

2019 CPDF Workshop Manual

Smarter Forecasting and Planning

Dr. Hans CPDF®

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Errata: www.cpdftraining.org/errata.htm

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Certified Professional Demand Forecaster (CPDF®)

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WHY Demand Forecasting Is So Important to Supply Chain Professionals and Managers

The Supply Chain

1. Analyzing Customer Demand: What should we make and when?

Based on customer demand, product design, cost, and pricing considerations, the ice cream manufacturer (as in Cases 1A, 3A–8A, 10A, 13A–15A) sets the supply chain in motion. For instance, cocoa beans for making chocolate will be sourced from Africa or South America.



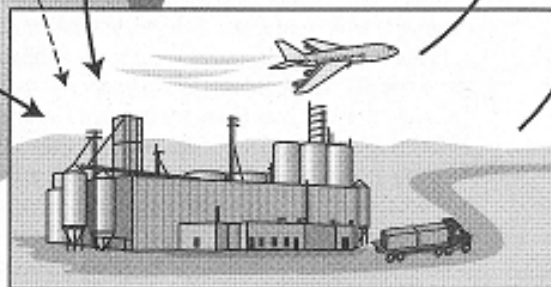
3. Bill of Materials: Are we producing the right amount of the right product?

Pulling together components and knowing exactly how many components are needed for a given product, manufacturers utilize demand signals to assure the most efficient and cost effective manufacturing process.

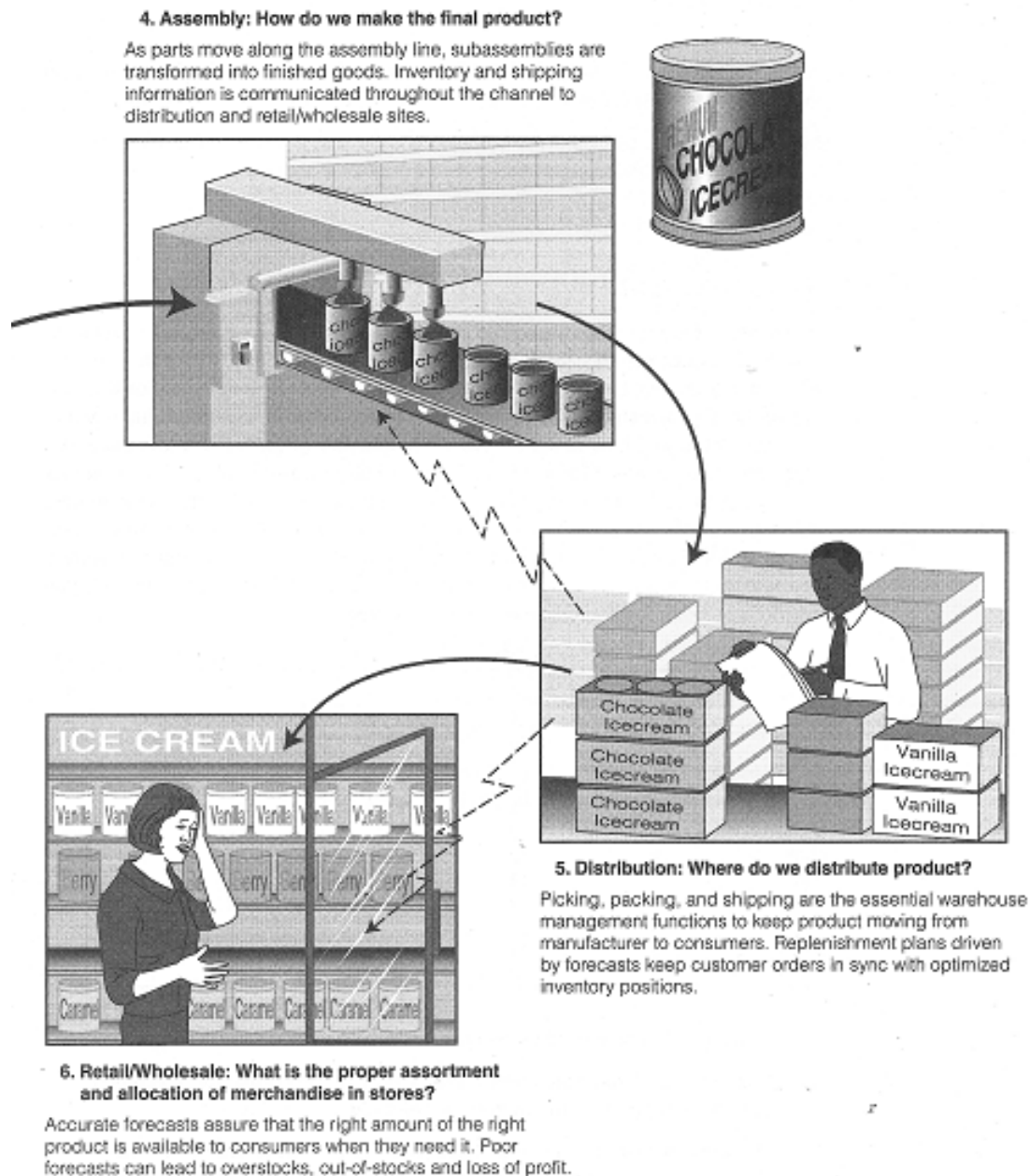


2. Raw Material: Who do we buy from and how much?

Using timely order forecasts, the manufacturer orders raw materials from suppliers worldwide. For instance, a supplier of chocolate obtains cocoa beans from a number of overseas locations. When raw materials or parts are sourced overseas, shipping may need to comply with tariffs and trade agreements. This results in lead-time variation in demand patterns.



THE GLOBAL SUPPLY CHAIN OF AN ICE CREAM MANUFACTURER



CPDF Smarter Forecasting and Planning

Day 1

Part 0 - Pre-course Computer Workshop

Part I - Why Demand Forecasting is So Important to a Planning Cycle in the Supply Chain

What is demand forecasting?

Demand Forecasting and the evolution of Supply Chain

Who will use the forecast and what are their data needs?

Forecasting as a structured process- The PEER Model

Workshop A: Targeting the Environment - How to Uncover Drivers of Demand for Products and Services

Part II - Improving Data Quality through Data Exploration and Visualization

Data exploration- Learning from actual examples

Judging the quality of data

Handling unusual events and outliers

What are forecasting models?- Quantitative vs. qualitative methods

Evaluating forecasts and forecasting models

Combining and reconciling the final forecast

Computer Workshop B: Exploring Trend and Seasonal Variation.

Part III - How To Use Components of a Time Series

Moving averages for smoothing kinks out of data

Finding the lift in promotions with moving medians

Identifying day-of-week effects through ANOVA methods

Creating additive and multiplicative seasonal factors

Seasonal adjustment of time series

Computer Workshop C: Creating Projections with the Adjustments with RMA Decomposition Technique.

Part IV - Baseline Forecasting with State Space Forecasting Models

Why use Naïve forecasting techniques?

Types of smoothing weight

Forecasting profiles for exponential smoothing

Applying univariate time series techniques

Handling special events with exponential smoothing model

Scenario forecast

Product lifecycle

Computer Workshop D: Automated, Data-driven Baseline Forecasting with Exponential Smoothing Models

Day 2

Part V - Big Data: Data Mining, Exploration and Quality Management

Predictive Analytics- something new?

