M349R (Unique 54230)

Instructor: Gustavo Cepparo

Project 6

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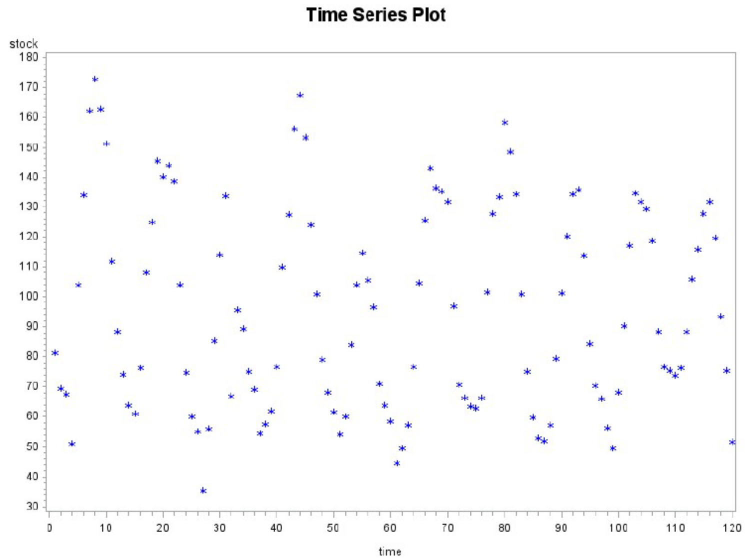
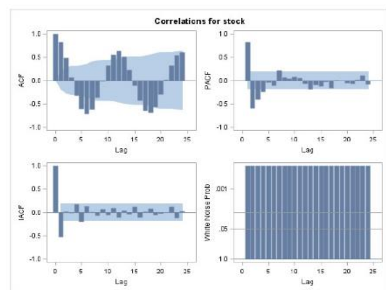
<u>Problem 1 Use Stock dataset (50 points)</u>

a) Graph the data with a time series plot and describe the time series plot. (5 pts)



b) What can we learn from the ACF and Test for White Noise? (5 pts)



It is clearly seasonal and there is no need for transformation but clear patterns indicate that we need to consider Arima models. It appears to be cutting off in the ACF and dying down on the PACF therefore an MA model seems appropriate with some differencing

c) Provide a differencing analysis. (10 pts)

Analyzing the results from:

```
proc arima data=stock;
identify var=stock;
identify var=stock(1);
identify var=stock(12);
identify var=stock(1, 12);
identify var=stock(6);
identify var=stock(1, 6);
identify var=stock(1, 6, 12);
run;
```

We conclude that a differencing of (1, 12) provides the best fit.

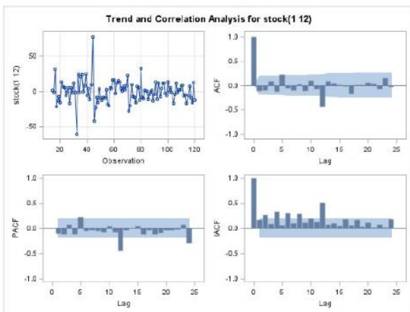
d) Check the models Arima(0 , 1, 1)(0, 1, 1) and Arima(1, 1, 0)(0, 1, 1) check the fit of both models and compare AIC, L'Jung Box and Standard error. (10 pts)

The ARIMA Procedure

Name of Variable = stock	
Period(s) of Differencing	1,12
Mean of Working Series	-0.16832
Standard Deviation	15.81306
Number of Observations	107
Observation(s) eliminated by differencing	13

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	10.71	6	0.0977	-0.105	-0.103	0.091	-0.127	0.213	-0.055
12	38.95	12	0.0001	-0.100	0.017	-0.117	0.099	-0.070	-0.439
18	43.47	18	0.0007	0.086	0.047	0.007	-0.024	-0.158	0.010
24	48.06	24	0.0025	0.003	0.056	0.038	-0.065	0.152	-0.035



Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.66041	0.07628	8.66	<.0001	12
AR1,1	-0.15006	0.09663	-1.55	0.1234	1

Variance Estimate	177.1621
Std Error Estimate	13.31022
AIC	859.5799
SBC	864.9255
Number of Residuals	107

