# Homework 5

## Deanna Springgay

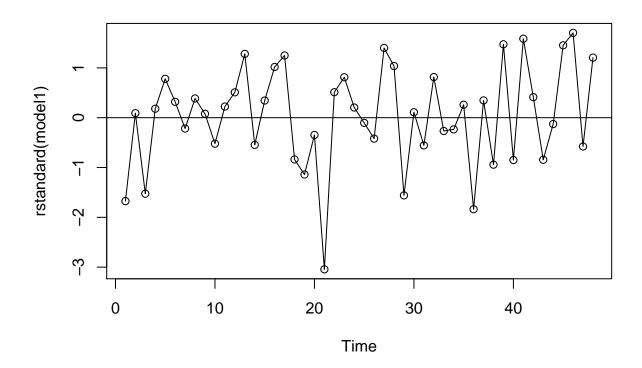
## 4/22/2021

### Problems

Written questions are attached at the end

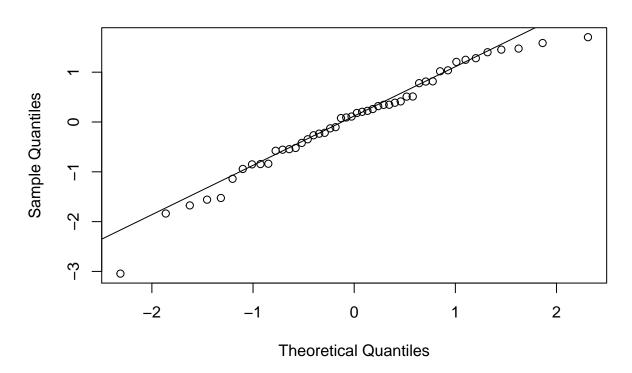
### 8.6

a) The residuals seem to be random around a zero mean.



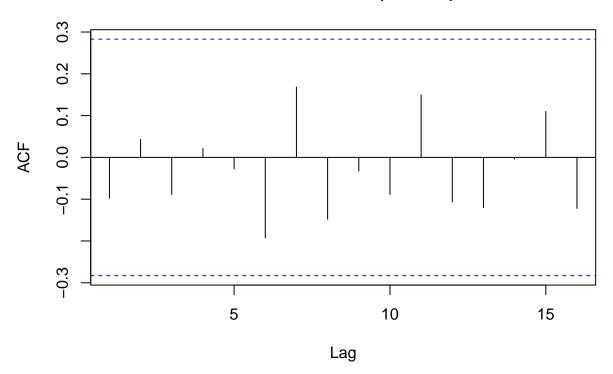
b) The residuals seem to follow a normal distribution.

## Normal Q-Q Plot



c) None of the lags are significant.

## Series rstandard(model1)



d) From the Ljung-Box test we fail to reject the null hypothesis of independent residuals.

```
##
## Box-Ljung test
##
## data: residuals from model1
## X-squared = 8.9256, df = 10, p-value = 0.5392
```

