Using JMP® Version 4 for Time Series Analysis

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Abstract

Three examples of time series will be illustrated. One is the classical airline passenger demand data with definite seasonal variation. The other two will be daily closing price data from a steady growth series (CSCO) and an accelerated growth series (CIEN).

Introduction

Among the many new enhancements to JMP in the version 4 release is the ability to do time series forecasting. The procedures include smoothing models, a seasonal smoothing method (Winter's method), and ARIMA (Autoregressive Integrated Moving Average) modeling. In this paper we will arrive at final forecast from:

- highly seasonal airline passenger data
- a steady growth stock (CSCO)
- an accelerated growth stock (CIEN)

Data Sources and Data Cleansing

A good free source of daily close stock data for CSCO and CIEN is provided via the Internet at:

http://moneycentral.msn.com/investor/charts/charting.asp?Symbol=csco and http://moneycentral.msn.com/investor/charts/charting.asp?Symbol=cien.

You can export a year's worth of daily data directly into Microsoft® Excel by choosing "Export Data". Once in Excel, strip off the first 4 rows and Save as with the default .csv file extension. Then within JMP choose Import from the File platform and the text file can be directly into JMP. Once within JMP we resort with the earliest dates appearing first and eliminate the holidays that have missing stock data. We will use only the daily close value, CLOSE, and not use HIGH, LOW or VOLUME. For the airline passenger data we use the Seriesg.jmp dataset supplied in the Time Series folder found in the Sample Data that comes with JMP4.

Smoothing and ARIMA Methods

Simple forecasting using smoothing models is based on the premise that reliable forecasts can be realized by modeling patterns in the data that are visible in a time series and/or spectral density plot. We in fact will use this approach to try our first forecasts of the Seriesg data. ARIMA modeling uses additional pattern information including differencing, autocorrelation and partial autocorrelation, and plots of AR coefficients to help identify the model. The advantage of ARIMA over smoothing methods is that they are more flexible in fitting the data. However the iterative approach of fitting several ARIMA models, checking adequacy, and comparing results is more demanding. This approach is alleviated somewhat by using JMP's Model Comparison Table. This table summarizes the fit statistics for each model under consideration. Included in the table output are three criteria useful for model selection. They are:

- AIC (Akaike's Information Criterion)
- SBC (Schwartz's Bayesian Criterion)
- –2LogLikelihood

Smaller values of each of these criteria indicate better fits.

Example 1: Forecasting Airline Passenger Volume

An analyst at a major international airline wants to forecast passenger demand for the next 15 months. Excessive demand in any of these months cold impact the flight schedule and/or the number of flights offered. Seriesg has 12 years of data on a monthly basis and wants to forecast monthly demand as input to projecting seating capacity and number and type of flights. The last 15 months will be contrasted with the forecasted values to understand incremental changes forecasted by month. (This actually is a classic seasonal time series from Box and Jenkins (1) page 531). The time series variable is international airline passengers in thousands, Passengers, and the time ID is Time in months. The last two years of the Seriesg passenger time series data is depicted in Figure 1a, and default graphs of the complete time series together with acf (autocorrelation function) and pacf (partial autocorrelation function) charts are depicted in Figure 1b. To assess that periodicity=12 we produce a Spectral Density plot in Figure 1c and as a "screening" forecast we attempt a seasonal Winter's Method forecast in Figure 1d. After realizing that the residuals are increasing in time from the residual plot we continue our iterative forecasting with Log Passengers as the dependent time series variable. We note also that Winter's method produces a non-invertible forecast.

Results:

On Log_{10}(Passengers) we iteratively fit a seasonal Winters, a seasonal ARIMA(1,1,1)(1,1,1)12, and two ARIMA(0,1,1)(0,1,1)12 models. Finally a reduced model with the lowest AIC and SBC emerged as best: Seasonal ARIMA(0,1,1)(0,1,1)12 No Intercept. Look at the Model Comparison table in Figure 1e. By saving results and creating a subset comparing the next 15 months predicted with the last 15 months of actual passengers we find there are two months, March and August of the first year, where we expect passenger demand in excess of 60,000 in Figure 1f.

