WHY ARE FORECASTS SO WRONG?
WHAT MANAGEMENT MUST KNOW ABOUT FORECASTING

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ASA WEB LECTURE
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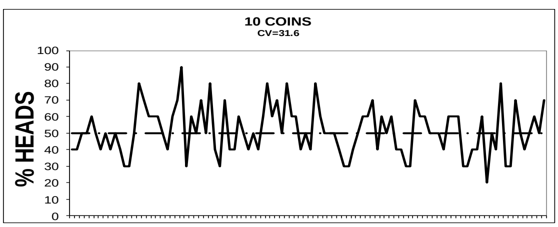
FORECASTING CONTEST

P10: 10 fair coins are tossed

P100: 100 fair coins are tossed

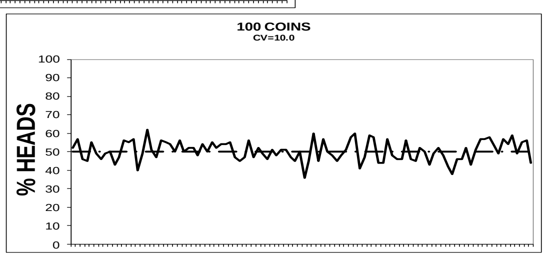
P1000: 1000 fair coins are tossed

What is your forecast for the % of Heads in each daily trial?



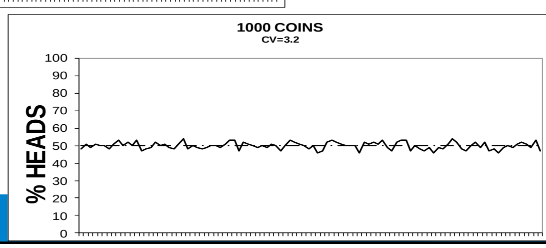
P10

Accuracy = 77.0%



P100

Accuracy = 92.2%



P1000

Accuracy = 97.5%

FORECASTING CONTEST - IMPLICATIONS

- Forecast accuracy is ultimately limited by the *nature of the behavior* being forecast – its *forecastability*
- Understand what forecast accuracy is reasonable to expect
- Seek alternative solutions when forecasting alone can't solve the business problem

OBJECTIVE OF THE FORECASTING FUNCTION

To generate forecasts as accurate and unbiased as you can reasonably expect them to be … and do this as efficiently as possible

WHY FORECASTS ARE WRONG

WHY FORECASTS ARE WRONG

- Unforecastable behavior
  - Not forecastable to the degree of accuracy desired
    - » Nature of the behavior sets a limit on accuracy (e.g. coin tossing)
    - » Must manage operations to account for forecast error – or shape demand to reduce the error

Examples:

- ***Oil prices or interest rates ➔ hedging***
- ***House fires ➔ insurance***

WHY FORECASTS ARE WRONG

- Politicized forecasting process
  - Should be objective, scientific, dispassionate
  - Should be an "unbiased best guess"
    - » Instead expresses the personal agendas of forecasting process participants

Examples:

- ***Soliciting sales rep forecasts for quota setting***
- ***Product manager forecast for new product***

WHY FORECASTS ARE WRONG

- Inexperienced / untrained forecasters
  - Understanding of forecast modeling?
  - Understanding of the business?
  - Intuitive understanding of variation and randomness?
    - » Using inappropriate models & methods
    - » Over-adjustment of forecasts ("fiddling")

Examples:

- ***Small adjustments to a statistical forecast***
- ***Overriding forecasts for no good reason***

WHY FORECASTS ARE WRONG

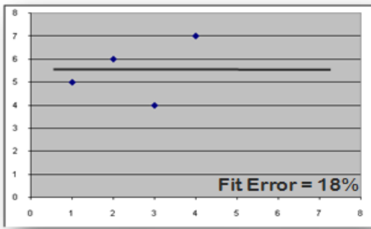
- Inadequate / unsound / misused software
  - Lacks necessary range of model types and capabilities
  - Facilitates inappropriate methods
  - Mathematical errors
  - Sound but misused

