Capabilities of Autobox

Agenda

- Our Company & Awards
- Autobox Functionality
- Outliers will skew your model and forecast if not addressed
- Using Causal Variables
- Three Examples
- Questions

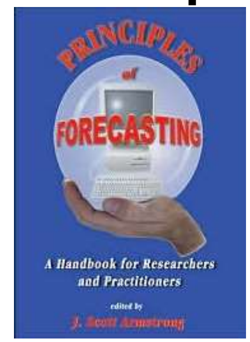
Our Company

- Incorporated in 1975
- First-to-market Forecasting package
- “AutoBJ” available in 1976 on Mainframe Time-sharing Services – IDC, CSC and Compuserve
- Autobox 1.0 launched DOS version on the PC in 1982
- Windows Version in 1991
- Batch Version 1996
- UNIX/AIX/SUN Version in 1999
- Callable DLL Version in 1999 for “plug and play” into ERP systems
- Java bean success in 2004
- .NET DLL version in 2013
- Delivering Price Elasticities using a Robust model 2014
- LLamasoft Integration 2014
- SIPmath Tools Certified 2015 – Delivering a distribution of forecasts for shortfall simulation “Simulated Forecasting
- Launched Autobox Integrated in R 2016
- Gartner Hype Cycle 2016 for our Probability Management Work delivering Simulated Forecasts

AUTOMATIC FORECASTING SYSTEMS

Awards

- Picked as the “Best Dedicated Forecasting” Software in the “Principles of Forecasting” textbook (Go to page 671 for overall results)



- Placed 12th in the “NN5” 2008 Forecasting Competition on “Daily data” (See www.neural-forecasting-competition.com results), but 1st among <u>Automated</u> software.

- Placed 2nd in the “NN3” 2007 Forecasting Competition on “Monthly data” (See www.neural-forecasting-competition.com), but 1st on more difficult data sets.

Specific Uses of Time Series Data Applied to any Industry or What Can Autobox Be Used For?

- Data Cleansing - Correct historical data to what it should have been due to misreporting or removing the impact of unexpected events(ie outliers)
- Causation – Does my advertising(sentiment data) generate sales? Is Unemployment important? Evaluate historical data to determine if a variable is important and what is the exact time lag or lead? Outliers? Flagging a change in the model?
- Forecasting – Forecast incorporating future expected events
  - Short-Term(ATM) and Long-Term Demand of anything needing to be tracked and measured including regions
  - Daily Call Center Planning or Staffing at Departments (ie Hospital)
  - Intermittent Demand Data (Spare Parts with many zeroes in the data set)
  - Financial/Marketing- Probability of Hitting the Monthly/Quarterly #'s (Daily Data)
  - Capacity Planning or Risk of Insolvency
- What-if Analysis – Forecast using different scenarios to assess expected impact by changing future causal values (ie 1% increase in unemployment)
- Early Warning System/Detecting Change – Where are we underperforming/performing? or Fraud Detection Identify "most unusual" based on markers like outliers or changes in ---- trends/level/parameters/variance
- Price Elasticities with a robust model vs. the error prone log/log modeling with not outlier checking.
- Safety Stock for Inventory Control
- Simulated Forecasts – Certified by ProbabilityManagement.org for compatible SIPMath output – Providing more realistic confidence limits by way of sampling the errors, allowing outliers to "play"

Recent Advancements

- Univariate and Multivariate (Two-stage Monte Carlo) Simulation
- Resample the Errors
- Model and account for the outliers, but then allow outliers to “play” (ie exist) in the forecast
- Confidence Limits are too tight!!
- Symmetrical Confidence Limits → Asymmetrical Confidence Limits
- Averages aren’t added, but Distributions are. A 1,000 forecasts from Autobox can be integrated into Probability Management’s Capacity/Shortfall model
- User supplied estimates of expectations(ie Delphi forecast) with probabilities and ranges can be included as a causal

Capabilities of Autobox

Some Customers

National Defence

BRIDGESTONE
Your Journey, Our Passion

PRAXAIR
Making our planet more productive

monroe plan
FOR MEDICAL CARE

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

TEXAS
Department of Assistive and Rehabilitative Services

AUTOMATIC FORECASTING SYSTEMS

Journals

- Autobox has been used in articles published in a variety of Journals as it has unique strengths not found in other software. Read the articles in our 'News" section on the website

- Journal of Forecasting
- Journal of Business Forecasting
- North American Actuarial Journal
- Forest Research and Management Institute
- Environmental and Resource Economics
- Technological Forecasting and Social Change

- Fraud Magazine
- Canadian Journal of Forest Research
- Applied Economics
- Journal of applied Pharmacology
- Journal of Endocrinology and Metabolism
- Journal of Urban Studies

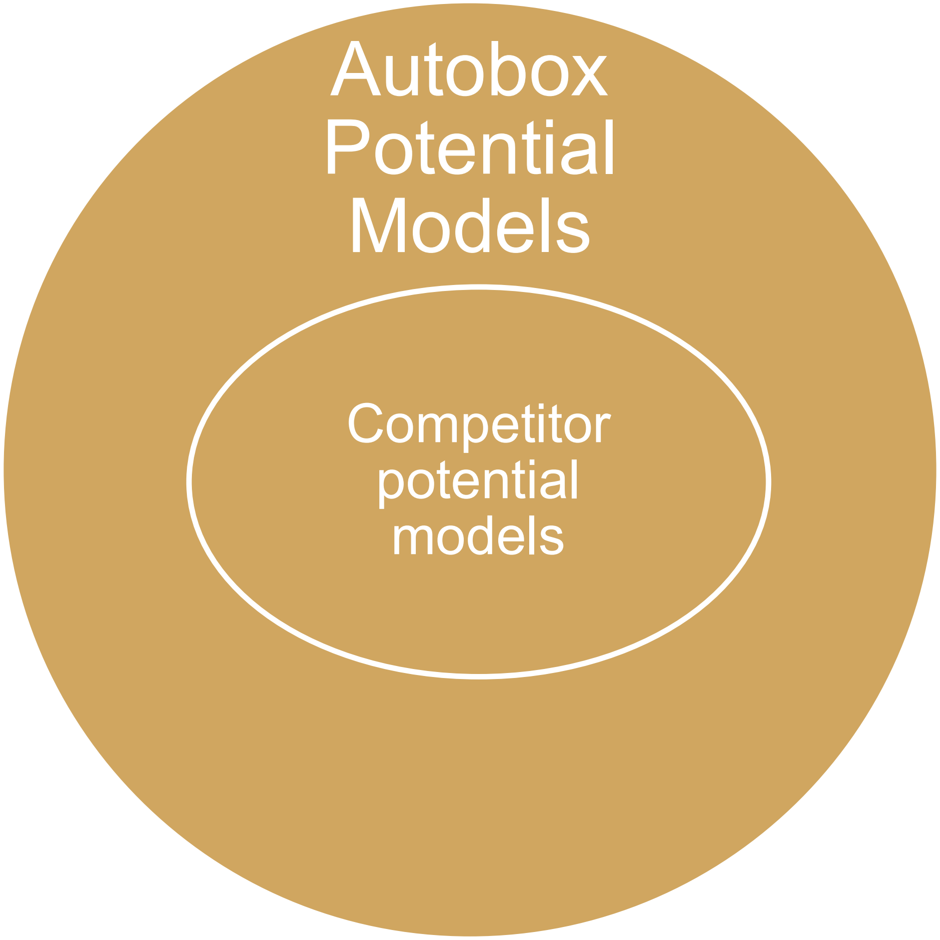
AUTOMATIC FORECASTING SYSTEMS

Autobox Functionality

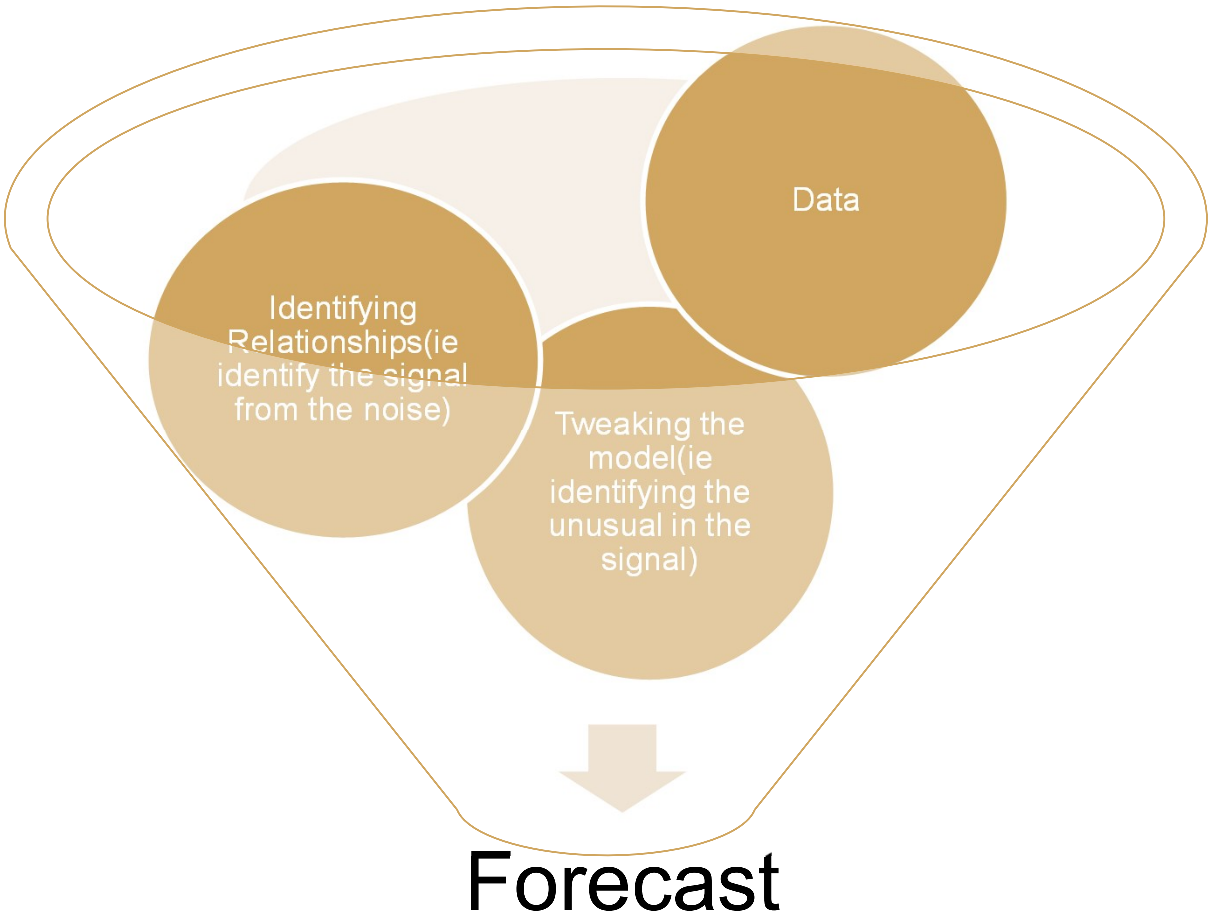
What kinds of Products do you Offer?

- There are a couple of ways to engage Autobox
  - Autobox Interactive – Run one series at a time in a Windows environment
  - Autobox Batch
    - Interactive and DOS – Read from Excel to run Univariate problems and post results to Excel
    - Interactive – Read flat files for Univariate and Multivariate problems
    - Command Line – Read flat file for Univariate and Multivariate problems – Parallel processing as it can run up to as many CPUs on your machine
  - Autobox for R – callable within R(not free ☺)
  - Integrated - Call the Autobox DLL directly from your application

Statistical Modeling Sample Space
Autobox vs i2 (You can substitute any “pick best“ here)



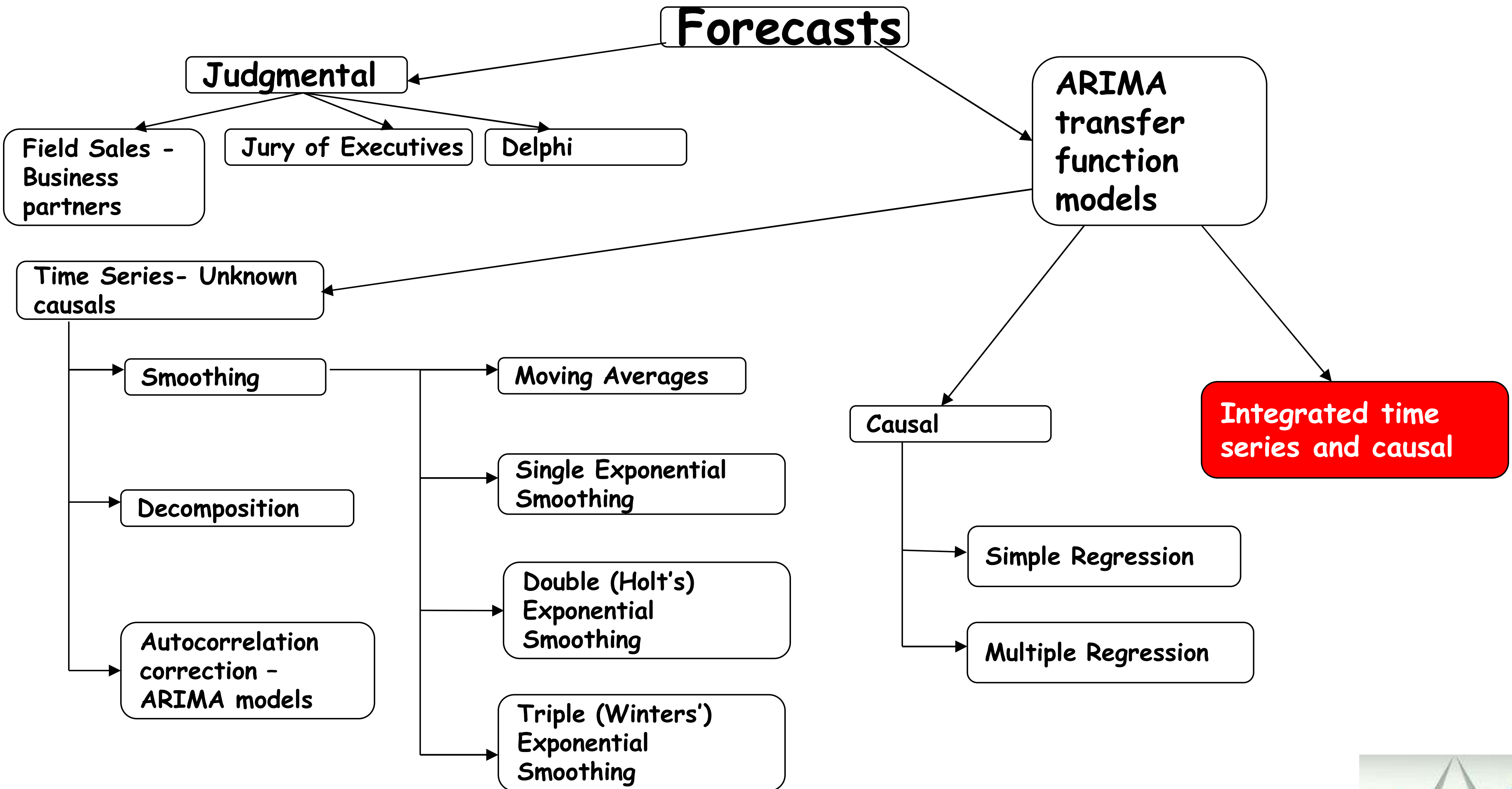
Autobox - Process



Autobox Functionality

Data	Identifying Relationship	Tweaking the model	Forecasting
Historical Data Historical Causal Data(ie Price, Customer Insight, GNP, Unemployment, Population, etc.) Historical Knowledge of Events (outliers, mergers, promotions, holidays etc.) Future Values of Causals Future Values of Promotions	Autobox Algorithm (Can be customized by user) Autocorrelation Function Partial Autocorrelation Function Cross Correlation Function ARIMA models Transfer Function models	Autobox will identify the lead/lag relationship in the causals Autobox will remove unimportant Causals Autobox will potentially identify and Add 4 Types of Outliers providing "Early Warning Detection" Check for Constancy of Parameters and Variance	Forecast What if scenarios to evaluate different scenarios using different future values of causals

Forecasting Methods Family Tree

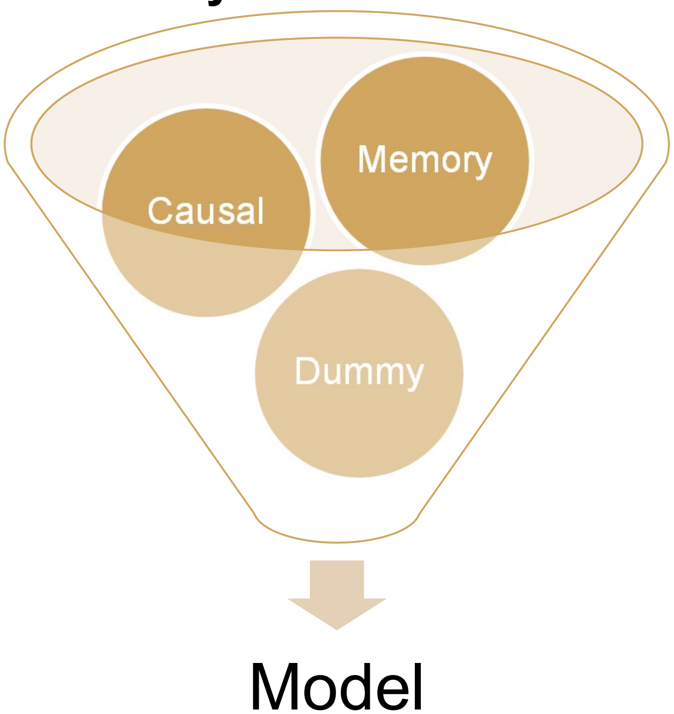


Regression Modelling

- **Causal variables - Variables like Price, Unemployment, Population might have a lead or lag relationship and that exact period may be difficult to identify.**

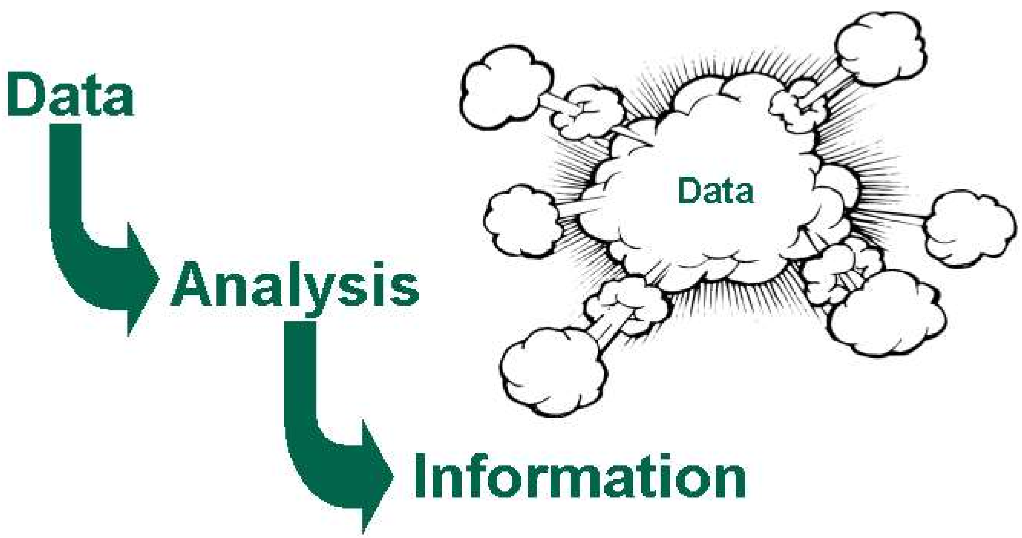
- **Dummy variables – Outliers like Promotions, Earthquakes, mergers should be provided and/or identified and adjusted for by the system.**

- **Memory – There is a period to period relationship that exists in the data like this month to last month and to last year.**



Autobox – It's information Rich – White box not Black Box

- Reports on
  - Analytical Steps, Interventions, Equations and Overall Summary
  - Early Warning System showing series with unusual values in the latest data period and Pulse Report showing outliers at similar periods
  - Forecasts, Forecasts of causals if no forecast exists, Cleansed historical data, Safety Stock for 90% service level



Why is Autobox's Methodology Different?

