## Homework 5 Solutions

Due: Thursday 3/13/19 by 12:00pm (noon)

We graded 1. on a 0-2 scale as follows:

- 0 points for nothing written.
- 1 point for some correct steps but not quite complete.
- 2 points for the whole thing correct.

You didn't have to show every single step I did, but you should have shown where you applied the trigonometric identities that were supplied.

We graded 2. on a 0-3 scale as follows:

- 0 points for nothing written.
- 1 point for some plot and answer attempts but nothing is quite right.
- 2 points for some correct plots and responses.
- 3 points for everything correct.

## **Spectral Analysis**

1. Show that  $\gamma_x(h) = \sum_{k=1}^q \sigma_k^2 \cos(2\pi\omega_k h)$  if

$$x_{t} = \sum_{k=1}^{q} v_{k} \cos\left(2\pi\omega_{k}t\right) + u_{k} \sin\left(2\pi\omega_{k}t\right), v_{k}, u_{k} \overset{i.i.d.}{\sim} \mathcal{N}\left(0, \sigma_{k}^{2}\right)$$

You will find the following trigonometric identities helpful:

- $\cos(a) = \cos(-a);$
- $\sin(-a) = -\sin(a);$
- $\cos(a+b) = \cos(a)\cos(b) \sin(a)\sin(b)$ .

$$\begin{split} &\gamma_{\Xi}\left(h\right) \equiv \mathbb{E}[x_{t}x_{t-h}] \\ &= \mathbb{E}\left[\left(\sum_{k=1}^{q} v_{k}\cos\left(2\pi\omega_{k}t\right) + u_{k}\sin\left(2\pi\omega_{k}t\right)\right) \left(\sum_{l=1}^{q} v_{l}\cos\left(2\pi\omega_{l}\left(t-h\right)\right) + u_{l}\sin\left(2\pi\omega_{l}\left(t-h\right)\right)\right)\right)\right] \\ &= \sum_{k=1}^{q} \sum_{l=1}^{q} \mathbb{E}\left[(v_{k}\cos\left(2\pi\omega_{k}t\right) + u_{k}\sin\left(2\pi\omega_{k}t\right)\right) (v_{l}\cos\left(2\pi\omega_{l}\left(t-h\right)\right) + u_{l}\sin\left(2\pi\omega_{l}\left(t-h\right)\right))\right] \\ &= \sum_{k=1}^{q} \sum_{l=1}^{q} \mathbb{E}\left[\left[v_{k}v_{l}\right]\cos\left(2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{l}\left(t-h\right)\right) + \mathbb{E}\left[u_{k}v_{l}\right]\sin\left(2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{l}\left(t-h\right)\right)\right) + \mathbb{E}\left[u_{k}v_{l}\right]\sin\left(2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{l}\left(t-h\right)\right)\right) \\ &= \sum_{k=1}^{q} \mathbb{E}\left[v_{k}^{2}\right]\cos\left(2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{l}\left(t-h\right)\right) + \mathbb{E}\left[u_{k}^{2}\right]\sin\left(2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{k}\left(t-h\right)\right)\right) \\ &= \sum_{k=1}^{q} \mathbb{E}\left[v_{k}^{2}\right]\cos\left(2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{k}\left(t-h\right)\right) + \mathbb{E}\left[u_{k}^{2}\right]\sin\left(2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{k}\left(t-h\right)\right)\right) \\ &= \sum_{k=1}^{q} \sigma_{k}^{2}\left(\cos\left(2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{k}\left(t-h\right)\right) + \sin\left(2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{k}\left(t-h\right)\right)\right) \\ &= \sum_{k=1}^{q} \sigma_{k}^{2}\left(\cos\left(2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{k}\left(t-h\right)\right) - \sin\left(-2\pi\omega_{k}t\right)\sin\left(2\pi\omega_{k}\left(t-h\right)\right)\right) \\ &= \sum_{k=1}^{q} \sigma_{k}^{2}\cos\left(-2\pi\omega_{k}t\right)\cos\left(2\pi\omega_{k}\left(t-h\right)\right) \\ &= \sum_{k=1}^{q} \sigma_{k}^{2}\cos\left(-2\pi\omega_{k}t + 2\pi\omega_{k}\left(t-h\right)\right) \\ &= \sum_{k=1}^{q} \sigma_{k}^{2} \\ &= \sum_{k=1}^{q} \sigma_{k}^{2} \end{aligned}$$

2. In this question, we're going to examine the shape of the spectral density functions for several different  $\mathbf{AR}(p)$  models. I'm not aware of an R function that takes  $\mathbf{AR}(p)$  parameters and returns the spectral density, so we'll do this by simulating many time series according to the same  $\mathbf{AR}(p)$  model, computing the scaled periodogram for each, and then averaging the scaled periodograms across all simulations. We're going to do this on the log scale, just because sometimes the shape of the scaled periodogram is easier to examine on the log scale.