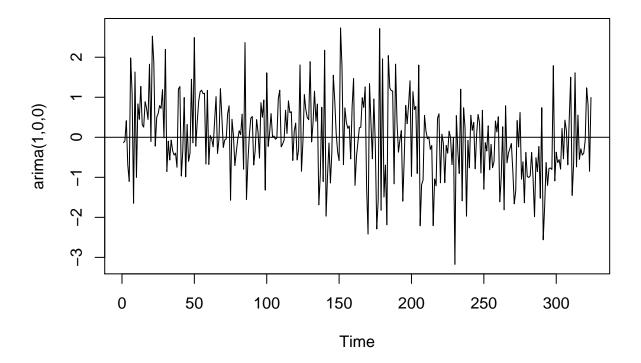
#### 8.9

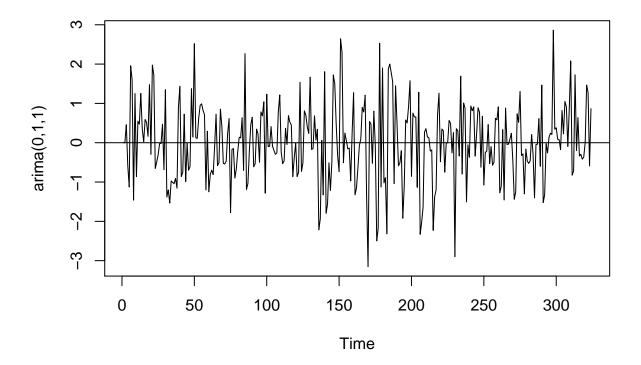
While both models are significant, the arima(0,1,1) model has a better log likelihood and AIC.

```
## Call:
## arima(x = robot, order = c(1, 0, 0))
##
## Coefficients:
##
                 intercept
            ar1
         0.3074
                    0.0015
##
                    0.0002
        0.0528
## s.e.
## sigma^2 estimated as 6.482e-06: log likelihood = 1475.54, aic = -2947.08
##
## Call:
## arima(x = robot, order = c(0, 1, 1))
## Coefficients:
```

```
## ma1
## -0.8713
## s.e. 0.0389
##
## sigma^2 estimated as 6.069e-06: log likelihood = 1480.95, aic = -2959.9
```

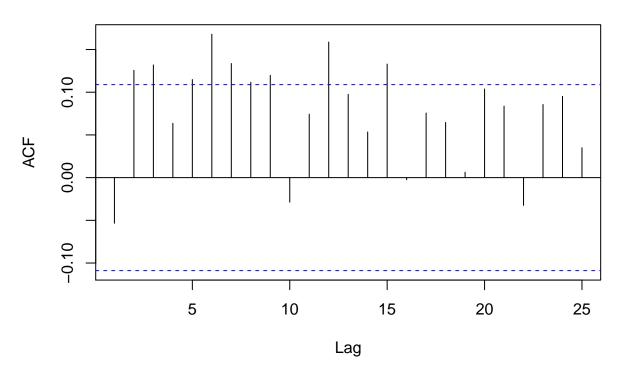
The arima(1,0,0) model might have some drift, but arima(0,1,1) doesn't seem to have any problems at this point.





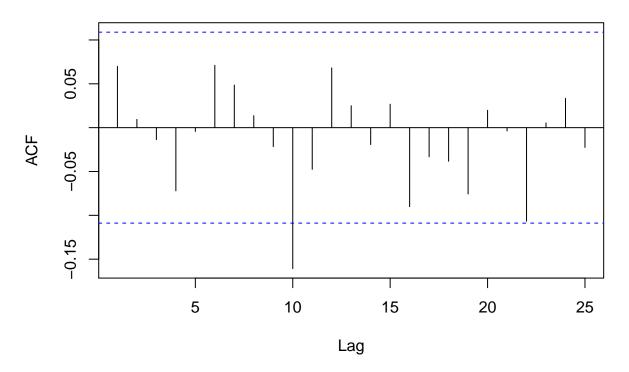
The arima(1,0,0) model has a lag problem with many lags being significant. The arima(0,1,1) model doesn't have any significant lags except for lag100 and the Ljung-Box test gives a good result of failing to reject the null hypothesis of not showing lack of fit. We will only move forward with the arima(0,1,1) model from this point on.

# arima(1,0,0)



```
##
## Box-Ljung test
##
## data: residuals from model2
## X-squared = 52.512, df = 11, p-value = 2.201e-07
```

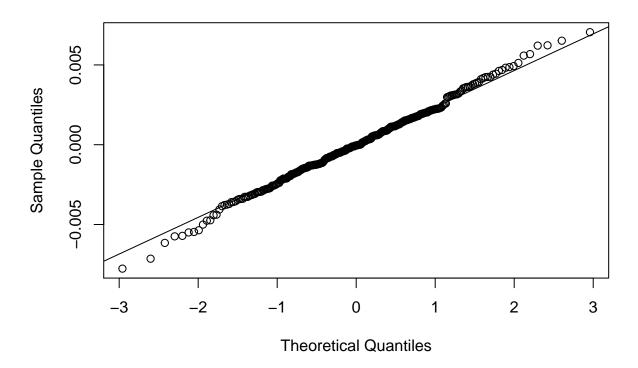
# arima(0,1,1)



```
##
## Box-Ljung test
##
## data: residuals from model3
## X-squared = 17.081, df = 11, p-value = 0.1055
```

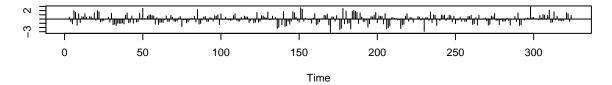
From the following outputs, we can conclude that the arima(0,1,1) model fits well - normality is good, the residuals are also good, and the p-values are acceptable.