- <u>Automatically</u> creates a customized model for every data set. Not "pick best"
- <u>Automatically</u> identifies and corrects outliers in the historical data <u>and</u> for the causal variables to keep the model used to forecast unaffected (Pulses, seasonal pulses, level shifts, local time trends)
- <u>Automatically</u> will identify and incorporate the time lead and lag relationship between the causal variables the variable being predicted
- <u>Automatically</u> will delete older data that behaves in a different "model" than the more recent data (i.e. Parameter Change detection via Chow Test)
- <u>Automatically</u> will weight observations based on their variance if there has been changes in historical volatility (i.e. Variance Change detection via Tsay Test)
- <u>Automatically</u> will identify intermittent demand data and use a special modelling approach to forecast the lumpy demand

How Autobox Treats Different Data Intervals
You can (optionally) let the system do it all by itself!

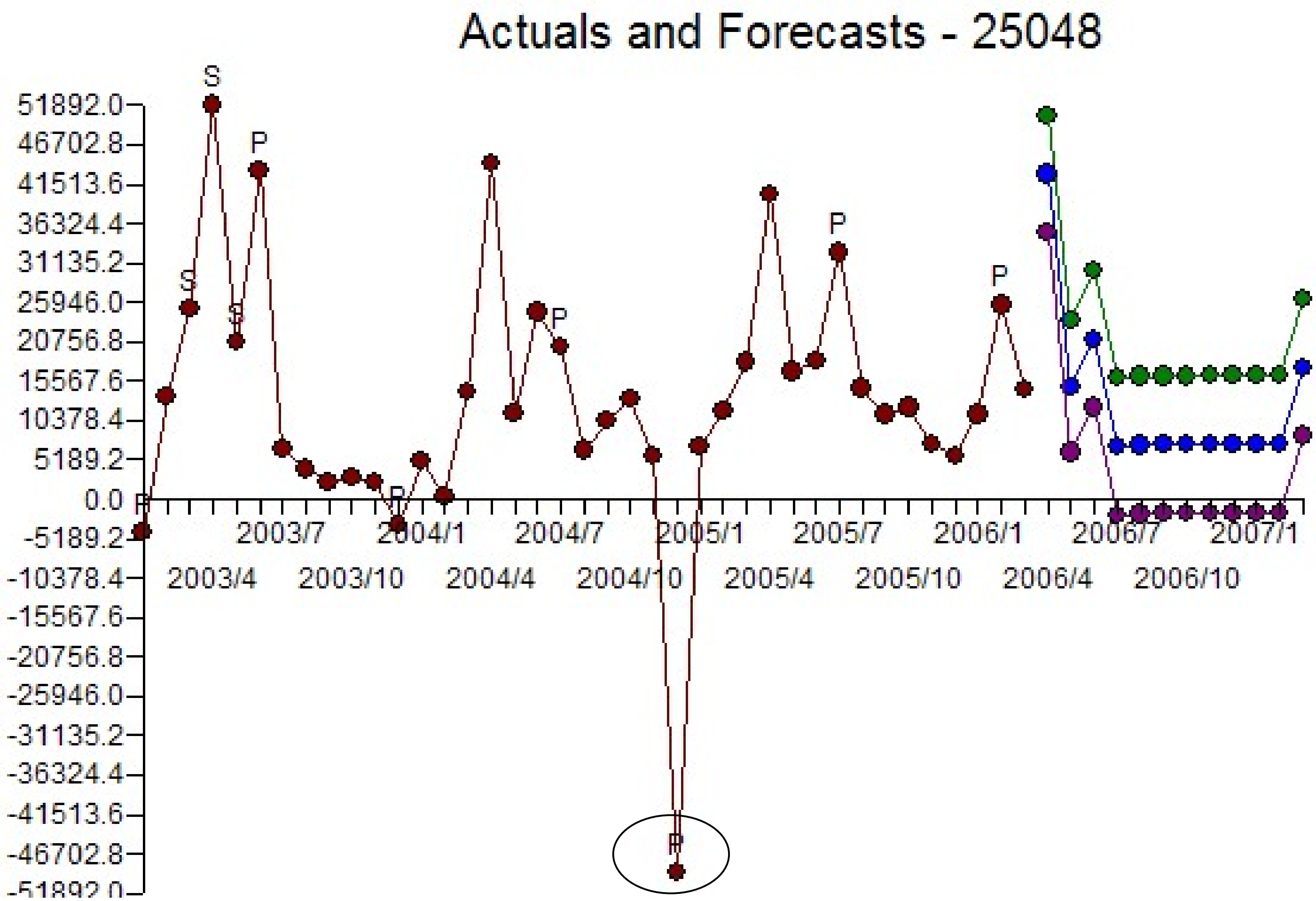
- **Incorporates variables for Hourly Data - Brings in Daily History and Forecast as a Causal Variable for the 24 separate regressions**
- **Incorporates variables for <u>Daily</u> data <u>*Automatically*</u>:**
  - Day of the week (i.e. Sundays are low)
  - Special Days of the month (i.e. Social Security checks are delivered on the 3rd of the month)
  - Week of the Year (i.e. 51 dummies Capturing seasonal variations) or Month of the Year (i.e. 11 dummies Capturing seasonal variations)
  - Adds in holiday variables (including "Fridays before" holidays that fall on Mondays and Monday after a Friday Holiday AND a separate effect "long weekends")
  - End of the Month Effect – when last day of month is a Friday, Saturday or Sunday
- **Incorporates variables for <u>Weekly</u> data:**
  - Trading Days (i.e. 19,19,22,20,21,21, etc.)
  - Week of the Year (i.e. Capturing seasonal variations) <u>***Automatically***</u>
- **Incorporates variables for <u>Monthly</u> data:**
  - Trading Days (i.e. 19,19,22,20,21,21, etc.)
  - Month of the Year (i.e. 11 dummies Capturing seasonal variations)
  - Accounting effect (i.e. 4/4/5)
    - Accounting practice of uneven grouping of weeks into <u>monthly</u> buckets where there is a 4/4/5 pattern that is repeated
- **Incorporates variables for <u>Quarterly</u> data:**
  - Quarterly effect (i.e. High in Q2)

Outliers will skew your model and forecast if not addressed

Time Series Analysis ASSUMES that the errors are N.I.I.D. with a constant mean and constant variance. Most ignore this assumption and don't even provide graphs to show if it is or isn't!

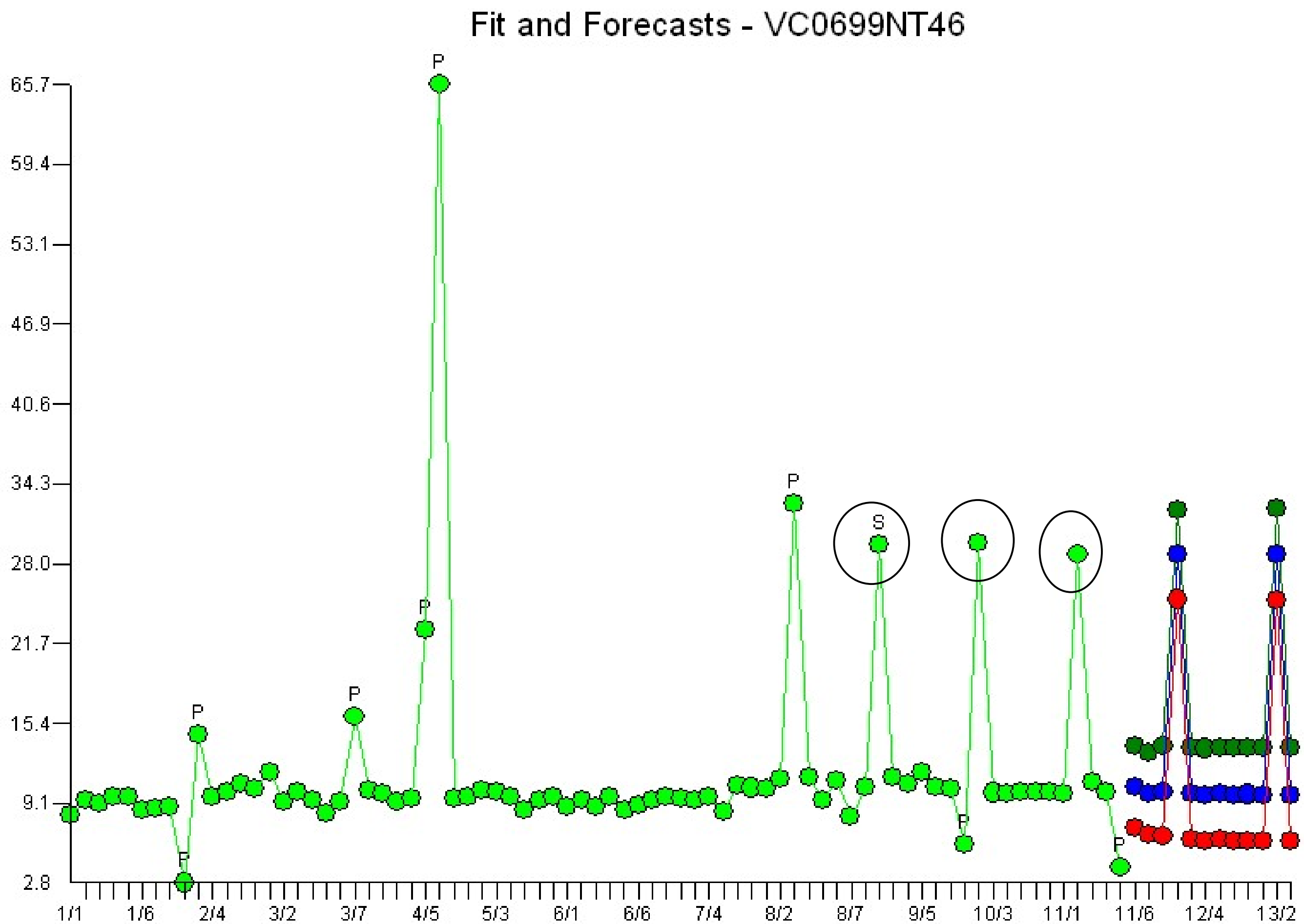
Outlier Detection – Pulse(s)
(FIXING THE HISTORICAL DATA)

- **Pulse – Fire in the warehouse in April (0,0,0,0,0,0,0,0,1,0,0,0,0,0)**



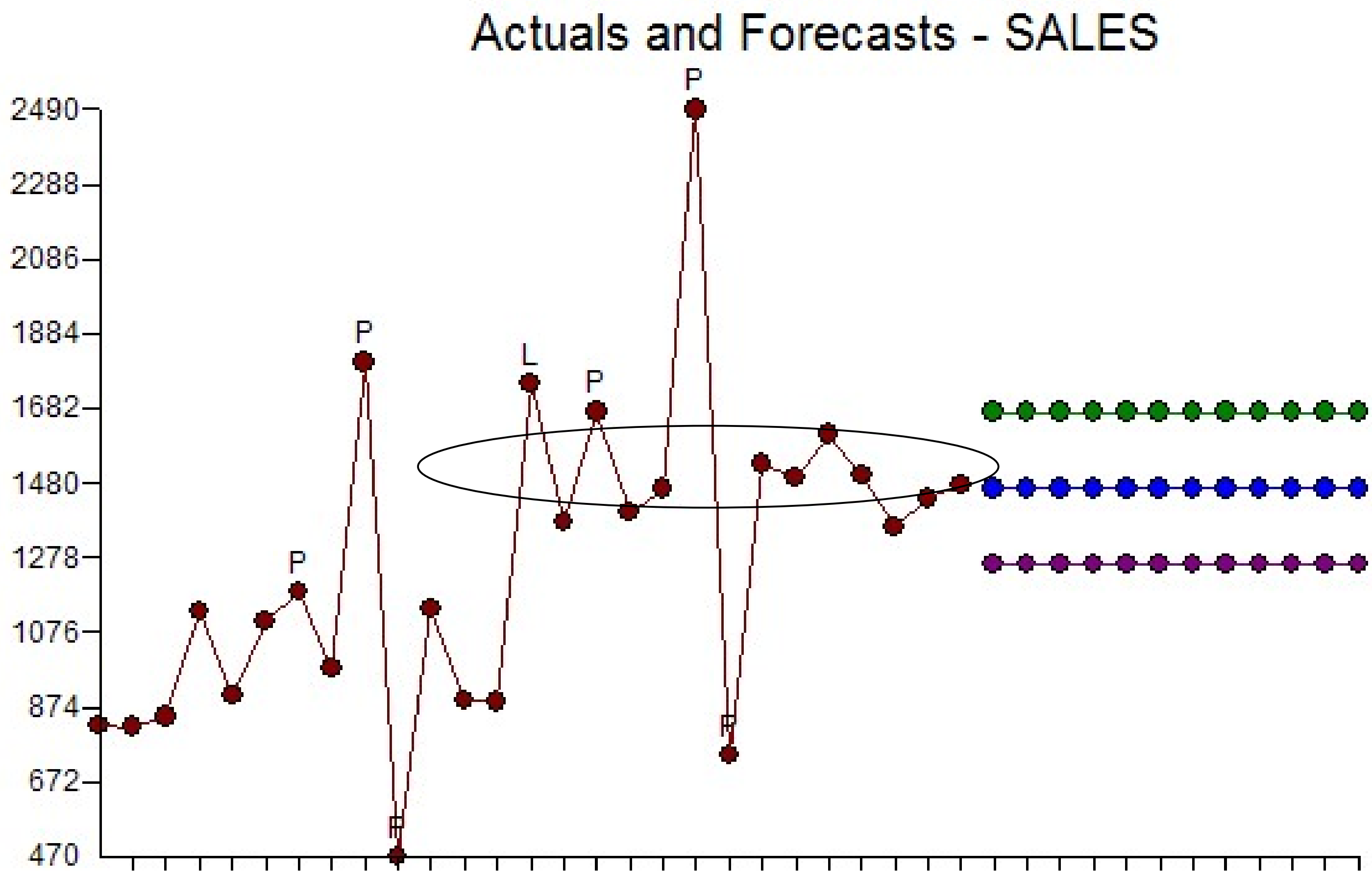
Outlier Detection – Seasonal Pulse(s)
(ADAPTING TO THE DATA)

- **Seasonal Pulse – February emerges later during the year (0,1,0,0,0,0,0,0,0,0,0,0,0,1)**



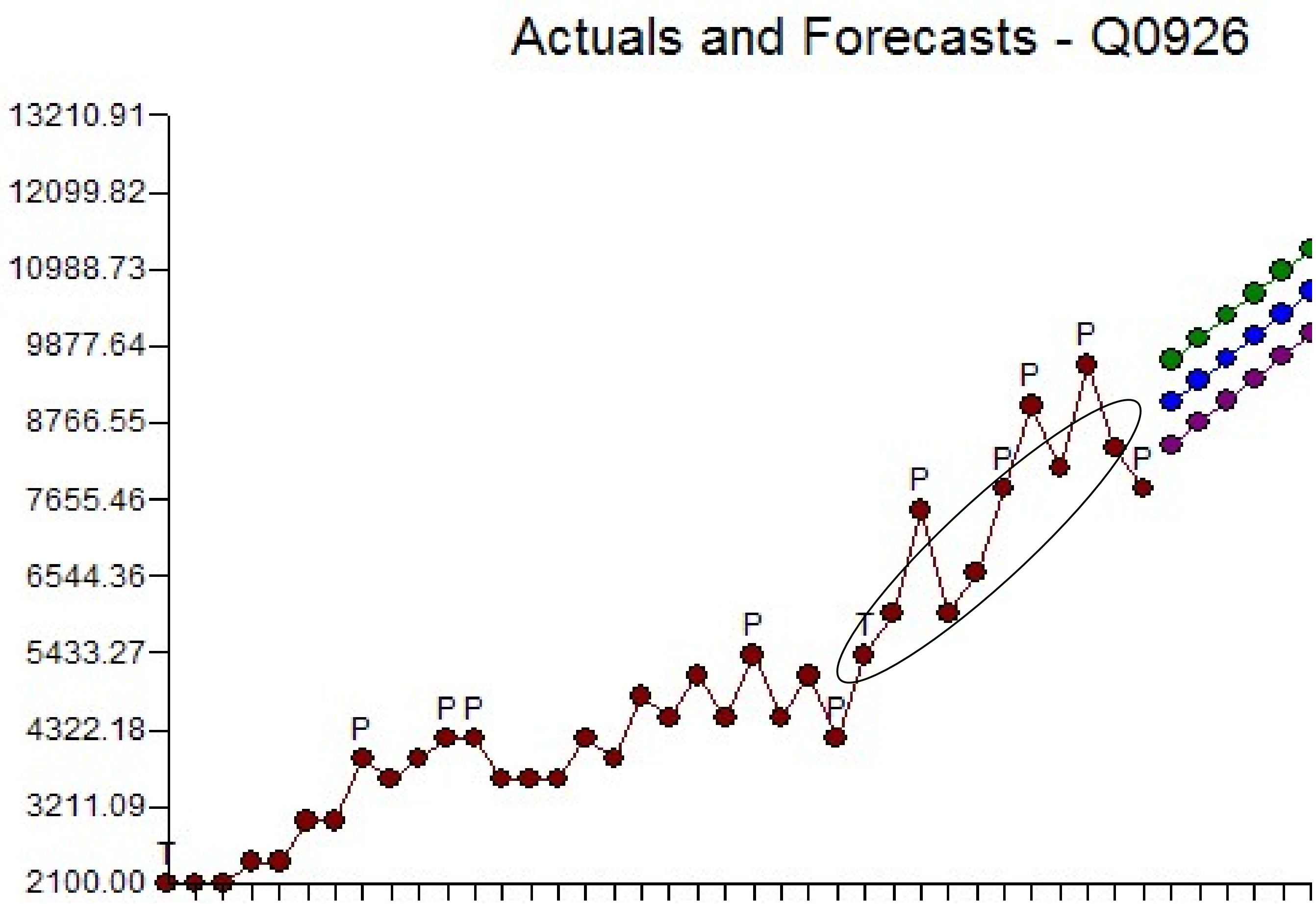
Outlier Detection – Level Shift(s)
(ADAPTING TO THE DATA)

