Anheuser-Busch Companies

- $15.7 billion gross sales operation in 2002 … four primary subsidiaries
  - Anheuser-Busch Domestic Beer Operation
  - Anheuser-Busch International Beer Operations
  - Busch Entertainment Corporation - Entertainment Operations
  - Packaging Group … cans, lids, crown liners, and can recycling
- 2001 Fortune 500 Company listing:
  - AB #41 based on Profits
  - AB #159 based on Net Sales

Anheuser-Busch Inc. – Domestic Operations

- Accounts for 78% of AB Companies sales and 93% of the profits
- Number one brewery in sales and volume since 1957
- 2002 attained a 49.5% market share of a 204MM BBL domestic beer industry
- Sold 101.2MM BBLS or 1.4 Billion 24/12 oz cases of product in 2002 … 1.6% Increase over 2001
- 200% plus volume lead over our nearest competitor (Miller Brewing Company)

Anheuser-Busch Inc. – Distribution Network

- Three tier distribution system
  - *Anheuser-Busch to wholesaler*
  - *Wholesaler to retailer*
  - *Retailer to consumer*
- Thirty plus brands of beer … Bud, Bud Light, Michelob, Michelob Light, Busch, and Busch Light account for 85% of ABI volume
- Twelve breweries …
  - *St. Louis, Missouri*
  - *Newark, New Jersey*
  - *Los Angeles, California*
  - *Houston, Texas*
  - *Columbus, Ohio*
  - *Jacksonville, Florida*
  - *Merrimack, New Hampshire*
  - *Williamsburg, Virginia*
  - *Fairfield, California*
  - *Baldwinsville, New York*
  - *Fort Collins, Colorado*
  - *Cartersville, Georgia*
- Sales in all 50 states plus Puerto Rico

- Produce and ship 570 product containers (brand and package configurations)
- Seven hundred and fifty independent distributorships/wholesalers
- Thirteen company owned distributorships/branches
- Manage product inventory for 91M SKU's at the wholesaler/branch level.
- Wholesalers distribute to 500,000 retail locations.

- **1964 – Collaborative AB/wholesalers effort to:**
  - forecast sales to retailers
  - Fulfill orders
  - CPFR before it had a name.
- **1975 – Introduced linear programming to plan monthly production and distribution.**
- **1992 – Moved from monthly to weekly planning.**
- **1994 – Reengineered the supply chain to handle the explosion in small volume products.**
- **2000 – Began planning the last mile of the supply chain – wholesaler to retailer**

Retail Stock Outs

- Supply chain planning systems had reduced wholesaler stock outs to under 2%.
- How often did the retailer stock out? If they do stock out, the entire supply chain has failed.
- An internal study based on a sample of 270 retail outlets suggested they were an issue.
- External industry studies confirmed that they were an issue.

Retail Stock Outs External Studies

- Grocery Channel - (Grocery Manufacturers Association Study - 2002)
  - 5.0% OOS rate for beer category in grocery stores and 20.6% for items on promotion
  - 45% of beer customers avoid making a purchase in the store where the OOS is encountered and only 23% will attempt to buy the item elsewhere
- Convenience Channel (National Association of Convenience Stores Study – 1998)
  - 6.4% beer category OOS rate in C-Stores
  - 22% of customers (if faced with OOS on their favorite item) will leave the store without purchasing a substitute
  - The average store loses 3-6% of total sales due to OOS

Retail Stock Outs Three Solutions

- Proper shelf allocation – shelf space should be proportional to sales.
- Scheduled pull ups from back room – If the shelf is empty, this is a stock out even if there is some of the product in the back room – consumers rarely ask for a product not on the shelf.
- Improved ordering – make sure the right product mix gets to the store – This is the focus of the current presentation.

Current Order Generation Process

Performed by a wholesalers sales rep at each retailer 1 to 3 times a week.

- Uses intuitive & static build to quantities
- Fills shelves and/or displays from backroom inventory
- Takes inventory
- Calculates order by subtracting inventory from build to quantity…done by handheld
- Adjusts order as necessary
- Reviews order with store manager
- Transmits order to Route Accounting System

Improved Order Generation Process (Efficient Order Writing)

Suggested order is delivered to sales rep while in-store by:

- Using retailer scan data to forecast sales between delivery periods recognizing…
  - Weather
  - Future price
  - Holidays
- Adding safety stock to protect against stock-outs
- Subtracting up-to-date inventory

- *Uses intuitive & static build to build to quantities*
- Fills shelves and/or displays from backroom inventory
- Takes inventory
- *Calculates order by subtracting inventory from build to quantity…done by handheld*
- Adjusts order as necessary
- Reviews order with store manager
- Transmits order to Route Accounting System

Improved Ordering: Forecast – Two Processes

- Build Models
  - Done at startup and periodically (every 2 to 12 weeks) thereafter.
  - Based on two year history by store, brand, and package if active for at least a year.
  - ARIMA models with transfer functions for causal variables.
  - Since this is done in the background, computation time is not critical.
- Apply models to generate forecast
  - Done automatically each day and when reps request an order by wireless connection.
  - Computation time is very critical since a sales rep is waiting for the result.

Improved Ordering: Forecast – Causal Variables

- **Price – average price paid by consumers by store, brand, package, and day. = retailers revenue / retailers quantity sold.**
- **Price of similar AB products e. g. Bud Light 12 pack and 18 pack cans – price promotions of one cannibalizes sales of the other.**
- **Holidays – Indicator variables that are 1 on the day of the holiday and 0 otherwise.**
  - New Years, St. Patrick's Day, Easter, Cinquo De Mayo, Memorial Day, Mothers Day, Fathers Day, July 4th, Labor Day, Halloween, Veteran's Day, Thanksgiving, and Christmas.

Improved Ordering: Forecast – Causal Variables

- **Events – Indicator variables that are 1 on the day of the event and 0 otherwise.**
  - Super Bowl and Mardi Gras
- **Temperature = max(High Temp – 65, 0)**
- **Deep Discount Indicator = 1 if discount is more than 20% of front line price, 0 else.**
- **Deep Discount on Friday or Saturday Indicator = 1 if there is a deep discount and the day is Fri or Sat, 0 else.**
- **Day of week indicators (Automatically included by AUTOBOX)**

Improved Ordering: Forecast – Causal Variables

- **There is no limit to the number of potential causal variables – we will add new ones as we discover additional business relationships.**
- **Potentials:**
  - Weather – snowfall, precipitation, low temperature, cloudiness, heat index, wind chill, severe weather.
  - Events – home game schedules, local events, strikes, earth quakes.
- **The process of discovery of new causal variables**
  - Is unpredictable – It never ends up where we expected.
  - Driven by gleaning patterns from historical forecast error and outliers identified by Autobox.
  - Often leads to causal variables we didn't know existed – e.g. deep discounts on Friday and Saturday – Mothers Day – who would have imagined.

Improved Ordering: Forecast – AUTOBOX

- **Autobox automatically**
  - Identifies starting ARIMA structure
  - Estimates initial coefficients for ARIMA terms and causal variables including up to 4 days lead and lag on holidays and events.
  - Identifies three types of historical anomalies:
    - One time outliers or pulses
    - Level shifts
    - Outliers that are repeated on the same day every week.
  - Iteratively does necessity and sufficiency tests until all remaining variables are necessary and sufficient.

Improved Ordering: Safety Stock

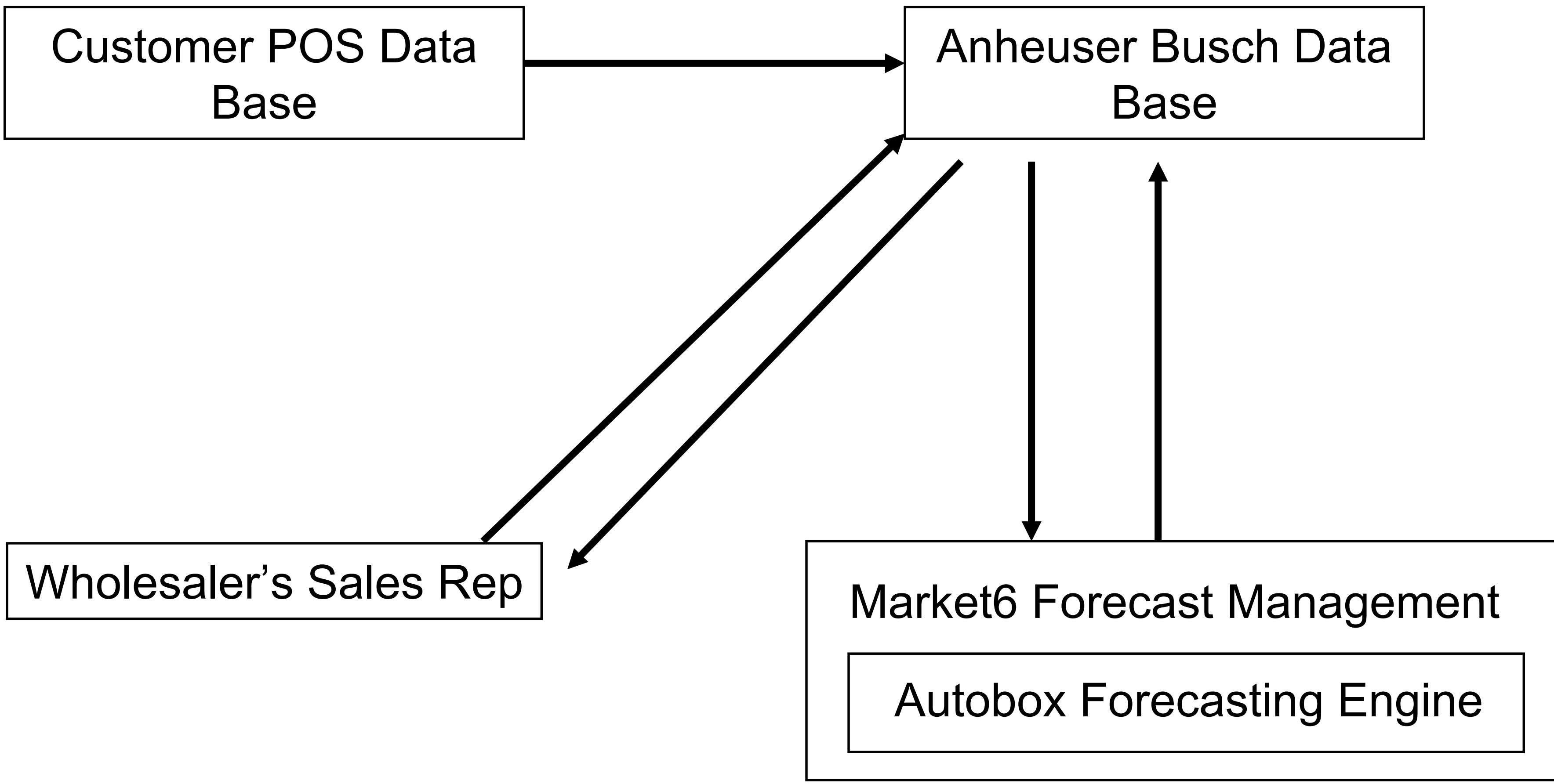
- **Based on:**
  - Historical daily forecast error
  - Days until next delivery
- **Historical forecast error:**
  - Build model – log(std of daily forecast error) = $A_0 + A_1 *$ log(average forecast sales) – an observation for the regression is one store, product, and package.
  - R^2 is generally > .8
  - Apply model to forecast and multiply by chosen protection factor.
- **Multiply the result by the square root of the number of days including the next delivery.**

Improved Ordering: Current Inventory

- **Can be difficult to count**
  - Odd locations
  - One product hidden behind another
  - Requires patience
- **When it's off, it's often way off**
  - Missed a display
  - Reported under wrong package
- **Requires quality control process where differences between physical and perpetual are reconciled.**

- = sales forecast from today through next delivery day (covers sales if the delivery arrives late in the day)
- + safety stock sufficient to assure low stock out chances
- - current inventory

Efficient Order Writing (EOW) Systems Structure



- In the 4th Quarter of 2000, an AB customer requested our participation in a joint-supplier effort to reduce out-of-stocks.
- Three suppliers were asked to participate, and to develop unique "solutions" that address the out-of-stock issue.
- AB proposed all three processes (shelf allocation, pull ups, EOW)
- Pilot results were promising.