Example 2: Forecasting Stock Prices for a steady grower (CSCO)

An investor buys 100 shares of CSCO stock on 5/25/00 and decides to sell a short term call option that expires 15 trading days in the future on 6/16/00. What call option should he write to be reasonably certain that the stock will not be called away? For this problem, which is characteristic to short term options traders, what is needed is a short term forecast with a confidence interval. We could either do this with regression or time series methods. For purposes of this paper we will only look at time series estimates. Using the same techniques as in Example 2 we find from the residuals and using the ace plot and the AR coefficients plot that Log (Log (CSCO) (Log = Log_{10}) modeled with a simple AR1 process gives us a stable and invertible series with excellent fit Square= .99 and smallest values for AIC and SBC with several model contenders (Figure 2a). Figure 2b shows the short-term forecast, 95% confidence limits and a good-looking residual pattern. Figure 2c indicates what call option we would have sold (the June 70) if we wanted to 95% confident of not being exercised. By saving the results and generating predicted values for the upper 95% confidence limit and comparing it with actual close values we see the stock ended up at 67.813 and we were close but not in jeopardy of having the call exercised.

Example 3: Forecasting Stock Prices for a volatile stock (CIEN)

We repeat the same scenario as Example 2 but with an even more volatile response, Log(Log(CIEN). Again an AR1 model fits best and even though the stock rises 40% within the 15 day period we do not come close to exercising either a June 165 or June 170 option!

Summary

We have shown several instances of forecasting using time series techniques. In the passenger demand example using various tools and graphs led us to a seasonal ARIMA model. Here we introduced the useful Model Comparison report. And iteratively used reports about stability and invertibilty and residuals to converge on a “best” candidate.

Whereas the Spectral Density plot confirmed the annual cyclical nature of passenger demand the acf plot confirmed the autoregressive nature of the response for the Log(Log) of the two stocks

Notation

(1) and (2) are good references for a discussion of ARIMA modeling

B is the lag operator $By_t = y_t - y_{t-1}$
p is the order of the Autoregressive polynomial $\Phi(B)$
d is the differencing order
q is the order of the Moving Ave. polynomial $\Theta(B)$

where: $\Phi(B)(w_t - \mu) = \Theta(B)a_t$

and where $w_t = (1 - B)^d y_t$ is the response series after differencing and a_t are a sequence of random shocks.

The ARIMA model is described as ARIMA(p.d,q) and the seasonal as ARIMA(p.d,q) (P,D, Q) s

where: s is the number of periods per season.

References

1. G. E. P Box and G. M, Jenkins (1976), ***Time Series Forecasting and Control***, Holden-Day Inc., San Francisco

2, W. Vandaele (1983) Applied Time Series and Box-Jenkins Models, Academic Press Inc, New York

