JMP® ACADEMIC CASE STUDY

JMP054: Forecasting Copper Prices

Time Series, Exponential Smoothing, Forecasting

Produced by

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jmp® STATISTICAL DISCOVERY

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Key Ideas

The case study deals with forecasting a univariate time series. Before the time series are modeled and forecasted, it is necessary to observe the patterns and trends in the data. It is better to smooth out the data before forecasting. Time-series data may exhibit a trend over the period or seasonality and sometimes both period and seasonality. Depending on the pattern of the data, different smoothing techniques are applied before forecasting. This case deals with different exponential smoothing techniques available in JMP.

Background

Copper is a base metal with a vast number of industrial applications. The copper prices in India were found to be highly volatile during 2017-18. The price was around ₹375 per kilogram at the beginning of 2017. During the two-year period, at one time the price touched a maximum of ₹490, plummeted to ₹350, and closed at ₹415 by end of 2018. Arun, a researcher at the Commodity Research Centre of a leading investment advisory firm in Mumbai, was trying to understand the behavior of copper prices. He wanted to forecast the price using an appropriate technique.

Task

Arun performed the following tasks:

- Collected daily copper prices for two years
- Analyzed the pattern of price movements
- Applied various smoothing techniques
- Selected the most suitable model based on information criteria

Data Copper.jmp

Arun collected the daily spot price of copper from Bloomberg for two years, from Jan. 1, 2017, to Dec. 31, 2018. The data set is saved as Copper.jmp. There are 475 observations. The data set has two series: date and daily copper prices.

Date: Day on which the copper price is collected
Copper: Copper price on a specific date/day

Copper price is a continuous time-series variable, whereas Date is time-variable.

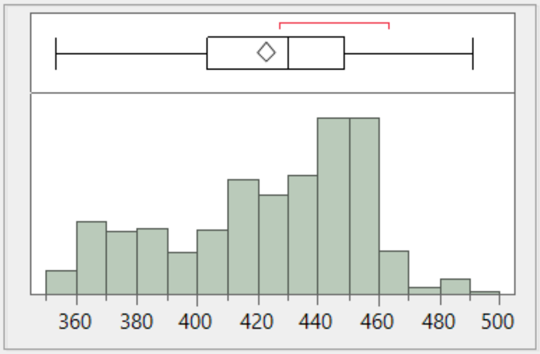
Descriptive Statistics

Arun explored the data using Distribution and Graph Builder.

Exhibit 1 Summary Statistics of Copper Prices

Distributions

Copper



Quantiles

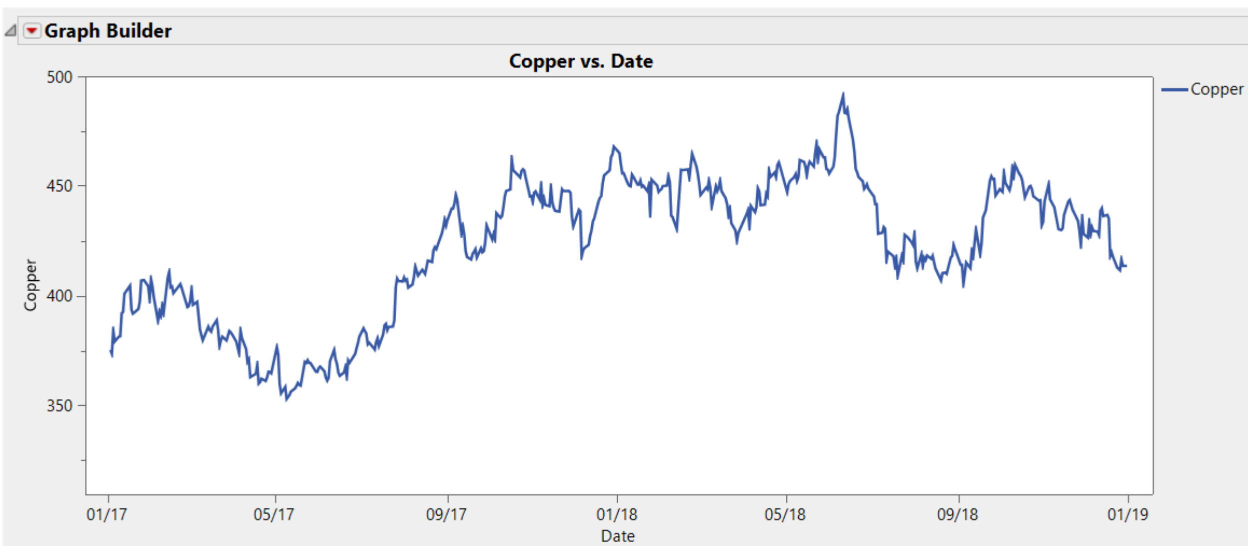
100.0%	maximum	491.25
99.5%		484.675
97.5%		466.925
90.0%		457.29
75.0%	quartile	448.65
50.0%	median	429.75
25.0%	quartile	403.2
10.0%		372.27
2.5%		360.27
0.5%		355.054
0.0%	minimum	353