Stock-outs	**55%**
Sales	**7.4%**
Inventory	**Up slightly… more volume**
Deliveries	**No change**

Selling the Concept – Pilot Implementations

- Due to the success of the first pilot and convinced that stock outs were a wide spread problem, the team was asked to test EOW as a stand alone effort without the shelf allocation or pull ups.
- Results were again favorable
  - Stock-outs reduced 51%
  - Sales (stat cases) up 5.8%
  - Retailer inventory down .1%
  - Deliveries remain unchanged
- **Showing increased sales was key to obtaining management buy in.**

Automatic Forecasting Systems

P.O. Box 563
Hatboro, PA 19040
Tel: (215) 675-0652
Fax: (215) 672-2534

sales@autobox.com

www.autobox.com

Autobox 5.0 is the recipient of the best **dedicated forecasting package in J. Scott Armstrong's book titled "Principles of Forecasting" (p. 671)**

Since 1976

*Principles of Forecasting: A Handbook for Researchers and Practitioners,*J. Scott Armstrong (ed.): Norwell, MA: Kluwer Academic Publishers, 2001

DIFFUSION OF FORECASTING PRINCIPLES: an assessment of FORECASTING SOFTWARE PROGRAMS

Len Tashman* and Jim Hoover**

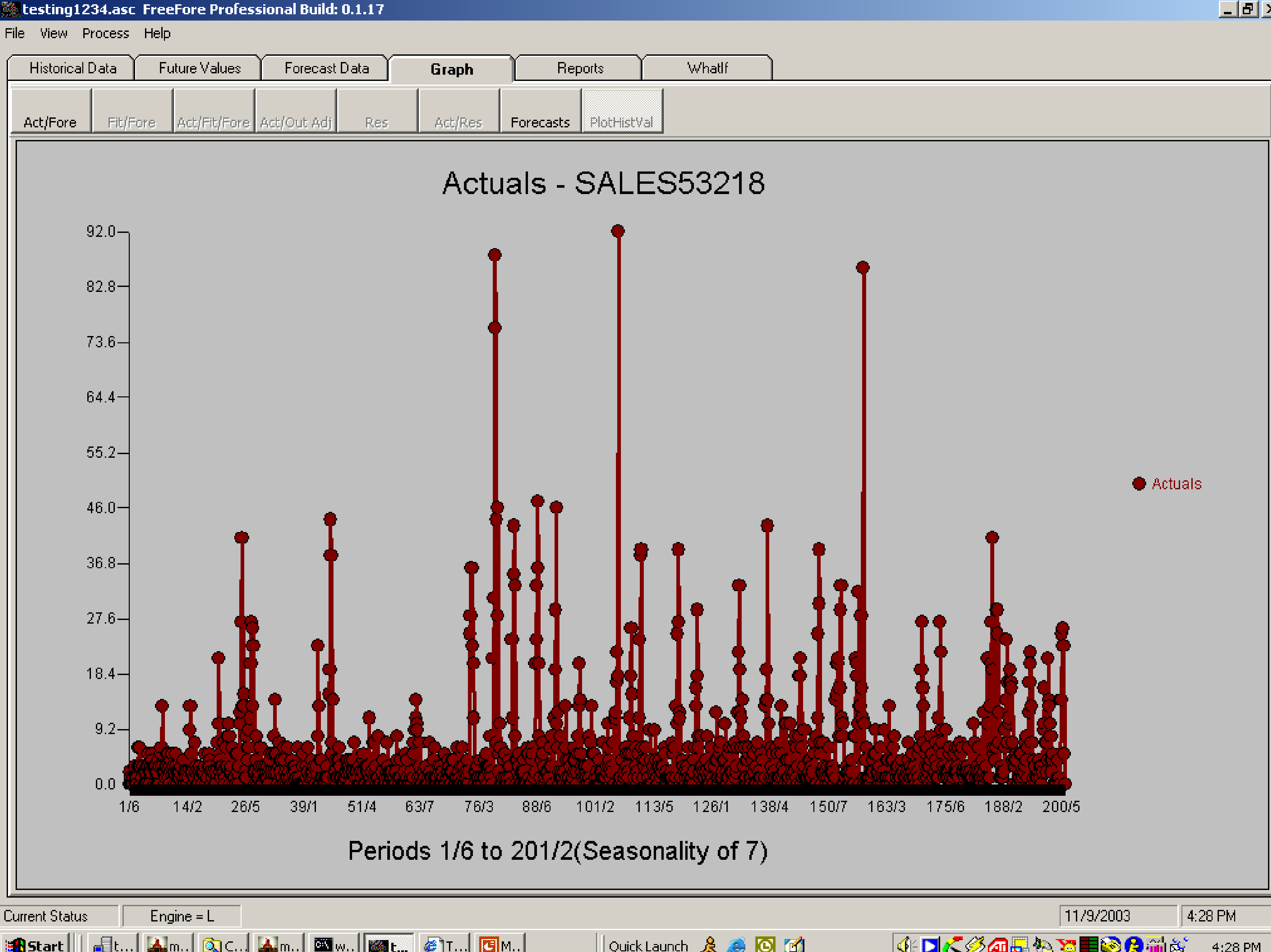
*School of Business Administration, University of Vermont

Burlington, VT 05405

**United States Department of the Navy

2000 Navy Pentagon (N412H)

Washington, D.C. 20350-2000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Periods 1/6 to 201/2(Seasonality of 7)
Actuals
Current Status
Engine = L
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4:28 PM
Start
Quick Launch
4:28 PM

Outliers

- One time events that need to be “corrected for” in order to properly identify the general term or model
- Consistent events (i.e. holidays, events) that should be included in the model so that the future expected demand can be tweaked to anticipate a pre-spike, post spike or at the moment of the event spike.
- If you can’t identify the reason for the outlier than you will not get to the root of the process relationship and be relegated to the passenger instead of the driver

OUTLIERS: WHAT TO DO ABOUT THEM?

- **OLS procedures are INFLUENCED strongly by outliers. This means that a single observation can have excessive influence on the fitted model, the significance tests, the prediction intervals, etc.**

  Outliers are troublesome because we want our statistical models to reflect the MAIN BODY of the data, not just single observations.

Outliers

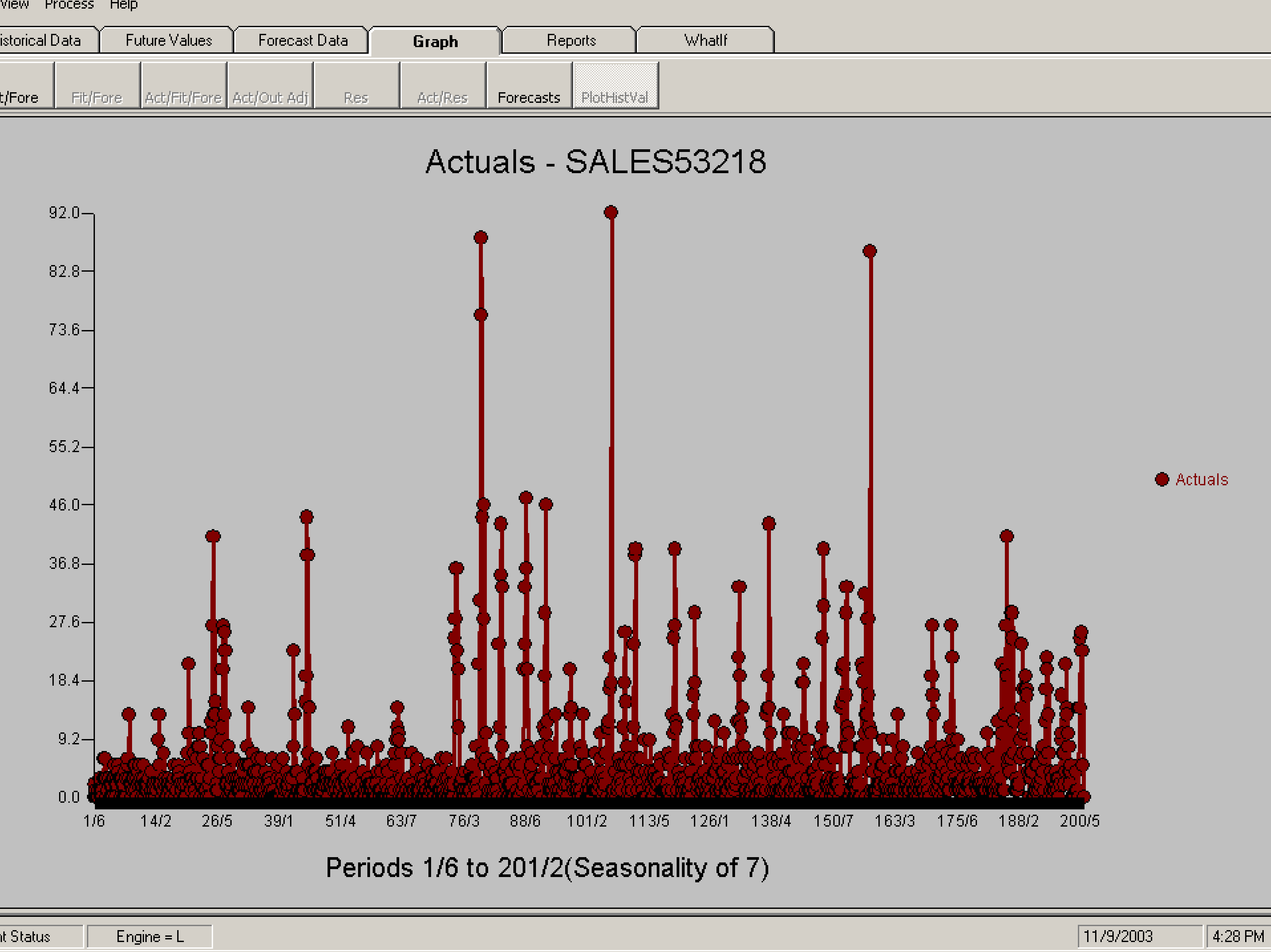
- **Working definition**
  - An outlier x_k is an element of a data sequence S that is inconsistent with out expectations, based on the majority of other elements of S.
- **Sources of outliers**
  - Measurement errors
  - Other uninteresting anomalous data
    - valid data observations made under anomalous conditions
  - *Surprising observations that may be important*

Peculiar Data

- **Zhong, Ohshima, and Ohsuga (2001):**
  - Hypotheses (knowledge) generated from databases can be divided into three categories
    - Incorrect hypotheses
    - Useless hypotheses
    - New, surprising, interesting hypotheses
- **To find last class, authors suggest looking for *peculiar data***
  - A data is peculiar if it represents a peculiar case described by a relatively small number of objects and is very different from other objects in the data set.