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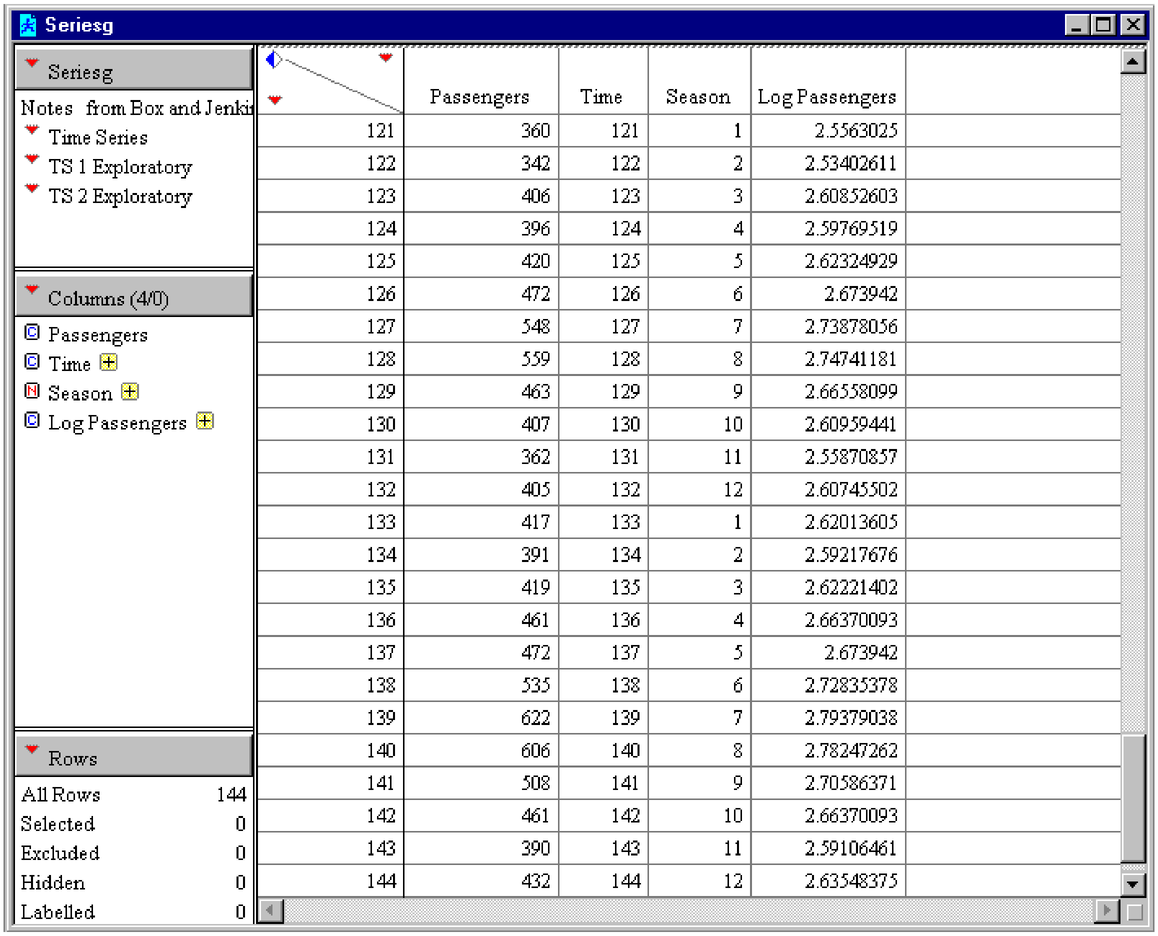
Bill is a consulting statistician for the Statistical Instruments Division. He joined SAS in 1977 and has seen many changes. He has been a part of the JMP team since its inception in 1989.

Trademark



	Passengers	Time	Season	Log Passengers
121	360	121	1	2.5563025
122	342	122	2	2.53402611
123	406	123	3	2.60852603
124	396	124	4	2.59769519
125	420	125	5	2.62324929
126	472	126	6	2.673942
127	548	127	7	2.73878056
128	559	128	8	2.74741181
129	463	129	9	2.66558099
130	407	130	10	2.60959441
131	362	131	11	2.55870857
132	405	132	12	2.60745502
133	417	133	1	2.62013605
134	391	134	2	2.59217676
135	419	135	3	2.62221402
136	461	136	4	2.66370093
137	472	137	5	2.673942
138	535	138	6	2.72835378
139	622	139	7	2.79379038
140	606	140	8	2.78247262
141	508	141	9	2.70586371
142	461	142	10	2.66370093
143	390	143	11	2.59106461
144	432	144	12	2.63548375

Figure 1a: In this table Passengers is the number of international airline passengers (in thousands) who flew each month. Time is the cumulative month number (only the last 24 months depicted), Season is month if the year and Log Passengers is $\log_{10}$(Passengers). For many time series a log transformation together with differencing will produce stationary series with sensible forecasts.