## Normal Q-Q Plot

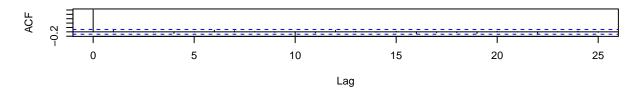


```
##
## Shapiro-Wilk normality test
##
## data: residuals(model3)
## W = 0.99689, p-value = 0.791
```

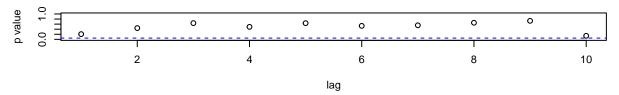
### Standardized Residuals



### **ACF of Residuals**



### p values for Ljung-Box statistic



### 9.16

##

```
a)

##

## Call:

## arima(x = series2, order = c(0, 2, 2))

##

## Coefficients:

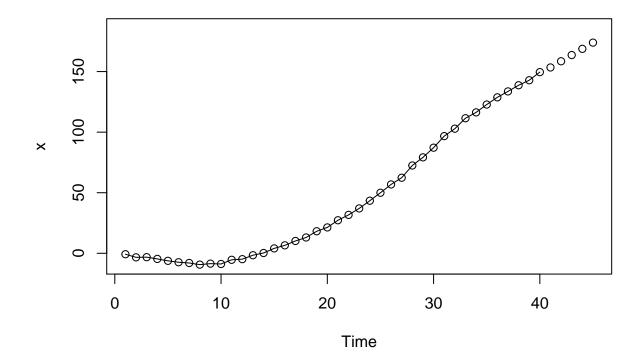
## ma1 ma2

## -0.9462 0.8548

## s.e. 0.1342 0.2646
```

## sigma^2 estimated as 1.299: log likelihood = -60.36, aic = 124.71

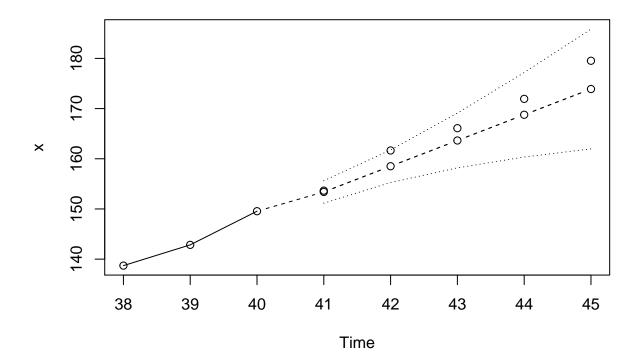
b) The forcasts are linear when the rest of the plot isn't.



c) The forecast appears to be underestimating the actual values.

```
## Time Series:
## Start = 41
## End = 45
## Frequency = 1
## actual forecast
## 41 153.6557 153.3885
## 42 161.6516 158.5156
## 43 166.0946 163.6428
## 44 171.9380 168.7699
## 45 179.5304 173.8971
```

d) The actual values fall within the 95% CI except the point at 42 which appears to be on the CI boundary. From the actual values, time 42 is just below the upper CI bound.

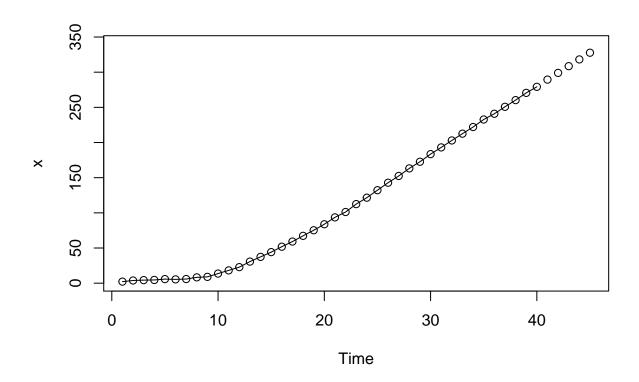


```
## 41 151.1538 153.6557 155.6232
## 42 155.2688 161.6516 161.7625
## 43 158.1863 166.0946 169.0992
## 44 160.3482 171.9380 177.1917
## 45 161.9705 179.5304 185.8236
  e) At this different seed, the forecast is overestimating the actual values.
##
## Call:
## arima(x = series3, order = c(0, 2, 2))
##
## Coefficients:
##
             ma1
                      ma2
##
         -0.8626
                  0.7992
                  0.1028
          0.1249
## s.e.
## sigma^2 estimated as 0.9572: log likelihood = -54.24, aic = 112.47
```