Examples:

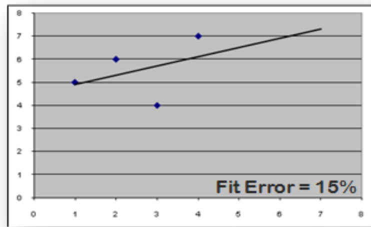
- ***McCulloch, B. "Is It Safe to Assume That Software is Accurate?" International Journal of Forecasting 16 (2000), 349-357.***
- ***Overfitting***

WORST PRACTICES (AND BETTER ALTERNATIVES)

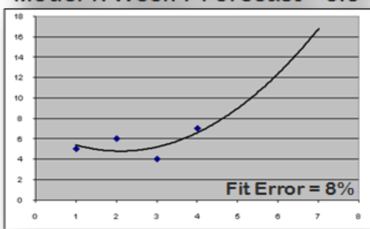
"BEST FIT TO HISTORY" MODEL SELECTION



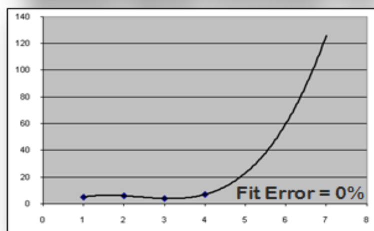
Model 1: Week 7 Forecast = 5.5



Model 2: Week 7 Forecast = 7.2



Model 3: Week 7 Forecast = 16.5



Model 4: Week 7 Forecast = 125

Worst Practice: Confusing "fit to history" with "appropriateness for forecasting"

INAPPROPRIATE ACCURACY EXPECTATIONS

- There is no "magic algorithm" to guarantee perfect forecasts
- Accuracy is determined more by the *nature of the behavior* being forecast than by the methods used
- With unrealistic goals (e.g. call coin toss 60%), people either give up or cheat

Worst Practices:

- ***Squandering resources to pursue unachievable levels of forecast accuracy***
- ***Punishing forecasters for failing to reach unachievable goals***

BETTER PRACTICE: USE NAÏVE FORECAST

- Perhaps the only reasonable forecasting performance goal:

Do no worse than a naïve model

- The naïve forecast sets the baseline against which all other methods are evaluated

GOALS BASED ON INDUSTRY BENCHMARKS

- Three potential problem areas
  - Self-reported survey data, or audits?
  - Lack of common definitions / standards
    - What metric (MAPE, MAD, RMSE, Accuracy?)
    - What level of product and location?
    - What time bucket (week, month?) and lead time lag
  - No consideration of "forecastability" of the demand

See Stephan Kolassa, "Can We Obtain Valid Benchmarks from Published Surveys of Forecast Accuracy?" *Foresight*, Fall 2008.

IGNORING DEMAND VOLATILITY

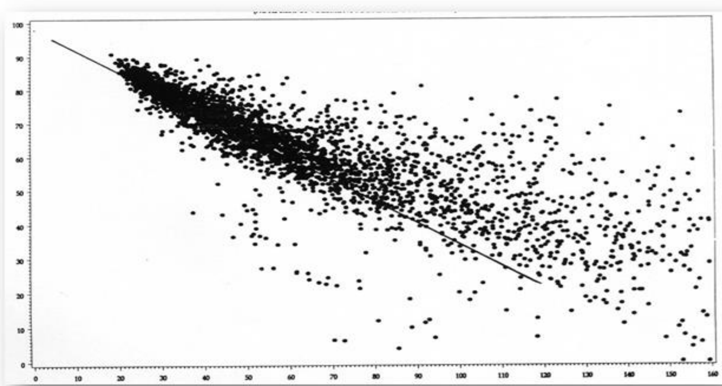
- Volatility (i.e. variability) of a demand pattern is an important consideration in forecasting
  - Low volatility ➔ easier to forecast
  - High volatility ➔ generally more difficult to forecast

- Volatility is measured by the coefficient of variation:

CV = Standard Deviation / Mean

BETTER PRACTICE: COMET CHART

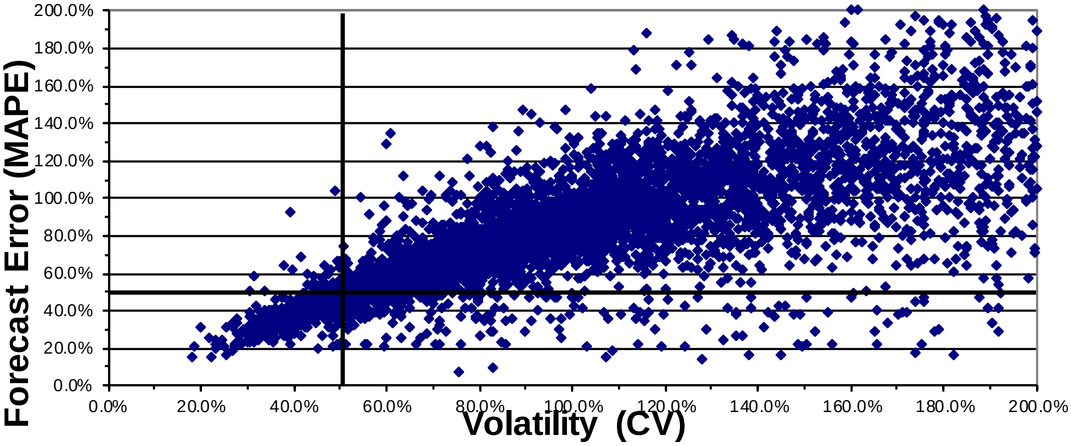
Forecast Accuracy



Volatility (CV)

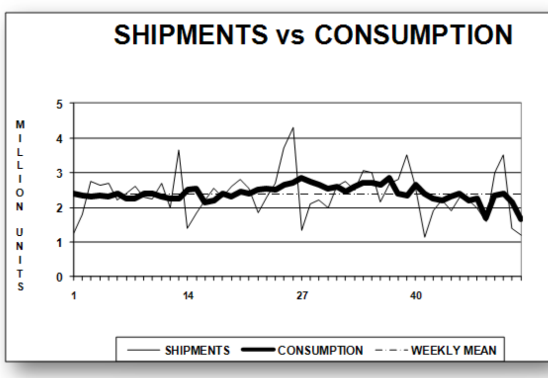
Reducing volatility will likely result in better forecasts

BETTER PRACTICE: COMET CHART



- 36 months of data for 6000 items
- 87% of items had both MAPE and CV > 50%

ADDING VARIATION TO DEMAND



Shipment Volatility is 3X Consumption Volatility

Identify *inherent* volatility and *artificial* volatility

BETTER PRACTICE: FIND WAYS TO REDUCE VOLATILITY

- Re-engineer incentives to encourage predictable demand
- Product design (modularity / common components / postponement) – fewer things to forecast
- Inventory / distribution network design
- Avoid SKU proliferation – prune obsolete items

The surest way to get better forecasts is to make the demand forecastable

FORECAST VALUE ADDED

DEFINITION OF FORECAST VALUE ADDED

Forecast Value Added ≡

The change in a forecasting performance metric that can be attributed to a particular step or participant in the forecasting process

RELATIVE ERROR METRICS

Theil's U =

RMSE / RMSE of naïve model

- The closer Theil's U is to 0, the better the model
- Theil's U < 1.0 indicates value added
- Theil's U > 1.0 indicates making the forecast worse

RELATIVE ERROR METRICS

Relative Absolute Error (RAE) =

| forecast error | / | naïve forecast error |

- RAE closer to 0 is better
- RAE < 1 means positive FVA "adding value"
- RAE > 1 means negative FVA

RELATIVE ERROR METRICS

RAE ~ 0.5 is "best case" forecast error you can expect to achieve

RAE > 0.5 is "avoidable error"

