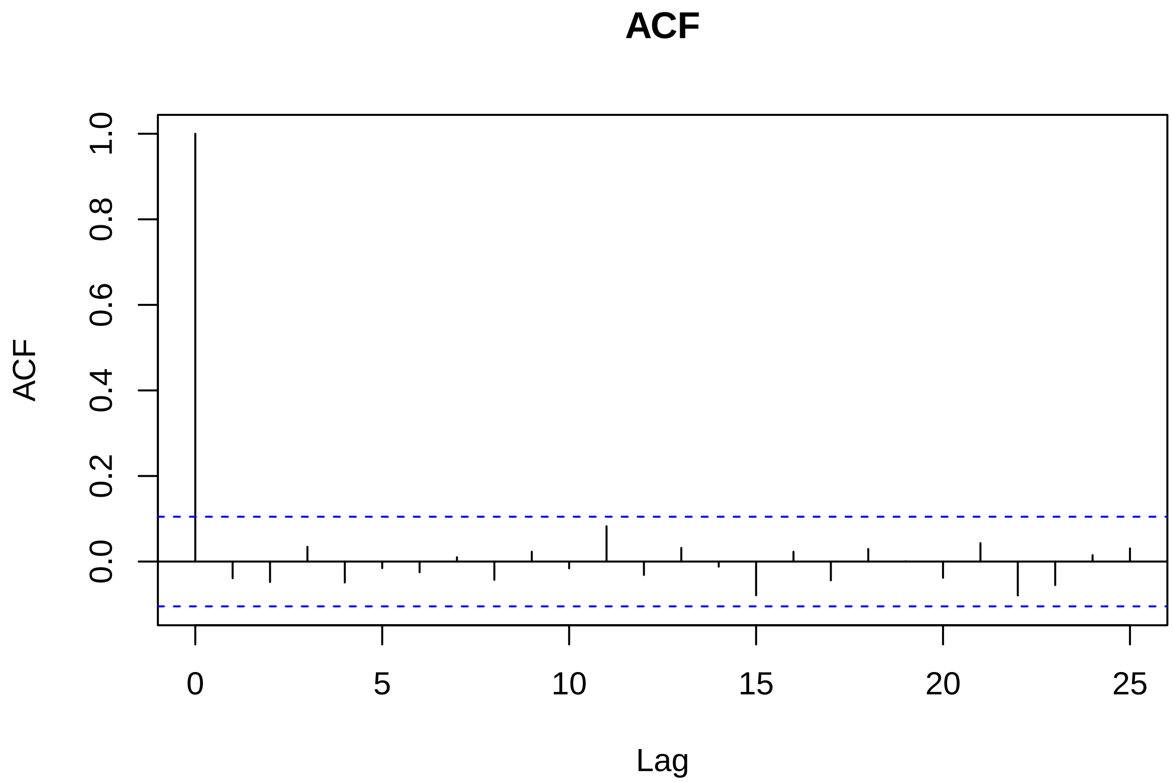


(b)

```r
# Defining Y using Z
Y <- Z^2
plot.ts(Y, xlab = "time", ylab = "Y")
```




```r
acf(Y, main = "ACF")
```



(c) - Series Z holds constant mean and variance, and series Y also do not shows trend and various variance over time. The value of mean in Z and Y on the graph looks different. Comparing only series graph is not enough for knowing whether it is stationary or not. Additional test of autocorrelation is need. - There is not noticeable difference in the plots of acf function between Z and Y. Combined with nearly constant mean and variance from series graph, it is highly possible that both Z and Y are stationary since both acf graph exhibits autocorrelations close to zero for all lags except at lag 0, where it is always 1. Y is described as non-Gaussian white noise due to its non-zero mean and white noise properties. (d)

```
maen_y <-mean(Y);maen_y
```

```
## [1] 0.9312976
```

```
std_Y <- sd(Y);std_Y
```

```
## [1] 1.308956
```

The calculations indeed support my observations in (c), by considering non-zero but constant mean and variance, and uncorrelated property. More proof on below.