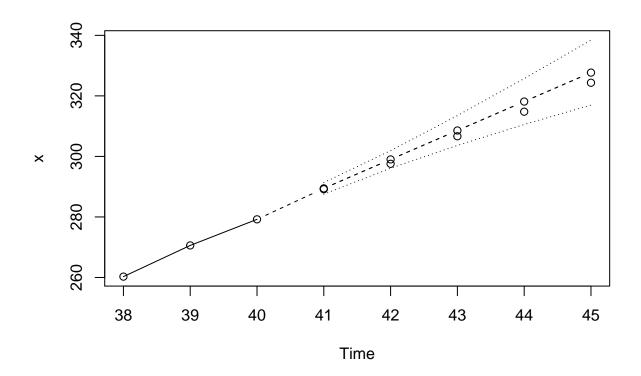
## Time Series:
## Start = 41
## End = 45
## Frequency = 1

lower

actual



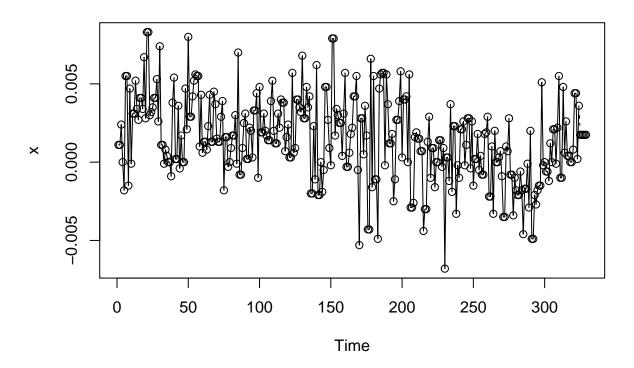
```
## Time Series:
## Start = 41
## End = 45
## Frequency = 1
## actual2 forecast
## 41 289.1566 153.3885
## 42 297.5557 158.5156
## 43 306.6612 163.6428
## 44 314.7725 168.7699
## 45 324.3426 173.8971
```



```
## Time Series:
## Start = 41
## End = 45
## Frequency = 1
## lower2 actual2 upper2
## 41 287.5230 289.1566 291.3583
## 42 296.0985 297.5557 301.9069
## 43 303.6402 306.6612 313.4893
## 44 310.5389 314.7725 325.7148
## 45 316.9714 324.3426 338.4064
```

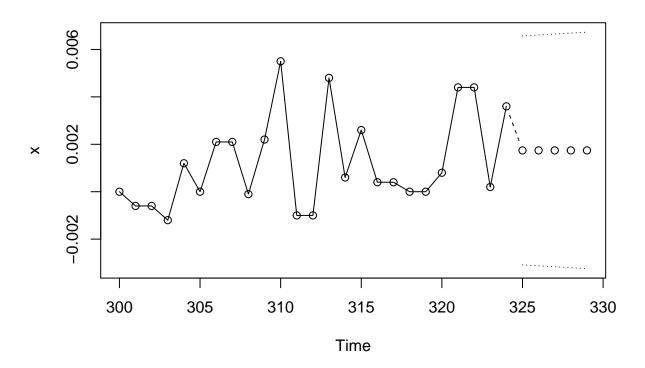
### 9.23

a)