Methodologies for large-scale data exploration

Basic statistical tools for summarizing data

Traditional and nonconventional measures of variability

Data framework for demand forecasting in the cloud

Identifying criteria for assessing data quality

Handling exceptions in large data sets

Data process frameworks and job checklists

Computer Workshop E: Data Exploration, Outlier Correction, and Predictive Visualization

Part VI - Forecasting Short-term Trends with ETS State Space Forecasting Models

Creating a flexible model building strategy

Detecting autocorrelation in time series

Identifying seasonal and non-seasonal ARIMA models

Diagnostic checks and ARIMA modeling checklist

Computer Workshop F- How to Create Short-term Trend and Seasonal ARIMA Models

Part VII - Taming Uncertainty: What You Need to Understand about Measuring Forecast Accuracy

Basis of accuracy measurement- Bias and Precision

Forecasting errors and waterfall charts

Goodness of fit versus forecast performance

Cost of inaccurate forecasts

Traditional and conventional accuracy measurement

Computer Workshop G- Improve Forecast Accuracy Through Gap Analysis and Exception Reporting

Part VIII - Graphical Tools for Forecast Process Improvement

Ladder charts for monitoring forecast modeling results

Prediction- Realization diagrams and business cycles

Prediction intervals for controlling judgemental overrides

Cumulative tracking signals- Trigg's approach

Computer Workshop H- How to Visually Track and Monitor Forecasting Performance

Part IX - Implementing Demand Forecasting Within an Integrated Business Planning Process

The Delphi Method

The forecasting audit

A framework for setting forecasting standards

Planning for process improvement

Overcoming barriers and closing gaps

CPDF Smarter Forecasting and Planning

Day 3

Part X – Practical Uses of Predictive Analytics Modeling for Business Planning

Marketing– Promotion planning
Sales– Pricing; Elasticities
Operations– Safety stock and inventory forecasting
Finance– Rolling forecasts and budgeting

Computer Workshop I: Using a Time-phased Order Forecasting Model for Customer Replenishment Planning

Part XI – Designing Regression Models for Demand Forecasting

Finding a linear association between two variables
Checking ordinary correlation with a nonconventional alternative
What are regression model assumptions?
What is a "best" fit?
The least square assumption demystified
The ANOVA table output for regression analysis
Paring the output for use in forecasting
Creating forecasts and prediction limits

Computer Workshop J– Using Causal Models for Advertising and Promotion Analysis

Part XII– Taming Volatility— Root Cause Analysis and Exception

Dealing with lack of normality in time series regression modeling
Looking out for "Black Swans"
How good was the fit and what does it say about forecasting ?
Dealing with nonrandom patterns in residuals
Impact of error term assumptions on prediction interval determination
Creating prediction intervals for forecast monitoring
Using prediction limits for quantifying uncertainty in forecasts
A checklist for multiple linear regression

Computer Workshop K - Working with Residuals and Forecast Errors to Improve Forecasting Performance

Part XIII - Improving Forecasts with Informed Judgment

When to make judgmental adjustments to forecasts
Judgmental traps in forecasting
Melding quantitative and qualitative approaches for forecast development and process improvement
Creating the final forecast with Change and Chance numbers

Computer Workshop L– GLOBL Case:

Simulating The Forecasting Work Cycle (You may bring your own data).
Global Electronics Manufacturer (a fictitious company) provides consumer electronic technology products to a broad range of customers worldwide
Participants will evaluate and reconcile forecasts and prediction limits for three product lines based on univariate exponential smoothing and multiple linear regression models.

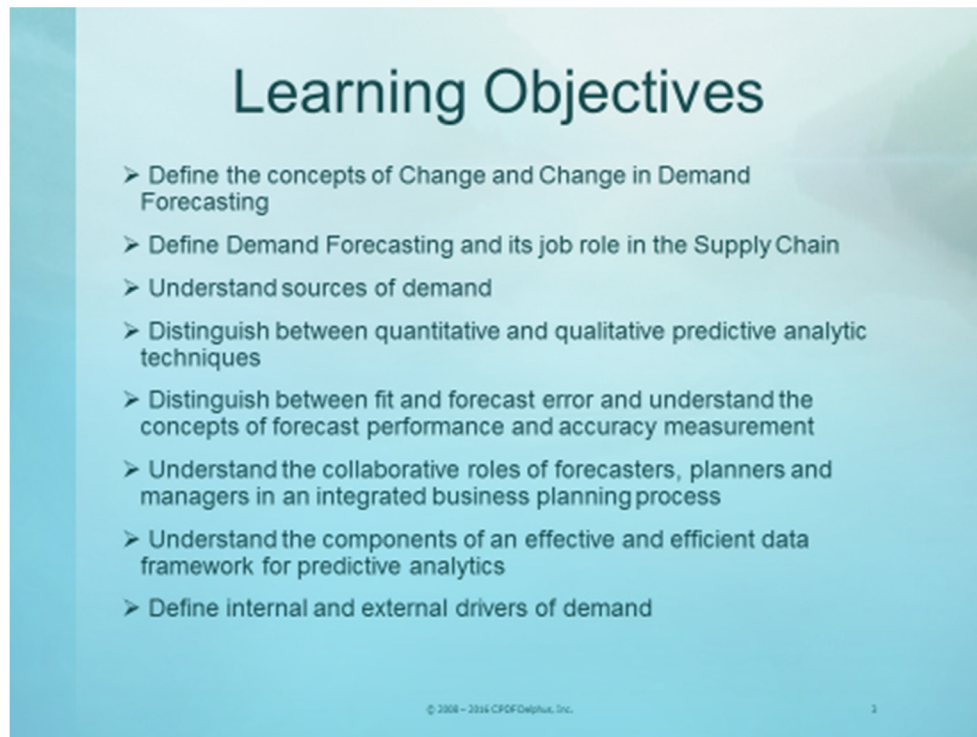
Workshop Take-Aways and Closing Remarks





Part I

Why Demand Forecasting is So Important to a Planning Cycle in the Supply Chain



What You Should Be Able To Do

After completing this topic, you should be able to:

- Explain the nature of a demand forecast in a consumer-driven supply chain environment
- Understand why it is a necessary discipline for supply chain planners to become familiar with
- Recognize the components of an agile forecasting cycle
- Engage with a potential user to define their forecast requirements
- Make recommendations on a forecast review, checklists and measurement activities