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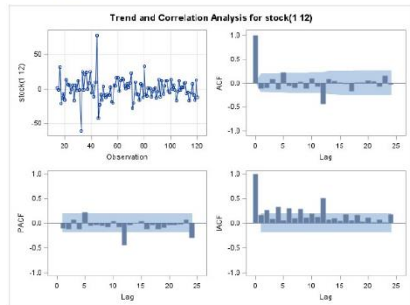
Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	10.71	6	0.0977	-0.105	-0.103	0.091	-0.127	0.213	-0.055
12	38.95	12	0.0001	-0.100	0.017	-0.117	0.099	-0.070	-0.439
18	43.47	18	0.0007	0.086	0.047	0.007	-0.024	-0.158	0.010
24	48.06	24	0.0025	0.003	0.056	0.038	-0.065	0.152	-0.035



Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.15808	0.09641	1.64	0.1041	1
MA2,1	0.65766	0.07649	8.60	<.0001	12

Variance Estimate	176.9491
Std Error Estimate	13.30222
AIC	859.4512
SBC	864.7968
Number of Residuals	107

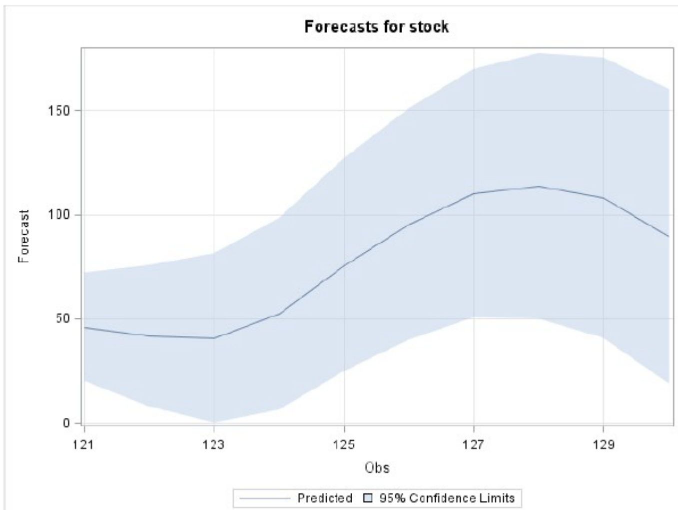
The model Arima(0 , 1, 1)(0, 1, 1) has slightly lower values for AIC and Standard error and the fit is better in terms of the ACF, PACF and white noise

e) Write the model on d in terms of the backshift operator, and then without using the backshift operator. (10 pts)

$$\hat{Y}_t = Y_{t-12} + Y_{t-1} - Y_{t-13} - \theta_1 e_{t-1} - \Theta_1 e_{t-12} + \theta_1 \Theta_1 e_{t-13}$$

f) Forecast 10 periods. (10 pts)

Forecasts for variable stock				
Obs	Forecast	Std Error	95% Confidence Limits	
121	46.0021	13.3022	19.9302	72.0739
122	41.7252	17.3890	7.6434	75.8070
123	40.7170	20.6835	0.1781	81.2558
124	52.3638	23.5209	6.2637	98.4639
125	75.7339	26.0511	24.6747	126.7932
126	95.0498	28.3565	39.4721	150.6275
127	110.0657	30.4880	50.3103	169.8210
128	113.7943	32.4799	50.1348	177.4537
129	107.8433	34.3566	40.5057	175.1809
130	89.2701	36.1359	18.4451	160.0952



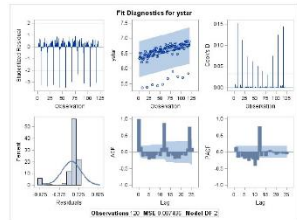
Problem 2 Use Sales dataset (50 points)

Follow the four steps of arima modeling. Forecast 6 periods

Sales did not have constant variance therefore, I applied the logarithmic function

a) From looking at the plot, ACF and PACF graphs I computed the following differencing:

```
proc arima data=sales;
identify var=ystar;
identify var=ystar(1);
identify var=ystar(12);
identify var=ystar(1, 12);
run;
and concluded that Log(sales)(1, 12) was preferred
```



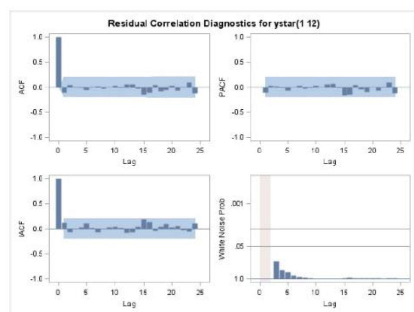
b) Tentative model since it cuts off on the ACF and dies down on the PACF is an MA at 1 and 12. MU was not statistically different from 0 and retried with noconstant.