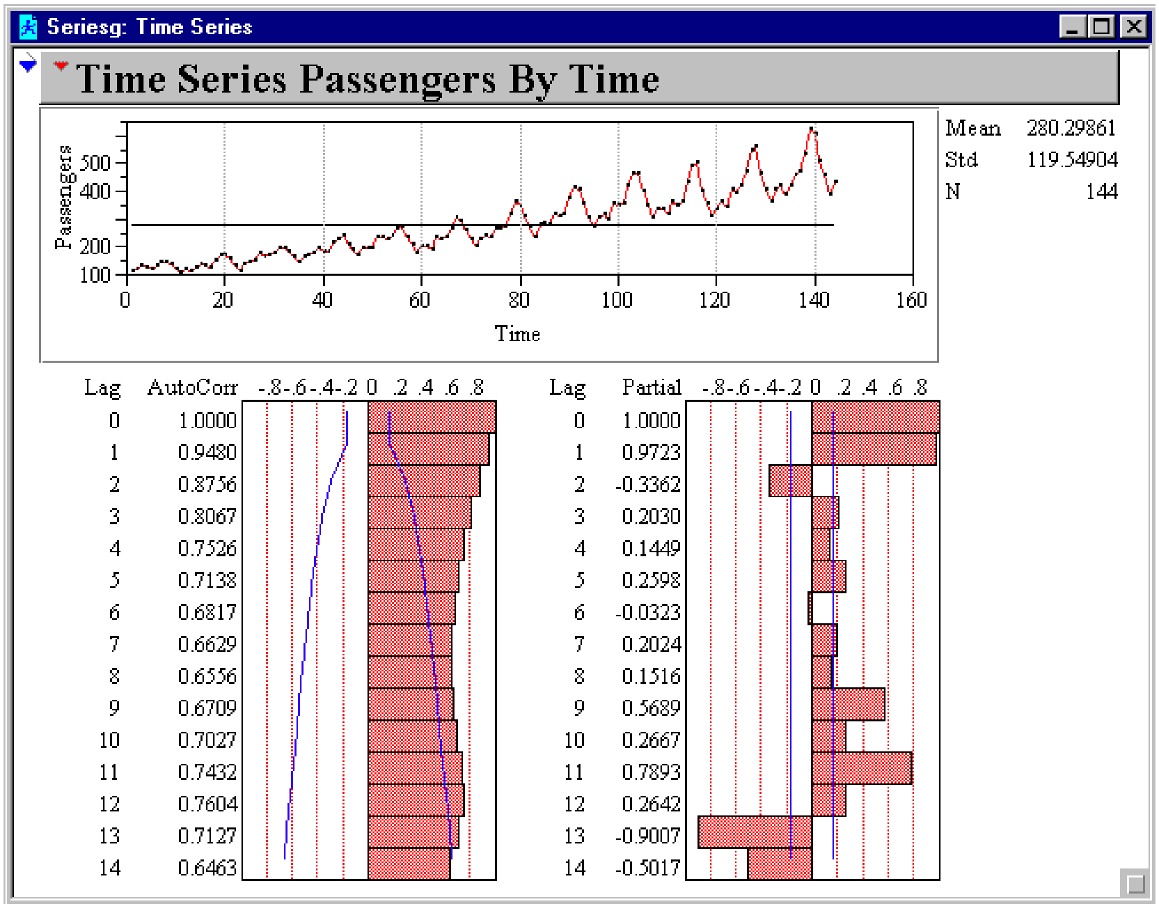


Figure 1b: Default plot of the time series and the acf and pacf functions. Even without a model and residual plot we see the series in increasing in variation as we increase in time.

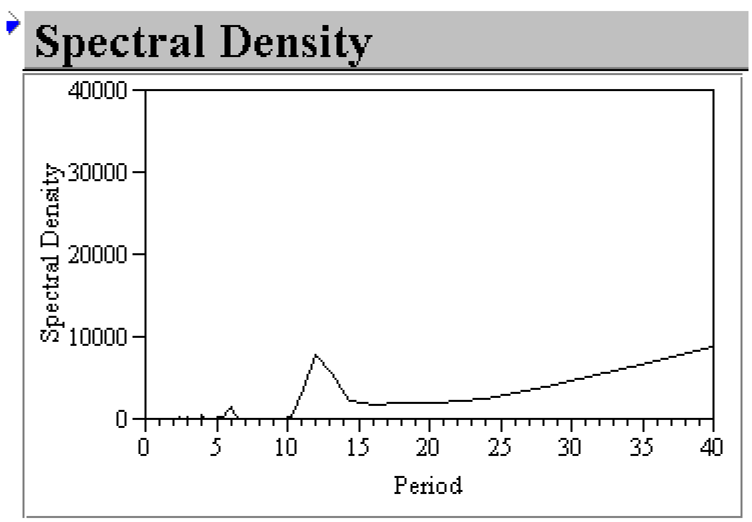


Figure1c: There is a definite periodicity of 12.