How You Will Check Your Progress

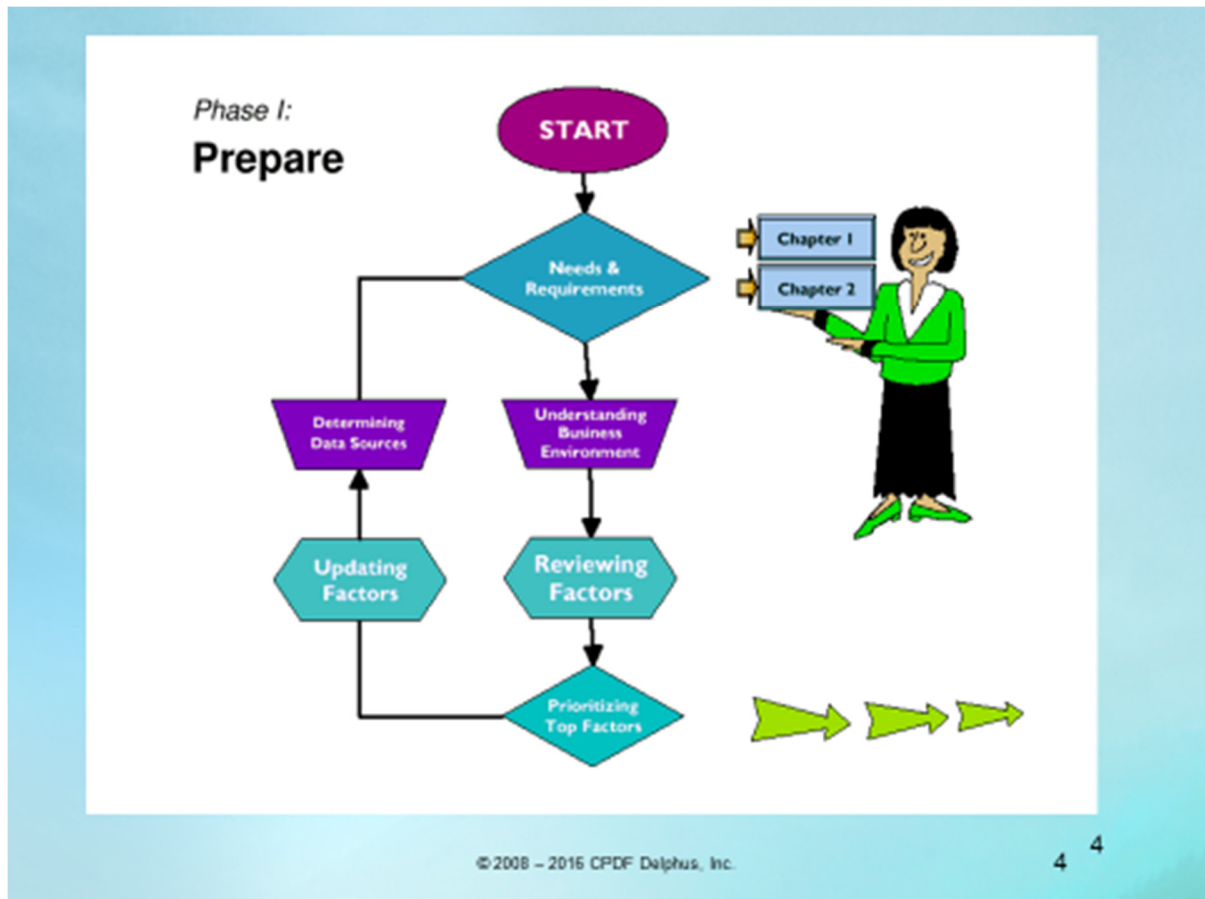
Develop a needs analysis checklist for your job, incorporating such issues as

- Who will need to use a forecast?
- What are their data needs?
- How, when, where and by whom the demand forecasting job is performed
- What data and driver information do they need from the forecaster?

Resources

1. **H. Levenbach (2017) Embracing Change&Chance: Achieving Agility with Smarter Forecasting in the Supply Chain– Chapter 1.** Henceforth, abbreviated as C&C.
2. A sample checklist for demand forecasting principles can be downloaded from http://www.cgdev.org/doc/ghprn/Demand_Forecasting_Principles,Sept-06.pdf

Step 1 - The Preparation phase in the PEER process



Step 1 - What is the Preparation phase in the Forecasting and Planning process?

- It takes a systematic process to efficiently execute a recurring forecasting cycle
- Typical forecasting cycles are monthly (e.g., Automotive), although weekly (e.g., FMCG), daily and hourly (e.g. Electricity) cycles are also common
- First step in the process is the collection of historical data, updated assumptions, including the latest month's actual – This is the Prepare step
- The Prepare step has several sub-parts, but the process is not sequential
- More often than not, it requires a feedback loop, which allows you to update or modify data and information before proceeding to the next step.
- The avatar holding the labeled boxes is referring to the Chapters 1 and 2 of the text book describing this in more detail. The original source is **Forecasting: Practice and Process for Demand Management** by H. Levenbach and J.P. Cleary (2005).

What Is Demand Forecasting for Fast Moving Consumer Goods (FMCG) All About?

- Demand Forecasting for Fast Moving Consumer Goods has all the usual challenges of sales forecasting, but is characterized most of all by the high impact of promotions carried out by companies and their competitors.
- Frequent promotional activity complicates the already difficult tasks of historical data cleansing and seasonal analysis
- There is the task of estimating and integrating the effect of future promotions into the forecast.
- Although many companies choose to forecast on a weekly rather than monthly basis for various practical reasons, the dominance of promotions in FMCG weighs heavily towards weekly forecasting.
- With weekly forecasting, seasonal analysis becomes more difficult. FMCG forecasting is most commonly approached using time series forecasting such as exponential smoothing, but the possibilities for causal analysis such as price sensitivity analysis should not be overlooked.
- What the FMCG forecaster often benefits from is a wide range of information including EPOS data and continuous market research information.
-

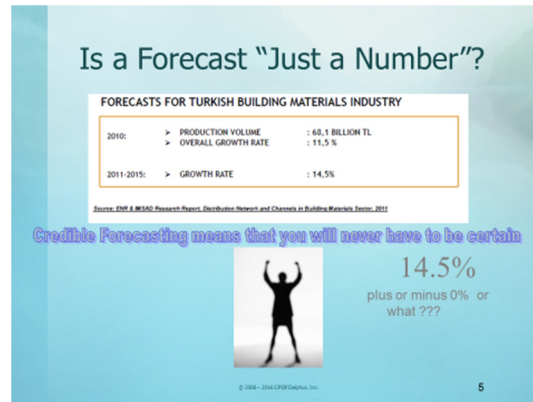
Example: China FMCG Industry

The drop is largely driven by a slowdown of consumption in Asia where FMCG growth is now at 5.2%, down 3.6 percentage points compared with last year – some \$15 billion. The contraction was felt acutely in China where FMCG growth has fallen by a third in the past two years from 15.8%, in the 12 months ending June 2012, to 5.6% in the period ending June 2014.

“China makes up 69% of the emerging Asian market and influences the whole region. Packaged food is the largest element of Chinese consumers’ budgets and sales have been particularly affected by the overall slowdown, growing by just 1.8% compared with 16.0% in the 12 months ending June 2012. China’s FMCG momentum will resurge when growth on packaged food spending recovers.

Credible forecasting means that you will never have to be certain. Uncertainty is a certain factor!

Question: Is a forecast 'just a number'?



Example: 2018 Economic Forecasts - Latin America




Brazil, Colombia, Chile, Mexico LATIN AMERICA Growth to pick up in 2018 but risks to outlook are high Argentina Peru Venezuela Buoyed by business-friendly reforms adopted by the Macri administration, the economy is expected to rebound A strengthening mining sector and growing infrastructure investment to sustain growth The economy to remain vulnerable to fluctuations in global commodity prices Political noise is holding back economy's strength Pre-election spending to lift growth As oil prices continue to ascend, crippling political uncertainty persists Earthquakes and slower private consumption growth to weaken economic growth 2.3 % 2.7%, 3.9%, 2.8 %, 3.0 %, 2.3 % - 3.2 % Focus Economics Consensus Forecast for Latin America, October 2017-2018 GDP Growth Forecasts for select countries (Annual Variation in %)

A Demand Forecast Is All About CHANGE and CHANCE

One forecast number
can imply many
different decisions

For example,

- 14.5 % +/- 0 %
- 14.5 % +/- 2 %
- 14.5 % + 3 or -1 %



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Why is a forecast more than just a number?