Why 3-sigma fails

- **Outlier sensitivity of mean and standard deviation**
  - mean moves towards outliers
  - standard deviation is inflated
- **Too few outliers detected (e.g., none)**



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188/2
200/5
Actuals
Periods 1/6 to 201/2(Seasonality of 7)
t Status
Engine = L
11/9/2003
4:28 PM

```
Y  = SALES53218
X1 = PRICE53218
X2 = PRICE53246
X3 = MOVE_NEWYEARS
X4 = MOVE_SUPERBOWL
X5 = MOVE_MEMORIALD
X6 = MOVE_JULY4TH
X7 = MOVE_LABORDAY
X8 = MOVE_CHRISTMAS
X9 = DEEP_FRI_SAT
10 = HIGH_DAYS
11 = DEEP_DISCOUNT
12 = MOVE_HALLOWEEN
13 = MOVE_CINQUOMAY
14 = STRIKE
```

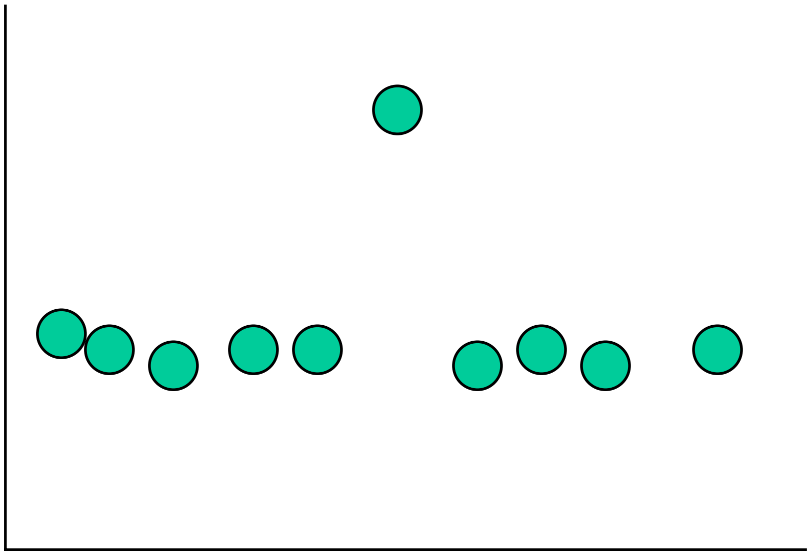
Types of Outliers

- Pulse
- Seasonal Pulse
- Level Shift (changes in intercepts)
- Time Trends (changes in slopes)

Example of a Pulse Intervention

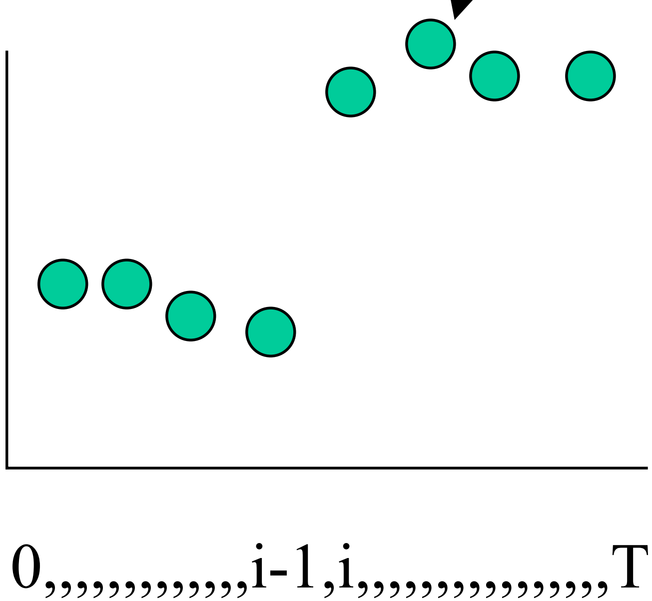
Z_t represents a pulse or a one-time intervention at time period 6.

$Z_t = 0,0,0,0,0,1,0,0,0$



Modeling Interventions - Level Shift

If there was a level shift and not a pulse then it is clear that a single pulse model would be inadequate thus $Y_t = BO + B3Z_t + U_t$



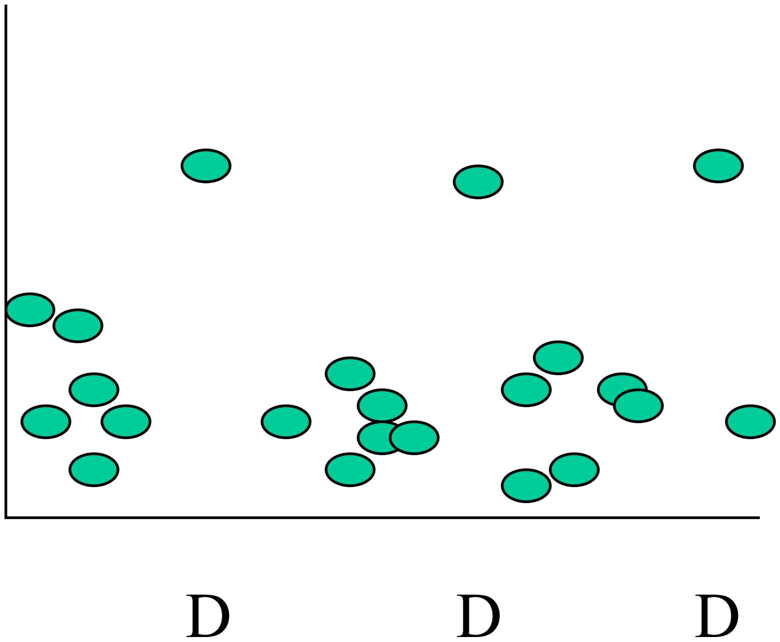
Assume the appropriate Z_t is

$Z_t = 0,0,0,0,1,1,1,1,1,1,,,,,,,,T$

or $Z_t = 0 \quad t < i$

$Z_t = 1 \quad t > i\text{-}1$

There are other kinds of pulses that might need to be considered otherwise our model may be insufficient. For example, December sales are high.



The data suggest this model

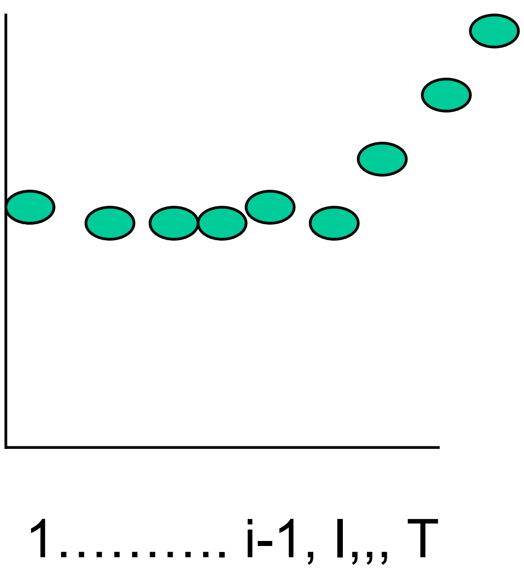
$$Y_t = BO + B3Z_t + U_t$$

$$Z_t = 0 \quad i <> 12,24,36,48,60$$

$$Z_t = 1 \quad i = 12,24,36,48,60$$

Modeling Interventions - Local Time Trend

The fourth and final form of a deterministic variable is the the local time trend. For example,



The appropriate form of Z_t is

$Z_t = 0 \quad t < i$

$Z_t = 1 \quad (t-(i-1)) * 1 >= i$

$Z_t = 0,0,0,0,0,0,1,2,3,4,5,,,,,$

- 99.9% of all Academic presentation of statistical tools REQUIRES independent observations.
- In time series data, this is clearly not the case.
- For example Multiple Regression is taught using cross-sectional data (i.e. non-time series) and practitioners try to apply these limited tools to time series data.

The advantages of a time-series Box-Jenkins approach versus a classic multiple regression approach are:

Advantages of Box-Jenkins

- Omitted stochastic series can be proxied with the ARIMA structure
- Omitted Deterministic series can be empirically identified (Intervention Detection)

Advantages of Box-Jenkins

- The form of the seasonality can either be auto-projective (i.e. project from seasonal lags) or use one or more Seasonal Dummies versus using them all.
- Furthermore the intensity of the seasonal factors may have changed over time.

- The form of the non-stationarity can be one or more local trends and/or level shifts or differencing versus the assumption of one monotonic trend

- The form of the relationship can be either fixed for a number of periods or dynamic (ripple effect) and can have a period of delay as compared to a pure fixed effect (i.e. change in x immediately effects y but no other y)

From <u>500 Miles High</u> This is a Straight-forward Business Intelligence Problem

- **We observe sales data for a particular SKU for a particular store for 1397 consecutive days where we know the SKU price and the price of two other products which are possible substitutes.**
- **We know what the weather was and when 8 major holidays occurred.**
- **We also put on special discounts on Fri/Sat and also had periods of time where Deep Discounts were in effect.**
- **Additionally there was a period where a Strike was in effect.**

From <u>0 Miles High</u> This is a Difficult Statistical Modeling Problem !