Iteration History

Specify Winters Method Model

Confidence Intervals	0.95
Periods Per Season	12
Constraints	Zero to One

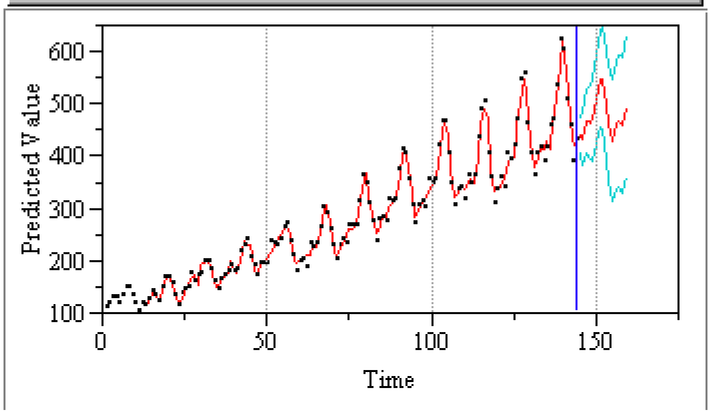
Estimate Cancel Help

Model Summary

DF	128	Stable	Yes
Sum of Squared Errors	40651.8871	Invertible	No
Variance Estimate	317.592868		
Standard Deviation	17.8211354		
Akaike's 'A' Information Criterion	760.660906		
Schwarz's Bayesian Criterion	769.286498		
RSquare	0.97311871		
RSquare Adj	0.97269869		
-2LogLikelihood	781.357887		

Parameter Estimates

Forecast



Residuals

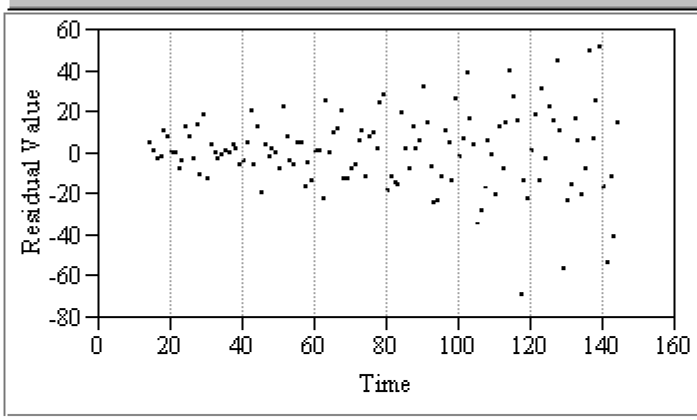


Figure 1d: Generating a Winter's method seasonal forecast produces a non-invertible result (unreliable forecast) and a residual pattern calling for a log transformation for the response

Model Comparison

Model	DF	Variance	AIC	SBC	RSquare	-2LogLH
Winters Method (Additive)	128	0.0002843	-1063.69	-1055.065	0.9900	-1066.414
Seasonal ARIMA(1, 1, 1)(1, 1, 1)12	126	0.0002619	-1070.446	-1056.07	0.9911	-1080.623
Seasonal ARIMA(0, 1, 1)(0, 1, 1)12	128	0.0002601	-1075.312	-1066.686	0.9910	-1079.699
Seasonal ARIMA(0, 1, 1)(0, 1, 1)12 No Intercept	129	0.0002582	-1078.288	-1072.538	0.9910	-1079.671