- The 14.5% is the number and represents **CHANGE**
- The 'plus or minus' range represents the measured or quantified uncertainty ;it represents **CHANCE**
- A sound, credible demand forecast should have both components to be meaningful for decision-making
- A forecasting *method* (e.g. moving average) can only be used to make point forecasts (CHANGE.)

With a forecasting **model**, you can create forward-looking numbers and quantify uncertainty (*CHANGE & CHANCE*.).

With a forecasting **method**, this is not possible; You can just get numbers.

Demand Forecasting Defined

- Demand Forecasting is all about *numbers* (CHANGE) and *uncertainty* (CHANCE)
- Demand is about the quantity of health outcomes needed by a particular population
- Revolves around predicting future quantities needed by consumers & customers with the ability to pay, BUT
 - Excludes forecasting natural disasters (floods, earthquakes, etc.), and forecasting weather, stocks and sports, election results, etc.
 - And must **not** be confused with Business Planning as a business function!



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What is demand forecasting and how is it distinguished from planning?

- Generally, forecasting is a process that has as its objective the prediction of future events or conditions. More precisely, forecasting attempts to predict change in the presence of uncertainty. Forecasting is all about CHANGE & CHANCE.
- In particular, **Demand Forecasting** is the process of predicting future customer/consumer demand for a firm's goods and services in a supply chain.
- Business forecasting has a more broad usage and could involve forecasting business trends, future economic developments, budget forecasting and forecasting financial markets
- **Planning**, on the other hand, is defined (in Webster's) as the act of constructing a detailed program of action. It carries many similarities with forecasting. However, 'planning' has as its main objective laying out the best course of action to reach a goal. Planning and demand forecasting are often performed by the same people in an organization, but are fundamentally different disciplines, each having its own objectives, skill sets and job descriptions.
- Planning can be viewed as a *complicated* process, in contrast to Forecasting, which is a *complex* process.

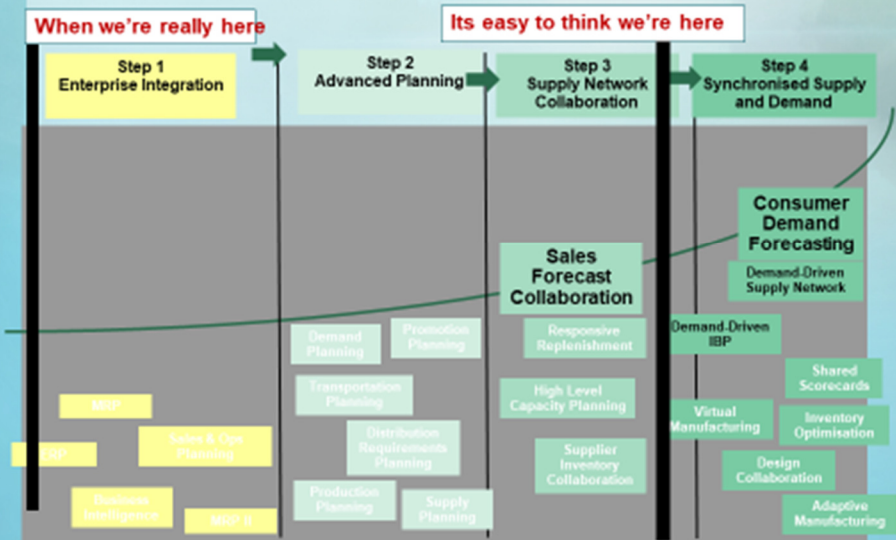
Roles for Forecasting, Planning and Management

- **Demand Forecasting** is all about *CHANGE* and *CHANCE*; an unbiased view of what consumers desire (and are willing to purchase) in products and services
- **Demand Planning** is about action to help create and shape demand for the business
- **Demand Management** is about preparing for and providing of the *right* amount of the *right* product/service to be in the *right* place at the *right* time at the *right* price

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Maturity Levels in Supply Chain Planning and Management



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How Does Demand Forecasting Fit in the S&OP Process?

Sales & Operations Planning (S&OP) is

- **A Process (40% +/- 10%)**
 - driven by rolling baseline demand forecasts
- **A Methodology (Tools: 10% +/- 5%)**
 - Often ignored
 - Most use spreadsheets (Excel) for flexibility
 - But multiple versions of spreadsheets remain unsynchronised
 - Lacking data integrity of a relational Database
- **People (50% +/- 25%)**
 - The 3 C's and 4 P's



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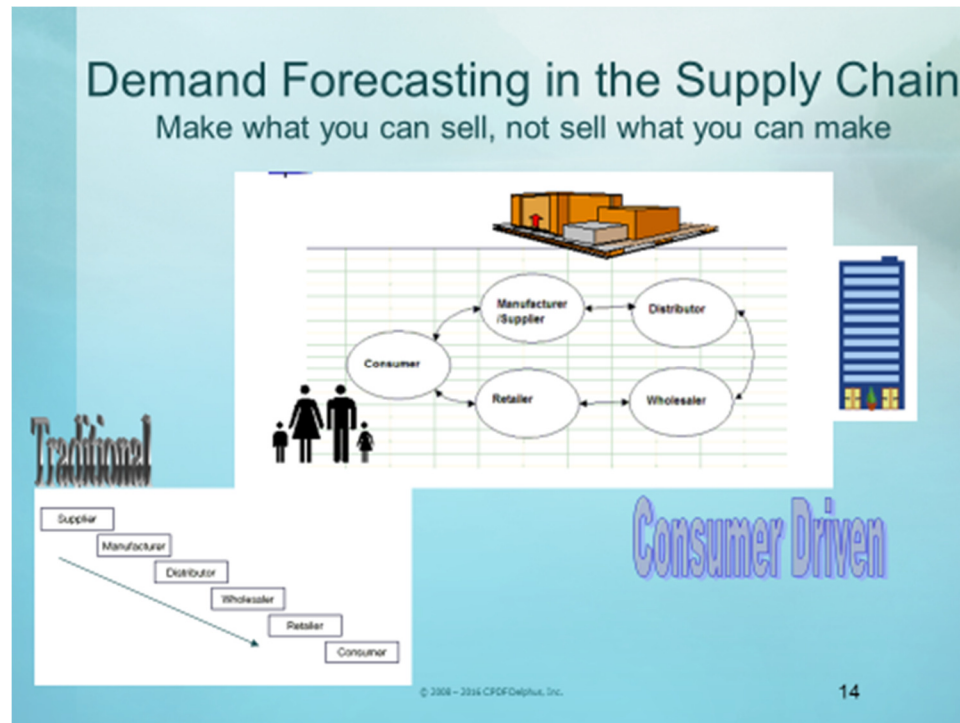
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Characteristics of an Effective S&OP Process

- **Visibility** – can cover all areas of S&OP through ERP connection
- **Real-time Data** – can capture current level data, aggregate and cumulate
- **Modeling** – can assess impact of changes
- **Simulation** – can resolve misalignment between supply & demand to optimize profitability; use scenario building
- **Collaboration** – seek among all stakeholders, including clinical centers and partners
- **Monitoring & Alerting** – measure performance of forecasts, budgets and forecasters

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What is sales forecasting versus demand forecasting?

