

```
Call:
ar.ols(x = xt, order.max = 2, demean = F, intercept = T)

Coefficients:
      1
 -0.48

Intercept: 1.994 (0.1465)

Order selected 1  sigma^2 estimated as  0.7228
```

Sup 1

a) Donezo

b) After not demeaning and getting an intercept, here are the results. Pretty close to the true values I set for $B_0 = 2$ and $B_1 = -0.5$

c) These residuals seem to trail off, They never fully really reach 0

d) The output states the Variance of wt is .7728

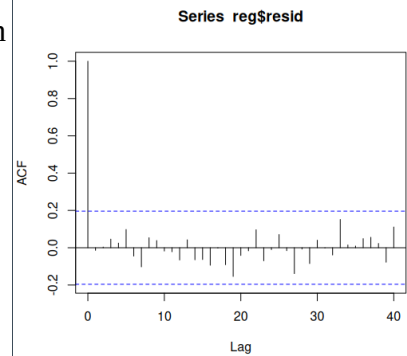
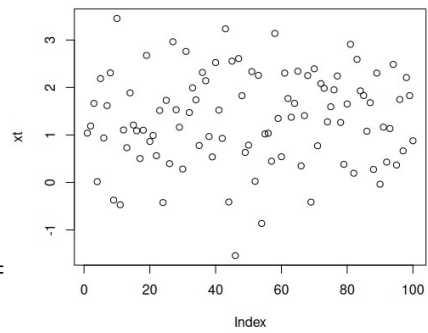
e)

f) The coefficient for B_1 is close, but the intercept term according to the book's model is α , which is $\mu * (1 - \phi_1 - \phi_2 - \dots - \phi_p)$

```
# e)
# The variance in Wt should just be 1, and the variance of Xt is going
# to be related by the B1 coefficient of Xt, since we multiply B1 * Xt
# every step of the time series. We get 1 more Wt than we do B1, from
# the very first step where t=0, so since we multiply B1 in twice, we
# can show that the variance is related by (1-B1^2) * V(Xt) = V(Wt)
```

```
Coefficients:
      ar1  intercept
 -0.4757    1.3461
s.e.    0.0873    0.0575

sigma^2 estimated as 0.7164: log likelihood = -125.34, aic = 256.69
```



Sup 2

a) I did this. Xt looks strange... almost too correct

b) Fit did well!

c) The ACF is kinda all over the place. Never really hits 0

d) The GLS fit also seemed to do really well. Estimates are in the value column, std. Error in the std. Error column.

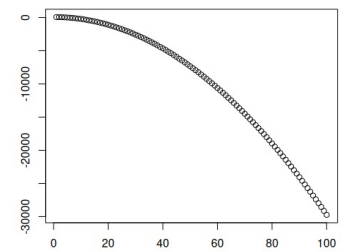
e) The standard error for the gls model is larger, but overall the models both seemed to perform almost the same. The GLS error is larger than the other since it takes into consideration potential correlation with previous time points, like we defined it in the xt definition, so there is more variance in the xt portion of each xt point.

f) I'm not going to paste it here, it's literally the exact same as the Xt ACF graph

```
Residuals:
      Min       1Q   Median       3Q      Max
-12.4961  -3.0575   0.6702   3.2866   8.4873

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -9.979e+03  4.911e-01  -20322  <2e-16 ***
poly(data$t, 2)1 -8.688e+04  4.911e+00  -17692  <2e-16 ***
poly(data$t, 2)2 -2.236e+04  4.911e+00  -4554   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.911 on 97 degrees of freedom
Multiple R-squared:  1, Adjusted R-squared:  1
F-statistic: 1.669e+08 on 2 and 97 DF, p-value: < 2.2e-16
```

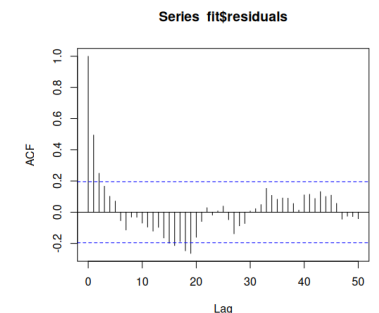


```
Phl
0.5372072

Coefficients:
              Value Std. Error t-value p-value
(Intercept)  -9979.41  0.913407  -10925.478    0
poly(t, 2)1  -86876.26  0.917091  -9742.669    0
poly(t, 2)2  -22362.02  0.715233  -2565.855    0

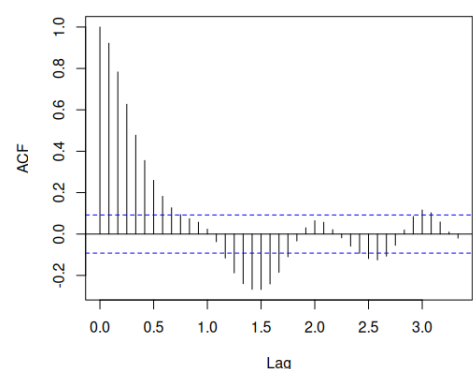
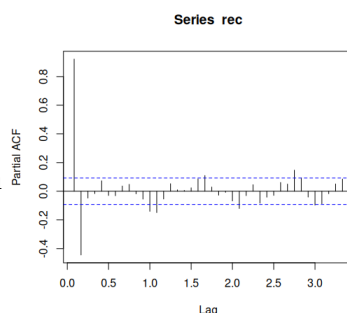
Correlation:
(Intr) p(,2)1
poly(t, 2)1  0.000
poly(t, 2)2 -0.047  0.000

Standardized residuals:
      Min       Q1      Med       Q3      Max
-2.4708353 -0.5961113  0.1369584  0.6392268  1.6776416
```



Sup 4

a) The ACF function trailed off, while the PACF function gave a hard cutoff after lag 2. This

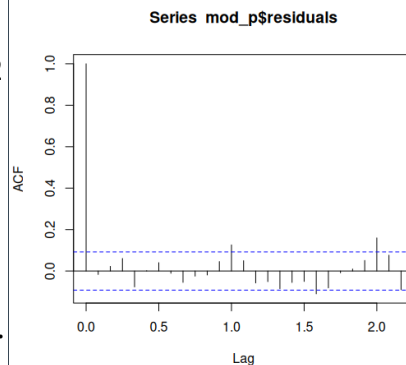


suggests that the AR(2) model fits best, and that we shouldn't use an MA term since there is no significance in including one

b) Yes! The model I picked (ARMA(2,0)) at the top had the best AIC

c) I used the predict function to predict 24 data points ahead, or 2 years worth of data.

d) The ACF of the residuals seems to definitely have a periodic nature over the 1 year marks. This is expected, as we were working with seasonal data.



```
> print(mod_p$aic)
[1] 3331.019
> print(mod_p_min_1$aic)
[1] 3437.273
> print(mod_p_1$aic)
[1] 3332.215
> print(mod_0_2$aic)
[1] 3599.712
> print(mod_p_2$aic)
[1] 3334.152
```

e) Yep, I get what all the code does!

f) These residuals are significantly less close to 0. This doesn't seem like a good fit. The prediction doesn't turn out very well....