- **Level Shift –Competitor drops out of the market and an ‘one-time’ increase in market share gain (0,0,0,0,1,1,1,1,1,1,1,1). Not a trend!**



Outlier Detection – Local Time Trend(s)
(ADAPTING TO THE DATA)

- **Local Time Trend – A new trend up or down very different from the past (0,0,0,0,1,2,3,4,5,6,7,8,9,etc.)**



AUTOMATIC FORECASTING SYSTEMS

Outlier Detection – Local Time Trend(s)
(ADAPTING TO THE DATA)

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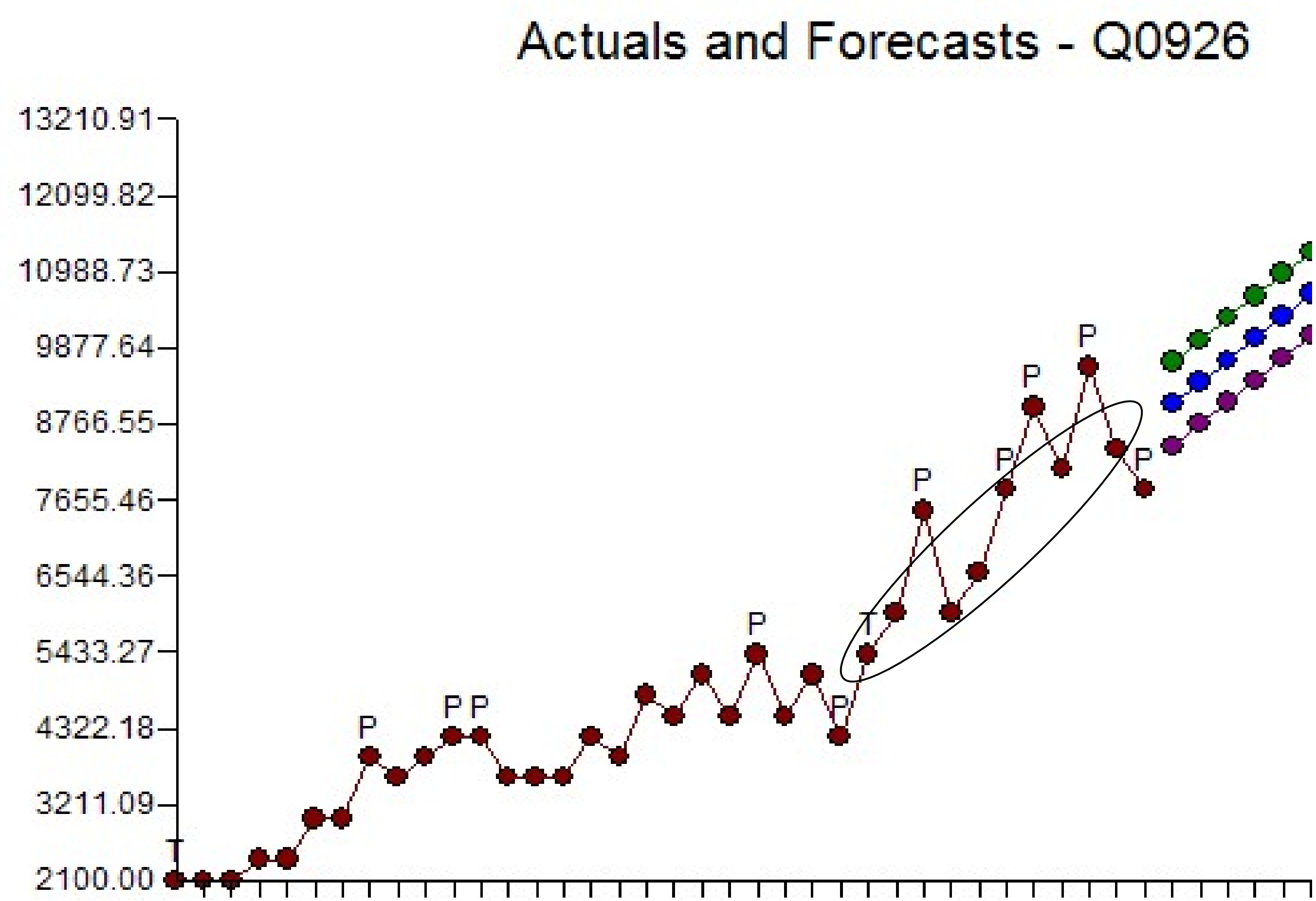
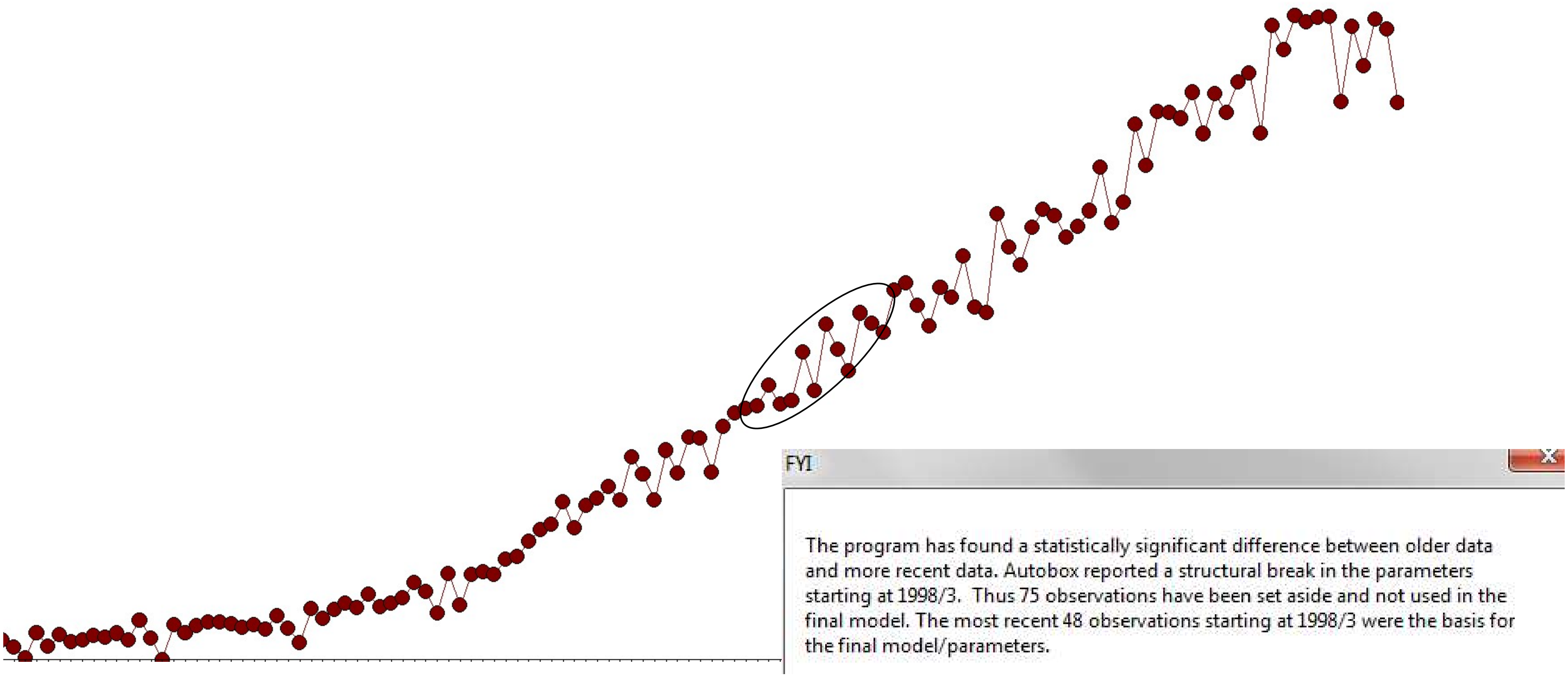


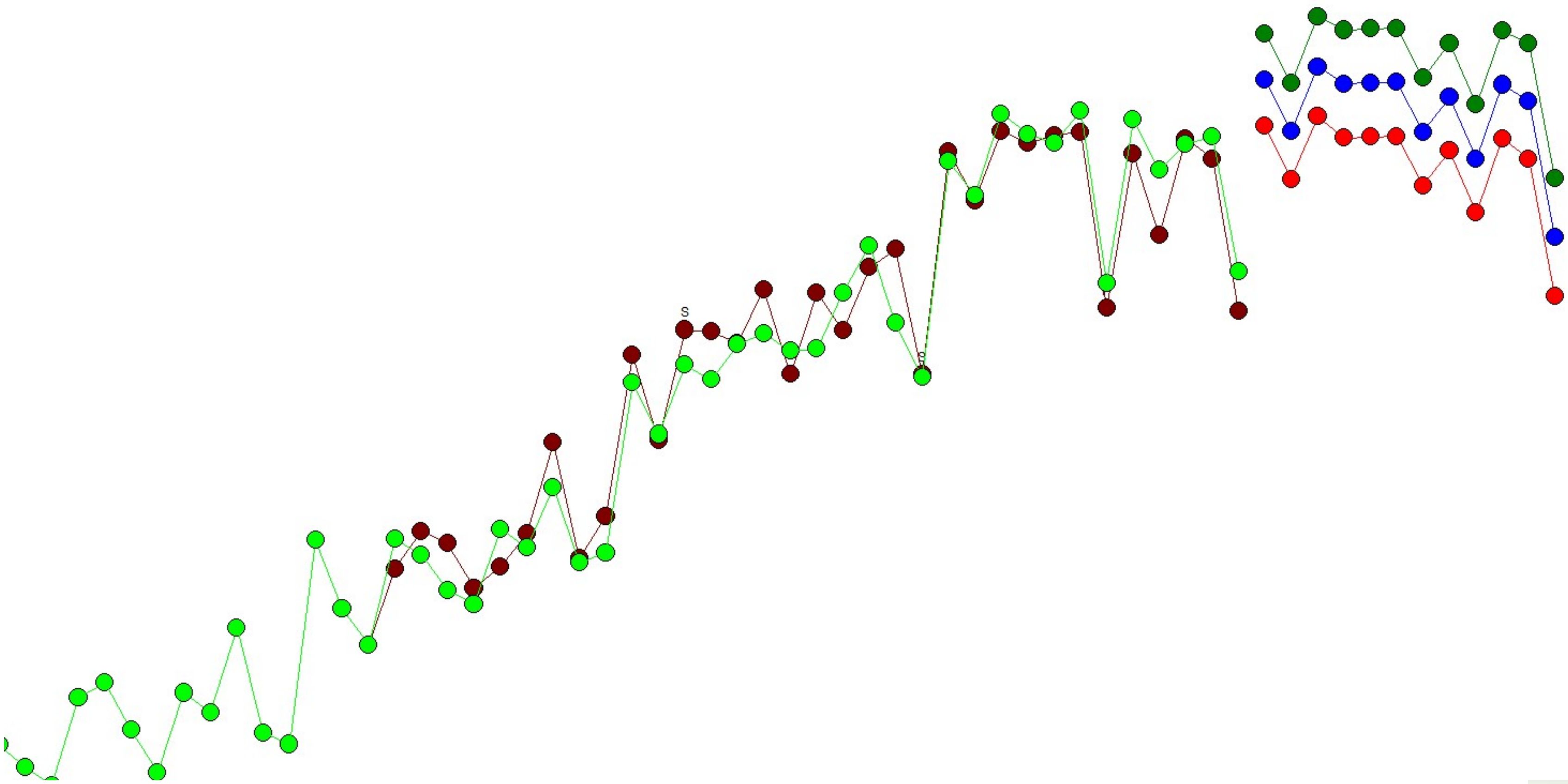
Parameter Change Detection – Chow Test
(DELETING OLDER DATA)

- **Gregory Chow applied an approach and F Test to determine if two models were similar. We apply this to time series and find the model has changed.**



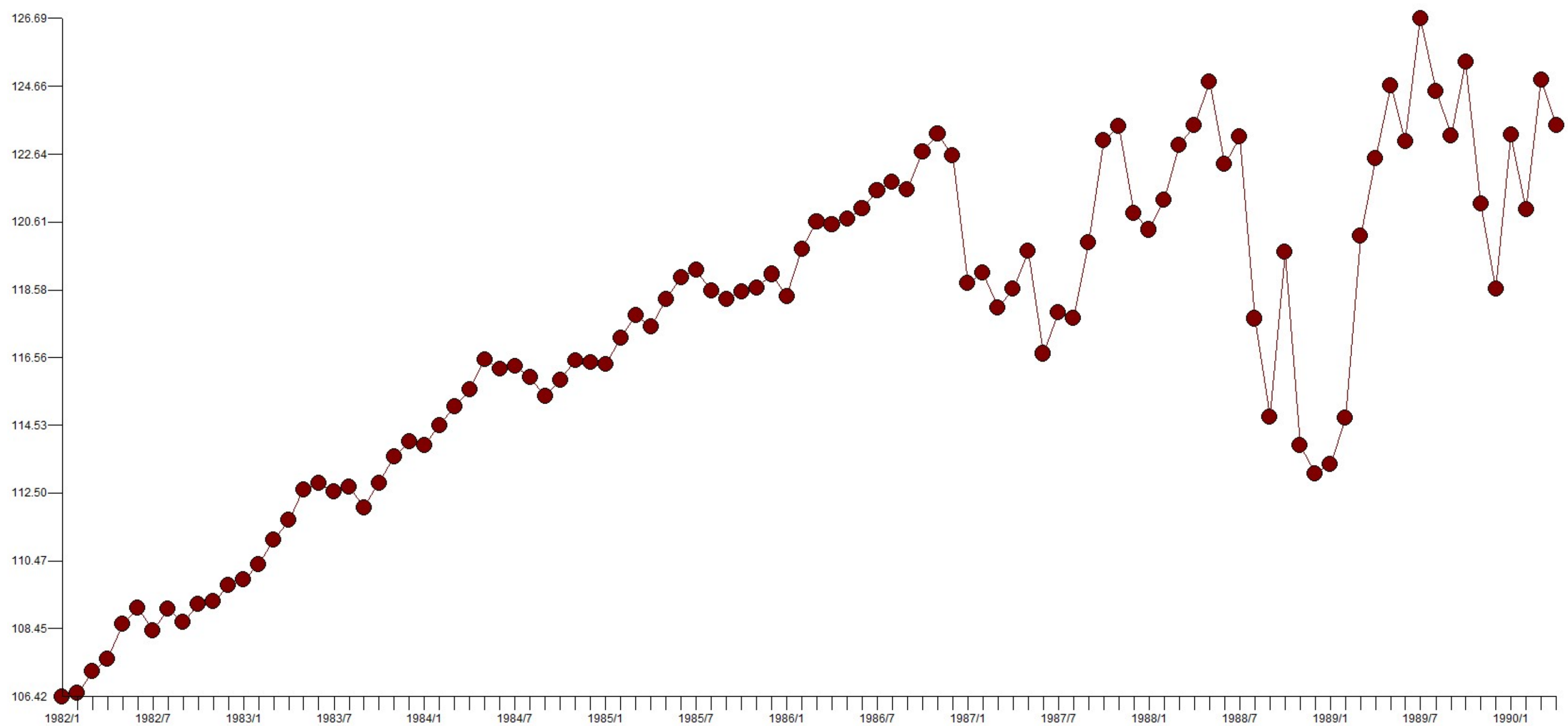
Parameter Change Detection – Chow Test
(DELETING OLDER DATA)

- Older data is truncated and not used



Variance Change Detection – Tsay Test
(WEIGHTING DATA)

- **Weighted Least Squares**



Variance Change Detection – Tsay Test
(WEIGHTING DATA)

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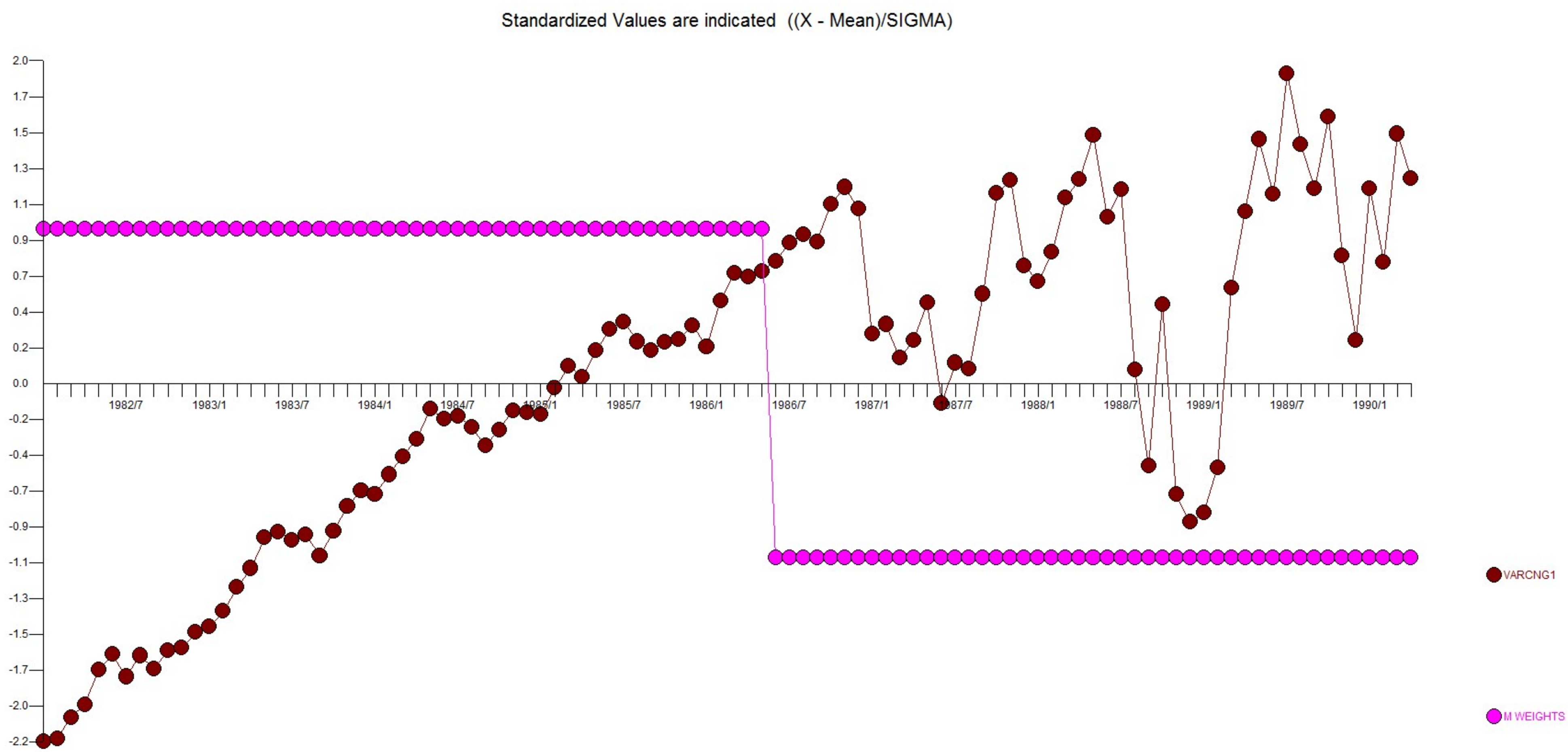


What is unusual?