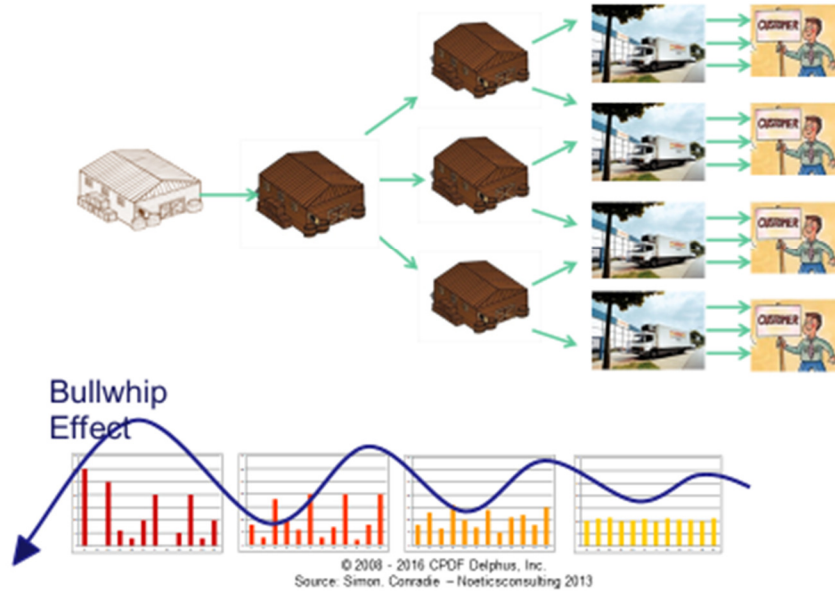
- Sales Forecasting is the process of estimating what your business's sales are going to be in the future.
- Sales forecasting is an integral part of demand management. Without a solid idea of what your sales plans need to be in the future, you can't manage your inventory or your cash flow or plan for growth. The purpose of sales forecasting is to provide information that you can use to make intelligent business decisions.
- This defines a "supply-push" or **internally-driven** notion of forecasting.
- In many companies, sales forecasting is done on a monthly or quarterly cycle, so that managers will acquire a much more realistic prediction of how your business will perform than one "lump" sales forecast for the year. That was THEN.

Where does demand forecasting fit in the supply chain NOW?

- Demand forecasting is most commonly performed in a **Consumer-Driven Supply Chain**
- Consumer- and data-driven forecasts are needed nowadays to provide improvements in manufacturing, distribution, and the operations of multinational corporations
- This represents a "demand-pull" or **externally-driven** notion of forecasting
- Demand forecasting involves the creation of detailed elements of the demand for goods and services that include areas, regions, plants, warehouses, distribution centers, channels, accounts, and consumers
- One often-quoted adage: Demand-driven forecasting requires *the right amount of the right product in the right place at the right time (and at the right price)* in order to be successful in the supply chain. This is NOW

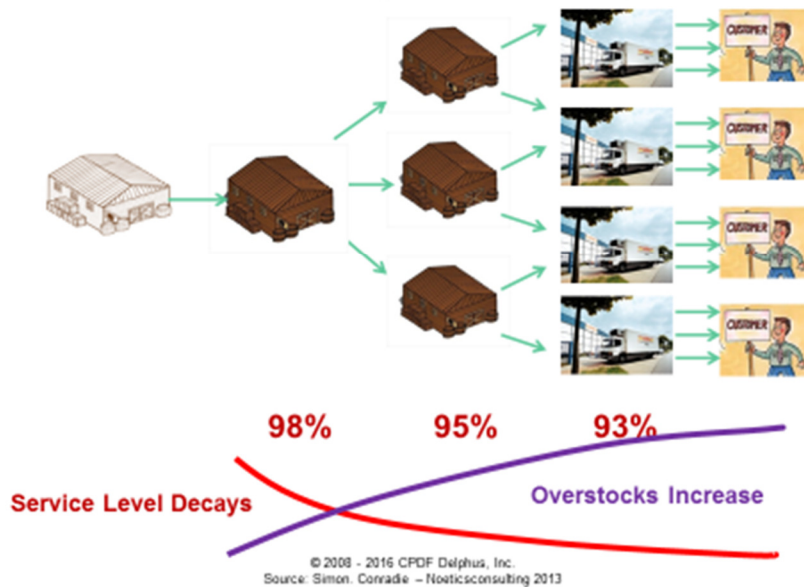
Why Is Forecasting a Complex Process?

Supply Chain Dynamics Add to Complexity



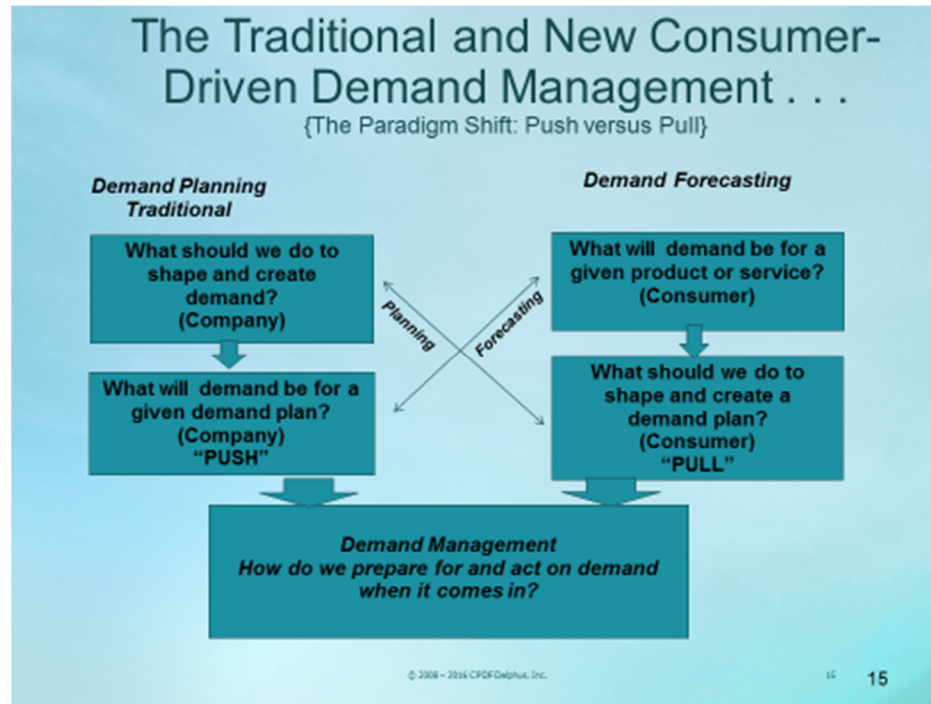
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Downstream Impact of Bullwhip Effect



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A Traditional versus the Modern Consumer-driven Supply Chain Paradigms




How are demand forecasting, demand planning and demand management organized?