TYPICAL BUSINESS FORECASTING PROCESS

DATA	• Historical "demand" (e.g., orders, shipments, sales, etc.) • Historical (and future) pricing, promotional activity, competitive activity, weather, events, etc.
FORECASTING SOFTWARE	• Used for developing models and generating a forecast (e.g. SAS Forecast Server, SAS Forecasting for Desktop, or often just Excel)
STATISTICAL FORECAST	• Forecast generated by the forecasting software
OVERRIDE FORECAST	• Manual adjustment to the statistical forecast by forecast analyst / demand planner
CONSENSUS FORECAST	• Manual adjustment to the forecast by consensus/collaboration • May involve Sales, Marketing, Finance, Operations, CPFR, etc.
APPROVED FORECAST	• "Final" forecast as adjusted/approved by executive management • Feeds into downstream planning systems

FAILINGS OF TRADITIONAL METRICS

- Dozens of forecasting performance metrics available
  - Some flavor of MAPE is the most commonly used
- Traditional metrics like MAD or MAPE tell you the size of your forecast error
- But the traditional metrics <u>*by themselves*</u> are not sufficient for properly evaluating performance:
  - They do not account for underlying "forecastability"
  - They do not indicate what error you should be able to achieve
  - They do not measure the efficiency of your process

WHAT IS FVA ANALYSIS?

- The application of scientific method to forecasting

H_0: Your forecasting process has no effect

- FVA Analysis attempts to determine whether forecasting process steps and participants are improving the forecast – or just making it worse

NAÏVE FORECAST AS A PLACEBO

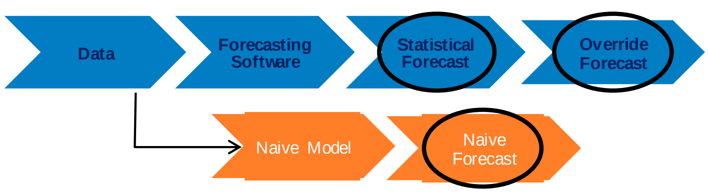
Analogy: Evaluating a new drug by comparing to a control group (receiving a placebo)

- Naïve forecast serves as the placebo in evaluating forecasting process performance
  - Provides a reference standard for comparisons
  - Is the forecasting process "adding value" by performing better than the placebo?

FVA ANALYSIS: SIMPLE EXAMPLE

- Consider a very simple forecasting process:

FVA ANALYSIS: SIMPLE EXAMPLE



- FVA Analysis compares the performance of the statistical forecast to the performance of the analyst's override forecast
- FVA Analysis also compares both to a "naïve" forecast

FVA "STAIRSTEP" REPORT

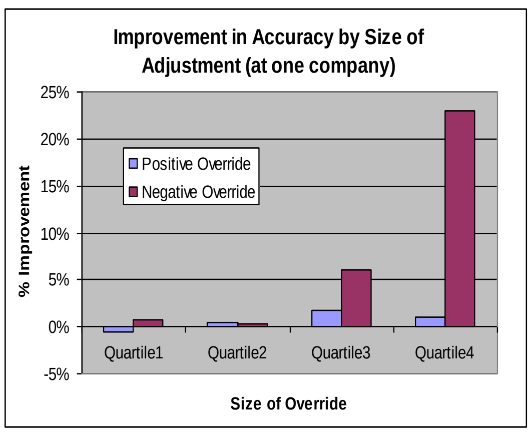
Process Step	Forecast Accuracy	FVA vs. Naïve	FVA vs. Statistical
Naïve Forecast	60%	-	-
Statistical Forecast	65%	5%	-
Analyst Override	62%	2%	-3%

Source: IBF conference presentation by Newell Rubbermaid, 2011.