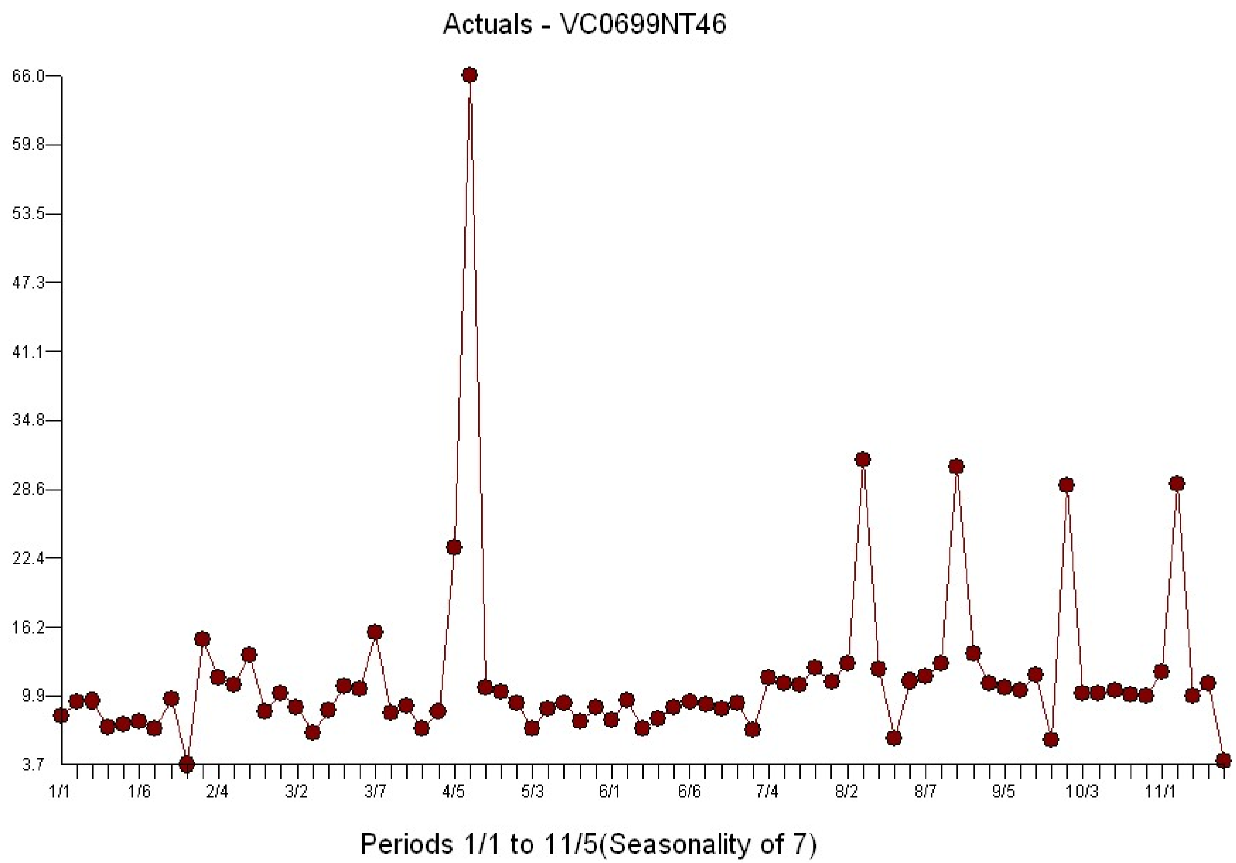
- When data needs to be cleansed this suggests that we have omitted an important variable in the modeling process. This omitted deterministic variable may be either known to us or unknown to us. Detecting this phenomenon often leads directly to "hypothesis generation" where data suggests theory, such as the need for an omitted event.

- Care must be taken not to falsely identify anomalies that are systematic such as a seasonal pulse variable.

What is unusual?

- We see a big outlier, but what about the pattern near the end?

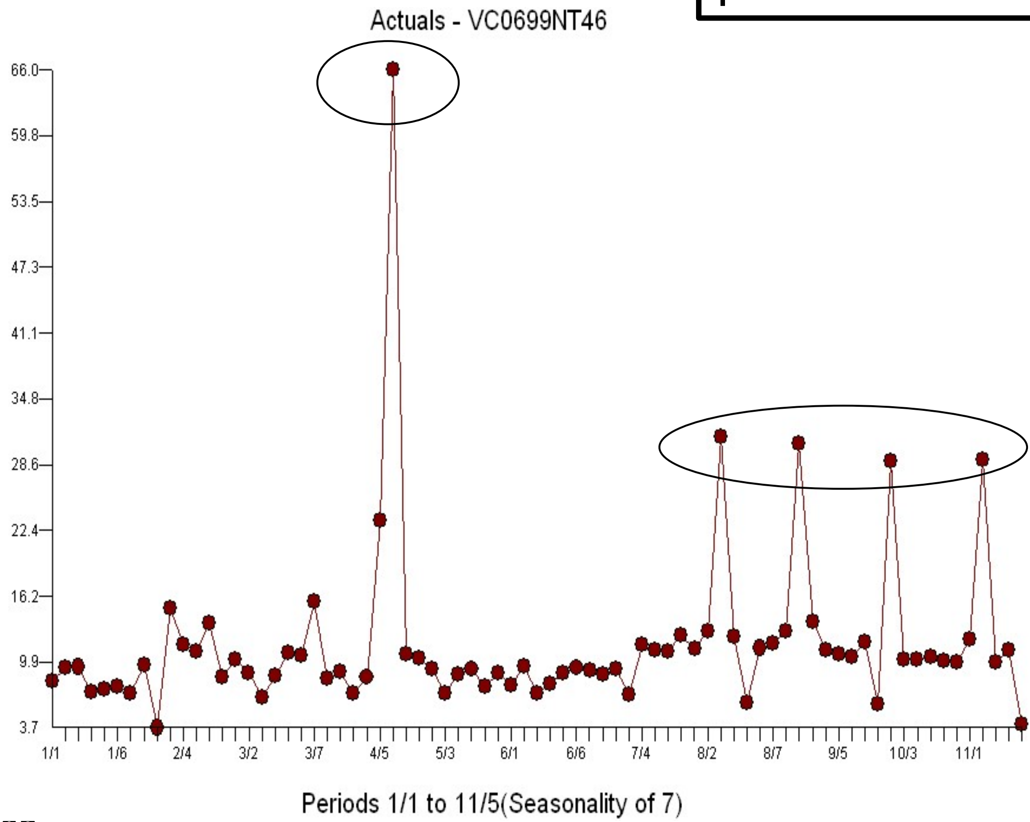
- Do we remove/fix those also? Do we adjust them to be an average of the previous data points?

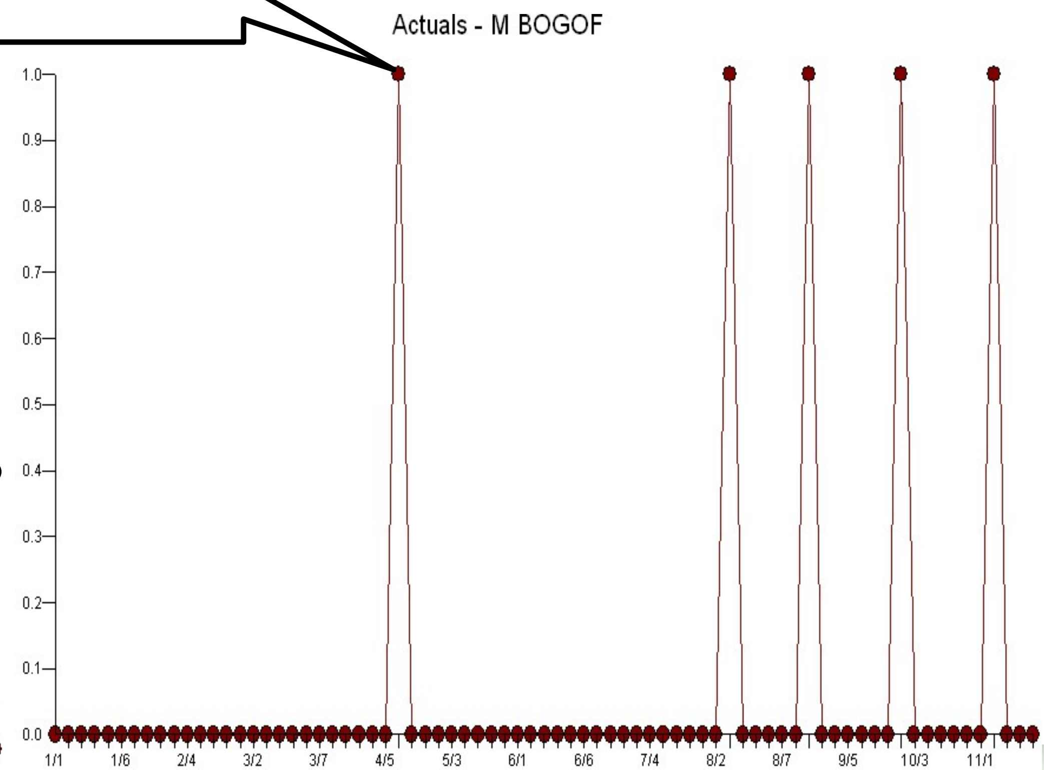


Was it a Causal Model Issue all along?

- **We realize that we shouldn't be data cleansing at all. We should be adding causal information to the process. The culprit was that there was a buy one get one free (BOGOF) promotion that caused the change in demand.**

A '1' where there is a promotion and a '0' where there is no promotion

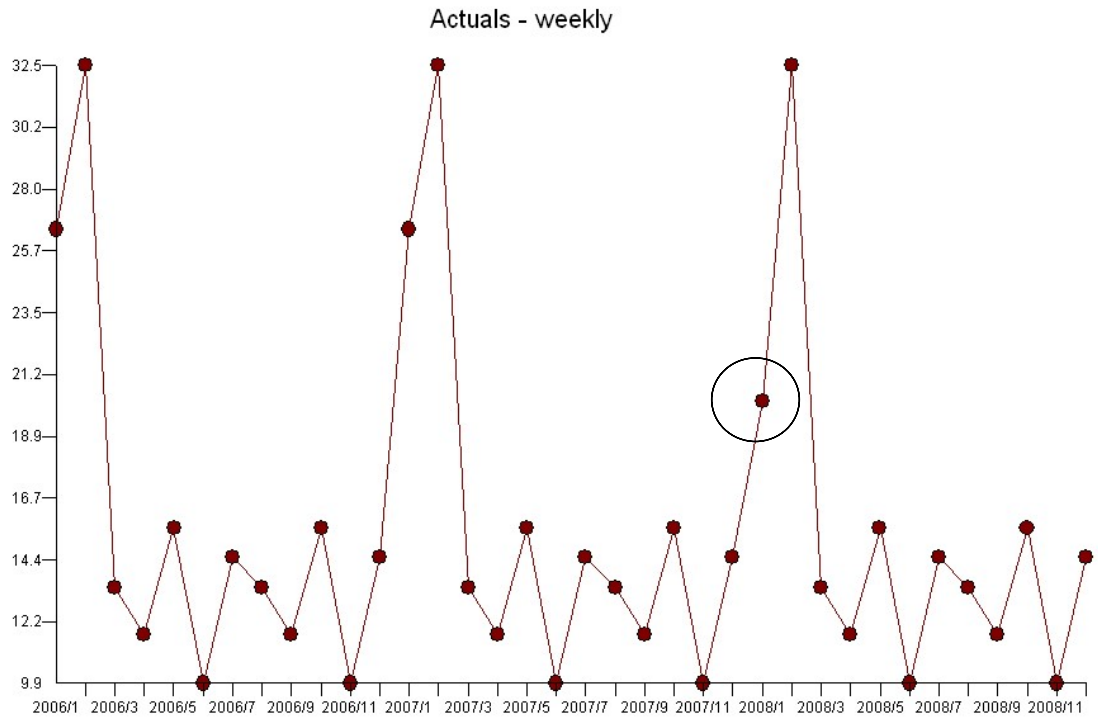




What is unusual?

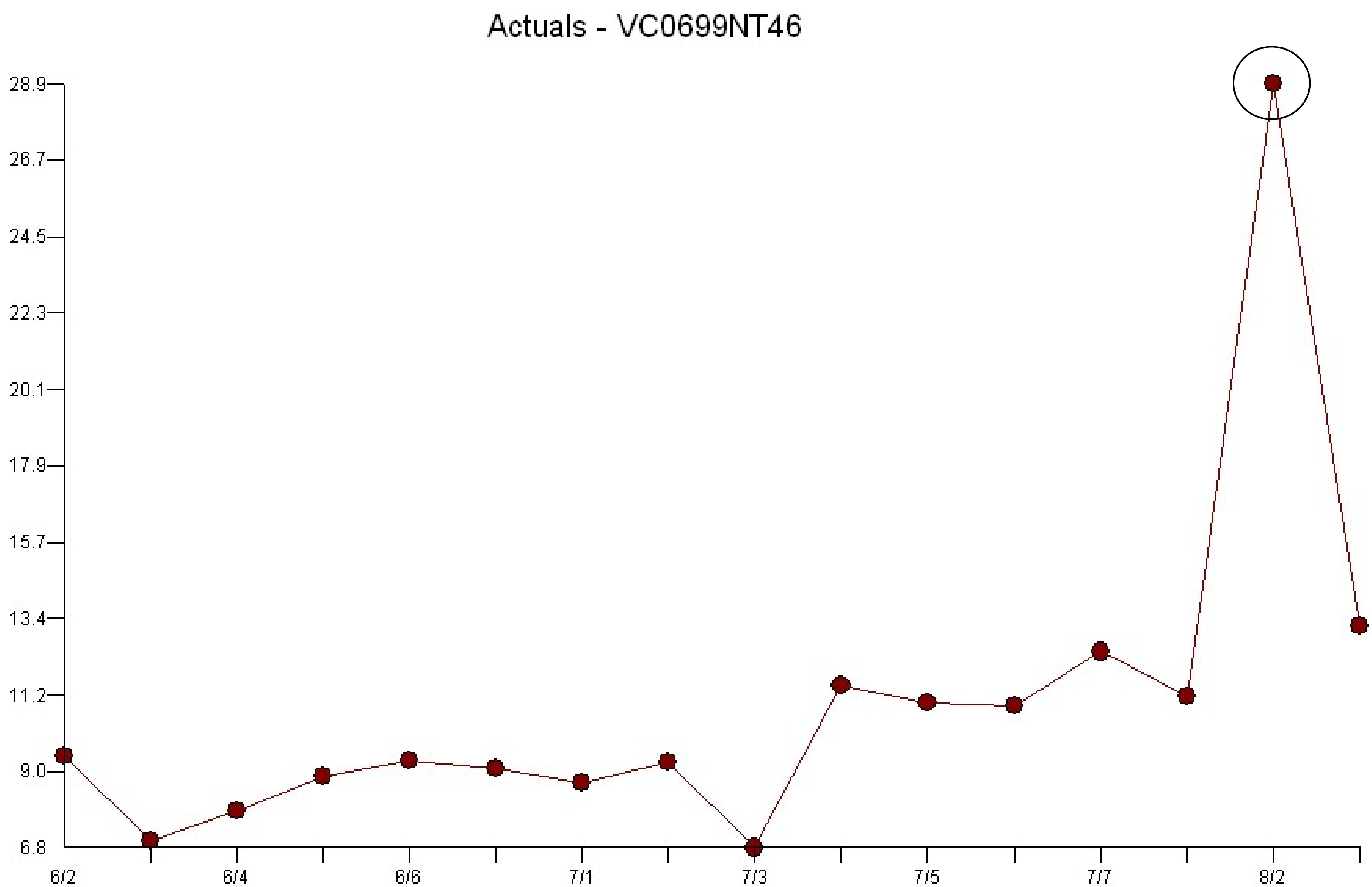
- **This is a example where the weekends have high sales. The last Saturday has a low value. Is this an "unusual value"? Yes, but how to identify and account for it. It is an <u>inlier</u> and the remedy is to "tweak" or adjust the observed value to ensure parameter optimization.**

- **If this value is not accounted for the model parameters and forecast will be affected**



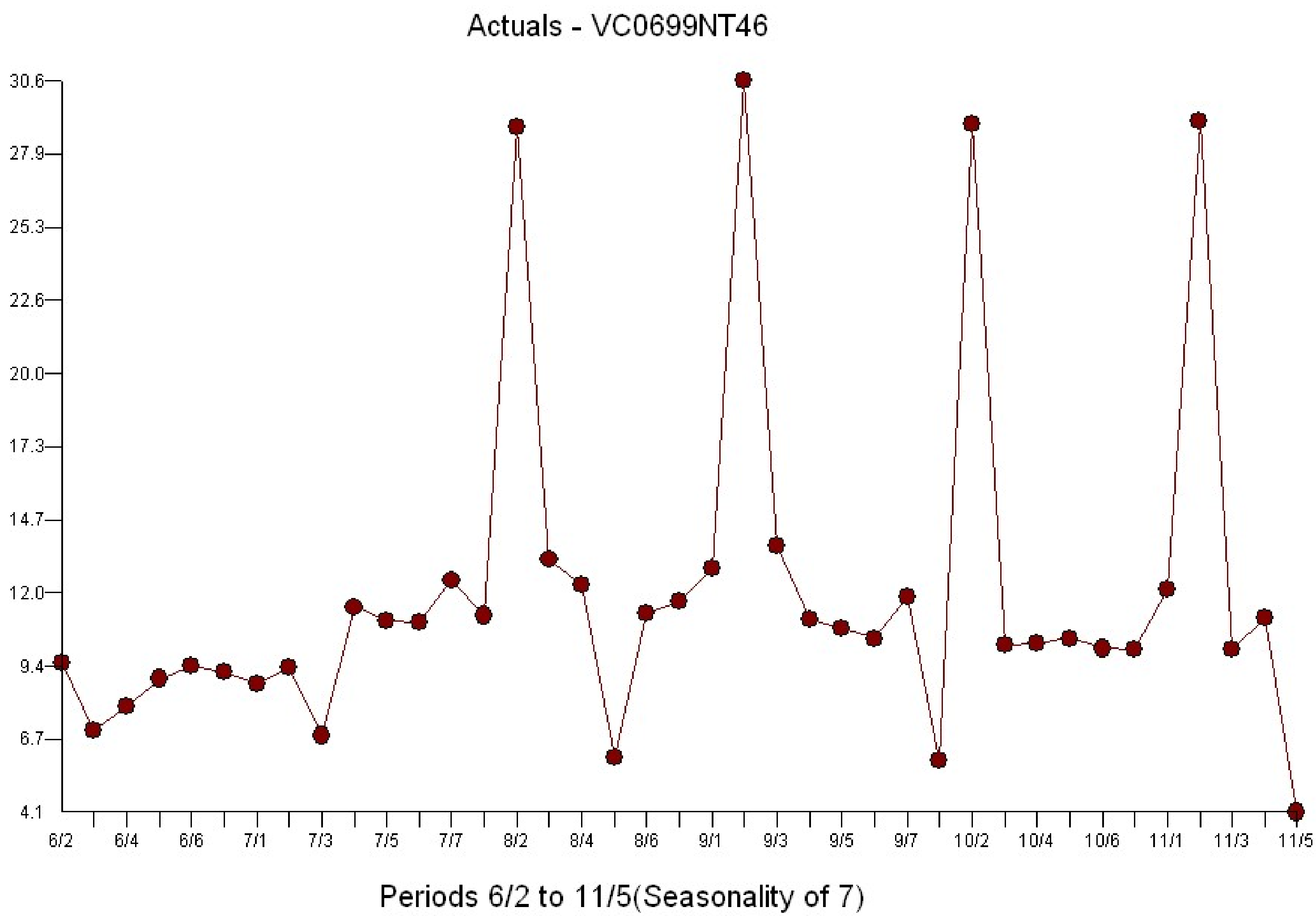
Here is an outlier, right?