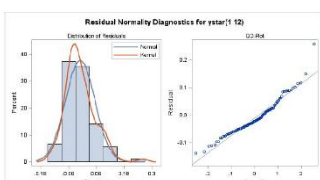
c)

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.78231	0.06216	12.59	<.0001	1
MA2,1	0.70587	0.07470	9.45	<.0001	12

Variance Estimate	0.004158
Std Error Estimate	0.06448
AIC	-281.025
SBC	-275.679
Number of Residuals	107

d) Residual analysis indicates model is adequate. White noise everywhere. Normality on the residuals.





Forecast:

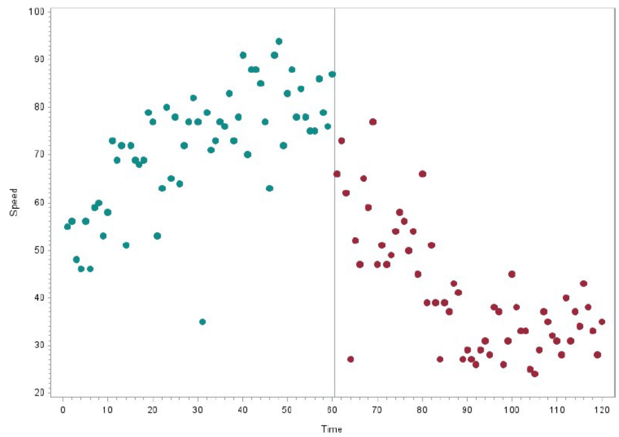
Forecasts for variable ystar				
Obs	Forecast	Std Error	95% Confidence Limits	
121	6.8716	0.0645	6.7453	6.9980
122	6.9221	0.0660	6.7928	7.0515
123	6.9738	0.0675	6.8416	7.1060
124	6.9064	0.0689	6.7714	7.0415
125	6.8564	0.0703	6.7185	6.9942
126	6.9534	0.0717	6.8129	7.0940

Obs	Forecast y	Std Error	95% CI	
121	964.4905167	1.06662558	850.0541	1094.442
122	1014.4481	1.06822672	891.406	1154.589
123	1068.27449	1.06983026	935.9855	1219.261
124	998.645639	1.07132907	872.5326	1143.101
125	949.9411165	1.07282998	827.5752	1090.291
126	1046.702474	1.074333	909.5045	1204.717

Problem 3

The data are the daily scores achieved by a patient with mental problems on a test of perceptual speed. The patient began receiving a powerful tranquilizer on the sixty-first day and continued receiving the drug for the rest of the sample period. It is expected that this drug will reduce perceptual speed.

Produce a time plot of the data showing where the intervention occurred. (5 pts)

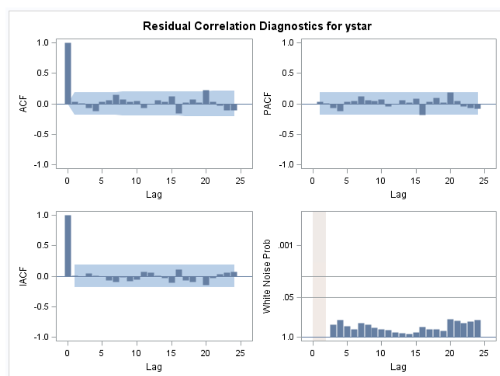


a) Fit an intervention model with a step function intervention to the series. Write down the model including the ARIMA model for the errors. (15 pts)
Used transformation log(y) to standardize variance in data. Fit model Arima(1,1,1) (sorry) to the data pre-intervention (data values 0 to 60). Fit the step function to the whole dataset

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	3.96939	0.12595	31.52	<.0001	0	ystar	0
MA1,1	0.72096	0.07407	9.73	<.0001	1	ystar	0
AR1,1	0.98473	0.02105	46.79	<.0001	1	ystar	0
SCALE1	-0.22315	0.13555	-1.65	0.1025	0	S	0

Constant Estimate	0.060631
Variance Estimate	0.039471
Std Error Estimate	0.198672
AIC	-42.206
SBC	-31.1573
Number of Residuals	117



b) What does the model say about the effect of the drug? (5 pts)