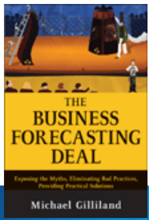
- Can report on an individual time series, or for an aggregation of many (or all) time series
  - If you are doing better than a naïve forecast, your process is "adding value"
  - If you are doing worse than a naïve forecast, then you are simply wasting time and resources

ACADEMIC RESEARCH

- Studied 60,000 forecasts at four supply chain companies
- 75% of statistical forecasts were manually adjusted
- Large adjustments tended to be beneficial
- Small adjustments did not significantly improve accuracy and sometimes made the forecast worse
- Downward adjustments were more likely to improve the forecast than upward adjustments

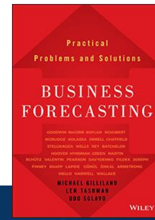


Source: Robert Fildes and Paul Goodwin, "Good and Bad Judgment in Forecasting." *Foresight*, Fall 2007.



The Business Forecasting Deal

Business Forecasting: Practical Problems and Solutions



FOR MORE INFORMATION ON FVA

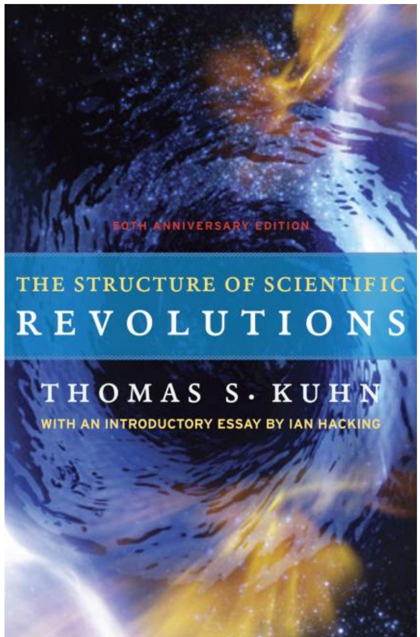
What Management Must Know About Forecasting (SAS whitepaper)

Forecast Value Added Analysis: Step-by-Step (SAS whitepaper)

FVA: A Reality Check on Forecasting Practices (*Foresight* 29, Spring 2013)

The Business Forecasting Deal (blogs.sas.com/content/forecasting)

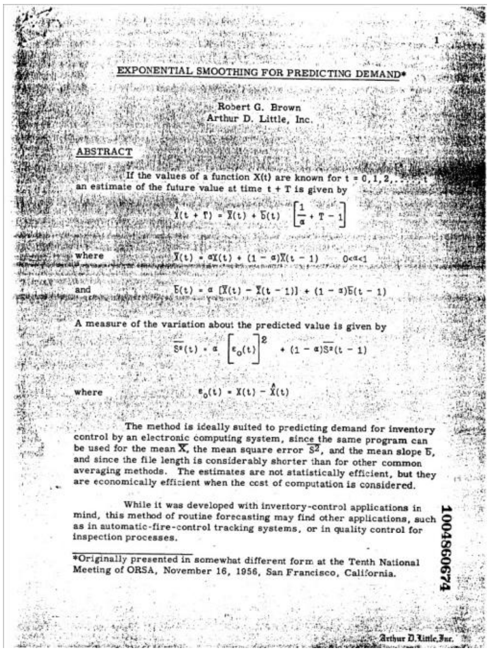
CHANGING THE PARADIGM FOR BUSINESS FORECASTING



Paradigms organize our perceptions…

…and make them understandable

Normal Science



1

EXPONENTIAL SMOOTHING FOR PREDICTING DEMAND*

Robert G. Brown
Arthur D. Little, Inc.

ABSTRACT

If the values of a function X(t) are known for t = 0, 1, 2, ..., t an estimate of the future value at time t + T is given by

$$\hat{X}(t + T) = \bar{X}(t) + \bar{b}(t) \left[\frac{1}{\alpha} + T - 1\right]$$

where $$\bar{X}(t) = \alpha X(t) + (1 - \alpha)\bar{X}(t - 1) \qquad 0<\alpha<1$$

and $$\bar{b}(t) = \alpha\,[\bar{X}(t) - \bar{X}(t - 1)] + (1 - \alpha)\bar{b}(t - 1)$$

A measure of the variation about the predicted value is given by

$$\overline{S^2}(t) = \alpha \left[\varepsilon_0(t)\right]^2 + (1 - \alpha)\overline{S^2}(t - 1)$$

where $$\varepsilon_0(t) = X(t) - \hat{X}(t)$$

The method is ideally suited to predicting demand for inventory control by an electronic computing system, since the same program can be used for the mean $\bar{X}$, the mean square error $\overline{S^2}$, and the mean slope $\bar{b}$, and since the file length is considerably shorter than for other common averaging methods. The estimates are not statistically efficient, but they are economically efficient when the cost of computation is considered.