- **This value is <u>not</u> an unusual data point**



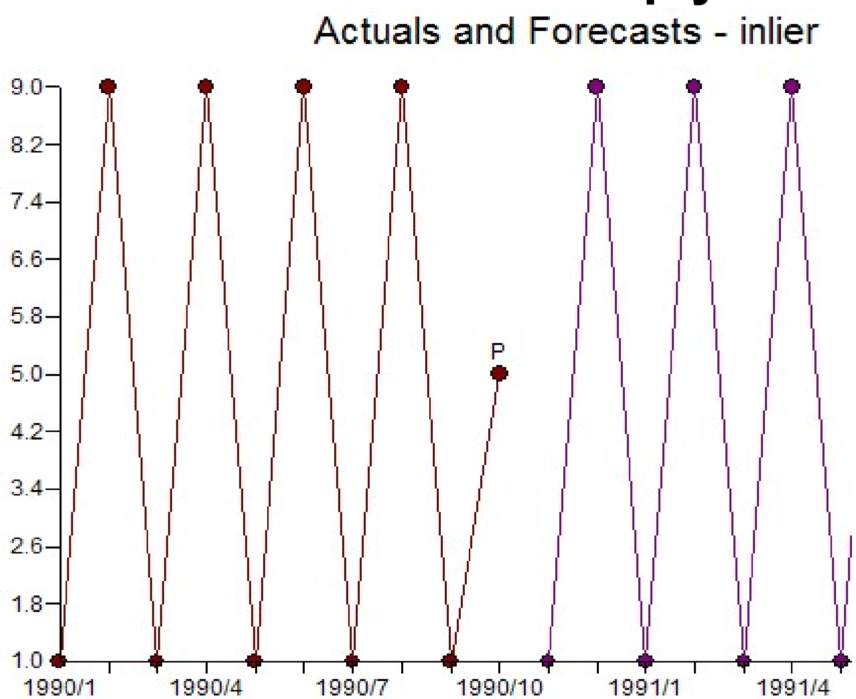
Seasonal Pulses

- **The outlier is really a series of outliers called a seasonal pulse**



Autobox and Inliers

- This is a dramatic example, but it illustrates the power of the methodology
- Can your software detect an outlier at the mean?
- Or Does it just use 2 sigma around the mean and hope for the best?
- In order to detect what is unusual, you need to detect what is usual
- This is why we create a model and not simply a force an existing model to data



Outlier Detection – What should you do about it?

- **User Provides knowledge(APRIORI) before the modelling process begins – If there is some domain knowledge that there was an event in the past then this information should be included in the model(ie Intervention modeling) as a possible input variable. In this case, an actual variable now has a coefficient and can be used to explain the impact(lift or decrease) which will yield a better model and forecast.**

- **Action - You don't want to believe a pulse and you should adjust the pulse to "where it should have been" thus providing a robust estimation of the model parameters.**

- **No Action - If you do not adjust for outliers then the coefficients in the model will be skewed creating a bad model and forecast.**

Early Warning System Reports Tells you the Probability of the last observation being "out of control" Statistically

- You can inform senior management which SKU's seem to be out of control based on the latest observation.
- Instead of using an arbitrary measure to detect unusual behavior (i.e. % change from last year or % difference using the last two periods), Autobox tells you "the probability of observing that last observation before it was observed" .
- Autobox will test and report on the probability that the last observation is unusual. It will write out a report for every series analyzed which can then be sorted to identify those series that look to be unusual.
- Here we run the series "inlier" and the report shows no warning in the "probability" field when the actual last value was 9.0. When we change that value to a 5.0 and rerun then AUTOBOX reacts and the small P-value reported showing us significance.

EARLYSIG - Notepad

File Edit Format View Help

ITEM	NOB	PROBABILITY	ACTUAL	EXPECTED
inlier			9.0000000000	
inlier	10	.0000	5.00000	9.0000000000

Autobox's Pulse/Level/Seasonal Pulse Trend/Variance/Parameter Early Warning Reports

- **Autobox reports all outliers across all time periods so you can easily identify out of control behavior from a macro level suggesting a widespread event (known or possibly unknown) for research or just understanding.**
- **Just import the report into into Excel, sum the columns and transpose to identify time periods with multiple pulses in the same time period. 2 of the 3 SKUs show period 30, 41, and 52 with an intervention. This might spark some discussion as to why this is occurring. It may be random or part of a systematic event. If so, then a causal variable could be introduced into Autobox to "model" its effect and plan for the impact in the future.**

SERIES	#	NOB	1	2	3	4
a	4	54				
b	2	54				
c	4	54				
			0	0	0	0
time period		count				
30		2				
41		2				
52		2				
23		1				
26		1				
28		1				
31		1				
1		0				
2		0				

Autobox's Forecast Reconciliation

- Top level and SKU level forecasts are reconciled in two ways:
  - "Top-down" reconciliation
    - Create Forecast for the Top level
    - Force the bottom level to match the top level using an allocation of the forecast period by period
  - "Bottom-Up" with no reconciliation
    - Create Forecast for the Bottom level
    - Aggregate the Bottom level to be the Top level forecast

Using Causal Variables

Two Types of Users
Rear View Mirror vs. Rear and Front Windshield

- Use the History of the data only

- Use the History of the data AND causal variables (i.e. holidays, price, marketing promotions, advertising) and the future values of these variables.

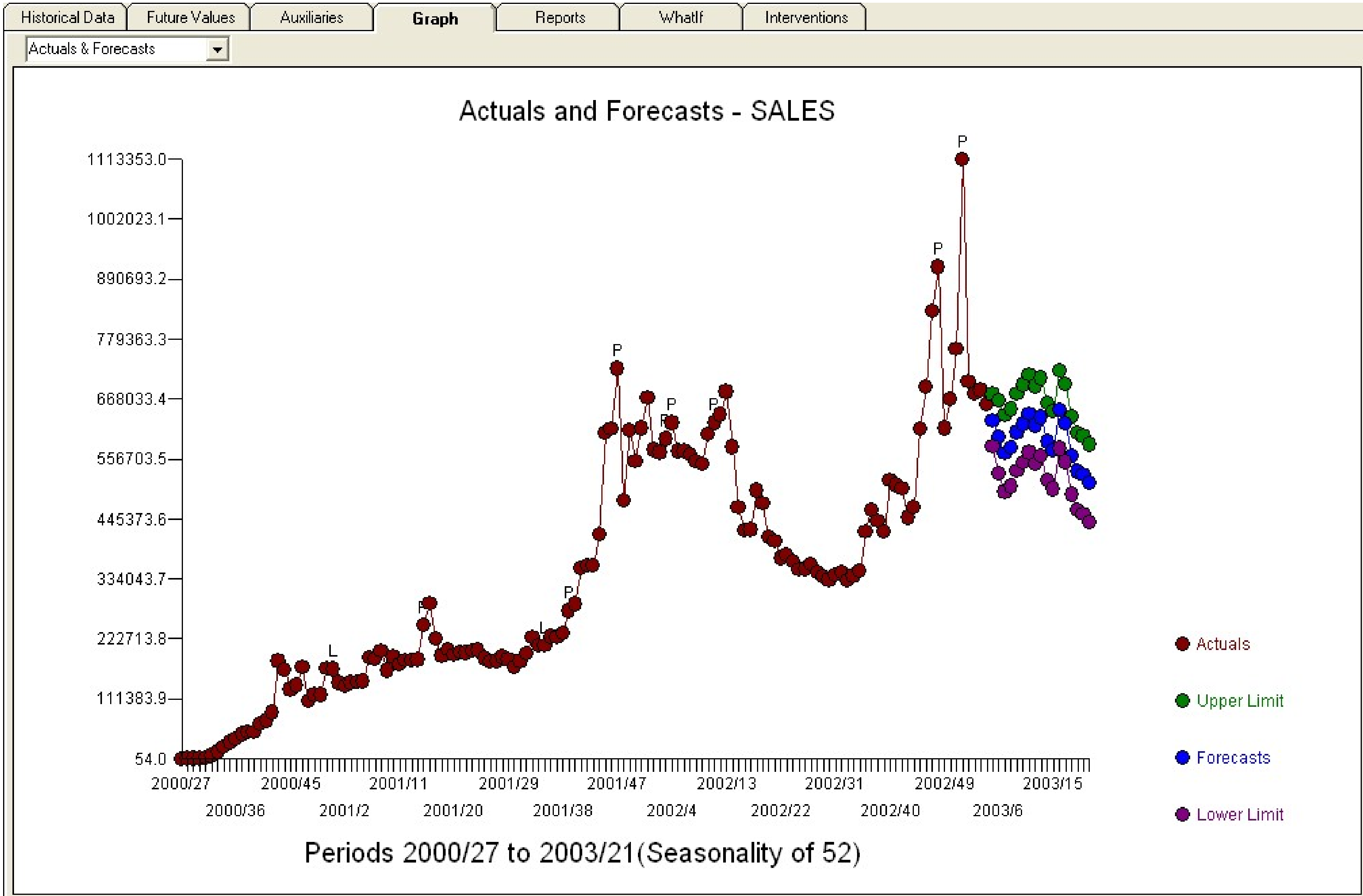
+

AUTOMATIC FORECASTING SYSTEMS

Case Study – What-if Analysis

- Client wanted a national model using the ability to incorporate causal variables and create scenarios using different levels of causal variables using weekly data. Here are the causals:
    - Average unit Price
    - Total number of stores
    - Marketing Index
    - Holiday variables
    - TV GRPs

Case Study – What-if Analysis
Baseline Forecast



Case Study – What-if Analysis
Baseline Future Values of Causals

Historical Data | Future Values | Auxiliaries | Graph | Reports | **WhatIf** | Interventions

WhatIf Instructions:
Expand 'WhatIf'
Select WhatIf Spreadsheet
Make Change(s)
Press Enter after each change
Select Process\RunWhatIf
Review Forecasts and Graphs
There is a limit of 20 Scenarios

- Base Case
  - **Spreadsheet**
  - Graph
- What If
  - Spreadsheet

BY/BP	ORIGINAL FCSTS	ORIGINAL FVs	ORIGINAL FVs	ORIGINAL FVs	ORIGINAL FVs	ORIGINAL FVs
	SALES	**AUP**	**QM**	**TD**	**TPR**	**TV**
2003/5	628043.5144928	2.8400000	6.0000000	290.0000000	12.0000000	11.0000000
2003/6	597231.7794854	2.8400000	6.0000000	290.0000000	12.0000000	9.0000000
2003/7	566508.0505367	2.8400000	6.0000000	290.0000000	12.0000000	7.0000000
2003/8	577341.4330286	2.8400000	6.0000000	290.0000000	12.0000000	13.0000000
2003/9	606537.2666946	2.8600000	11.0000000	288.0000000	15.0000000	18.0000000
2003/10	621441.2477218	2.8600000	11.0000000	288.0000000	15.0000000	21.0000000
2003/11	640911.2200548	2.8600000	11.0000000	288.0000000	15.0000000	17.0000000
2003/12	619179.2825224	2.8600000	11.0000000	288.0000000	15.0000000	21.0000000
2003/13	634167.3511686	2.8600000	11.0000000	288.0000000	15.0000000	24.0000000
2003/14	588622.8739270	2.9300000	4.0000000	285.0000000	10.0000000	19.0000000
2003/15	572643.5683388	2.9300000	4.0000000	285.0000000	10.0000000	22.0000000
2003/16	648279.8666278	2.9300000	4.0000000	285.0000000	10.0000000	25.0000000
2003/17	623012.8538965	2.9300000	4.0000000	285.0000000	10.0000000	20.0000000
2003/18	562561.9268201	2.9400000	4.0000000	283.0000000	4.0000000	16.0000000
2003/19	533357.5281203	2.9400000	4.0000000	283.0000000	4.0000000	13.0000000
2003/20	526991.3015895	2.9400000	4.0000000	283.0000000	4.0000000	10.0000000
2003/21	511611.8728510	2.9400000	4.0000000	283.0000000	4.0000000	8.0000000
SUM	10058442.9378767					

Case Study – What-if Analysis
Scenario #1 Adjust Price and TV Spots Up

Historical Data | Future Values | Auxiliaries | Graph | Reports | **WhatIf** | Interventions

WhatIf Instructions:
Expand 'WhatIf'
Select WhatIf Spreadsheet
Make Change(s)
Press Enter after each change
Select Process\RunWhatIf
Review Forecasts and Graphs
There is a limit of 20 Scenarios

BY/BP	AUP	QM	TD	TPR	TV
2003/5	2.8400000	6.0000000	290.0000000	12.0000000	11.0000000
2003/6	2.9000000	6.0000000	290.0000000	12.0000000	13.0000000
2003/7	2.8400000	6.0000000	290.0000000	12.0000000	12.0000000
2003/8	2.8400000	6.0000000	290.0000000	12.0000000	13.0000000
2003/9	2.8600000	11.0000000	288.0000000	15.0000000	18.0000000
2003/10	2.8600000	11.0000000	288.0000000	15.0000000	21.0000000
2003/11	2.8600000	11.0000000	288.0000000	15.0000000	17.0000000
2003/12	2.8600000	11.0000000	288.0000000	15.0000000	21.0000000
2003/13	2.8600000	11.0000000	288.0000000	15.0000000	24.0000000
2003/14	2.9300000	4.0000000	285.0000000	10.0000000	19.0000000
2003/15	2.9300000	4.0000000	285.0000000	10.0000000	22.0000000
2003/16	2.9300000	4.0000000	285.0000000	10.0000000	25.0000000
2003/17	2.9300000	4.0000000	285.0000000	10.0000000	20.0000000
2003/18	2.9400000	4.0000000	283.0000000	4.0000000	16.0000000
2003/19	2.9400000	4.0000000	283.0000000	4.0000000	13.0000000
2003/20	2.9400000	4.0000000	283.0000000	4.0000000	10.0000000
2003/21	2.9400000	4.0000000	283.0000000	4.0000000	8.0000000