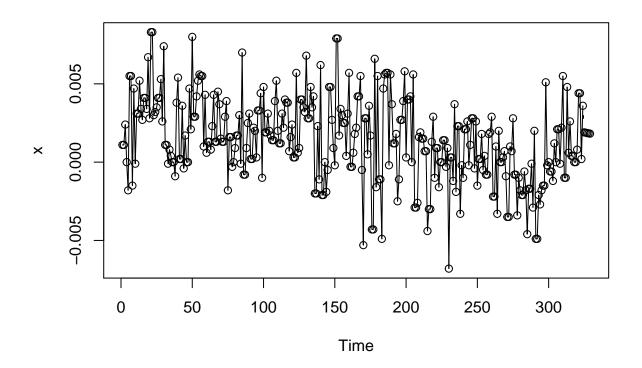


```
## Time Series:
## Start = 325
## End = 329
## Frequency = 1
## lower predicted upper
## 325 -0.003086000 0.001742672 0.006571344
## 326 -0.003125839 0.001742672 0.006611183
## 327 -0.003165355 0.001742672 0.006650699
## 328 -0.003204555 0.001742672 0.006689898
## 329 -0.003243446 0.001742672 0.006728790
```

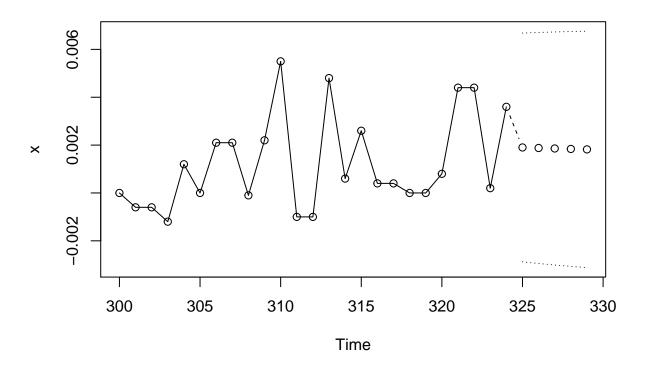
b) The forcasts are basically constant and the CI is very wide, likely due to the variance seen in previous values.



c) Both of these models produce very similar forecasts.



```
## Time Series:
## Start = 325
## End = 329
## Frequency = 1
## lower predicted upper
## 325 -0.002878776 0.001901348 0.006681473
## 326 -0.002947994 0.001879444 0.006706881
## 327 -0.003010803 0.001858695 0.006728193
## 328 -0.003067889 0.001839041 0.006745972
## 329 -0.003119851 0.001820424 0.006760700
```



9. | a) 
$$\hat{\chi}(b) = \mu_1 \phi(\gamma_{e-M}) = 10.8 + (-0.5)(12.2 - 10.8) = 10.1$$
b)  $\hat{\chi}_{1}(a) = \lambda_{1} \phi(\hat{\chi}_{1}(a) - \lambda_{2}) = 10.8 + (-0.5)(10.1 - 10.8) = 11.15$ 
 $\hat{\gamma}_{1}(a) = \lambda_{1} \phi(\hat{\chi}_{1}(a) - \lambda_{2}) = 10.8 + (-0.5)^{2}(12.2 - 10.8) = 11.15$ 
c)  $\hat{\chi}_{1}(a) = \lambda_{1} \phi(\hat{\chi}_{1}(a) - \lambda_{2}) = 10.8 + (-0.5)^{2}(12.2 - 10.8) = 10.801$ 

6. 2 a)  $\hat{\chi}_{1} = 5 + 1.1 \hat{\chi}_{1-1} - 0.5 \hat{\chi}_{1-2} = \frac{10.8}{10.801} = 10.801$ 

6. 2 a)  $\hat{\chi}_{1} = 5 + 1.1 \hat{\chi}_{1-1} - 0.5 \hat{\chi}_{1-2} = \frac{10.8}{10.801} = 0.5(1) = 10.5 \hat{\chi}_{1}(10.5) = 0.5(10)$ 

10.3	Y	L= a+h	t +5, +	X,	ARTMA	Lp,0,4	) + (P.I.	(a),			
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		-				6-5 bs			.f-2		
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		MIZZN	M(p, c	),q)×(	P,0,0)	5					
		N.									
10.5	(w)			-	r I	16-5 + e		_ ,			
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			-	0.5(4	6-1- 4-4	)·ce-	v.3e <sub>l-1</sub>				
		<b>1</b> 5 = 0	.5 θ <sub>i</sub> =	0.3	ARIMA	(1,0,1)×	(0,1,0)	4			
	<i>b</i> )	Y6= Y	6-1 + 1/6-	12-YE-	13 + CE-	0.5e6-1	-0.54-	12+0.29	C4-13		
						et- 0.5				L-12	
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