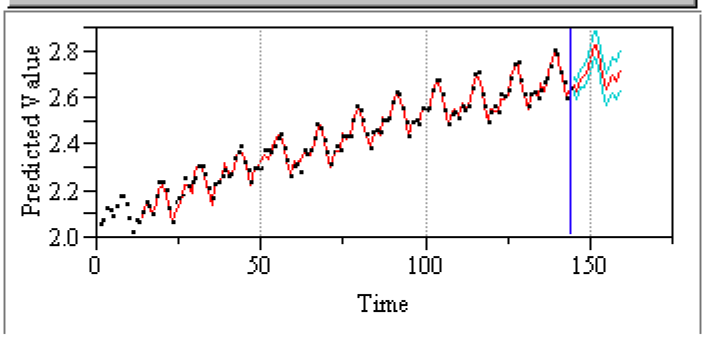
Model Summary

DF	129	Stable	Yes
Sum of Squared Errors	0.033309	Invertible	Yes
Variance Estimate	0.00025821		
Standard Deviation	0.01606889		
Akaike's 'A' Information Criterion	-1078.288		
Schwarz's Bayesian Criterion	-1072.5376		
RSquare	0.99097293		
RSquare Adj	0.99090295		
-2LogLikelihood	-1079.6714		

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t	Prob>|t|
MA1,1	1	1	0.40182266	0.0896223	4.48	<.0001
MA2,12	2	12	0.55694078	0.0731031	7.62	<.0001

Forecast



Residuals

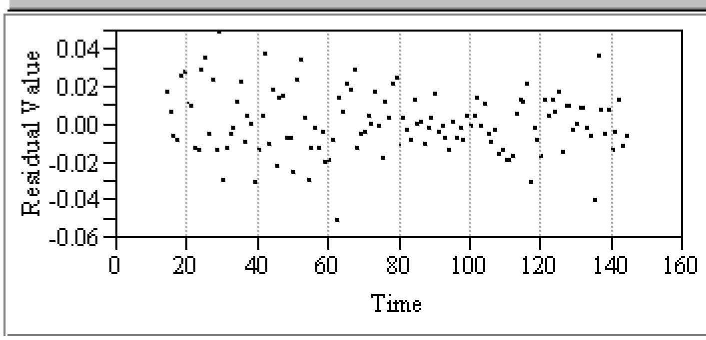


Figure 1e: Final model of Seasonal ARIMA(0, 1, 1)(0, 1, 1)12 No Intercept . It has the lowest AIC and SBC, is stable and invertible, and has good-looking forecasts and residuals

Increment

Increment
Source

Columns (4/-1)
- Pred Passenger
- Passengers
- Monthly increment
- Month #

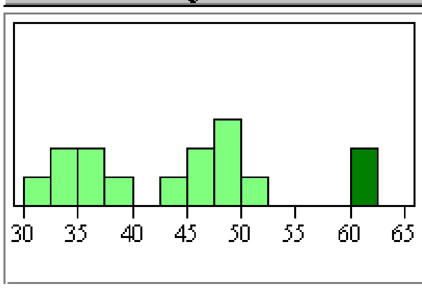
Rows

All Rows	15
Selected	2
Excluded	0
Hidden	0
Labelled	0

	Pred Passenger	Passengers	Monthly increment	Month #
1	450.422297	417	33.422	1
2	425.717069	391	34.717	2
3	479.006548	419	60.007	3
4	492.404342	461	31.404	4
5	509.054841	472	37.055	5
6	583.344798	535	48.345	6
7	670.010663	622	48.011	7
8	667.077472	606	61.077	8
9	558.189144	508	50.189	9
10	497.207659	461	36.208	10
11	429.8718	390	39.872	11
12	477.242327	432	45.242	12
13	495.929835	450.422297	45.508	1
14	468.728562	425.717069	43.011	2
15	527.402039	479.006548	48.395	3

Distributions

Monthly increment



Quantiles

100.0%	maximum	61.077
99.5%		61.077
97.5%		61.077
90.0%		60.435
75.0%	quartile	48.395
50.0%	median	45.242
25.0%	quartile	36.208
10.0%		32.615
2.5%		31.404
0.5%		31.404
0.0%	minimum	31.404