Base Case
Spreadsheet
Graph
What If
Spreadsheet

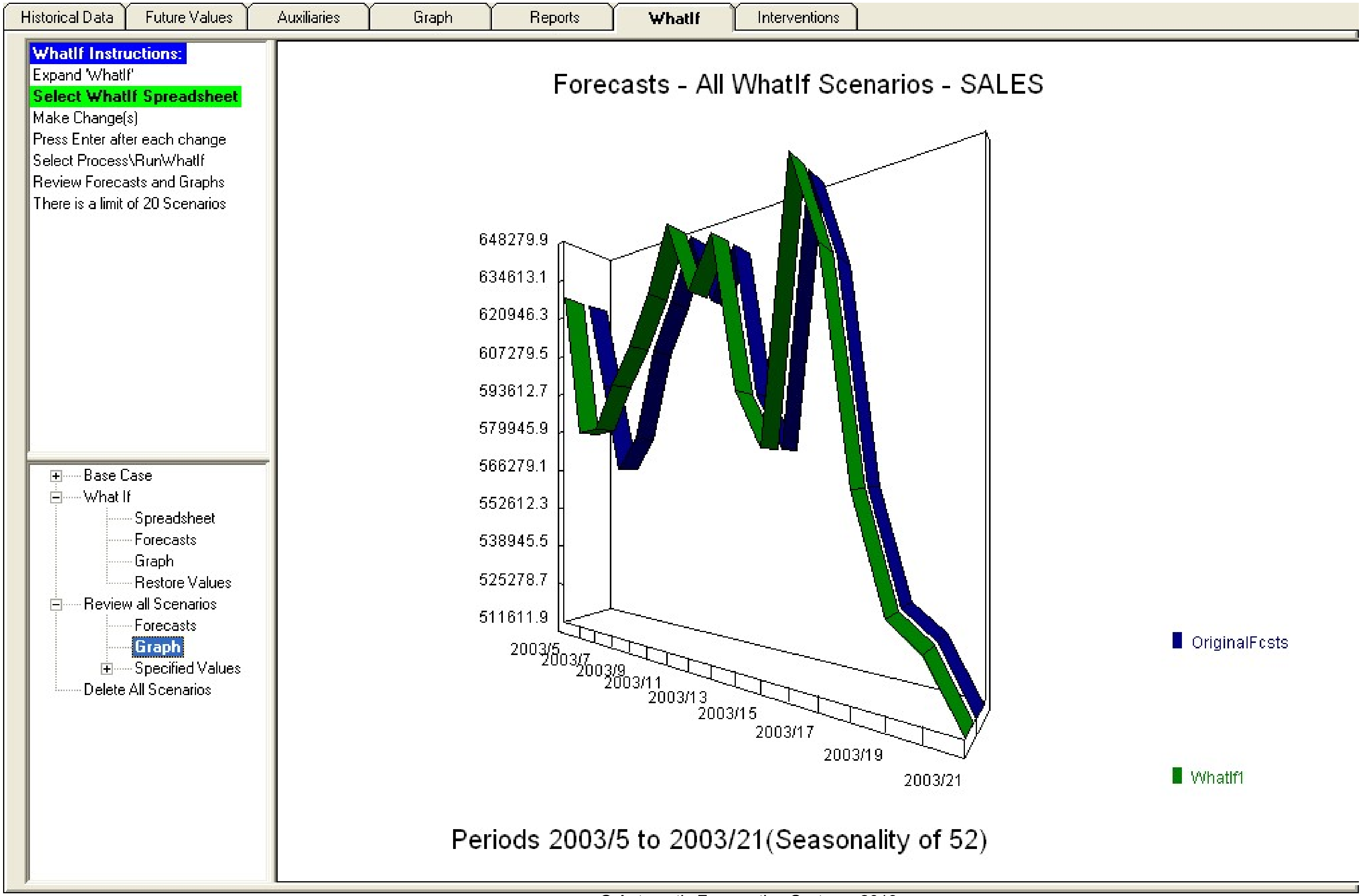
Autobox WhatIf Progress

Elapsed Time: 00:00:02

EXECUTION COMPLETED

OK

Case Study – What-if Analysis
Graph of Baseline and Scenario #1



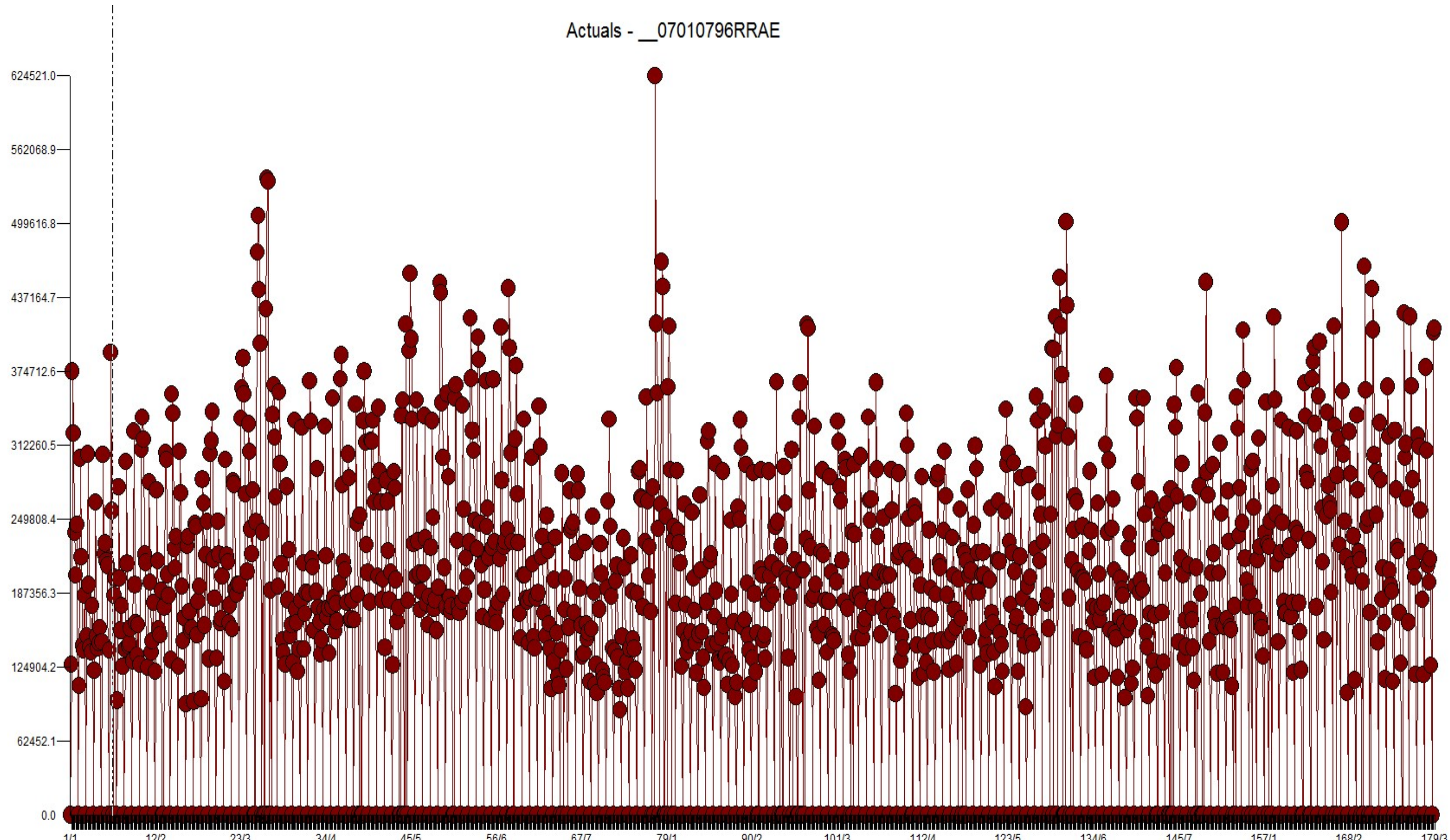
Three Examples

Financial Forecasting Example
How is your Finance Team doing this now?

What's the probability of making the month end targeted number given the most recent daily observation?

- The 2008 financial crises caught a few companies unable to quickly identify when month end numbers were not going to be met.
- Simplistic approaches use a ratio estimate (ie 5 days into the month 30/5 so multiply current month total by 6 to get month end estimate) are simplistic and incorrect. Promotions and day of the week effects are not considered using ratio estimates and need to be modeled at a DAILY level as part of a comprehensive model and forecast which can then be used to determine probabilities of making the month end number.
- Autobox reports out a variety of Probabilities which the target can be evaluated against. A summary report can then be used to identify which SKU's are likely NOT to make the month end number.

Graph of 3 ½ years of daily data – Clear as mud?

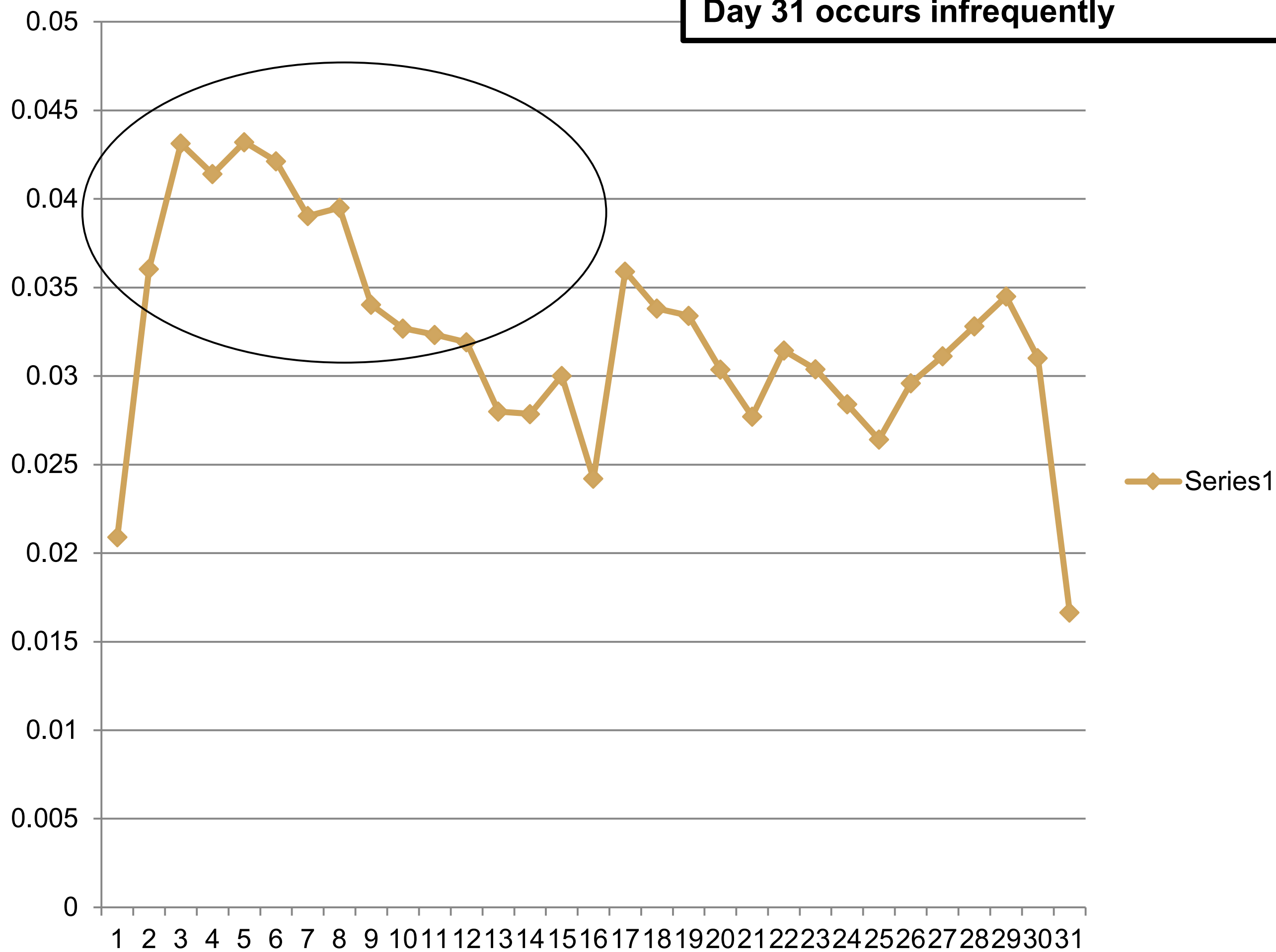


Daily Demand

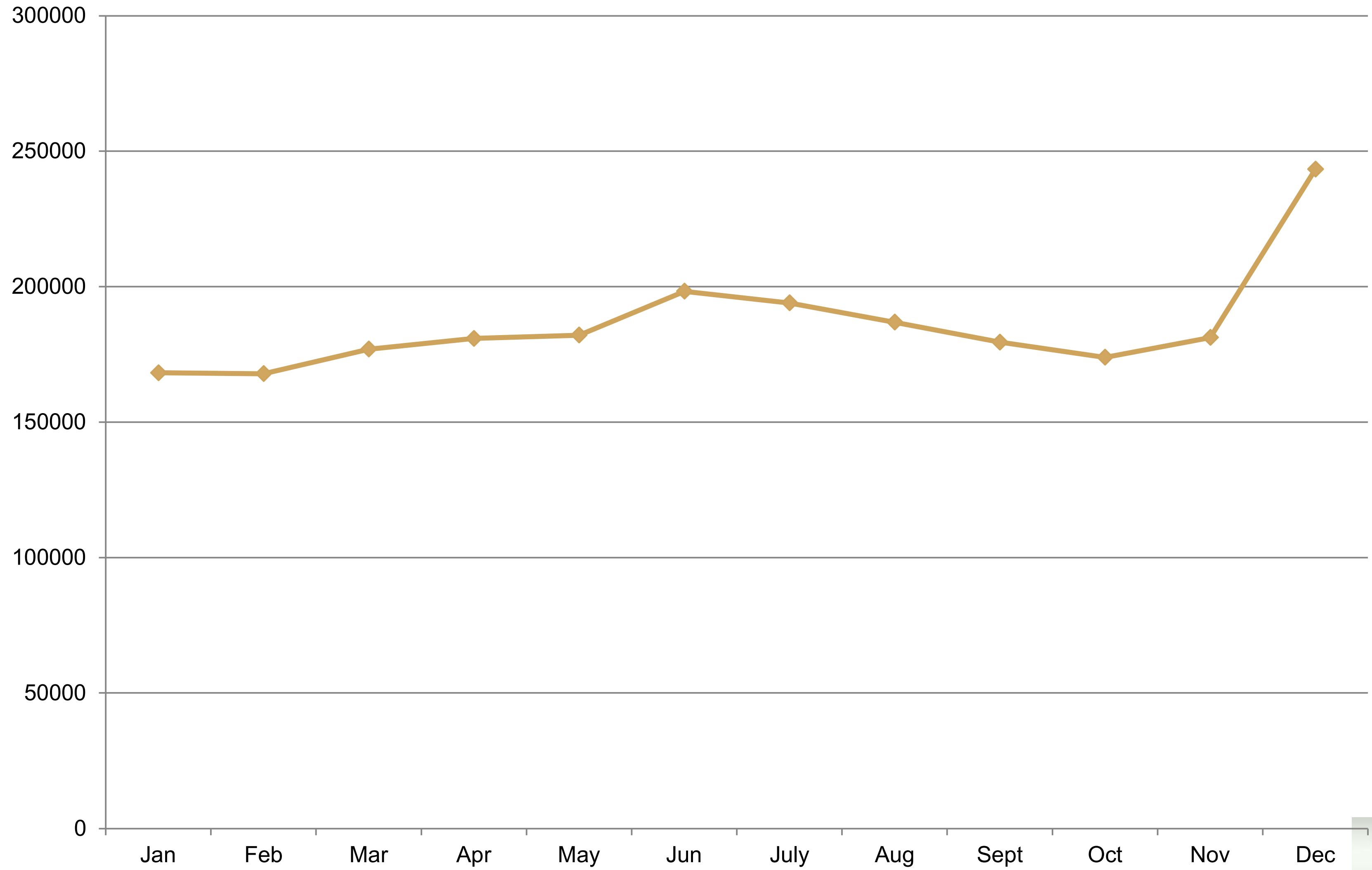
- Data begins on a Sunday, 7/1/2007
- Sundays are always 0
- There are many impacts on the data:
  - Trends
  - Seasonality
    - Monthly or Weekly patterns
  - Level
    - Big increases and drops, but not necessarily a trend
  - Autoregressive behavior
  - Day of the week
  - Fixed Day of the month
  - Seasonal Pulses - Changes in Day of the week
  - Interventions
  - Holidays plus before and after

Distribution of 3 ½ years of daily demand by day of month

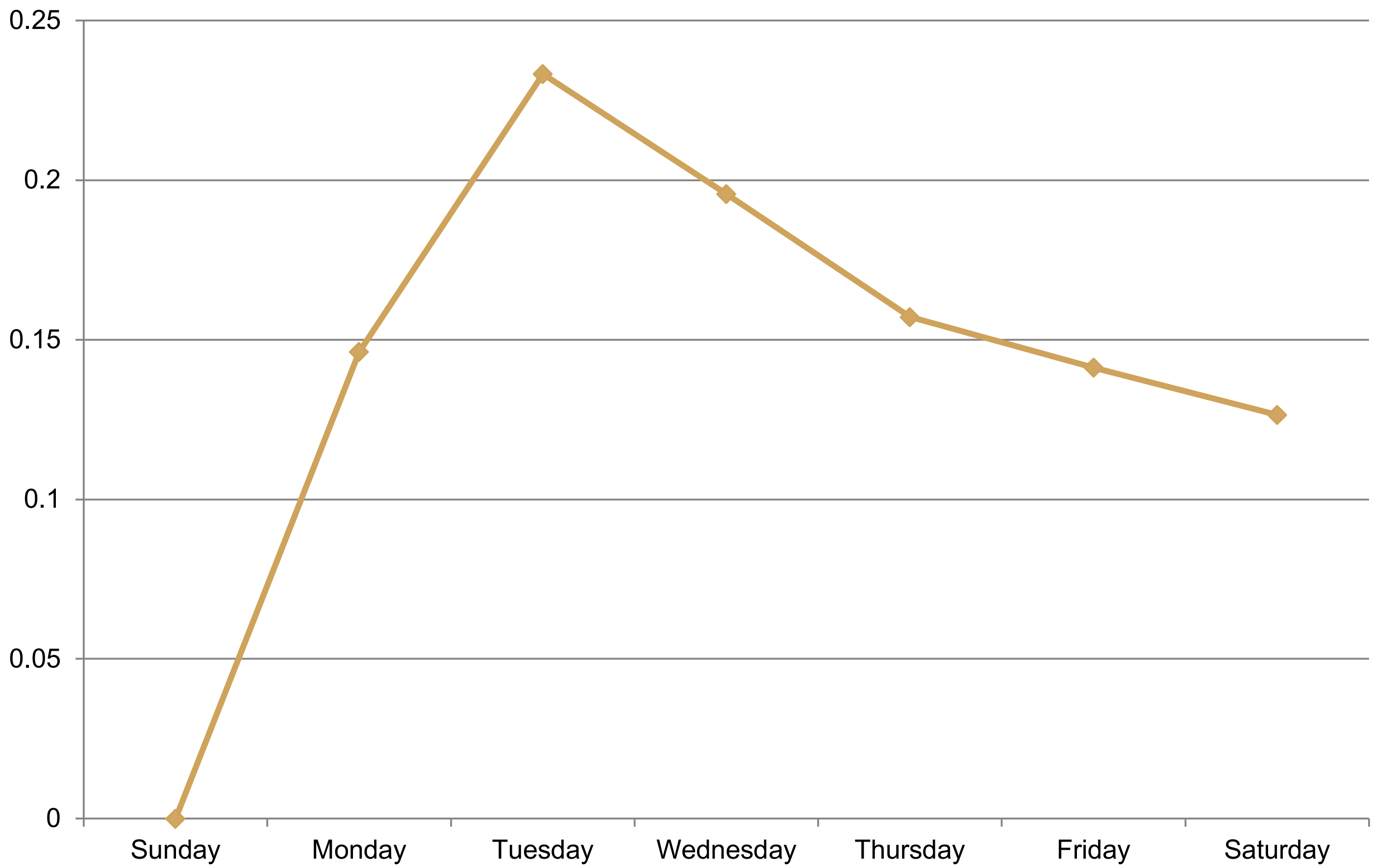
Volume skewed towards the beginning of the month
Day 1 is impacted by New Year's and Worker's Day
Day 31 occurs infrequently



Distribution of daily demand across 3 ½ years by month



Distribution of daily demand across 3 ½ years by day of week



Variables in the model (partial list)

```
Estimation/Diagnostic Checking for Variable Y    __07010796RRAE
                                            X1   G_WOMEN
                                            X2   G_HERITAGE
                                            X3   G_RECONCILE
                                            X4   M_XMAS
                                            X5   M_NEWYEARS
                                            X6   M_EASTER
                                            X7   G_FREEDOM
                                            X8   G_WORKERS
                                            X9   G_YOUTH
                                            X10  MONTH_EFF10
                                            X11  MONTH_EFF12
                                            X12  MONTH_EFF01
                                            X13  MONTH_EFF02
                                            X14  FIXED_EFF_N10107
                                            X15  FIXED_EFF_N10307
                                            X16  FIXED_EFF_N10407
                                            X17  FIXED_EFF_N10507
                                            X18  FIXED_EFF_N10607
             :  VERY SPECIAL DAY VARIABLE   X19  FIXED_DAY02
             :  VERY SPECIAL DAY VARIABLE   X20  FIXED_DAY03
             :  VERY SPECIAL DAY VARIABLE   X21  FIXED_DAY04
             :  VERY SPECIAL DAY VARIABLE   X22  FIXED_DAY05
             :  VERY SPECIAL DAY VARIABLE   X23  FIXED_DAY06
             :  VERY SPECIAL DAY VARIABLE   X24  FIXED_DAY07
             :  VERY SPECIAL DAY VARIABLE   X25  FIXED_DAY08
             :  VERY SPECIAL DAY VARIABLE   X26  FIXED_DAY09
             :  NEWLY IDENTIFIED VARIABLE   X27  I~S00814 09/21/09    SEASP
             :  NEWLY IDENTIFIED VARIABLE   X28  I~P00170 12/17/07    PULSE
             :  NEWLY IDENTIFIED VARIABLE   X29  I~P01038 05/03/10    PULSE
```

How complicated is this to do well?