- *SELL what you can MAKE.* The function of the **sales forecaster** illustrates an essentially internally driven, traditional 'push' model of the supply chain: . See Paul Goodwin (2018), **Profit from Your Forecasting Software – A Best Practice Guide for Sales Forecasters**, Wiley
- In a traditional supply chain, product flows sequentially through a system from one level to another in a linear fashion. Traditionally, each operation tended to maintain its own information system (mostly in spreadsheets) and communication flows that occurred between individual departments (often referred to as *silos*).
- *MAKE what you can SELL.* In a consumer demand-driven supply chain (which evolved in recent decades), information in the form of orders also flows back in the opposite direction (e.g. e-commerce), so that all operations have complete visibility to the whole supply process. Instead of being driven or supplied by the manufacturer, consumers are the drivers of demand, demanding cheaper, faster and higher quality products. A firm's success is a combination of an integrated supply chain, a sound infrastructure and a focus on consumers:
- In the context of an essentially, externally driven or 'pull' model of a supply chain, a demand forecaster is in the business of making detailed statements about future demand for products and services in the face of uncertainty.
- Demand forecasting and planning is the process that drives inventory levels to improve a company's ability to replenish or fulfill product to meet customer (and ultimate consumer) needs in a timely and cost-effective way. If forecasting does not have a good link to drive inventory stocks, improving it won't necessarily improve customer service levels or reduce costs. A forecast is not just a number, outcome or task. It is part of an ongoing process directly affecting sales, marketing, inventory, production and all other aspects of the modern supply chain

Setting Up An Agile Demand Forecasting Cycle

- Identify a Person-in-Charge (PIC)
- Involve the cross-functional organizations ("Silos")
- Determine the user needs for reports
- Set a firm time-table
- Communicate, communicate, communicate



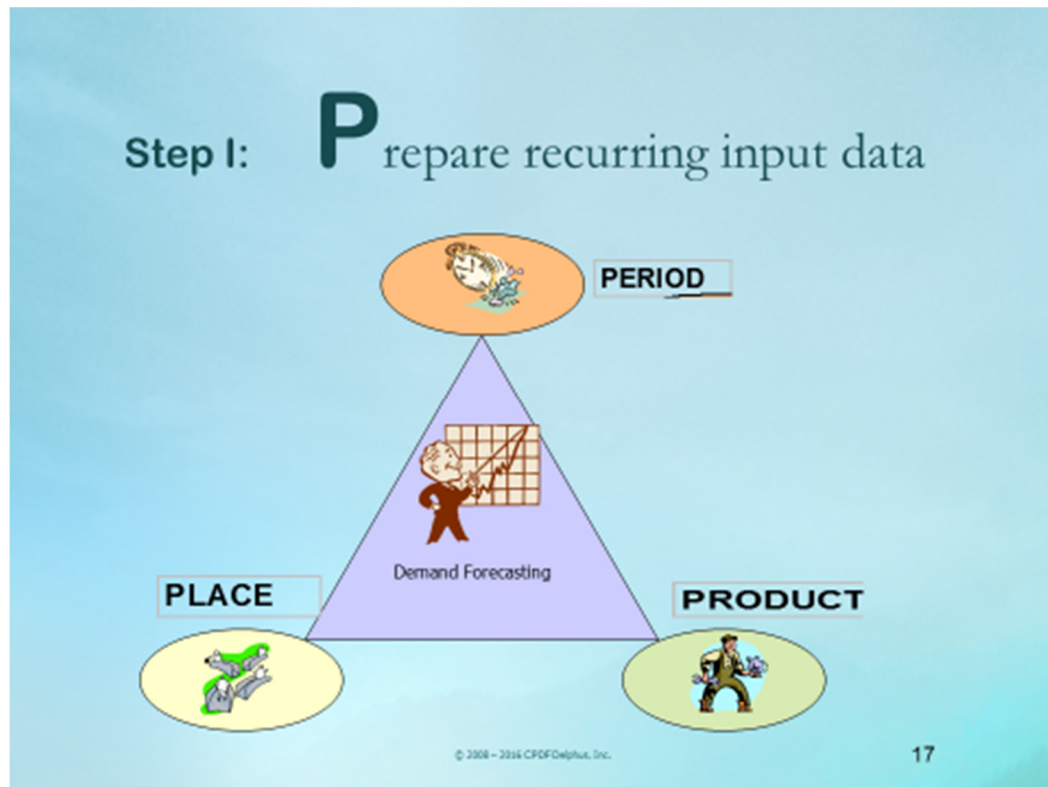
The diagram illustrates the Agile Demand Forecasting Cycle. It features a central figure of a person in a suit, labeled 'PIC' (Person-in-Charge), standing within a circular flow. The flow is composed of three large, curved arrows: a yellow arrow at the top, a red arrow on the left, and a blue arrow on the right, all pointing clockwise. The background of the slide is a light blue gradient with a faint image of a person's face on the left.

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How do you set up an agile demand forecasting cycle for demand management?

1. Identify an individual in the organization who champions the process. This is the PIC or Person-in-Charge who can socialize the requirements for a demand forecasting discipline among peers and higher management
2. All organizations requiring forecast output need to be involved
3. Periodic reports will need to be provided based on what users ('end-users') need
4. Provide a realistic schedule that can be kept and agreed upon by all users
5. Don't work in isolation (as the expert), but maintain ongoing communication via phone, email, memos, and conference calls.
6. Create a structured process, like this four-step PEER process
7. Create an independent forecasting organization reporting to VP Supply&Demand Planning

Demand management (DM) refers to getting the right amount of the right product to where it is needed, while managing unproductive inventory levels to achieve maximum return on assets



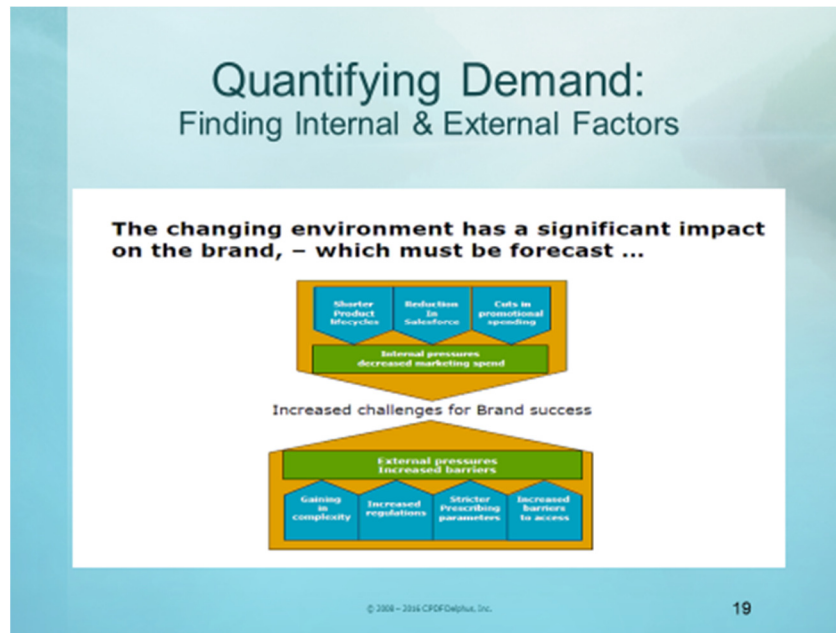
What are the requirements of the Data Preparation step?