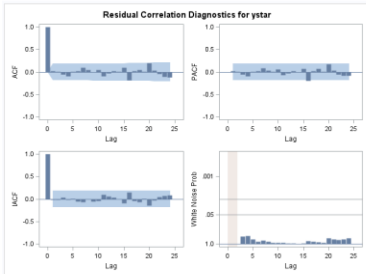
Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	3.96939	0.12595	31.52	<.0001	0	ystar	0
MA1,1	0.72096	0.07407	9.73	<.0001	1	ystar	0
AR1,1	0.98473	0.02105	46.79	<.0001	1	ystar	0
SCALE1	-0.22315	0.13555	-1.65	0.1025	0	S	0

The model says that the drug has a negative effect on speed. Therefore, it has the desired effect. Nonetheless, it is not "statistically" significant. Therefore, we would like to experiment with a delayed response.

c) Fit a new intervention model with a delayed response to the drug. (15 pts)

In this model we can see that SCALE is now statistically significant and our model is still a good fit



Conditional Least Squares Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	4.10592	0.10396	39.49	<.0001	0	ystar	0
MA1,1	0.68104	0.10152	6.71	<.0001	1	ystar	0
AR1,1	0.94083	0.05275	17.84	<.0001	1	ystar	0
SCALE1	-0.74489	0.23529	-3.17	0.0020	0	S	0

Constant Estimate	0.242959
Variance Estimate	0.038722
Std Error Estimate	0.196779
AIC	-44.4459
SBC	-33.3972
Number of Residuals	117

d) Which model fits the data better? Are the forecast from the models very different? (5 pts each)

The delayed effect model seems to be a better fit by means of the AIC and Std Errors. Moreover, the SCALE estimate is statistically significant in the delayed, while it is not in the Step Function. The forecasts are slightly different as we can see in this chart:

Delayed function (log(y))				
Obs	Forecast	Std Error	95% Confidence Limits	
121	3.4657	0.1968	3.08	3.8514
122	3.4595	0.2033	3.061	3.858
123	3.4537	0.2089	3.0442	3.8632
124	3.4482	0.2138	3.0292	3.8672
125	3.443	0.218	3.0158	3.8702

Delayed function				
Obs	Forecast	Std Error	95% Confidence Limits	
121	31.99885	1.2175	21.7584	47.0589
122	31.80107	1.22544	21.3489	47.3705
123	31.61716	1.23232	20.9932	47.6175
124	31.44374	1.23837	20.6807	47.8083
125	31.28066	1.24359	20.4054	47.952

Step Function (log(y))				
Obs	Forecast	Std Error	95% Confidence Limits	
121	3.5314	0.1987	3.1421	3.9208
122	3.5347	0.2055	3.132	3.9374
123	3.538	0.2118	3.1227	3.9532
124	3.5411	0.2179	3.1141	3.9681
125	3.5443	0.2235	3.1062	3.9824

Step Function				
Obs	Forecast	Std Error	95% Confidence Limits	
121	34.17177	1.21982	23.1524	50.4408
122	34.28473	1.22814	22.9198	51.2851
123	34.39805	1.2359	22.7076	52.1018
124	34.50485	1.24346	22.5132	52.884
125	34.61545	1.25045	22.336	53.6456

The delayed effect function has lower estimates for the forecasted values, and they keep decreasing, contrary to the step function which are actually increasing in the forecast.

e) Construct an ARIMA model ignoring the intervention and compare the forecast with those obtain from your preferred intervention model. How much does the intervention affect the forecast? (10 pts)

Ignoring Intervention						Ignoring Intervention				
Obs	**Forecast**	**Std Error**	**95% Confidence Limits**			**Obs**	**Forecast**	**Std Error**	**95% Confidence Limits**	
121	3.5293	0.1975	3.1421	3.9165		**121**	34.10009	1.21835	23.1524	50.2244
122	3.5335	0.2069	3.1279	3.939		**122**	34.24361	1.22986	22.826	51.3672
123	3.5376	0.2157	3.1148	3.9604		**123**	34.3843	1.24073	22.5289	52.4783
124	3.5417	0.224	3.1027	3.9808		**124**	34.52556	1.25107	22.258	53.5599
125	3.5458	0.2318	3.0914	4.0002		**125**	34.66741	1.26087	22.0079	54.6091
Delayed function (log(y))						**Delayed function**				
Obs	**Forecast**	**Std Error**	**95% Confidence Limits**			**Obs**	**Forecast**	**Std Error**	**95% Confidence Limits**	
121	3.4657	0.1968	3.08	3.8514		**121**	31.99885	1.2175	21.7584	47.0589
122	3.4595	0.2033	3.061	3.858		**122**	31.80107	1.22544	21.3489	47.3705
123	3.4537	0.2089	3.0442	3.8632		**123**	31.61716	1.23232	20.9932	47.6175
124	3.4482	0.2138	3.0292	3.8672		**124**	31.44374	1.23837	20.6807	47.8083
125	3.443	0.218	3.0158	3.8702		**125**	31.28066	1.24359	20.4054	47.952