Summary Statistics

Mean	422.93966
Std Dev	31.528757
Std Err Mean	1.4466386
Upper 95% Mean	425.78228
Lower 95% Mean	420.09705
N	475
Skewness	-0.503448
Kurtosis	-0.772115
N Missing	0
Minimum	353
Maximum	491.25

Analyze → Distribution → Y = GP → OK. Under the red triangle next to Distributions, select Stack. This will align the output horizontally. Under the red triangle next to Summary Statistics, select Customize Summary Statistics, and select N, Skewness, Kurtosis, Minimum and Maximum → OK.

Exhibit 2 Movement of Daily Copper Price (2017-2018)



Graph → Graph Builder → Y = GP, X = Date, Select Line graph from the Chart options → Done.

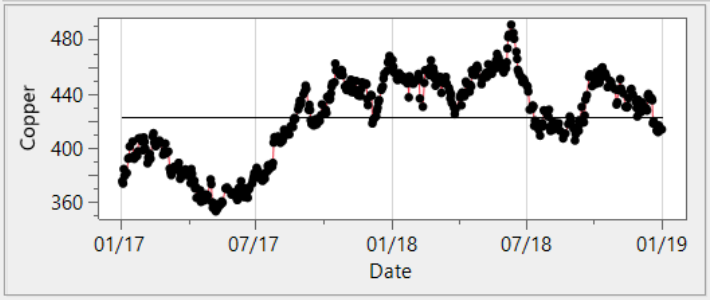
The basic descriptive characteristics of the data are presented in Exhibit 1, and the graph showing the movement of copper prices during the two years is given in Exhibit 2. The mean copper price was ₹422.94, with a maximum of ₹491.25 and a minimum of ₹353.00. The prices were negatively skewed with a negative kurtosis. It can be observed from Exhibit 2 that copper prices are highly volatile during the period. There is an overall increase in price during the period, but in between downward as well as upward movements are observed in the prices, which indicates the presence of some seasonality. The graph also indicates the need for applying smoothing techniques to the data before forecasting.

Time-Series Modeling

Before applying smoothing techniques to the data, Arun developed basic time-series plots. Time-series modeling is available under Analyze > Specialized Modeling. The default forecast period is 25, which can be changed as per the requirements.

Exhibit 3 Time-Series Output of Copper Prices

Time Series Copper



Mean	422.93966
Std	31.495551
N	475
Zero Mean ADF	0.1741613
Single Mean ADF	-2.131604
Trend ADF	-2.06343

Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.9835	462.319	<.0001*	1	0.9835
2	0.9691	912.179	<.0001*	2	0.0581
3	0.9555	1350.43	<.0001*	3	0.0206
4	0.9418	1777.14	<.0001*	4	-0.0058
5	0.9282	2192.44	<.0001*	5	-0.0064
6	0.9159	2597.66	<.0001*	6	0.0344
7	0.9043	2993.58	<.0001*	7	0.0228
8	0.8926	3380.18	<.0001*	8	-0.0047
9	0.8831	3759.36	<.0001*	9	0.0601
10	0.8755	4132.87	<.0001*	10	0.0645
11	0.8651	4498.35	<.0001*	11	-0.0773
12	0.8563	4857.14	<.0001*	12	0.0361
13	0.8456	5207.80	<.0001*	13	-0.0570
14	0.8342	5549.84	<.0001*	14	-0.0269
15	0.8256	5885.59	<.0001*	15	0.0833
16	0.8185	6216.28	<.0001*	16	0.0481
17	0.8093	6540.33	<.0001*	17	-0.0533
18	0.7999	6857.54	<.0001*	18	-0.0126
19	0.7892	7167.04	<.0001*	19	-0.0577
20	0.7791	7469.27	<.0001*	20	0.0032
21	0.7700	7765.17	<.0001*	21	0.0449
22	0.7604	8054.34	<.0001*	22	-0.0359
23	0.7498	8336.13	<.0001*	23	-0.0219
24	0.7392	8610.67	<.0001*	24	0.0053
25	0.7283	8877.77	<.0001*	25	-0.0359

Analyze → Specialized Modeling → Y, Time Series = Copper, X, Time ID = Date, → OK.