#	MODEL COMPONENT	LAG (BOP)	COEFF	STANDARD ERROR	P VALUE	T VALUE
1	CONSTANT		.148E+06	.357E+04	.0000	41.36
	INPUT SERIES X1 G_WOMEN					
2	Omega (input) -Factor # 1	0	-.233E+06	.214E+05	.0000	-10.90
	INPUT SERIES X2 G_HERITAGE					
3	Omega (input) -Factor # 2	0	-.187E+06	.178E+05	.0000	-10.53
	INPUT SERIES X3 G_RECONCILE					
4	Omega (input) -Factor # 3	-1	.895E+05	.211E+05	.0000	4.24
5		0	.279E+06	.256E+05	[illegible]	[illegible]
6		1	-.189E+06	.358E+05	[illegible]	[illegible]
	INPUT SERIES X4 M_XMAS					
7	Omega (input) -Factor # 4	-4	.162E+06	.257E+05	[illegible]	6.32
8		-3	-.146E+06	[illegible]	.0000	-6.93
9		-2	-.162E+06	.236E+05	.0000	-6.31
10		-1	[illegible]	.211E+05	.0000	-6.29
11		0	.243E+06	.211E+05	.0000	11.53
12		1	.215E+06	.211E+05	.0000	10.19
	INPUT SERIES X5 M_NEWYEARS					
13	Omega (input) -Factor # 5	-4	.295E+06	.257E+05	.0000	11.50
14		-3	-.159E+06	.256E+05	.0000	-6.22
15		-2	-.476E+05	.211E+05	.0241	-2.26
16		0	.206E+06	.208E+05	.0000	9.92

Impacts from 4 days in advance of the holiday, on the holiday and the day after the holiday

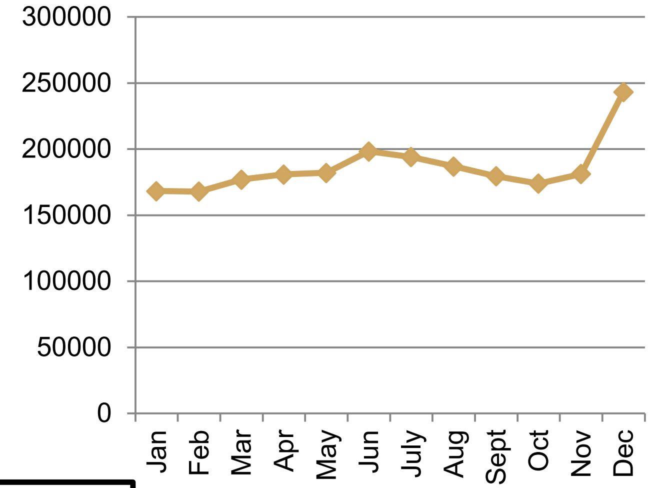
How complicated is this to do well?

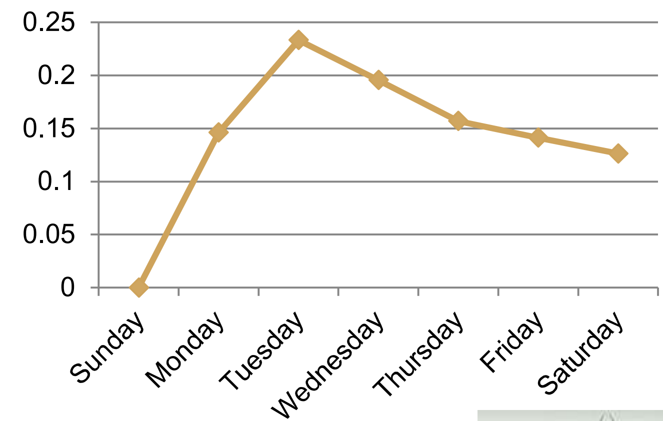
```
INPUT SERIES X6  M_EASTER

 17Omega (input) -Factor #  6   -3  -.800E+05   .207E+05   .0001    -3.87
 18                             -2   .201E+06   .207E+05   .0000     9.70
 19                             -1  -.727E+05   .206E+05   .0004    -3.52
 20                              1   .210E+06   .206E+05   .0000    10.16

INPUT SERIES X7  G_FREEDOM

 21Omega (input) -Factor #  7    0  -.768E+05   .251E+05   .0023    -3.06
 22                              1  -.777E+05   .251E+05   .0020    -3.09

INPUT SERIES X8  G_WORKERS

 23Omega (input) -Factor #  8   -2   .769E+05   .205E+05   .0002     3.75
 24                              0   .174E+06   .206E+05   .0000     8.45

INPUT SERIES X9  G_YOUTH

 25Omega (input) -Factor #  9    0  -.238E+06   .205E+05   .0000   -11.63
 26                              1  -.657E+05   .205E+05   .0014    -3.20
 27                              2  -.757E+05   .205E+05   .0002    -3.69
```

The model matches the data - December is High, January, February and October Lower

```
INPUT SERIES X 10 MONTH_EFF10

 28Omega (input) -Factor # 10     0  -.121E+05    .350E+04    .0006     -3.44

INPUT SERIES X 11 MONTH_EFF12

 29Omega (input) -Factor # 11     0   .240E+05    .524E+04    .0000      4.58

INPUT SERIES X 12 MONTH_EFF01

 30Omega (input) -Factor # 12     0  -.128E+05    .404E+04    .0015     -3.18

INPUT SERIES X 13 MONTH_EFF02

 31Omega (input) -Factor # 13     0  -.205E+05    .416E+04    .0000     -4.93

INPUT SERIES X 14 FIXED_EFF_N10107

 32Omega (input) -Factor # 14     0  -.170E+06    .360E+04    .0000    -47.28

INPUT SERIES X 15 FIXED_EFF_N10307

 33Omega (input) -Factor # 15     0   .135E+06    .359E+04    .0000     37.51

INPUT SERIES X 16 FIXED_EFF_N10407

 34Omega (input) -Factor # 16     0   .836E+05    .363E+04    .0000     23.05

INPUT SERIES X 17 FIXED_EFF_N10507

 35Omega (input) -Factor # 17     0   .339E+05    .365E+04    .0000      9.30

INPUT SERIES X 18 FIXED_EFF_N10607

 36Omega (input) -Factor # 18     0   .190E+05    .363E+04    .0000      5.25
```

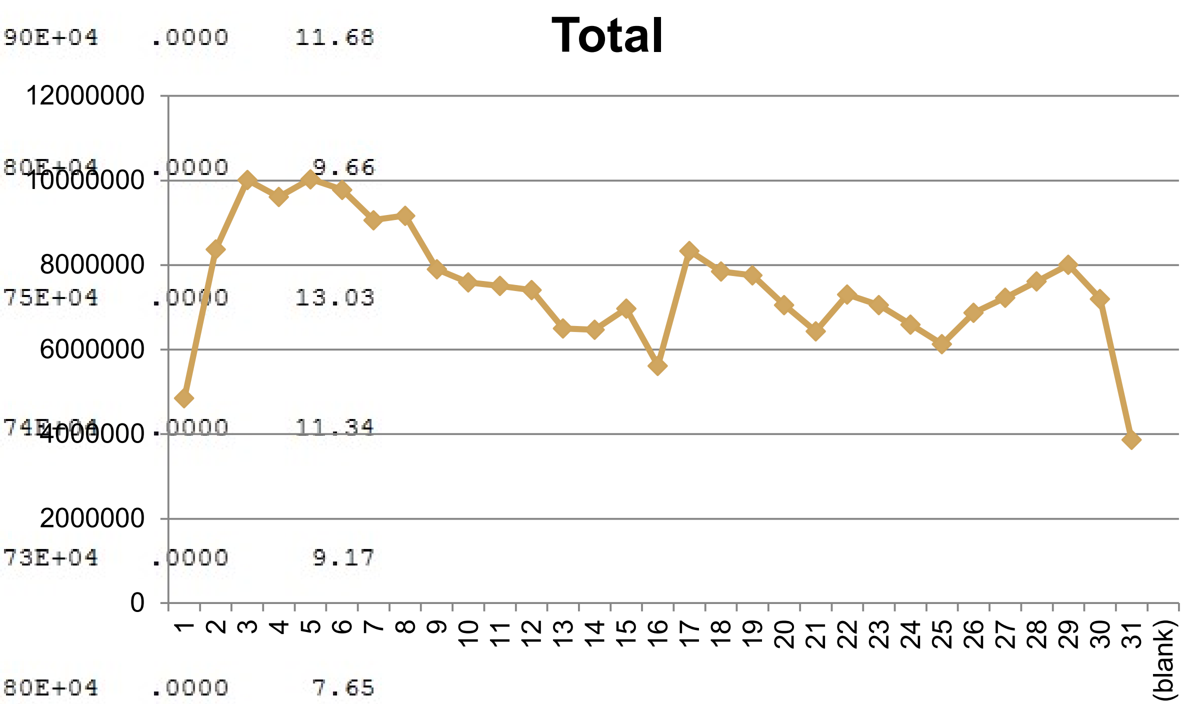
Remember Sunday is the first day of the series





Day 2 through 9 are higher than other days

```
INPUT SERIES X 19 FIXED_DAY02
 37Omega (input) -Factor # 19    0    .485E+05    .589E+04    .0000     8.22
INPUT SERIES X 20 FIXED_DAY03
 38Omega (input) -Factor # 20    0    .689E+05    .590E+04    .0000    11.68
INPUT SERIES X 21 FIXED_DAY04
 39Omega (input) -Factor # 21    0    .560E+05    .580E+04    .0000     9.66
INPUT SERIES X 22 FIXED_DAY05
 40Omega (input) -Factor # 22    0    .749E+05    .575E+04    .0000    13.03
INPUT SERIES X 23 FIXED_DAY06
 41Omega (input) -Factor # 23    0    .651E+05    .574E+04    .0000    11.34
INPUT SERIES X 24 FIXED_DAY07
 42Omega (input) -Factor # 24    0    .525E+05    .573E+04    .0000     9.17
INPUT SERIES X 25 FIXED_DAY08
 43Omega (input) -Factor # 25    0    .443E+05    .580E+04    .0000     7.65
INPUT SERIES X 26 FIXED_DAY09
 44Omega (input) -Factor # 26    0    .362E+05    .597E+04    .0000     6.05
```



How complicated is this to do well?

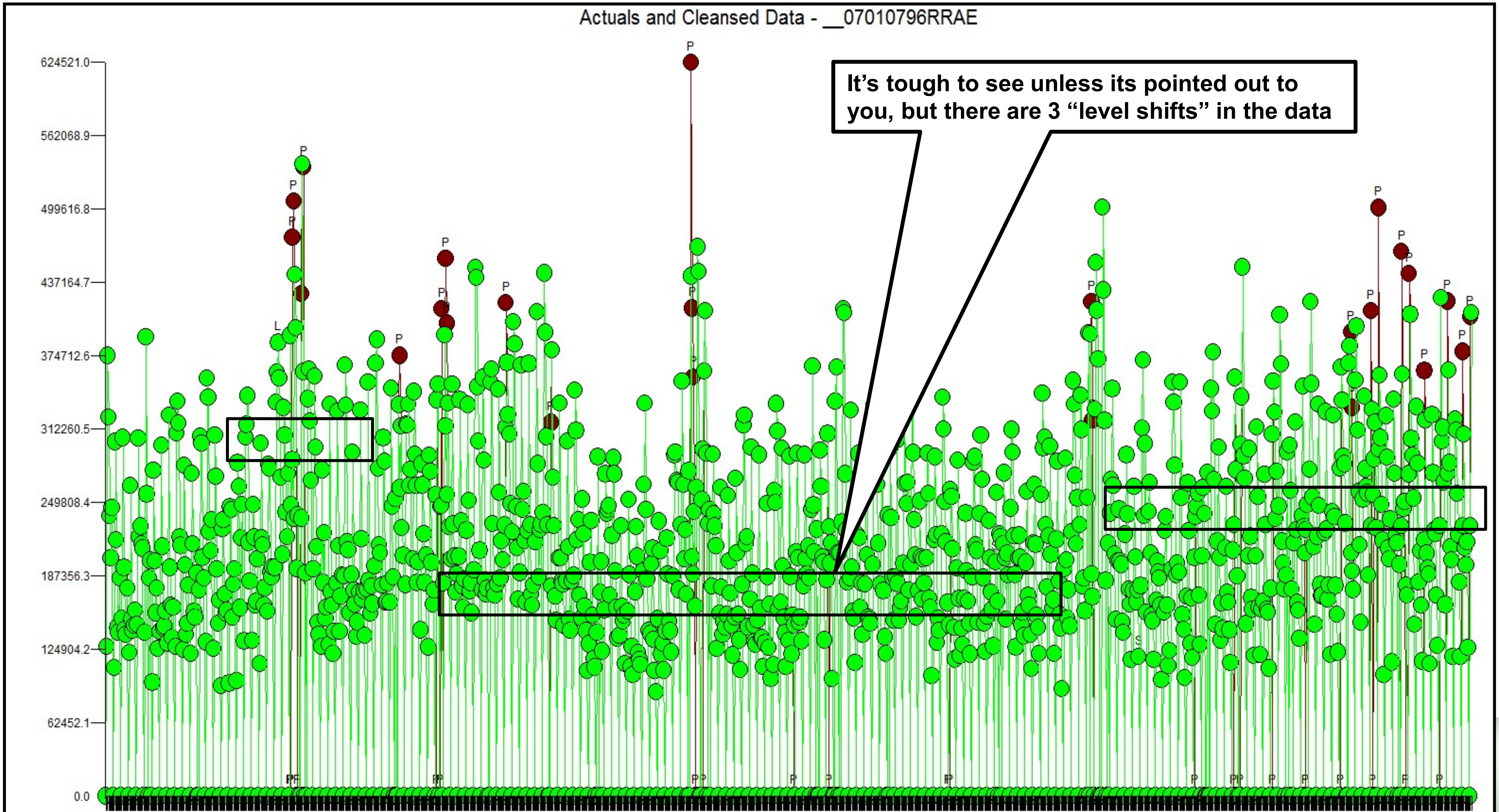
Monday was not identified as a day of the week variable, but half way through it was found to have become different than the average

Multiple outliers that need to be cleansed in order to measure the true patterns

The “average” volume had temporary changes 3 times over the 3 ½ years

```
INPUT SERIES X 27 I~S00814 09/21/09    SEASP

 45Omega (input) -Factor # 27    0   .574E+05   .576E+04   [illegible]

INPUT SERIES X 28 I~P00170 12/17/07    PULSE

 46Omega (input) -Factor # 28    0  -.392E+06   .502E+0[illegible]   [illegible]   -7.81

INPUT SERIES X 29 I~P01038 05/03/10    PULSE

 47Omega (input) -Factor # 29    0  -.299E+06   .362E+05   [illegible]

INPUT SERIES X 30 I~L00998 03/24/10    LEVEL

 48Omega (input) -Factor # 30    0   .270E+05   .307E+04   [illegible]    8.80

INPUT SERIES X 31 I~L00417 08/20/08    LEVEL

 49Omega (input) -Factor # 31    0  -.328E+05   .277E+04   .0000  -11.83

INPUT SERIES X 32 I~L00159 12/06/07    LEVEL

 50Omega (input) -Factor # 32    0   .307E+05   .380E+04   .0000    8.06

INPUT SERIES X 33 I~P01067 06/01/10    PULSE

 51Omega (input) -Factor # 33    0  -.307E+06   .355E+05   .0000   -8.65
```

Actual(Red) and Cleansed(Green) History – Clear now!

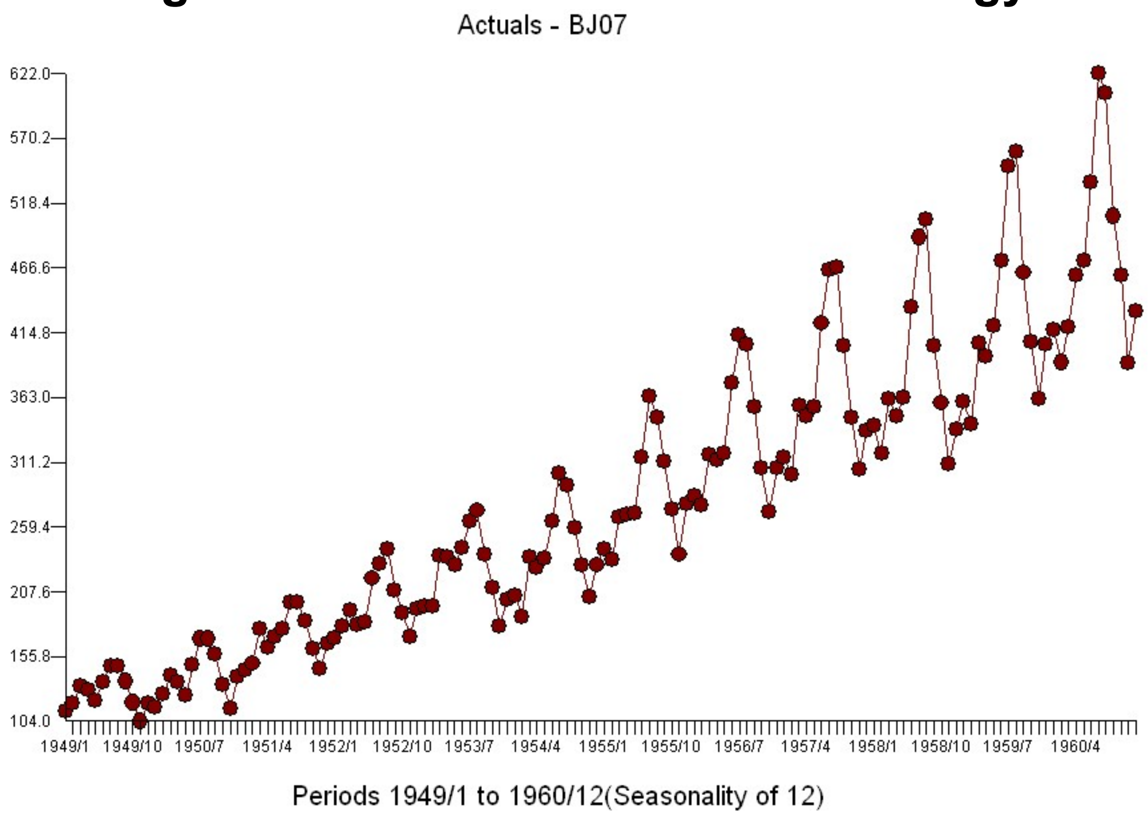


The “Airline Series”

- One of the most studied time series is the International Airline Passenger’s series(in thousands) for monthly data from 1949 through 1960.