Step Function (log(y))						Step Function				
Obs	**Forecast**	**Std Error**	**95% Confidence Limits**			**Obs**	**Forecast**	**Std Error**	**95% Confidence Limits**	
121	3.5314	0.1987	3.1421	3.9208		**121**	34.17177	1.21982	23.1524	50.4408
122	3.5347	0.2055	3.132	3.9374		**122**	34.28473	1.22814	22.9198	51.2851
123	3.538	0.2118	3.1227	3.9532		**123**	34.39805	1.2359	22.7076	52.1018
124	3.5411	0.2179	3.1141	3.9681		**124**	34.50485	1.24346	22.5132	52.884
125	3.5443	0.2235	3.1062	3.9824		**125**	34.61545	1.25045	22.336	53.6456

From the charts we can see that the intervention really affects the forecasted values. Moreover, the values retain the decreasing trend in the model with accounts for the intervention, while the one that ignores it does not present a decreasing trend (it is in fact increasing).

Code

Problem 0

```
meta$Gastfem <- meta$Gastric*meta$Sex

fit1 <- lm(Metabol ~ Gastric + Gastfem +0, data=meta)

summary(fit1)

est1 <- 1.9278/(1.9278 - 1.2021)

est1


newmeta <- meta[-c(31, 32), ]

fit2 <- lm(Metabol ~ Gastric + Gastfem +0, data=newmeta)

summary(fit2)

est2 <- 1.5989/(1.5989 - 0.8732)

est2

cov(newmeta$Gastric, newmeta$Gastfem, use = "everything")

vcov(fit2)
```

Problem 1

```
data stock;
SET stock;
time = _N_;
run;

proc print data=stock;
run;

proc gplot data=stock;
plot stock * time;
symbol1 v=star c=blue;
title "Time Series Plot";
run;
quit;
title;

proc autoreg data=stock;
model stock = time/dwprob;
run;

proc corr data=stock;
```

```
var stock time;
run;

proc timeseries data=stock plots=(series residual histogram corr);
var stock;
run;

proc arima data=stock;
identify var=stock;
identify var=stock(1);
identify var=stock(12);
identify var=stock(1, 12);
identify var=stock(6);
identify var=stock(1, 6);
identify var=stock(1, 6, 12);
run;

proc arima data=stock;
identify var=stock(1, 6, 12);
estimate q=(1) q=(6) q=(12)noconstant printall;
run;

proc arima data=stock;
identify var=stock(1, 12);
estimate p=(1) q=(12)noconstant printall;
run;

proc arima data=stock;
identify var=stock(1, 12);
estimate q=(1) q=(12)noconstant printall;
forecast lead=10 out=work.fcast;
data fcast2;
set work.fcast1;
forecasty=Exp(forecast);
L95CI=Exp(L95) ;
U95CI=Exp(u95) ;
proc print data= work.fcast2;
var forecasty L95CI U95CI;
run;
```

Problem 2

```
data sales;
SET sales;
time = _N_;
ystar=log(sales);
run;

proc print data=sales;
run;

proc gplot data=sales;
plot ystar * time;
symbol1 v=star c=blue;
```

```
title "Time Series Plot";
run;
quit;
title;

proc autoreg data=sales;
model ystar = time/dwprob;
run;

proc corr data=sales;
var ystar time;
run;

proc timeseries data=sales plots=(series residual histogram corr);
var ystar;
run;

proc arima data=sales;
identify var=ystar;
identify var=ystar(1);
identify var=ystar(12);
identify var=ystar(1, 12);
run;

proc arima data=sales;
identify var=ystar(1, 12);
estimate q=(1) q=(12)noconstant printall;
run;


proc arima data=sales;
identify var=ystar(1, 12);
estimate q=(1) q=(12)noconstant printall;
forecast lead=6 out=work.fcast;
data fcast2;
set work.fcast1;
forecasty=Exp(forecast);
L95CI=Exp(L95) ;
U95CI=Exp(u95) ;
proc print data= work.fcast2;
var forecasty L95CI U95CI;
run;
```