Exhibit 3 shows the descriptive statistics, autocorrelation function (ACF), and partial autocorrelation function (PACF) for copper prices. The ACF plot is not decaying and the PACF shows spikes up to the first lag. This indicates that the price series is not stationary. Now Arun could start to smooth the price curve.

Exponential Smoothing Techniques

One of the basic methods of smoothing a curve is applying a simple moving average, which attaches equal weight to all the observations in the averaging process. But exponential smoothing techniques give higher weights to more recent observations during averaging and are thus better.

Smoothing models are defined as follows:

$$Y_t = \mu_t + \beta_t t + s(t) + a_t$$

μ_t = time-varying mean term
β_t = time-varying slope term
S(t) = one of the s time-varying seasonal terms
a_t = random shocks

Models without a trend have $\beta_t = 0$ and nonseasonal models have S(t) = 0. The estimators for these time-varying terms are defined as follows:

L_t is a smoothed level that estimates μ_t
T_t is a smoothed trend that estimates β_t
S_{t-j} for j = 0, 1,..., s - 1 are estimates of the s(t)

Each smoothing model defines a set of recursive smoothing equations that describe the evolution of these estimators. The smoothing equations are written in terms of model parameters called smoothing weights:

α is the level smoothing weight
ϒ is the trend smoothing weight
φ is the trend damping weight
δ is the seasonal smoothing weight

While these parameters enter each model in different ways, they have the common property that larger weights are assigned to more recent data. Apart from simple moving average and state-space smoothing, JMP offers six exponential smoothing models. The table below lists these models along with model specifications.

#	**Name**	**Model**
1	Simple Exponential Smoothing	$Y_t = \mu_t + a_t$
2	Double Exponential Smoothing	$Y_t = \mu_t + \beta_1 t + a_t$
3	Linear (Holt) Exponential Smoothing	$Y_t = \mu_t + \beta_t t + a_t$
4	Damped Trend Linear Exponential Smoothing	$Y_t = \mu_t + \beta_t t + a_t$
5	Seasonal Exponential Smoothing	$Y_t = \mu_t + s(t) + a_t$
6	Winter's Model (Additive)	$Y_t = \mu_t + \beta_t t + s(t) + a_t$

(For details on exponential smoothing, please refer the JMP documentation guide under Help menu or visit https://www.jmp.com/en_us/support/jmp-documentation.htmli)

Arun started with Simple Exponential Smoothing. Exhibit 4 shows the result of simple exponential smoothing and includes a model summary, parameter estimates, and the forecast graph.

Exhibit 4 Simple Exponential Smoothing

Model: Simple Exponential Smoothing(Zero to One)

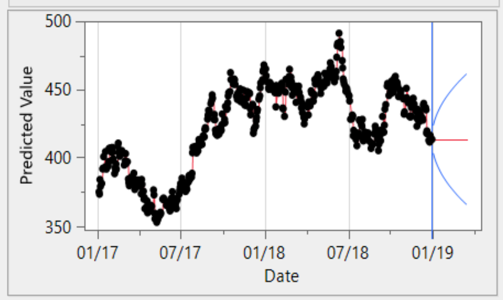
Model Summary

DF	473	Stable	Yes
Sum of Squared Innovations	13150.419	Invertible	Yes
Sum of Squared Residuals	13150.4448		
Variance Estimate	27.8021543		
Standard Deviation	5.27277482		
Akaike's 'A' Information Criterion	2922.26331		
Schwarz's Bayesian Criterion	2926.42452		
RSquare	0.97195565		
RSquare Adj	0.97195565		
MAPE	0.93080893		
MAE	3.93571812		
-2LogLikelihood	2920.26331		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.91747523	0.0453475	20.23	<.0001*

Forecast



Under the red triangle option, choose Smoothing Model → Simple Exponential Smoothing.

Arun followed the same procedure for the remaining exponential smoothing techniques. Prediction Intervals and Constraints are two inputs required for exponential smoothing techniques. Arun maintained the default settings for these two parameters. Every time a new model is estimated, JMP provides a Model Comparison listing. Model comparison for all the models estimated by Arun is shown in Exhibit 5.