- Box and Jenkins didn’t have the ability to detect outliers and used a log transformation to adjust the data as it seemingly had non-constant variance.

- The forecast was too high and the Box-Jenkins methodology was seen as too complicated.

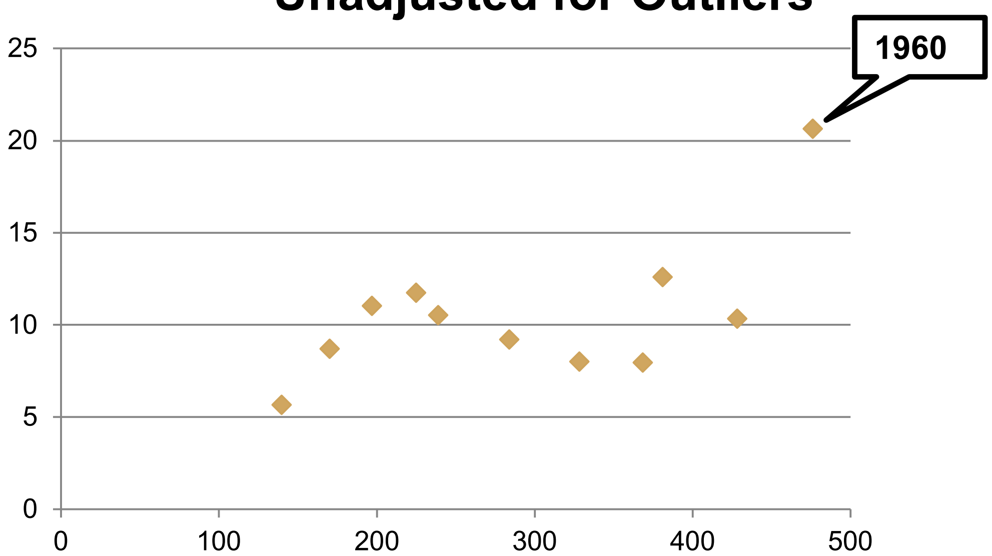


The "Airline Series"

- The 144 monthly observations were broken into 12 buckets (years) and they calculated the local means (assuming a model) and standard deviations for each bucket (year).

- The conclusion was that the standard deviation was increasing with the mean when it was really outliers in the last year that were skewing the situation by enlarging the standard deviation.

Standard Deviation vs Mean
Unadjusted for Outliers



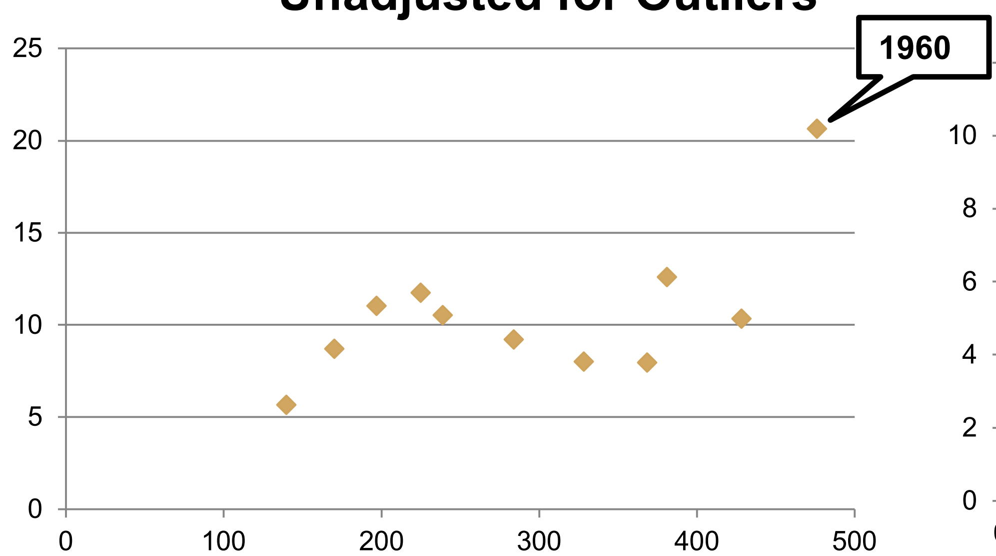
An example of "spurious correlation"

The “Airline Series”

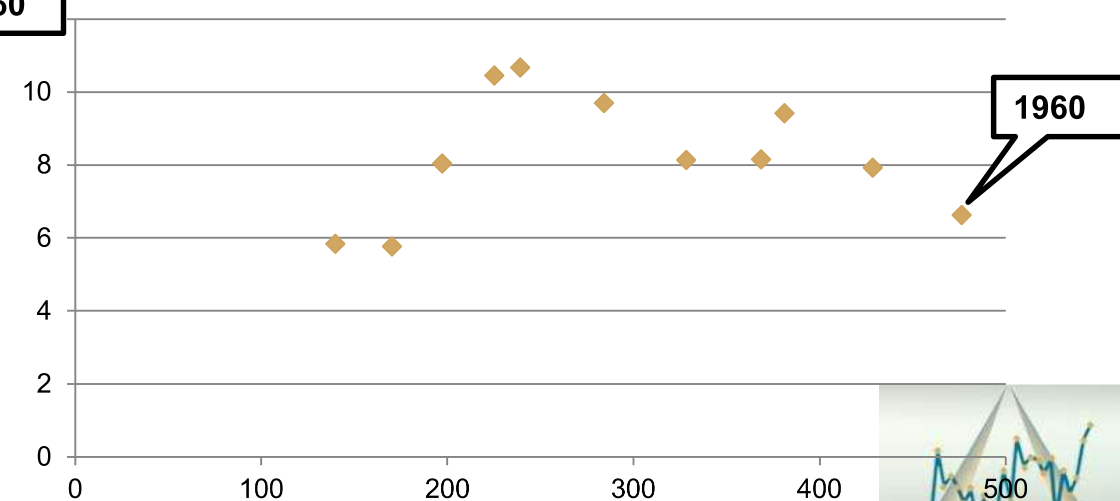
- If we then fit the “airline model”(seasonal differencing and an AR1), identifying and including five outliers (three of them in the last year) we can then use the residuals to calculate the standard deviation for each of the buckets. We then plot the standard deviations against the local means of the observed series and we get another story altogether.

- The conclusion was that the standard deviation was increasing with the mean when it was really outliers in the last year that were skewing the situation.

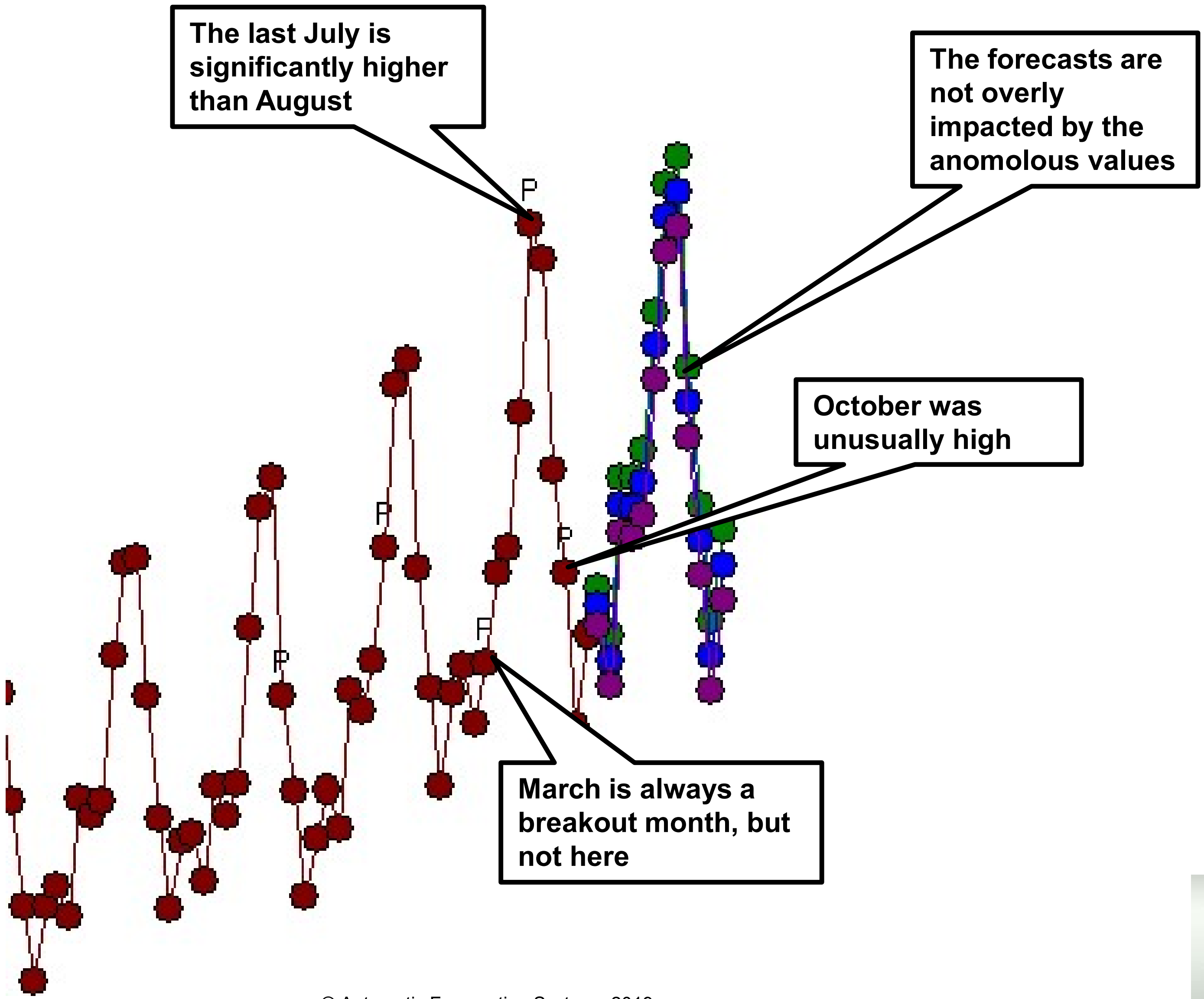
Standard Deviation vs Mean Unadjusted for Outliers



Standard Deviation versus Mean – Adjusted for Outliers



Did you spot the outliers in 1960?



SAP APO in the International Journal of Applied Forecasting Foresight Issue Fall 2006 – p 52

The Standard Forecasting Tools in APO

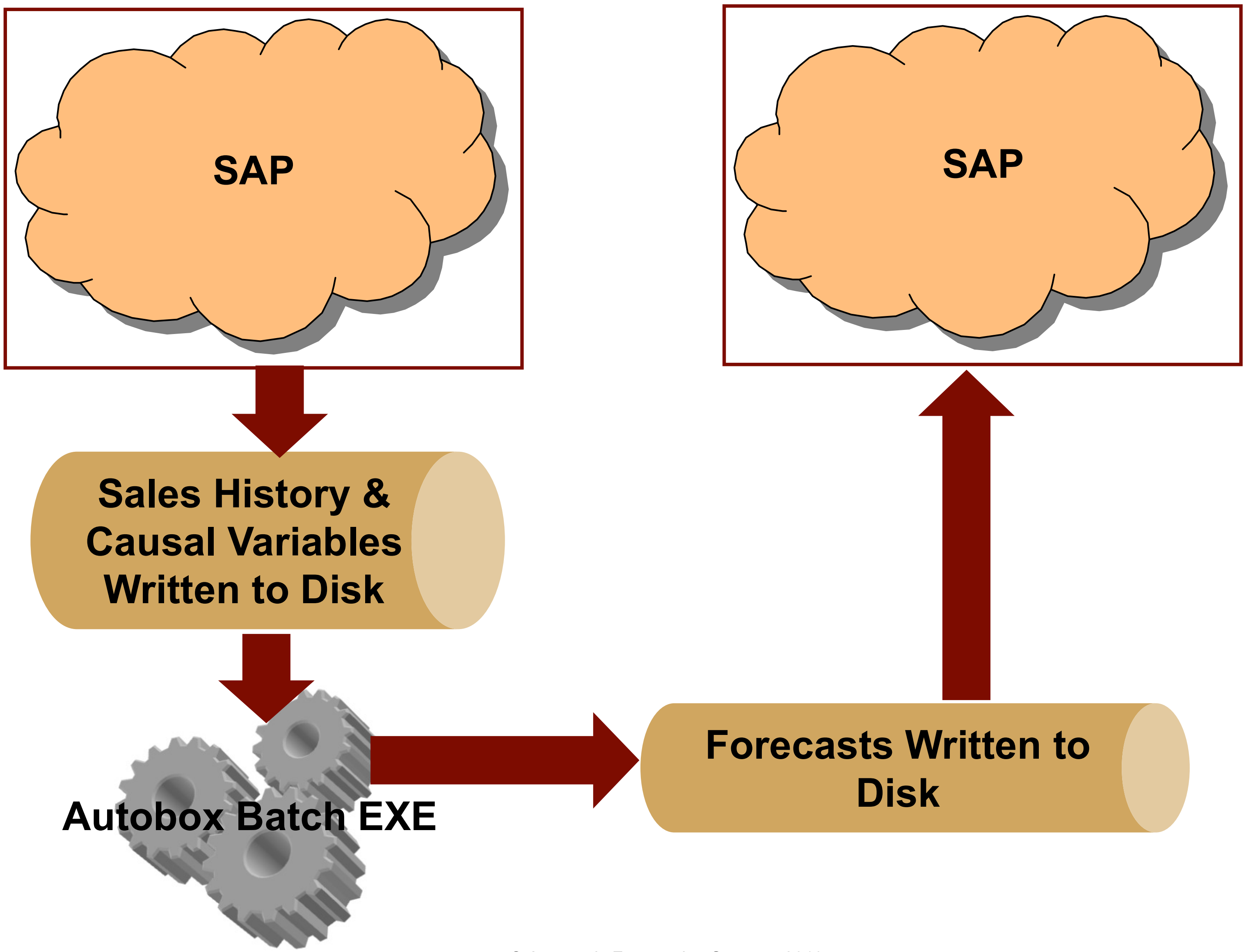
- **Moving Averages and weighted moving averages**
- **A portion of the family of exponential smoothing methods (a notable exclusion being the set of procedures that assume multiplicative seasonality)**
- **Automatic model selection in which the system chooses among included members of the exponential smoothing family**
- **Croston's model for intermittent demand (without the Syntetos and Boylan(2005) corrections)**
- **Simple and multiple regressions**

SAP APO in the International Journal of Applied Forecasting Foresight Issue Fall 2006 – p 54

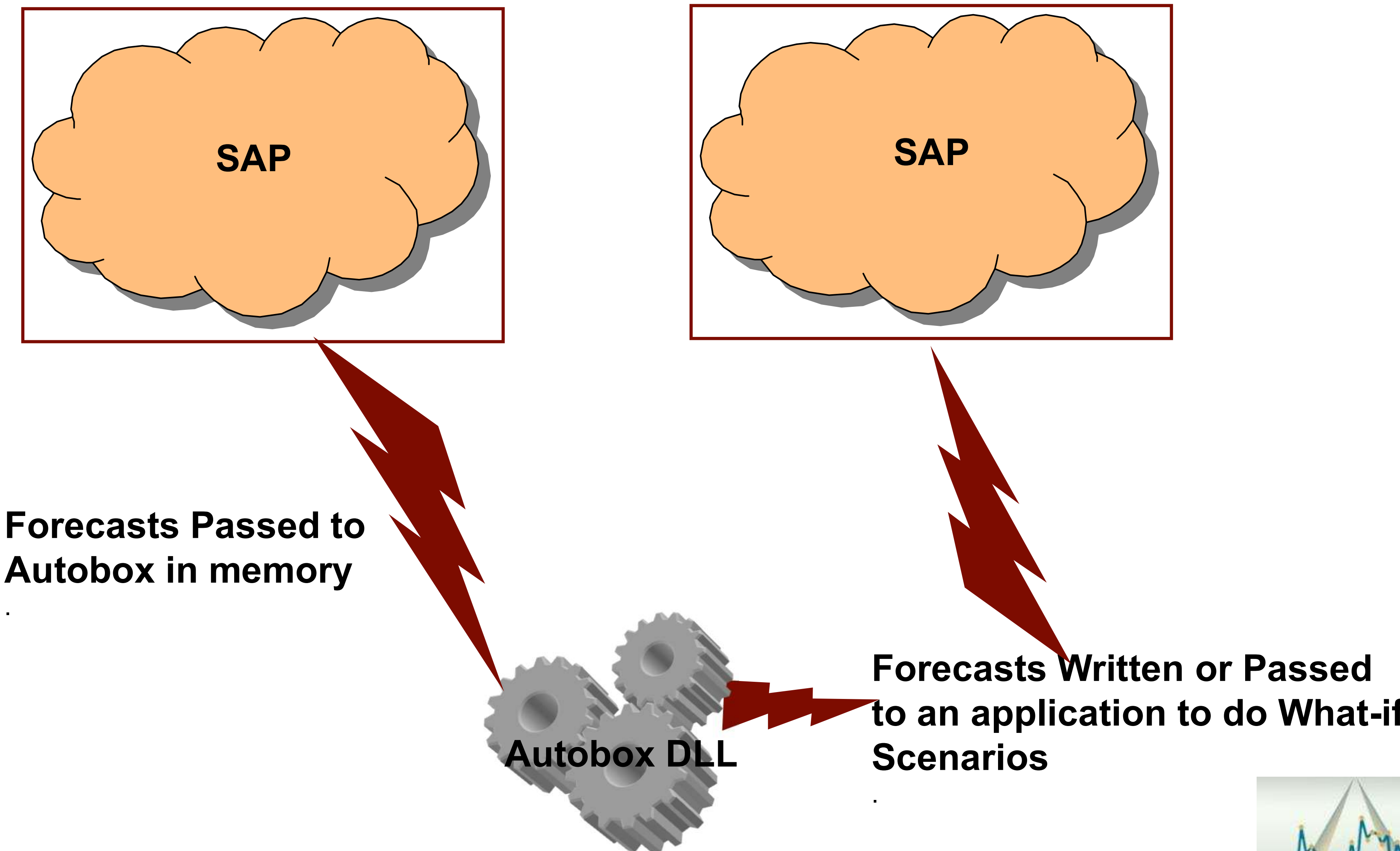
Summary

SAP APO is focusing on the whole supply chain and also on planning and process consistency. The mathematical accuracy of its forecasts may be worse than that of a stand-alone forecasting package, but the benefits to our company in terms of worldwide network planning and control more than compensate for this.

Integrating Autobox into SAP
Writing to Disk



Integrating Autobox into SAP
Calling a DLL and What-if Scenario



Linkedin.com

Make sure to join the Autobox discussion group on linkedin.com

Autobox User Group - Forecasting & Time Series Analysis, ARIMA, Outliers, Transfer Function & more!

For Forecasting professionals who use Autobox. You can discuss uses of modeling and problem solving and implementation of Automatic Forecasting Software, Autobox.