1. [6 marks] (R problem) Using arima.sim, generate examples of MA(2), AR(2), and (using the same coefficients) ARMA(2,2) time series. Plot the ACF and PACF for each of these, using the par(mfrow=c(3,1)) command to fit 3 plots on a single page, putting the three ACFs together and the three PACFs together. Write a short discussion of the features you see in these plots.

2. [7 marks] Consider two stationary time series

$$X_t = 0.4X_{t-1} + \beta_t$$
$$Y_t = Z_t - 3Z_{t-1}$$

where  $\beta_t \sim WN(0, \sigma_{\beta}^2)$  and  $Z_t \sim WN(0, \sigma_Z^2)$  are independent white noise processes, i.e  $\mathbf{E} [\beta_t Z_s] = 0$  for all s, t.

- a) Find the ACVF of  $H_t = X_t + Y_t$ , and verify that  $H_t$  is stationary.
- b) Determine which ARMA(p,q) model best fits  $H_t$ .

3. [5 marks] Compute the first four lags of the partial autocorrelation function for an arbitrary MA(2) process, similar to how we computed the PACF for an arbitrary AR(2) process in class.

4. [8 marks] Let  $\{X_t\}$  denote the unique stationary solution of the autoregressive equations

$$X_t = \phi X_{t-1} + Z_t, \qquad t = 0, \pm 1, \dots$$

where  $\{Z_t\} \sim WN(0, \sigma_Z^2)$  and  $|\phi| > 1$ . Then  $X_t$  can be expressed as

$$X_t = -\sum_{j=1}^{\infty} \phi^{-j} Z_{t+j}.$$

Define the new sequence

$$W_t = X_t - \frac{1}{\phi} X_{t-1},$$

show that  $\{W_t\} \sim WN(0, \sigma_W^2)$ , and express  $\sigma_W^2$  in terms of  $\sigma_Z^2$  and  $\phi$ . These calculations show that  $\{X_t\}$  is the (unique stationary) solution of the *causal* AR equations

$$X_t = \frac{1}{\phi} X_{t-1} + W_t, \qquad t = 0, \pm 1, \dots$$

(this is Question 3.8 in the text)

5. [12 marks] Read in the data set provided (Assign3\_ARMA.dat) on the website, and using everything you know about ACFs and PACFs, determine a suitable model to represent this data. Once you have the model, compute the theoretical ACVF and plot the sample ACVF on the same set of axes as the theoretical ACVF, and discuss any differences you see. Note: you should use the arma() function in R to find the model (from the tseries package). You are not expected to use the current material on model-fitting algorithms to do this work manually, but are expected to determine the model order as best you can.

(for graduate students, or undergraduates seeking extra credit)

6. [10 marks] Using the MA() sample generator that you created for Assignment 2, generate m = 100 different realizations of a MA(3) for sample lengths  $n = \{50, 100, 200, 500\}$ . To be clear, fix some  $\theta = \{\theta_0, \theta_1, \theta_2, \theta_3\}$ , then for each n in the set of lengths, generate m = 100 different realizations. In practice, this will be accomplished by calling your routine from Assignment 2 m = 100 times with the same n and  $\theta$ .

For each set of m = 100 realizations, use the arma() function from the tseries package (or equivalent in your programming language of choice) to fit an MA(3) model to each realization of sample data. Generate one plot per parameter showing the bias in the estimate as a function of n (i.e. y is bias, x is n). Discuss these results, especially in the context of the *sample autocorrelation* that is at the heart of the estimator. You should review Section 2.4 in your text.

Note that **bias** of an estimator is defined as the difference between this estimator's expected value and the true value of the parameter being estimated. In this case, you know the true value (since you generated the MA(q) in the first place), and the expected value will be the average of the 100 different realizations for each n.

(Aside: being able to fix q = 3 in the calls to arma() is cheating. Think about how we might choose q in general.)

7. [5 marks] Generalize your work from the previous question and create a function that takes q,  $\theta$  (as a vector), n (as a vector), and m, and returns the data necessary to create the plots that you displayed. Test this routine by passing it the inputs from the previous question and ensure the outputs are the same.

8. [5 marks] For a MA(2) process, find the largest possible values of  $|\rho(1)|$  and  $|\rho(2)|$ .