Exhibit 5 Model Comparison

Model Comparison

Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
✓		Seasonal Exponential Smoothing(12, Zero to One)	460	27.572602	2889.5889	2897.8600	0.969	2885.5889	0.937870		0.989641	4.170917
✓		Winters Method (Additive)	459	27.839216	2895.0176	2907.4243	0.969	2889.0176	0.062130		0.995273	4.194736
✓		Simple Exponential Smoothing(Zero to One)	473	27.802154	2922.2633	2926.4245	0.972	2920.2633	0.000000		0.930809	3.935718
✓		Linear (Holt) Exponential Smoothing	471	27.913236	2925.2994	2933.6176	0.971	2921.2994	0.000000		0.942849	3.983408
✓		Damped-Trend Linear Exponential Smoothing	471	27.92021	2926.2633	2938.7469	0.972	2920.2633	0.000000		0.930809	3.935718
✓		Double (Brown) Exponential Smoothing	472	32.681429	2993.9151	2998.0742	0.967	2991.9151	0.000000		1.036056	4.371689

Arun found that the model that best fits the data was Seasonal Exponential Smoothing. This can be identified by comparing the Akaike's information criterion (AIC) or Schwarz's Bayesian criterion (SBC) values. The model that minimizes the information criteria value is the most suitable one. The Seasonal Exponential Smoothing technique has both the lowest AIC and SBC values.

Forecasting Copper Prices

After this, Arun moved to forecasting the copper prices using Seasonal Exponential Smoothing. The parameter estimates and forecast graph are given in Exhibit 6.

Exhibit 6 Forecast with Seasonal Exponential Smoothing

Model: Seasonal Exponential Smoothing(12, Zero to One)

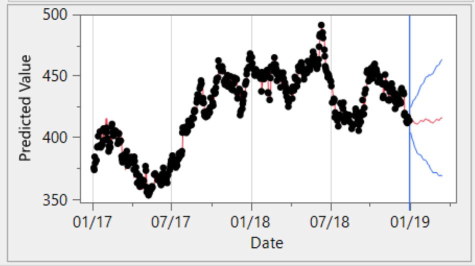
Model Summary

DF	460	Stable	Yes
Sum of Squared Innovations	12683.3969	Invertible	No
Sum of Squared Residuals	14160.3759		
Variance Estimate	27.572602		
Standard Deviation	5.250962		
Akaike's 'A' Information Criterion	2889.58886		
Schwarz's Bayesian Criterion	2897.85998		
RSquare	0.96879297		
RSquare Adj	0.96872513		
MAPE	0.98964082		
MAE	4.17091726		
-2LogLikelihood	2885.58886		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.91468326	0.0458625	19.94	<.0001*
Seasonal Smoothing Weight	0.00000000	0.2923827	0.00	1.0000

Forecast



Once the model was estimated, Arun generated a new data table containing the actual observations, predicted values, and standard errors. The last 25 observations in the data table represent the forecast of copper prices for the first 25 days of 2019. This data is shown in Exhibit 7.

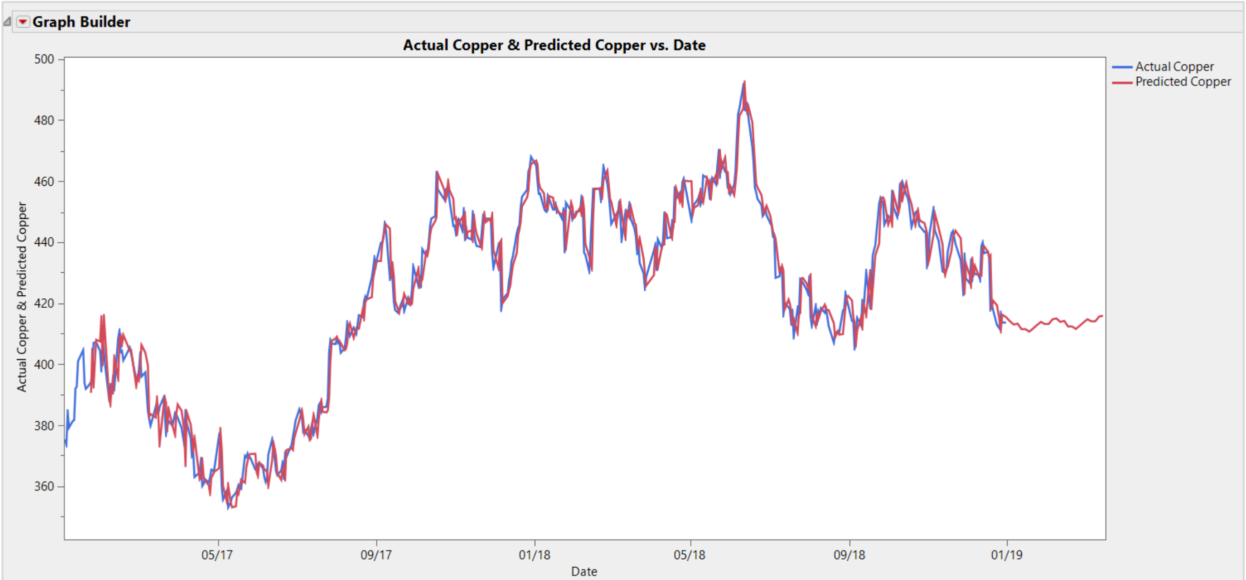
Exhibit 7 Forecast Values of Copper Prices