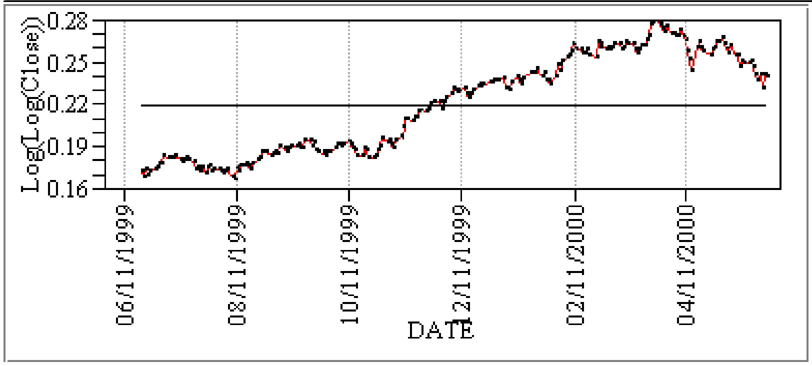
Moments

Mean	44.164
Std Dev	8.974
Std Err Mean	2.317
upper 95% Mean	49.134
lower 95% Mean	39.194
N	15.000

Figure 1f: Our airline analyst concludes that there are two months, March and August of the first year where we expect passenger demand in excess of 60,000

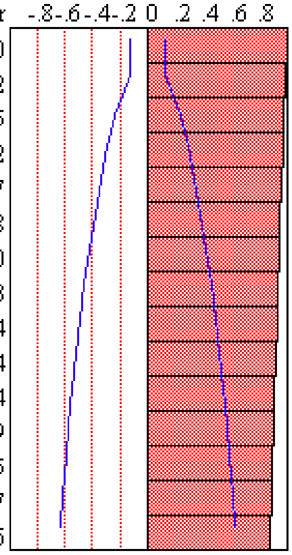
Cisco: Time Series

Time Series Log(Log(Close)) By DATE

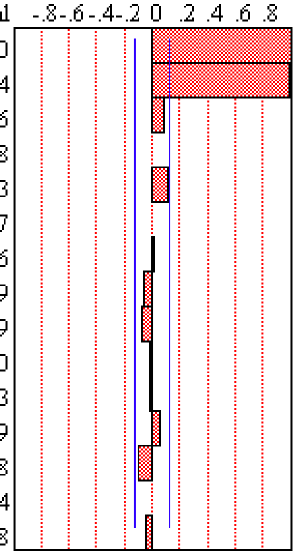


Mean	0.219965
Std	0.0347412
N	237

Lag	AutoCorr
0	1.0000
1	0.9902
2	0.9805
3	0.9722
4	0.9637
5	0.9558
6	0.9480
7	0.9393
8	0.9304
9	0.9214
10	0.9134
11	0.9059
12	0.8975
13	0.8887
14	0.8796



Lag	Partial
0	1.0000
1	0.9994
2	0.0826
3	0.0038
4	0.1093
5	0.0047
6	0.0206
7	-0.0549
8	-0.0739
9	-0.0150
10	-0.0153
11	0.0579
12	-0.0988
13	0.0034
14	-0.0468



Model Comparison

Model	DF	Variance	AIC	SBC	RSquare	-2LogLH
AR(1)	235	0.0000126	-2669.009	-2662.073	0.99	-2670.439
ARI(1, 1)	234	0.0000125	-2660.504	-2653.576	0.99	-2666.505
ARMA(1, 1)	234	0.0000126	-2667.521	-2657.117	0.99	-2671.945
ARIMA(1, 1, 1)	233	0.0000125	-2658.415	-2648.024	0.99	-2667.416

Model: AR(1)

Model Summary

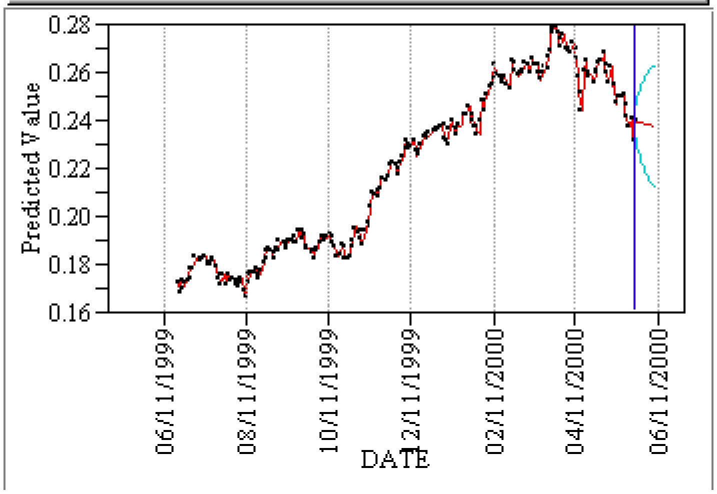
DF	235	Stable	Yes
Sum of Squared Errors	0.00297077	Invertible	Yes
Variance Estimate	0.00001264		
Standard Deviation	0.0035555		
Akaike's 'A' Information Criterion	-2669.0094		
Schwarz's Bayesian Criterion	-2662.0733		
RSquare	0.9895865		
RSquare Adj	0.989542		
-2LogLikelihood	-2670.4389		