- **What we don't know is which of the known variables have an effect and the temporal form of that effect.**
- **We don't know how to use historical sales , if at all.**
- **We don't know if there is a day-of-the-week effect.**
- **We don't know the nature of any lead effects and/or lag effects of the holidays.**
- **We don't know about the effect of unusual activity that may have occurred during the 1,397 days.**

- Select the correct input series

Regression Opportunities in Time Series Data

- Select the correct input series
- Select what lags are needed of the output series
- Select what leads and lags are needed for the input series
- Select how the variability changes over time
- Select how the parameters change over time

Types of Outliers in Cross-Sectional i.e.non-time series data

- **Pulse**

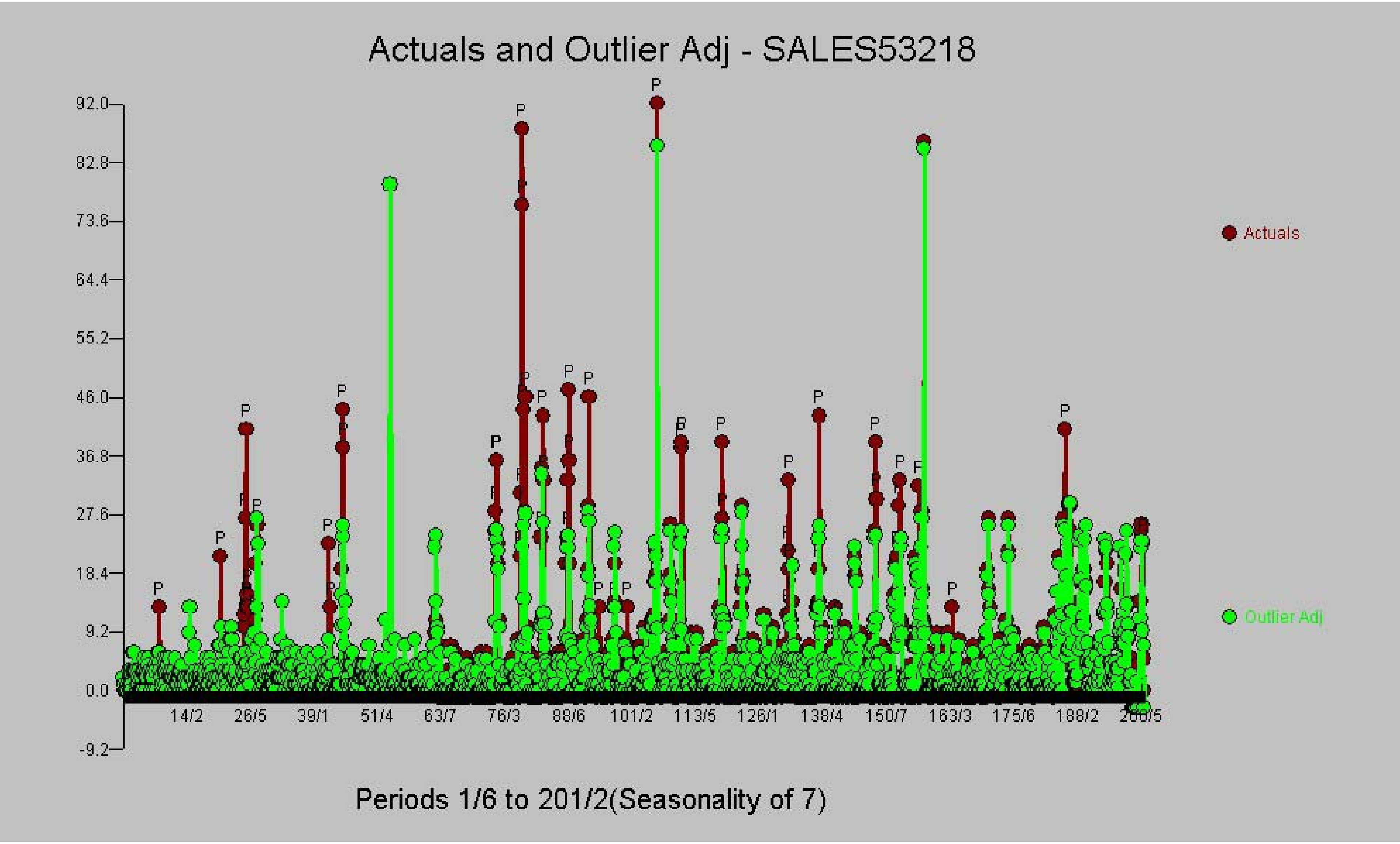
Types of Outliers in Time Series Data

- Pulse
- Seasonal Pulse
- Level Shift (changes in intercepts)
- Time Trends (changes in slopes)

```
Y(T) =  12.768
       +[X1(T)][(-  .896)]                                      PRICE53218
       +[X2(T)][(+  .155)]                                      PRICE53246
       +[X3(T)][(+ 2.9921     B**-2+ 76.3219     B**-1)]        MOVE_NEWYEARS
       +[X4(T)][(- 2.3934     B**-1)]                           MOVE_SUPERBOWL
       +[X5(T)][(+ 6.6926     B**-1+ 5.5635     )]              MOVE_MEMORIALD
       +[X6(T)][(+ 14.6042     B**-3+ 5.5530     B**-2          MOVE_JULY4TH
       + 4.9138     B**-1+ 18.9428     )]
       +[X7(T)][(+ 2.7749     B**-1+ 2.4098     )]              MOVE_LABORDAY
       +[X8(T)][(+ 9.4571     B**-1)]                           MOVE_CHRISTMAS
       +[X9(T)][(+ 11.5911     )]                               DEEP_FRI_SAT
       +[X10(T)[(+  .036)]                                      HIGH_DAYS
       +[X11(T)[(+ 5.5976     )]                                DEEP_DISCOUNT
       +[X12(T)[(- 2.5942     )]                                STRIKE



       NEWLY IDENTIFIED VARIABLE   13 = I~L01291  186/  1     LEVEL
       NEWLY IDENTIFIED VARIABLE   14 = I~L00432   63/  3     LEVEL

       +[X13(T)[(- 1.4595     )]
       +[X14(T)[(+ 1.0232     )]



         Number of Residuals (R)       1394
         Number of Degrees of Freedom  1259
         Sum of Squares                 4873.55
         Variance                       3.49609
         Adjusted Variance              3.87097
         R Square                       .948994
         Durbin-Watson Statistic        1.89535
```

Conclusions

- Price is important and one of the substitutes also has an effect.
- Six of the eight holidays have significant effects (pre, contemporaneous and post).
- The Fri/Sat discounting program was significant along with our Deep Discount program.
- There is a strong day-of-the-week effect.
- There were two statistically significant level shifts in sales.