Problem 3

```
data speed;
SET speed;
time = _N_;
run;

proc print data=speed;
run;
data anno;
   length function color $8;
```

```
   retain xsys ysys '2' when 'a';
   set speed;

   function='symbol';
   x=time;
   y=y;
   size=1.3;
   text='dot';
   if time gt 60 then color='depk';
   else color='vibg';
   output;
run;

proc gplot data=speed;
   plot y*time / haxis=axis1 vaxis=axis2 href=60.5 lvref=20 cvref=grp
annotate=anno;
   symbol1 interpol=none value=none color=white;
   axis1 label=("Time") offset=(2,2)pct;
   axis2 label=(angle=90 "Speed");

run;

data prespeed;
input y;
datalines;
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76
87
66
;
run;

proc arima data=prespeed;
identify var=y;
run;

data prespeed;
SET prespeed;
ystar = log(y);
run;

proc arima data=prespeed;
identify var=ystar;
run;

proc arima data=prespeed;
identify var=ystar;
estimate p=(1) q=(1) printall;
run;

data newspeed;
input y;
datalines;
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```
28
35
;
run;


data newspeed2;
set newspeed;
time=_n_;
ystar = log(y);
if time >=60 then S=1;
else S=0;
run;

data future;
input y ystar time S;
datalines;
. . 121 1
. . 122 1
. . 123 1
. . 124 1
. . 125 1
;
run;

data newspeed3;
update newspeed2 future;
by time S;
run;

proc arima data=newspeed3;
identify var=ystar crosscor=(S);
estimate p=(1) q=(1) Input=S printall altparm maxit=30 backlim= -3 plot;
forecast lead=5;
run;

data newerspeed;
input y S;
datalines;
55    0
56    0
48    0
46    0
56    0
46    0
59    0
60    0
53    0
58    0
73    0
69    0
72    0
51    0
72    0
69    0
68    0
69    0
```

79	0
77	0
53	0
63	0
80	0
65	0
78	0
64	0
72	0
77	0
82	0
77	0
35	0
79	0
71	0
73	0
77	0
76	0
83	0
73	0
78	0
91	0
70	0
88	0
88	0
85	0
77	0
63	0
91	0
94	0
72	0
83	0
88	0
78	0
84	0
78	0
75	0
75	0
86	0
79	0
76	0
87	0
66	0.016666667
73	0.033333333
62	0.05
27	0.066666667
52	0.083333333
47	0.1
65	0.116666667
59	0.133333333
77	0.15
47	0.166666667
51	0.183333333
47	0.2
49	0.216666667
54	0.233333333
58	0.25

```
56    0.266666667
50    0.283333333
54    0.3
45    0.316666667
66    0.333333333
39    0.35
51    0.366666667
39    0.383333333
27    0.4
39    0.416666667
37    0.433333333
43    0.45
41    0.466666667
27    0.483333333
29    0.5
27    0.516666667
26    0.533333333
29    0.55
31    0.566666667
28    0.583333333
38    0.6
37    0.616666667
26    0.633333333
31    0.65
45    0.666666667
38    0.683333333
33    0.7
33    0.716666667
25    0.733333333
24    0.75
29    0.766666667
37    0.783333333
35    0.8
32    0.816666667
31    0.833333333
28    0.85
40    0.866666667
31    0.883333333
37    0.9
34    0.916666667
43    0.933333333
38    0.95
33    0.966666667
28    0.983333333
35    1
;
run;

data newerspeed2;
set newerspeed;
time=_n_;
ystar = log(y);
run;

data future2;
input y ystar time S;
datalines;
```

```
. . 121 1
. . 122 1
. . 123 1
. . 124 1
. . 125 1
;
run;

data newerspeed3;
update newerspeed2 future2;
by time S;
run;

proc arima data=newerspeed3;
identify var=ystar crosscor=(S);
estimate p=(1) q=(1) Input=S printall altparm maxit=30 backlim= -3 plot;
forecast lead=5;
run;


data speed;
SET speed;
ystar = log(y);
run;

proc arima data=speed;
identify var=ystar;
estimate p=(1) printall;
run;

proc arima data=speed;
identify var=ystar;
estimate p=(1,2) q=(1) printall;
run;

proc arima data=speed;
identify var=ystar;
estimate p=(1) q=(1) printall;
forecast lead=5;
run;
```