While it was developed with inventory-control applications in mind, this method of routine forecasting may find other applications, such as in automatic-fire-control tracking systems, or in quality control for inspection processes.

*Originally presented in somewhat different form at the Tenth National Meeting of ORSA, November 16, 1956, San Francisco, California.

Arthur D. Little, Inc.

CHARACTERISTICS OF THE "OFFENSIVE" PARADIGM

- More is better
  - More data
  - More computational power
  - More complex forecasting models incorporating more variables
  - More elaborate collaborative processes

The Paradigm Limits What You See


(c) 2010 Daniel J. Simons

Anomalies:
The Beginning of a Crisis

The Crisis
in Business Forecasting

HIGH ON COMPLEXITY

Paul Goodwin, "High on Complexity, Low on Evidence: Are Advanced Forecasting Methods Always as Good as They Seem?" *Foresight*, Fall 2011.

- Analytical Network Process
- Seasonal Hybrid Procedure

Is Complexity Bad?

SIMPLE VS. COMPLEX FORECASTING

- Review of 32 papers, reporting on 97 comparative studies

None of the papers provides a balance of evidence that complexity improves forecast accuracy.

Remarkably, no matter what type of forecasting method is used, complexity harms accuracy.

…the need for complexity has not arisen.

Kesten Green and Scott Armstrong, "Simple versus Complex Forecasting: The Evidence." *Journal of Business Research* 68 (2015)

Implications for the Offensive Paradigm

Changing the Paradigm for Business Forecasting

Why the Attraction for the Offensive Paradigm?

WHY THE ATTRACTION?

- Forecasters' clients may be reassured by incomprehensibility
- Resistance to simple methods
- Complexity is often persuasive
- Researchers are rewarded for publishing in highly ranked journals which favor complexity
- Forecasters can use complex methods to provide forecasts that support decision makers' plans
- Can add complexity to a model to better fit the history

The New Paradigm for Business Forecasting

The “Defensive” Paradigm

Role of the Naïve Model

The Objective

To generate forecasts as accurate as can reasonably be expected…and to do this as efficiently as possible

Research Agenda Under the Defensive Paradigm

Identify and eliminate worst practices

The Aphorisms for the new Defensive Paradigm

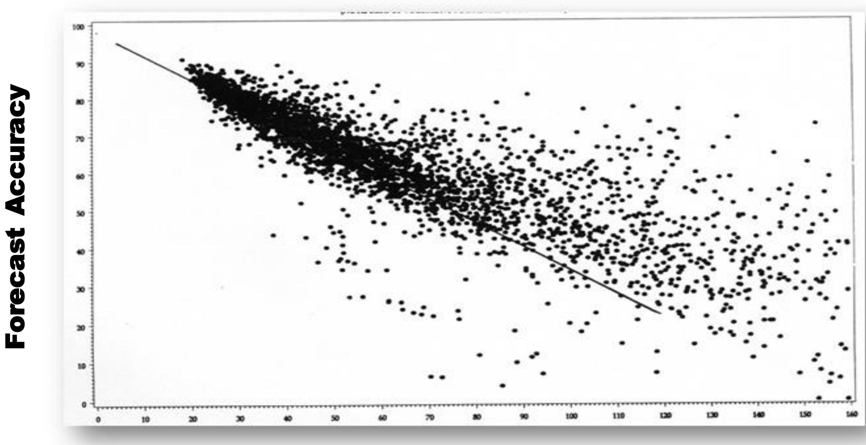
APHORISM 1

Forecasting is a Huge Waste of Management Time

APHORISM 2

Accuracy is Limited More by the Nature of the Behavior Being Forecast than by the Specific Method Being Used to Forecast It