Actuals and Outlier Adj - SALES53218
92.0
82.8
73.6
64.4
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46.0
36.8
27.6
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26/5
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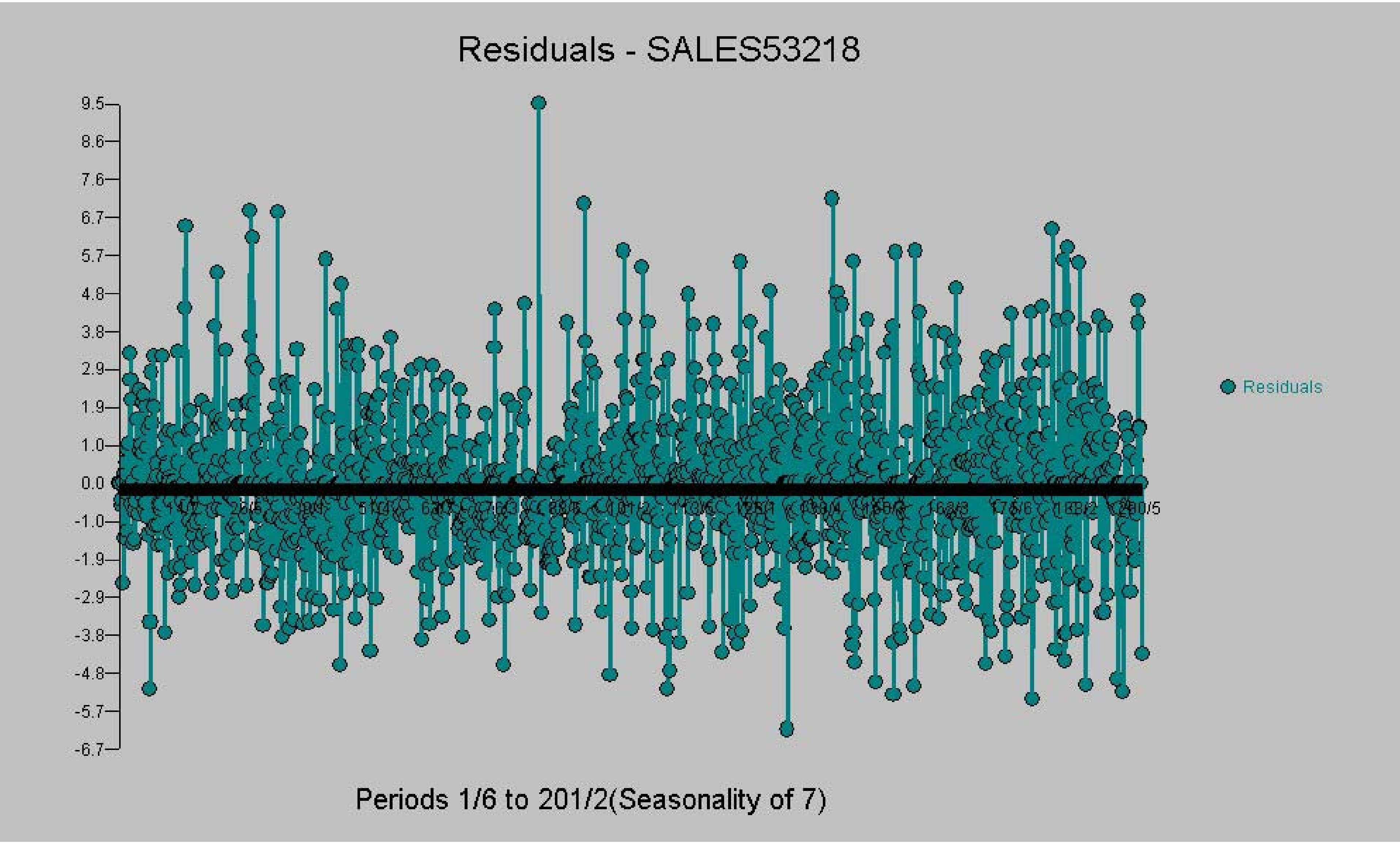
Actuals
Outlier Adj
Periods 1/6 to 201/2(Seasonality of 7)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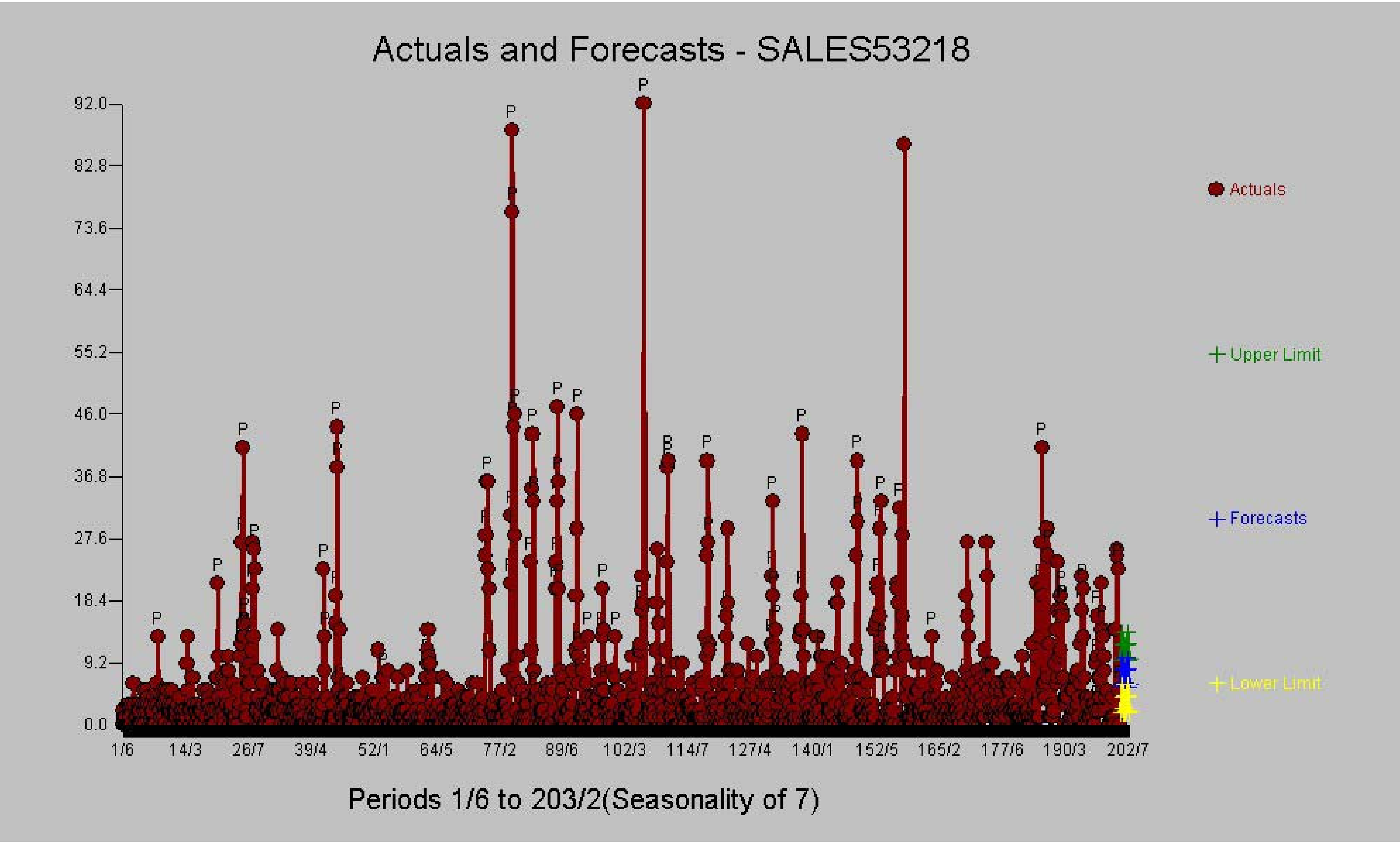
Periods 1/6 to 201/2(Seasonality of 7)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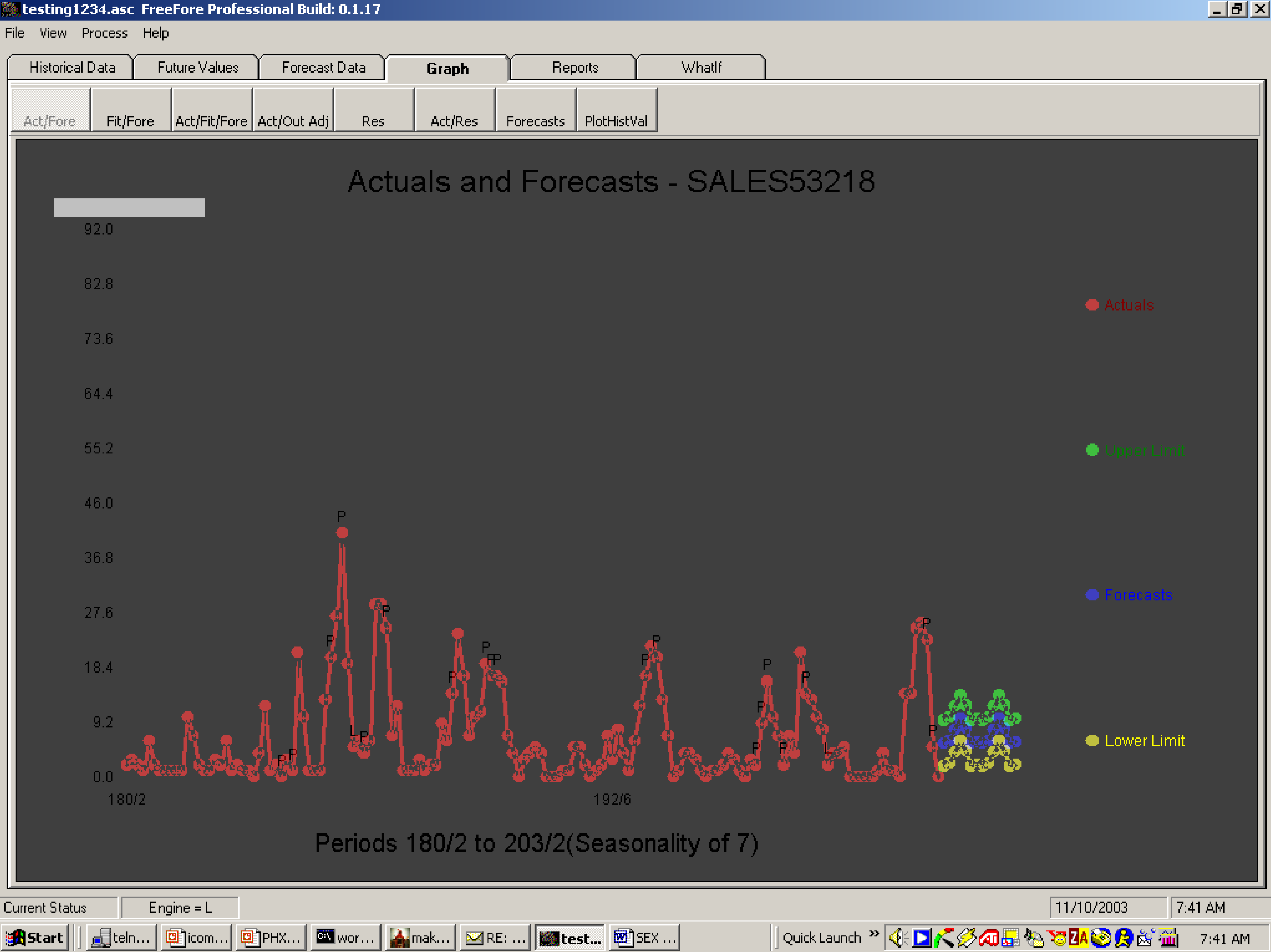
Periods 1/6 to 203/2(Seasonality of 7)
Actuals
Upper Limit
Forecasts
Lower Limit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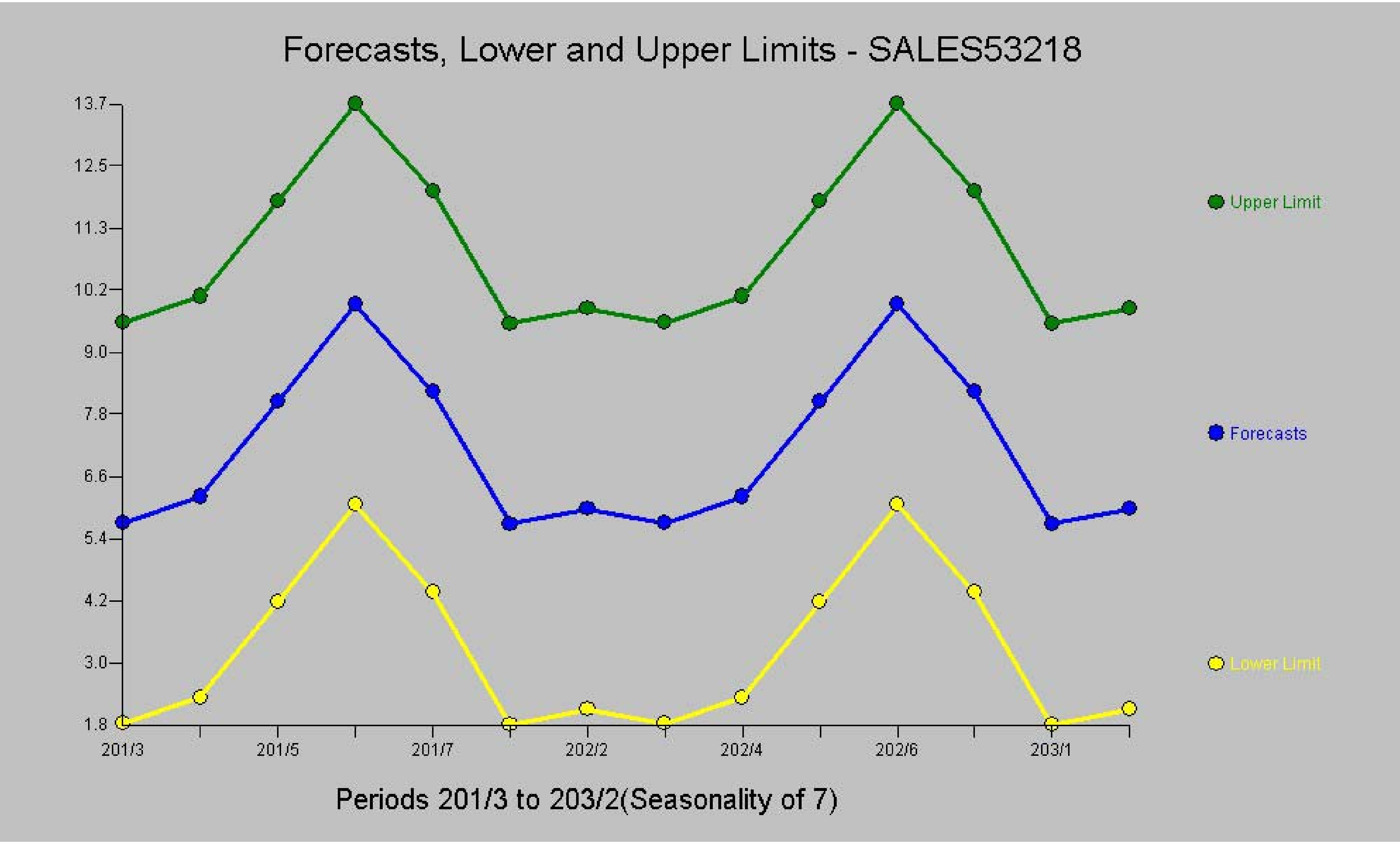
Quick Launch
7:41 AM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203/1
Upper Limit
Forecasts
Lower Limit
Periods 201/3 to 203/2(Seasonality of 7)