In class we computed the scaled periodogram of an observed time series x by hand. I have made a little R function called scaled periodogram that does what we did in class.

```
scaled.periodogram <- function(x) {</pre>
  n \leftarrow length(x)
  # Get number of columns in our design matrix
  Z <- matrix(nrow = n, ncol = n)
  # First column is always the intercept!
  Z[, 1] < -1
  for (i in 2:n) {
    if (i<mark>%%2 == 0</mark>) {
      Z[, i] <- cos(2*pi*floor(i/2)*1:n/n)</pre>
    } else {
       Z[, i] <- sin(2*pi*floor(i/2)*1:n/n)</pre>
    }
  }
  linmod <- lm(x - Z - 1)
  # Let's record the coef magnitudes
  m \leftarrow ifelse(n\%2 == 0, n/2, (n - 1)/2 + 1)
  coef.mags <- numeric(m)</pre>
```

```
for (i in 1:length(coef.mags)) {
    if (i == 1) {
        coef.mags[i] <- coef(linmod)[1]^2
    } else if (i == length(coef.mags) & n%/2 == 0) {
        coef.mags[i] <- coef(linmod)[length(coef(linmod))]^2
    } else {
        coef.mags[i] <- sum(coef(linmod)[1 + 2*(i - 2) + 1:2]^2)
    }
    return(list("coef.mags" = coef.mags, "freqs" = 0:(m - 1)/n, "Z" = Z))
}</pre>
```

- (i) Consider an AR(1) model with  $\phi_1 = 0.5$  and  $\sigma_w^2 = 1$ , and consider time series of lengths n = 25 and n = 100. Simulate 1,000 time series for each value of n according to this model, and record the scaled periodogram for each.
- (a) Make a pair of plots in a single plot window using par(mfrow = c(1, 2)) one for each value of n. For both plots, use the range (-20, 5) on the y-axis and (0, 0.5) on the x-axis. In each plot for a single value of n, plot the average log scaled periodogram on against the frequency across all of the simulations. To obtain the average log scaled periodogram, take the log of each scaled periodogram using the log function and then average over all 1,000 log scaled periodogram values that correspond to the same frequency. On the same plot, add the log scaled periodograms against frequency for ten randomly selected simulations.

```
pars <- list(c(0.5))
ns <- c(25, 100)
sim <- 1000
cm <- fr <- array(dim = c(length(ns), sim, max(ifelse(ns<sup>1</sup>/<sub>2</sub> == 0, ns<sup>2</sup>), (ns - 1)<sup>2</sup> + 1))))
for (n in 1:length(ns)) {
  for (i in 1:sim) {
    x <- arima.sim(n = ns[n], model = list("ar" = pars[[1]]))</pre>
    sp <- scaled.periodogram(x)</pre>
    cm[n, i, 1:length(sp$coef.mag)] <- sp$coef.mag</pre>
    fr[n, i, 1:length(sp$coef.mag)] <- sp$freq</pre>
  }
}
par(mfrow = c(1, 2))
for (n in 1:length(ns)) {
  plot(fr, log(cm), type = "n", xlab = "Frequency", ylab = "Log Scaled Periodogram")
  samp <- sample(1:sim, 10, replace = FALSE)</pre>
  for (s in samp) {
    lines(fr[n, 1, ], log(cm[n, s, ]), lty = 2, col = n)
  }
  lines(fr[n, 1, ], log(colMeans(cm[n, , ])), col = n, lty = 1, lwd = 2)
  legend("bottomleft", col = n, lty = c(1, 2), lwd = c(2, 1),
          legend = c("Average", "Selected"),
          bty = "n", cex = 0.75)
}
```

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(b) Based on the average log scaled periodogram, does any specific frequency dominate the periodogram of this AR(1) process? Answer with at most one sentence.