Figure2a: Showing a simple AR1 (ARIMA (1,0,0) process as being best from the Model Comparison Table and invertible and stable from the Model Summary.

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	0.0010879
AR1	1	0.99485408	0.0048626	204.59	<.0001		
Intercept	0	0.21141056	0.0277217	7.63	<.0001		

Forecast



Residuals

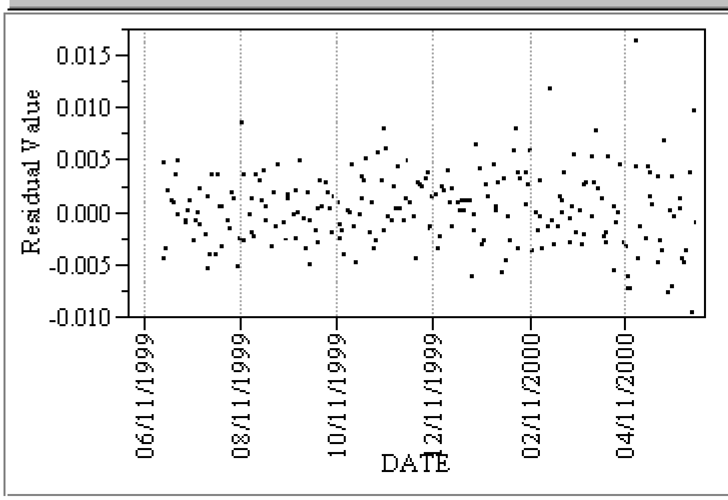


Figure 2b: The final AR1 forecast is shown together with its residuals.

Forecast for Option price of Cisco

	DATE	CLOSE	Pred UpperCL(Close)
1	05/25/2000	54.5	58.735084
2	05/26/2000	54.938	58.0621347
3	05/30/2000	59.875	59.5608883
4	05/31/2000	56.938	60.7149546
5	06/01/2000	60.938	61.688419
6	06/02/2000	64.375	62.5450642
7	06/05/2000	63.25	63.3177178
8	06/06/2000	61.313	64.0259512
9	06/07/2000	62.875	64.6825638
10	06/08/2000	63.688	65.2964804
11	06/09/2000	64.375	65.8742249
12	06/12/2000	62.125	66.4207427
13	06/13/2000	65	66.9398926
14	06/14/2000	65.188	67.4347566
15	06/15/2000	66.5	67.9078452
16	06/16/2000	67.813	68.3612371

Figure 2c: The choice of selling the June 70 call for CSCO based on the predicted confidence limit ending at 68.36 resulted in profit since the call would not have been exercised.

Forecast for Option Price of Ciena

	DATE	CLOSE	pred UCL
1	05/25/2000	104.5	111.973206
2	05/26/2000	99.688	119.97255
3	05/30/2000	121.5	126.805893
4	05/31/2000	119.688	132.191027
5	06/01/2000	130.188	136.813378
6	06/02/2000	138.313	140.939076
7	06/05/2000	133.625	144.704942
8	06/06/2000	137.875	148.192472
9	06/07/2000	131.438	151.454917
10	06/08/2000	135.125	154.529389
11	06/09/2000	139.875	157.443003
12	06/12/2000	139.375	160.216314
13	06/13/2000	144.938	162.865361
14	06/14/2000	144.438	165.402965
15	06/15/2000	145.5	167.839576
16	06/16/2000	145.25	170.18386

Figure 3: Similarly, the June 170 call for CIEN was not exercised.