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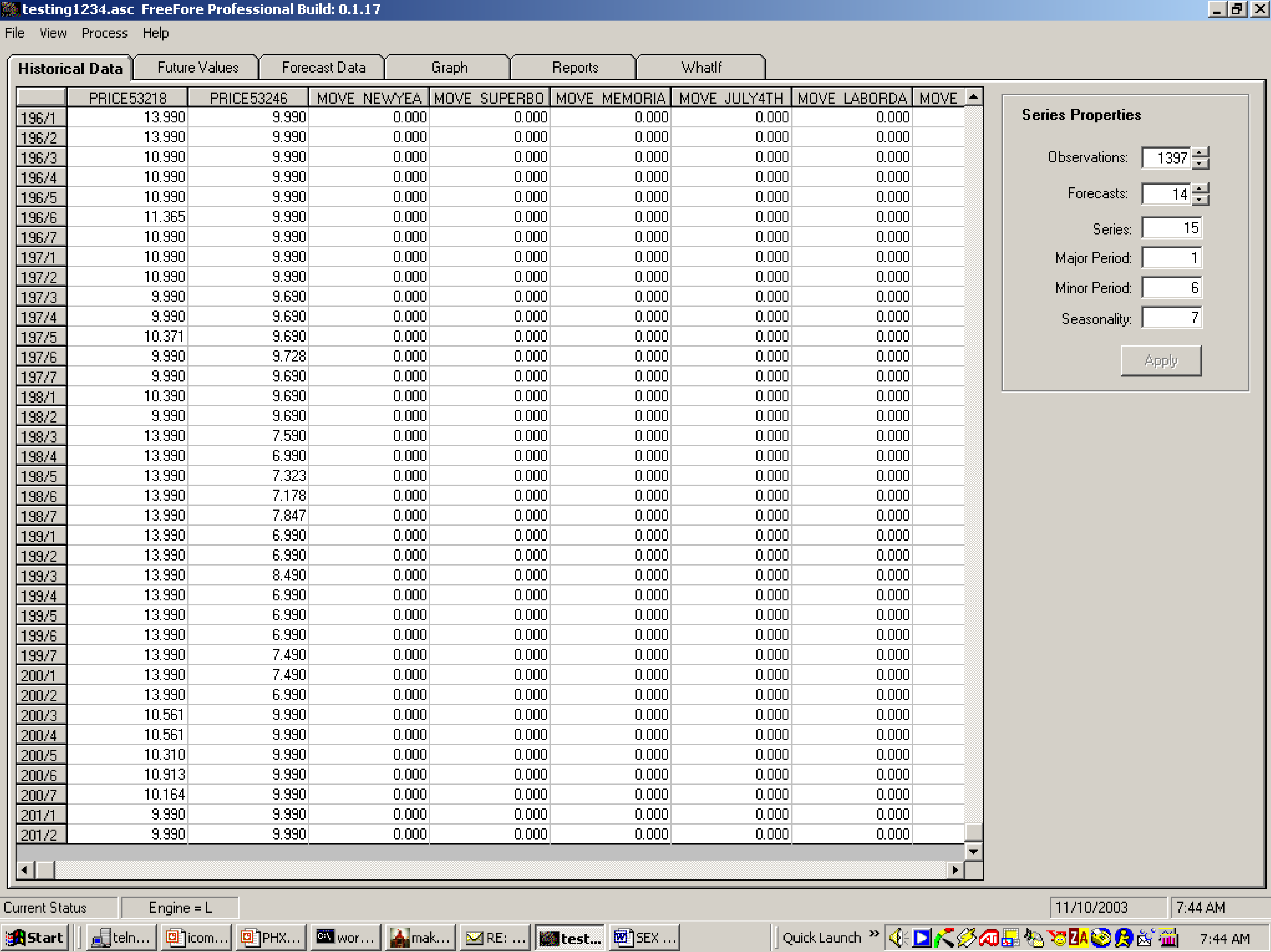
File View Process Help

Historical Data | **Future Values** | Forecast Data | Graph | Reports | WhatIf

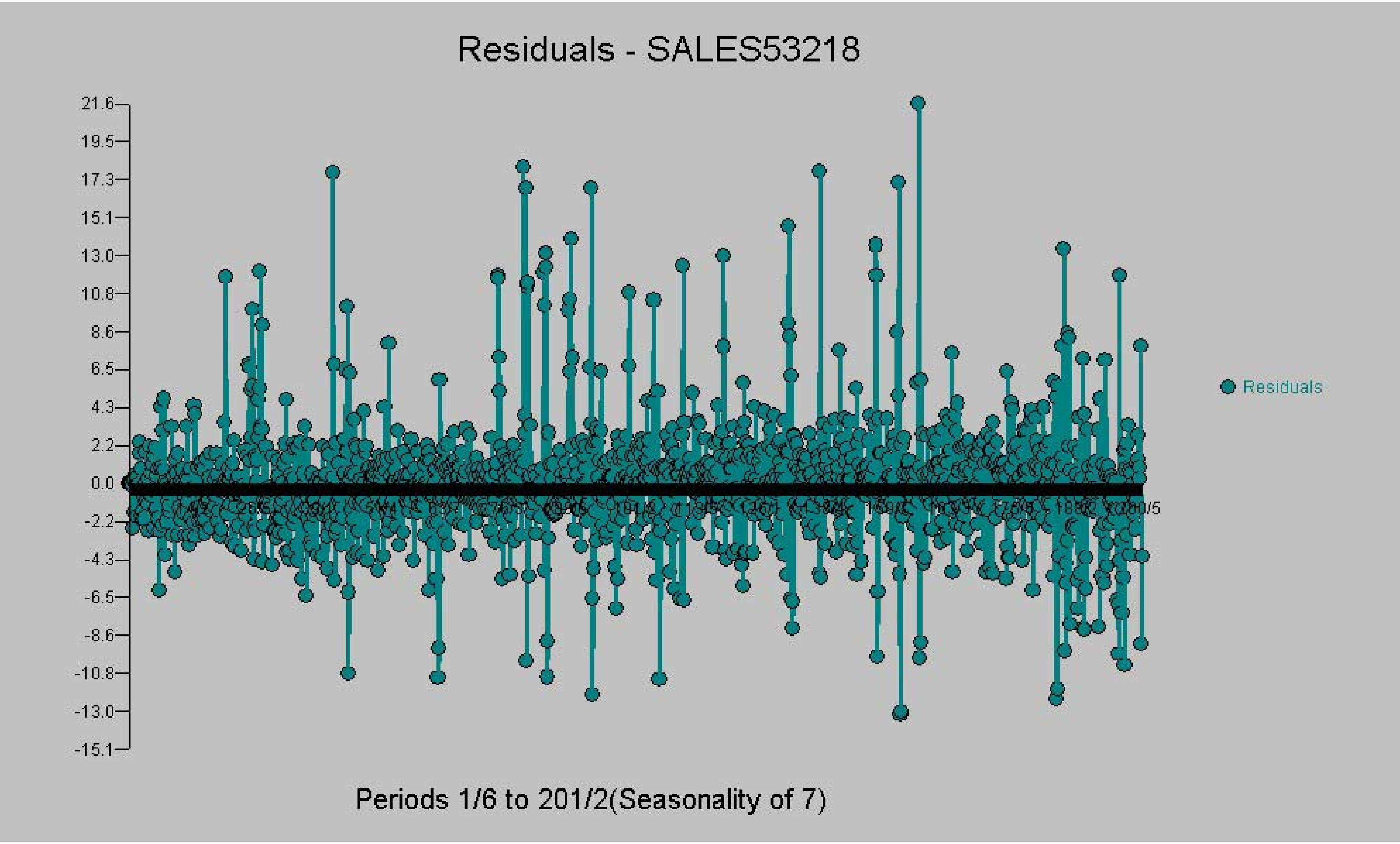
	PRICE53218	PRICE53246	MOVE NEWYEA	MOVE SUPERBO	MOVE MEMORIA	MOVE JULY4TH	MOVE LABORDA	MOVE CHRISTM	DEEP FRI SAT	HIGH DA'
201/3	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1
201/4	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
201/5	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
201/6	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
201/7	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/1	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/2	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/3	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/4	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/5	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/6	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
202/7	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
203/1	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
203/2	9.990	9.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Current Status | Engine = L | 11/10/2003 | 7:43 AM

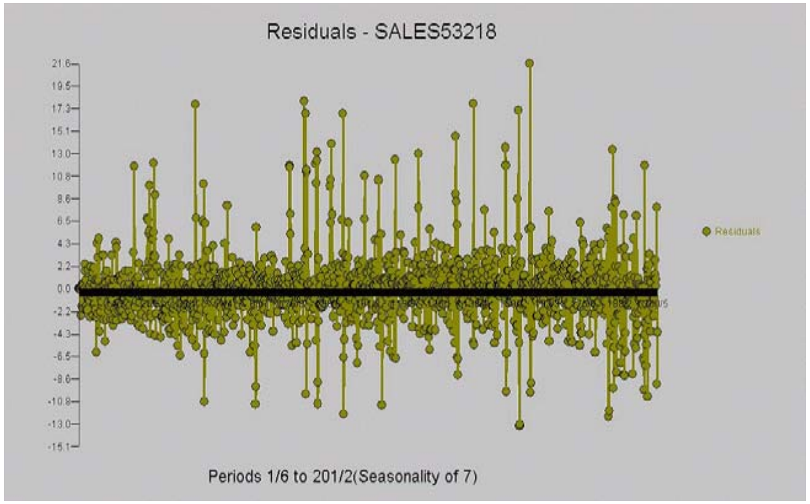
Start | teln... | icom... | PHX... | wor... | mak... | RE: ... | test... | SEX ... | Quick Launch | 7:43 AM

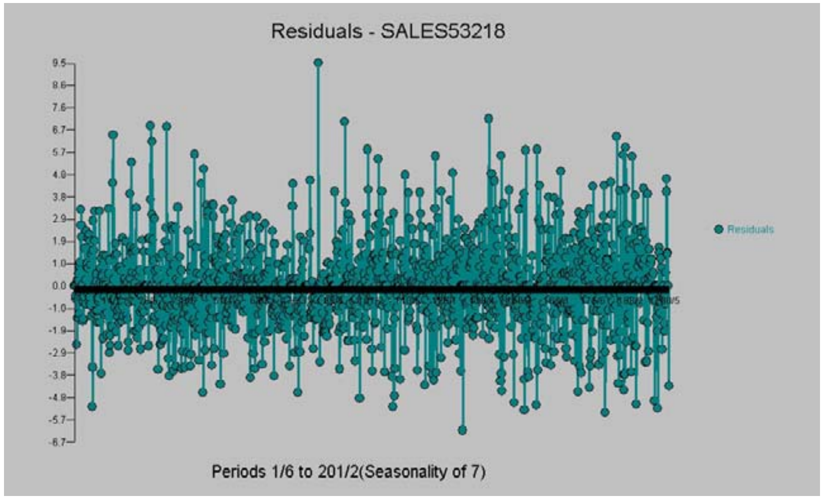


	PRICE53218	PRICE53246	MOVE_NEWYEA	MOVE_SUPERBO	MOVE_MEMORIA	MOVE_JULY4TH	MOVE_LABORDA	MOVE
196/1	13.990	9.990	0.000	0.000	0.000	0.000	0.000	
196/2	13.990	9.990	0.000	0.000	0.000	0.000	0.000	
196/3	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
196/4	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
196/5	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
196/6	11.365	9.990	0.000	0.000	0.000	0.000	0.000	
196/7	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
197/1	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
197/2	10.990	9.990	0.000	0.000	0.000	0.000	0.000	
197/3	9.990	9.690	0.000	0.000	0.000	0.000	0.000	
197/4	9.990	9.690	0.000	0.000	0.000	0.000	0.000	
197/5	10.371	9.690	0.000	0.000	0.000	0.000	0.000	
197/6	9.990	9.728	0.000	0.000	0.000	0.000	0.000	
197/7	9.990	9.690	0.000	0.000	0.000	0.000	0.000	
198/1	10.390	9.690	0.000	0.000	0.000	0.000	0.000	
198/2	9.990	9.690	0.000	0.000	0.000	0.000	0.000	
198/3	13.990	7.590	0.000	0.000	0.000	0.000	0.000	
198/4	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
198/5	13.990	7.323	0.000	0.000	0.000	0.000	0.000	
198/6	13.990	7.178	0.000	0.000	0.000	0.000	0.000	
198/7	13.990	7.847	0.000	0.000	0.000	0.000	0.000	
199/1	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
199/2	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
199/3	13.990	8.490	0.000	0.000	0.000	0.000	0.000	
199/4	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
199/5	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
199/6	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
199/7	13.990	7.490	0.000	0.000	0.000	0.000	0.000	
200/1	13.990	7.490	0.000	0.000	0.000	0.000	0.000	
200/2	13.990	6.990	0.000	0.000	0.000	0.000	0.000	
200/3	10.561	9.990	0.000	0.000	0.000	0.000	0.000	
200/4	10.561	9.990	0.000	0.000	0.000	0.000	0.000	
200/5	10.310	9.990	0.000	0.000	0.000	0.000	0.000	
200/6	10.913	9.990	0.000	0.000	0.000	0.000	0.000	
200/7	10.164	9.990	0.000	0.000	0.000	0.000	0.000	
201/1	9.990	9.990	0.000	0.000	0.000	0.000	0.000	
201/2	9.990	9.990	0.000	0.000	0.000	0.000	0.000	