No, there is a small peak at a very low frequency but the average log scaled periodogram values do not vary very much.

(c) In one sentence, when n gets bigger, do the log scaled periodograms become smoother?

No, it looks like the simulated periodograms are not clustering any more tightly around the average log scaled periodogram as n gets bigger.

(d) Redo part (a) for an **AR**(1) model with  $\phi_1 = 0$  and  $\sigma_w^2 = 1$ .

```
pars <- list(c(0))</pre>
ns <- c(25, 100)
sim <- 1000
cm < -fr < -array(dim = c(length(ns), sim, max(ifelse(ns)) = 0, ns/2, (ns - 1)/2 + 1)))
for (n in 1:length(ns)) {
  for (i in 1:sim) {
    x <- rnorm(ns[n])</pre>
    sp <- scaled.periodogram(x)</pre>
    cm[n, i, 1:length(sp$coef.mag)] <- sp$coef.mag</pre>
    fr[n, i, 1:length(sp$coef.mag)] <- sp$freq</pre>
  }
}
par(mfrow = c(1, 2))
for (n in 1:length(ns)) {
  plot(fr, log(cm), type = "n", xlab = "Frequency", ylab = "Log Scaled Periodogram")
  samp <- sample(1:sim, 10, replace = FALSE)</pre>
  for (s in samp) {
    lines(fr[n, 1, ], log(cm[n, s, ]), lty = which(s == samp) + 1, col = n)
  }
  lines(fr[n, 1, ], log(colMeans(cm[n, , ])), col = n, lty = 1, lwd = 2)
  legend("bottomleft", col = n, lty = c(1, 2), lwd = c(2, 1),
         legend = c("Average", "Selected"),
```



Frequency

Frequency

(e) Describe the shape of the average log periodogram from (d) in one sentence.

The average log periodogram from (d) is constant when the frequency is greater than zero.

(f) Consider the following  $\mathbf{AR}(p)$  models, all with  $\sigma_w^2 = 1$ .

i.  $p = 1, \phi_1 = 0.99$ ii.  $p = 2, \phi_1 = 0.04, \phi_2 = 0.92$ iii.  $p = 2, \phi_1 = 0.04, \phi_2 = -0.92$ iv.  $p = 3, \phi_1 = 0.42, \phi_2 = -0.29, \phi_3 = 0.15$ 

Set n = 100 and simulate 1,000 time series according to each of the models (i)-(iv), and record the scaled periodogram for each. Using the range (-6, 3) on the *y*-axis and (0, 0.5) on the *x*-axis, plot the average log scaled periodogram on against the frequency across all of the simulations for each model.

```
pars <- list(c(0.99), c(0.04, 0.92), c(0.04, -0.92), c(0.42, -0.29, 0.15))
n <- 100
sim <- 1000
cm <- fr <- array(dim = c(length(pars), sim, ifelse(n)) = 0, n/2, (n - 1)/2 + 1)))
for (p in 1:length(pars)) {
  for (i in 1:sim) {
    x <- arima.sim(n = n, model = list("ar" = pars[[p]]))</pre>
    sp <- scaled.periodogram(x)</pre>
    cm[p, i, ] <- sp$coef.mag</pre>
    fr[p, i, ] <- sp$freq</pre>
  }
}
plot(apply(fr, c(1, 3), mean), log(apply(cm, c(1, 3), mean)), type = "n",
     xlab = "Frequency", ylab = "Average Log Scaled Periodogram")
for (p in 1:dim(cm)[1]) {
  lines(fr[p, 1, ], log(colMeans(cm[p, , ])), col = p, lty = 1)
}
```

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legend("topright", col = 1:dim(cm)[1], legend = c("i.", "ii.", "iii.", "iv."), lty = rep(1, 4))

(g) In at most one sentence, comment on how the  $\mathbf{AR}(p)$  parameters affect the shape of the periodogram based on (f).

When the  $\mathbf{AR}(p)$  model includes some positive large coefficients, the low-frequency variability contributes a lot to the variability of  $\boldsymbol{x}$ , and when the  $\mathbf{AR}(p)$  model has at least one complex root, the periodogram may be dominated by a single frequency.