Product, Place, and Period are the three dimensions of a demand forecasting data framework

- PRODUCT refers to the items produced, shipped and sold
- PLACE represents the customer ship to's, consumer outlets and geographical regions
- PERIOD refers to the time periods of quarters, months, days, hours

How do you organize and prepare for a data structure to support a FDSS for demand forecasting and planning?

- Data structures for a Forecast Decision Support System (FDSS) cannot be merely spreadsheet-based – they should be formalized into a relational database system (e.g. MS Access, SQL) containing various organization-related data structures
- Sources of forecast input data can be both **internal** and **external** to the business; much of it not organized or standardized in terms of data definitions.
- To ensure data quality and timeliness of forecasts, demand forecasters must have ownership of the data used for data analysis and modeling.
- Hierarchical database systems will turn out to become unmanageable as the organization needs to periodically restructure product/location/time arrangements

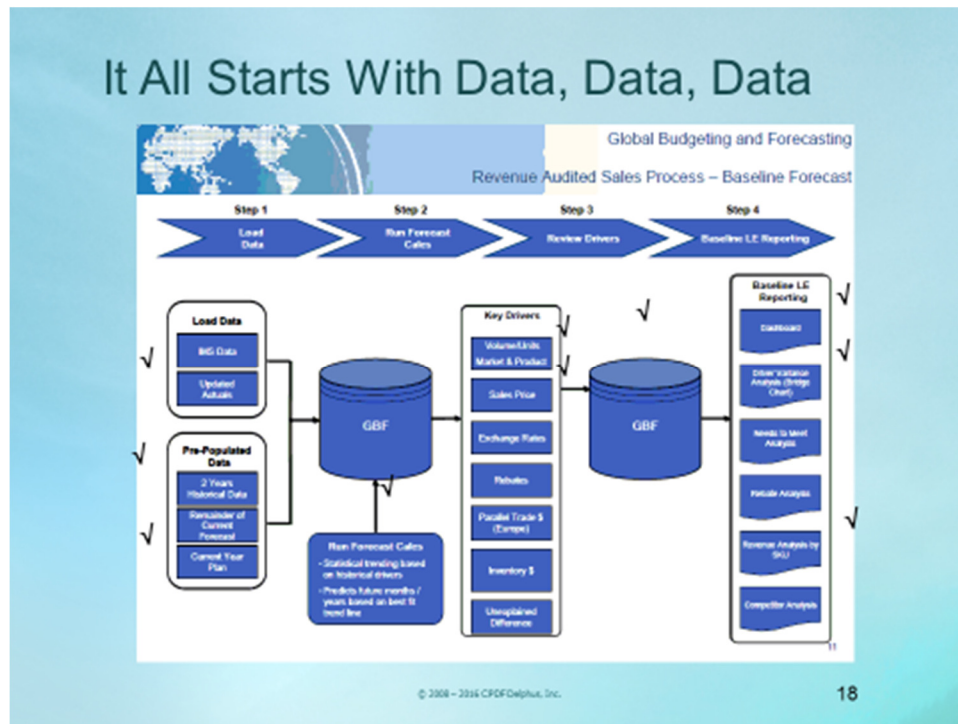


Too much data? Not the right kind? Where to get it?

- Taking into account forecast needs from various users and the data needs for a forecaster, the organization of data becomes a real issue
- Unless organized efficiently, this can lead to multiple hierarchies and a proliferation of data sources that need to be integrated and made consistent
- Such organization requires a view of all data in terms of products and, separately, customer/locations. Sourcing is a particular kind of location.

Why do you need to quantify factors affecting demand - both internal and external?

- After deriving external factors affecting demand, the forecaster also needs to consider the need for internal factors. The source – Sales and Marketing
- Some internal factors include
 - Customer (IT investment/total capital expenditures)
 - Product (a new product introduction, market share)
 - Competitive development (scalability, price)
 - Channel and internal sales (number and experience of sales force and channel partners)
- Some external factors include
 - Income – a consumer's ability to pay for a company's goods or services
 - Market potential – the total market for products or services being forecast
 - Fashion and consumer habit – innovation and change create new products and services, causing people's tastes and habits to change
 - Regulatory and Government Policy



Typical Database Size

Wal-Mart has

- 5,000 Stores
- 100,000 items

If a typical store carries a full line of items, one can then potentially expect **500,000,000 lowest level records**

A Japanese Online Store has

- 6 Distribution Centers
- 35,000 Items

Each distribution center carries a full line of items, one can then expect **210,000 lowest level records**

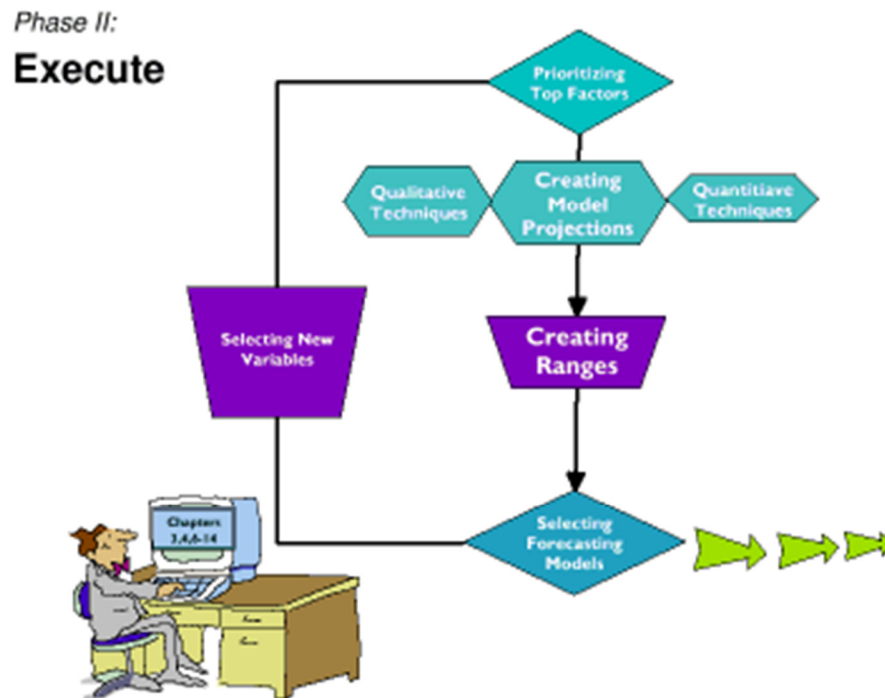
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Source: Elliott Mandelman - 2012 19



What do forecasters need to understand about data and information?

- Forecasters need data and information from others, including their users
- Forecasters need to be able to efficiently integrate such data into a database that can be readily updated and easily maintained. Hence, think small, flexible, but powerful.
- The spreadsheet paradigm will not be adequate for this task, though spreadsheets and statistical forecasting packages are very useful adjuncts to the forecasting job
- Forecasters need to use relational databases to setup and maintain their basic data tasks, while using spreadsheets to supplement the routine work. Such tasks should not be relegated to a third-party like an IT organization because forecasters need to be able to take 'ownership' of the data for quality control
- Forecasters need to be responsible for guaranteeing data accuracy, quality, reliability and database integrity
- Factors, or drivers of demand, are necessary to get an understanding of where demand comes from and how it evolves
- Factors can come from many sources, both external and internal to the organization
- Factors need to be checked for a number of properties, such as reliability and being empirically based

Step 2: The Execution phase of the PEER process



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Step 2: What is the Execution phase of the PEER process?