Residuals - SALES53218
21.6
19.5
17.3
15.1
13.0
10.8
8.6
6.5
4.3
2.2
0.0
-2.2
-4.3
-6.5
-8.6
-10.8
-13.0
-15.1
Residuals
Periods 1/6 to 201/2(Seasonality of 7)

If we limit the number of Pulses to be identified we get the first slide. Unrestricted we get the second slide





Forecasting on The Fly (ABOXLITE)

- **Models are developed and archived**
- **Models are recalled when needed to create a forecast.**

Speed is of the Essence

- **Time to compute forecasts is 1/500th of the time to develop a model**
- **Forecasting can be done on a hand-held since it simply is a Baseline plus Fluid Effects .**

Model is Decomposed into Fixed and Fluid Effects

- Fixed Effects which reflect variables that are not subject to last minute variation or change
- Fluid Effects which reflect variables that can change at the last minute just prior to the forecast e.g. yesterday's sales, tomorrow's price , tomorrow's weather

Forecasting Equation

$$Y_t = FIXED_t + FLUID_t$$

Sales Volume   Fixed Effects   Fluid Effects

Model is Decomposed into Fixed and Fluid Effects

- Baseline
- Lift (since the history of sales might be in the model this has to be integrated into the forecast)

Model is Decomposed into Fixed and Fluid Components

- Fixed Effects are Holidays, Day-of-the Week , Identified Intervention (Dummy) Variables leading to a Baseline Forecast
- Fluid Effects are Historical Values of Sales, Price,Weather et al which are known at the “Last Minute”.

Partitioning the Forecast

Y_t = FIXED EFFECTS + FLUID EFFECTS

$Y_t = B1X_t + B2I_t + B3Z_t + B4W_t$

BASELINE + ABOXLITE MODEL

where

X_t = user specified input or causal series :FIXED

I_t = Intervention variables found by AUTOBOX :FIXED

Z_t = user specified input or causal series :FLUID

W_t = Historical Sales :FLUID

Market6, Inc

- **Founded in 2001**
- **DemandChain Information Factory**
- **Semi-Custom Services in Supply Chain**
- **Consulting Services**
- **Offices in:**
  - San Ramon. CA. (San Francisco Area)
  - Deerfield, IL (Chicago Area)
- **www.market6.com**

Bringing the Forecasting/Ordering Process to Scale

- **Market6 was founded in 2001 to develop systems that enable store by store, product by product, real time distribution efficiencies**
- **Included in this are:**
  - Sophisticated forecasting techniques
  - Real Time detailed data management
  - Real Time order/forecast distribution
  - Automated systems to monitor and fine tune the above
- **Emphasis on overcoming “real-world” obstacles in the last mile of the supply chain.**

Bringing the Forecasting/Ordering Process to Scale

- **Market6 customers include:**
  - Large Consumer Packaged Goods Companies
  - Large Grocery Retailers

- **Market6 Principals have built and operated systems that maintained on-going daily systems supporting over 140 million forecasts each and every day for over 10 years**

Bringing the Forecasting/Ordering Process to Scale

- **A-B selected Market6 to build a custom environment that will allow A-B to scale the processes described in this presentation**
  - 100s of products
  - 10,000 to over 100,000 distribution outlets
- **We are building this environment in partnership with A-B's internal staff, their selected partners and Automated Forecasting Systems.**

Keys To Success

- Get the Data Right
- Resourcing Forecasts
- Understanding the Computing Requirements and Optimizing Processing Power

Scale

Get the Data Right

- **In the perfect world data for forecasting contains the following unrealistic elements:**
  - Real-time accurate information of product movement on all routes and destinations of the supply chain
  - Accurate information on past and upcoming sales drivers (price, promotion, advertising, competitive activity, and external events)
  - Unlimited processing and networking power to fully utilize all the information

Get the Data Right

- **“Real World” data for forecasting is somewhat less perfect:**
  - Product movement information is generally available for discrete time periods
  - Data is available for shipments to stores and, for some retailers, for sales at store
  - Historical Driver data is incomplete
  - Expectations of selling conditions (future drivers) is incomplete and subject to last minute change

Batched Intelligent Data Integration

Recent data on:
- Product Movement
- Sales Drivers
- Competitive Activity
- Future Sales Drivers

Batched Intelligent Data Integration

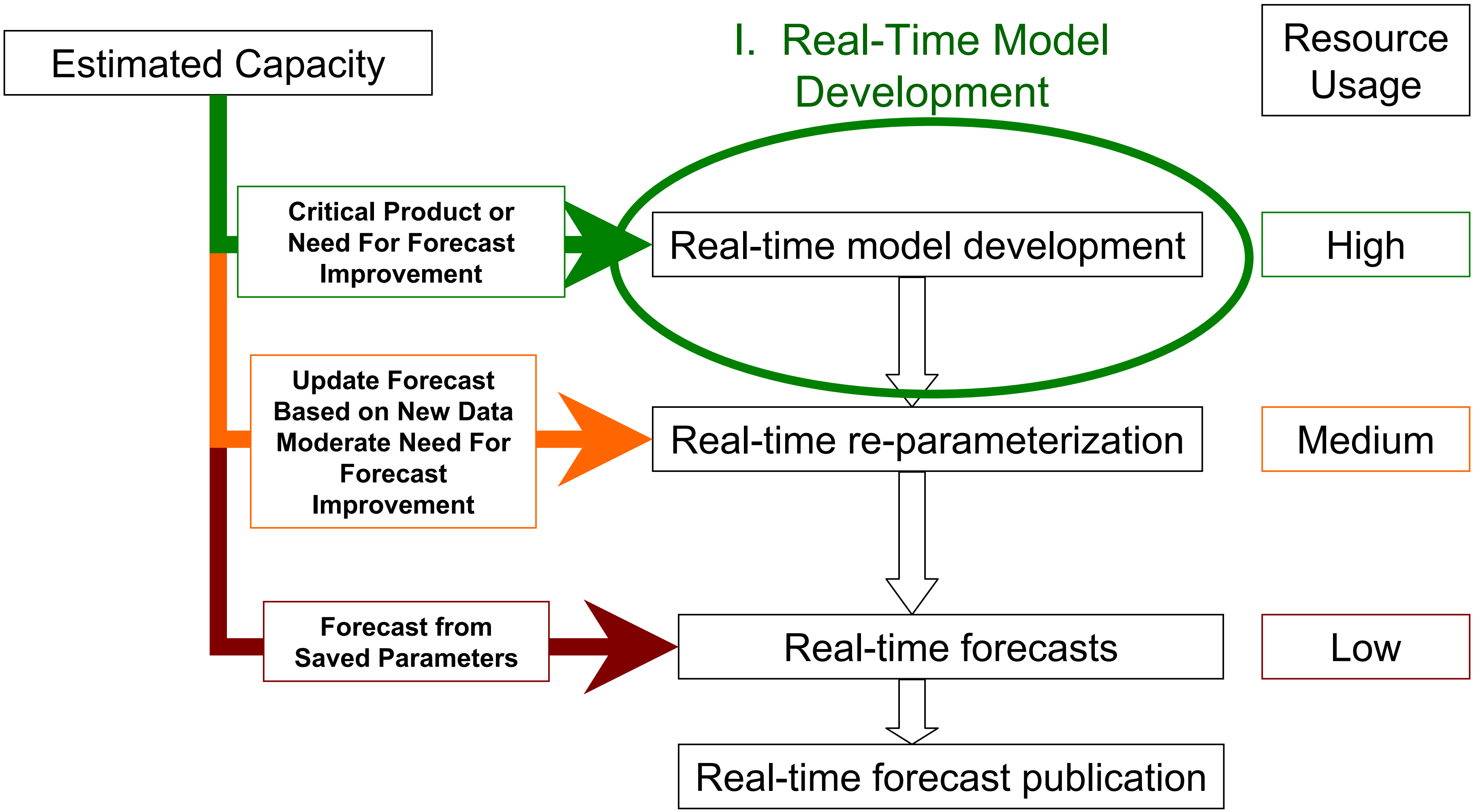
Real-time model development

Real-time forecasts

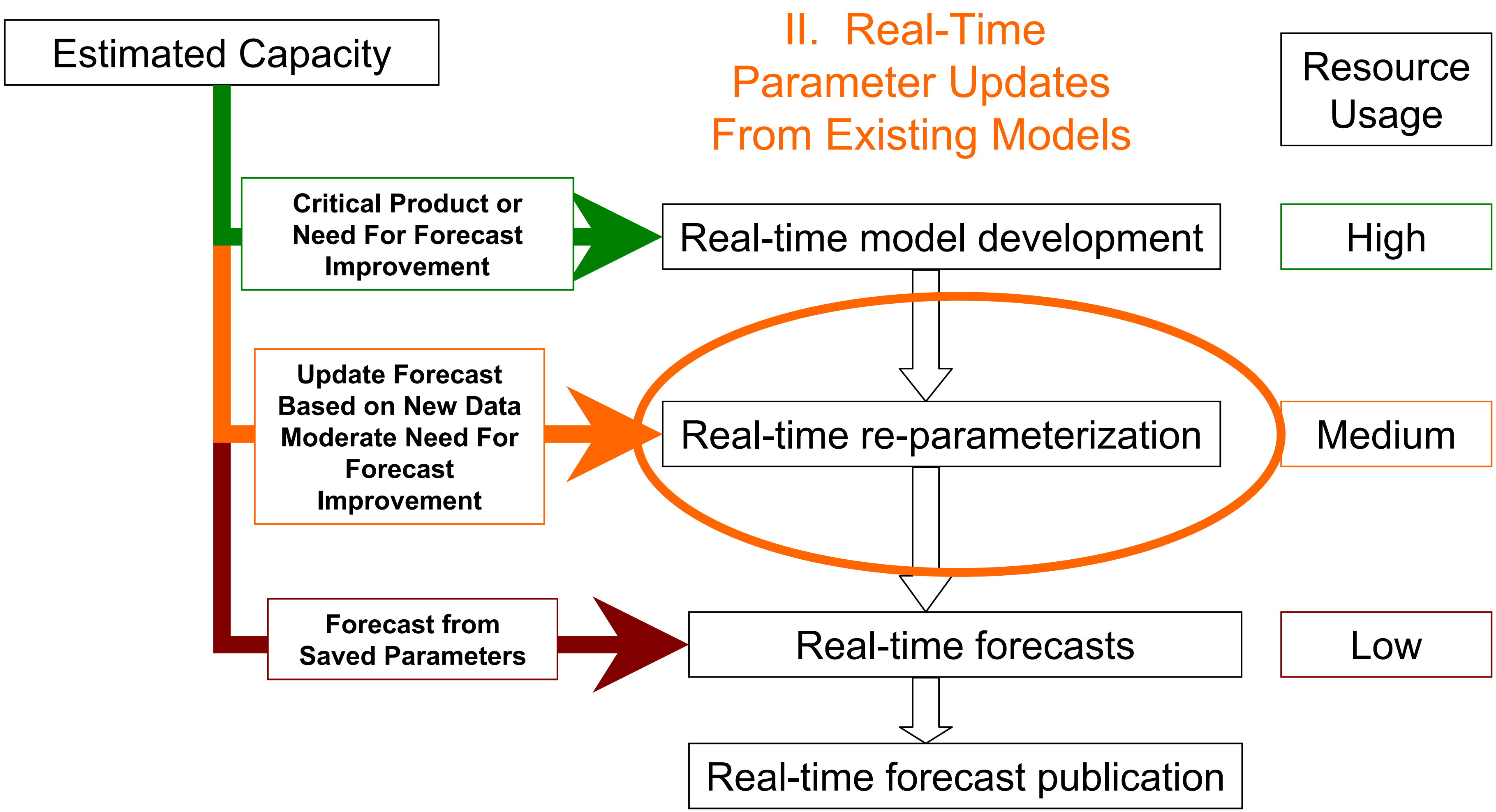
Real-time forecast publication

~~Real-time data integration~~

Real-Time Forecasting
Market6 Intelligent Forecast Process Optimization
Selecting the Forecast Path I