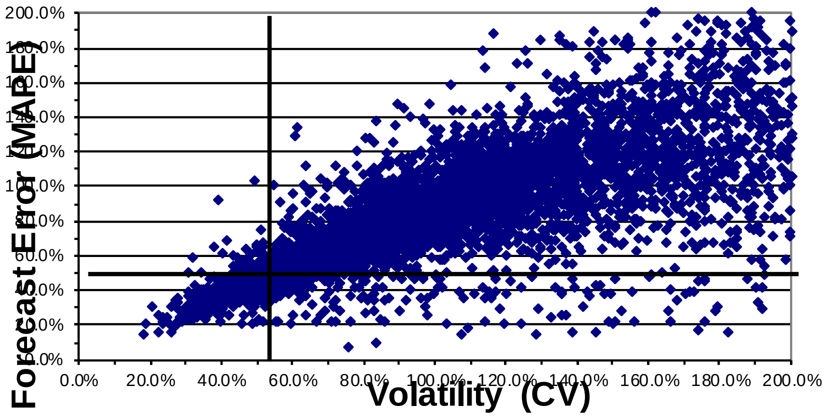
Comet Chart



Volatility (CV)

Reducing volatility will likely result in better forecasts

Comet Chart



- 36 months of data for 6000 items
- 87% of items had both MAPE and CV > 50%

APHORISM 3

Organizational Policies and Politics Can Have a Significant Impact on Forecasting Effectiveness

APHORISM 4

You May Not Control the Accuracy Achieved, But You Can Control the Process Used and the Resources You Invest

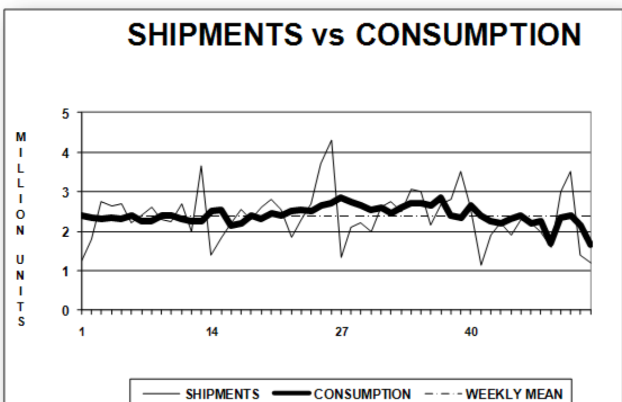
- Determine what level of accuracy is reasonable to expect
- Achieve this accuracy with the least cost in time and resources
- Automate wherever possible

Corollary: Do not squander resources in pursuit of unrealistic accuracy goals

APHORISM 5

The Surest Way to Get a Better Forecast Is to Make the Demand Forecastable

Identify *inherent* volatility and *artificial* volatility



Shipment Volatility is 3X Consumption Volatility

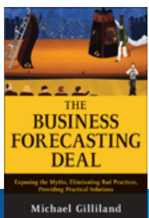
Corollary: Any knucklehead can forecast a straight line

APHORISM 6

Minimize the Organization's Reliance on Forecasting

APHORISM 7

Just stop doing the stupid $#!+



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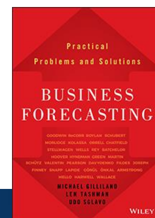
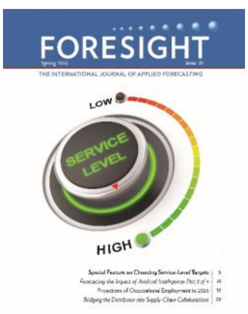


FURTHER READING



Foresight: The International Journal of Applied Forecasting

The Little Book of Operational Forecasting

Contact: mike.gilliland@sas.com