Actual Copper	Date	Predicted Copper	Std Err Pred Copper	Residual Copper	Upper CL (0.95) Copper	Lower CL (0.95) Copper
•	03/01/19	414.11771878	5.2509620029	•	424.40941519	403.82602237
•	06/01/19	412.99464186	7.116255648	•	426.94224663	399.04703708
•	09/01/19	413.31387263	8.5854287569	•	430.14100378	396.48674147
•	12/01/19	411.50361622	9.8375850406	•	430.78492859	392.22230384
•	15/01/19	411.50489827	10.947445909	•	432.96149797	390.04829856
•	18/01/19	410.68111142	11.95470888	•	434.11191027	387.25031257
•	21/01/19	411.71986142	12.883460595	•	436.97098018	386.46874266
•	24/01/19	412.85961142	13.749619973	•	439.80837137	385.91085147
•	27/01/19	413.87986142	14.564358616	•	442.42547976	385.33424308
•	30/01/19	413.15361142	15.335874099	•	443.21137233	383.09585051
•	02/02/19	413.18736142	16.070392866	•	444.68475266	381.68997019
•	05/02/19	414.73361142	16.772776138	•	447.60764857	381.85957427
•	08/02/19	415.00530439	17.446905509	•	449.20061083	380.80999795
•	11/02/19	413.88222747	18.095938891	•	449.34961596	378.41483897
•	14/02/19	414.20145824	18.722486396	•	450.89685727	377.5060592
•	17/02/19	412.39120183	19.328734809	•	450.27482592	374.50757773
•	20/02/19	412.39248388	19.916537897	•	451.42818085	373.3567869
•	23/02/19	411.56869703	20.487483357	•	451.72342654	371.41396752
•	26/02/19	412.60744703	21.042943397	•	453.85085822	371.36403584
•	01/03/19	413.74719703	21.584113586	•	456.0512823	371.44311176
•	04/03/19	414.76744703	22.112043139	•	458.10625521	371.42863885
•	07/03/19	414.04119703	22.627658833	•	458.3905934	369.69180066
•	10/03/19	414.07494703	23.131784124	•	459.41241081	368.73748325
•	13/03/19	415.62119703	23.625154587	•	461.92564915	369.31674491
•	16/03/19	415.89289	24.108430512	•	463.14454553	368.64123447

Under the red triangle of Model: Seasonal Exponential Smoothing (12, Zero to One), choose Save Columns. This will create a new data table containing the actual and predicted values together with standard errors, residuals, and 95% prediction intervals.

Arun also generated a graph showing the actual observations and predicted values using Graph Builder, which is shown in Exhibit 8.

Exhibit 8 Graph of Actual and Predicted Values



Summary

Statistical Insights

To summarize, in this case, the scheme of analysis using JMP involved the following:

- Generating summary statistics of the data series
- Visual representation of the data using Graph Builder
- Time-series representation of the data
- Estimation of various smoothing models
- Selection of the best smoothing models using model comparison and information criteria
- Forecasting using the most suitable smoothing model
- Generating forecast values and visualizing actual and predicted values

Implications

Arun drew the following conclusions from the analysis:

- The copper prices in India exhibited seasonality during 2017-18.
- Seasonal Exponential Smoothing is the most suitable model for understanding the pattern and forecasting copper prices during 2017-18.

JMP® Features and Hints

This case used the Time Series capability of the Analyze platform for forecasting. It also used various exponential smoothing features of the time-series analysis. Graph Builder was explored to visualize the time-series data.

Exercise

The price of lead for 2017-18 is available in Zinc.jmp. Perform the scheme of analysis explained in this case. Identify the most suitable exponential smoothing technique and forecast lead prices for the first 25 days of 2019.