Real-Time Forecasting
Market6 Intelligent Forecast Process Optimization
Selecting the Forecast Path II



Real-Time Forecasting
Market6 Intelligent Forecast Process Optimization
Selecting the Forecast Path III

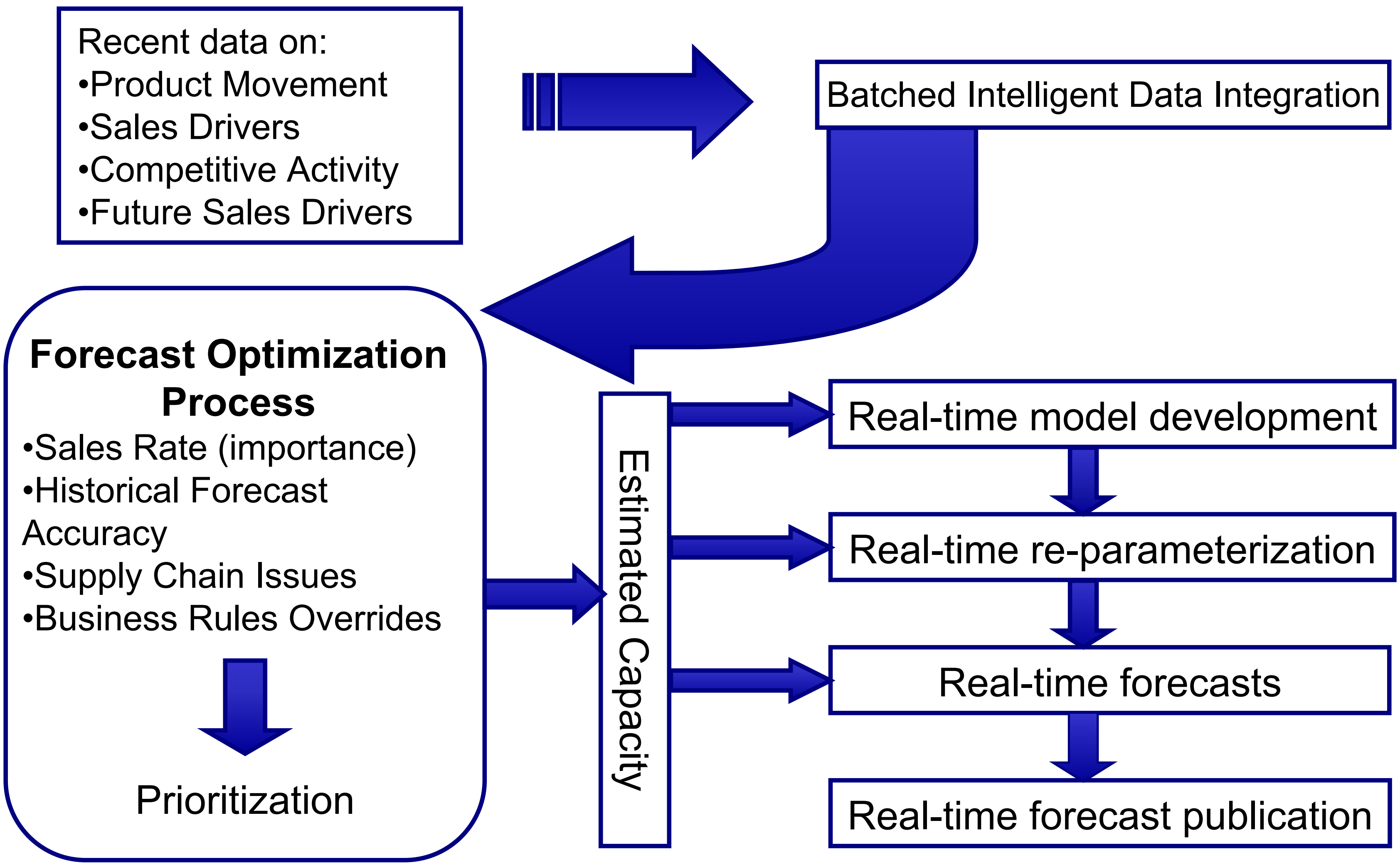
Estimated Capacity

III. Real-Time Forecasts from Existing Models

Resource Usage

Condition	Path	Resource Usage
Critical Product or Need For Forecast Improvement	Real-time model development	High
Update Forecast Based on New Data Moderate Need For Forecast Improvement	Real-time re-parameterization	Medium
Forecast from Saved Parameters	Real-time forecasts	Low
	Real-time forecast publication	

Real-Time Forecasting Part II
Intelligent Forecast Process Optimization



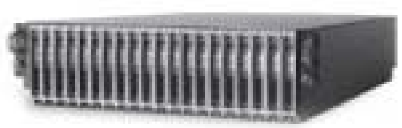
DCIF Architecture

Centralized
Control
System

Typical UNIX server

Central Status Database
Transaction Backups
Data Receipt
Data Aggregation
File Transfers
External Messaging
Internal Messaging

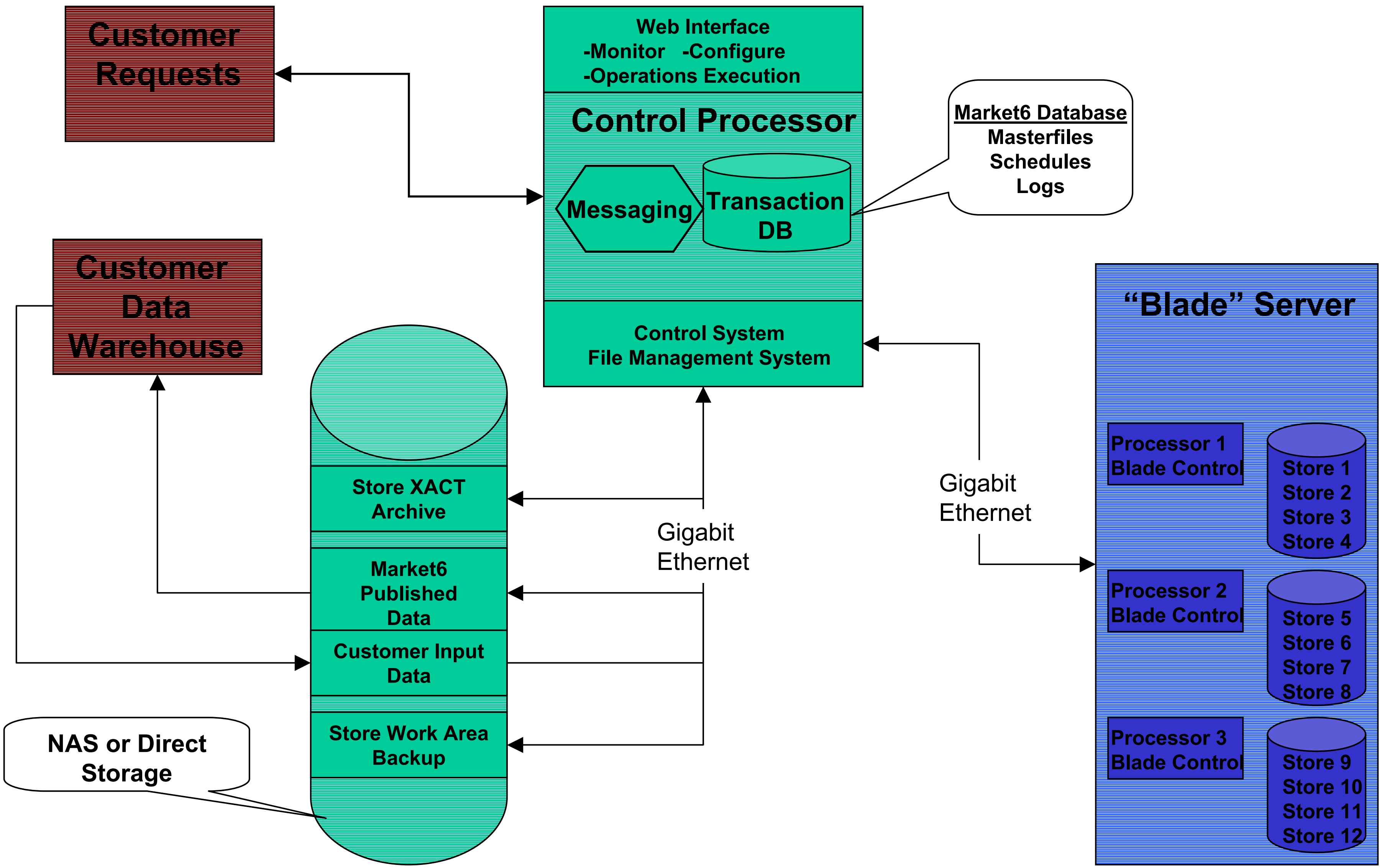
**Concurrent
and Independent
Processes**



Blade Server

<u>Store by Store</u>
Data Verification,
Data Consolidation,
Forecasting,
Publication,
Model Parameter Updates,
Store redundancy
Internal Messaging

Overview
DCIF Architecture



DCIF
DemandChain Information Factory

Adapters, Toolkits & Workbenches

Demand
POS Item Movement
POS Transaction
Frequent Shopper Card
RF-ID
Shipment

Retail Drivers
Display
Feature
Price
FS Price
Inventory

Media Drivers
Electronic
Coupons
Demos

Calendar Drivers
Day of Week
Day of Month
Seasonality
Holiday

Specific Drivers
Weather
Events
New Item
Competitive Activity
Logistics

Item Attributes
Data Catalog
UCCNet
Transora

I. Data Gathering and Communication

II. Integration, Alignment, & Pre-Processing

III. Data Quality and System Control

IV. Factory Engines (Forecast, Out-of-Stock, Promotion)

ERP & Supply Chain Adapter

Corporate Data Warehouse Adapter

Retail Partner Efficiency

Out-Of-Stock Reduction

Promotion Success

New Item Success

Key Account Manager

Marketing Manager

Forecast & Analytics