Once the forecasting context has been established, turn to the execution stage. Like the Prepare phase, this stage also includes a **feedback learning** step.

- The systematic execution of a forecasting methodology leads to a better understanding of the factors that influence the demand for a product or service.
- The forecaster who has a good handle on demographic, economic, political, land-use, competitive, and pricing considerations will develop an expertise in making the best possible forecasts of the demand for a company's products and services.

Step 2: **E**xecute Models



❖New ETS (Error-Trend-Seasonal) State Space Models include

- Exponential Smoothing Family
- Box-Jenkins (ARIMA)

❖And also available are

- Regression Models
- Neural Net Technology

❖BUT Moving Average methods are now outdated and outmoded for credible forecasting use

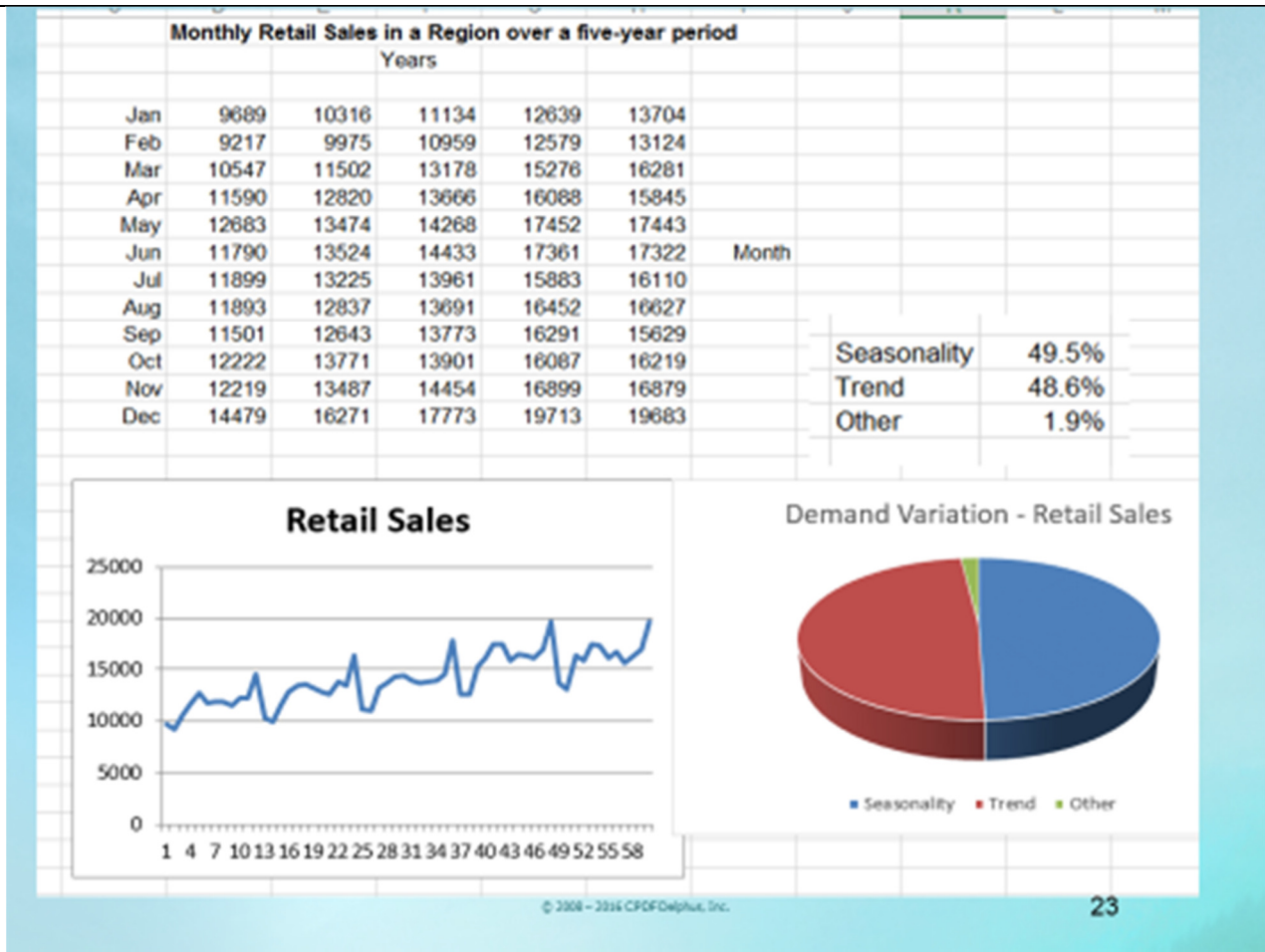
All must be blended with judgmental approaches

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Which are the most useful models for forecasting historical demand patterns?

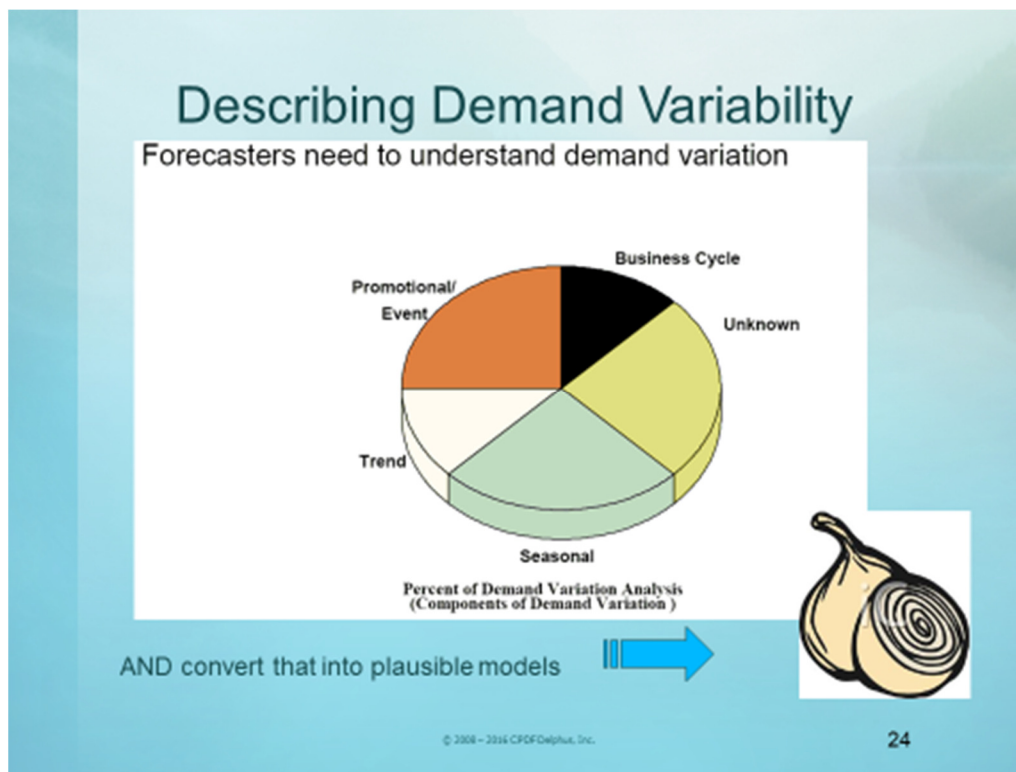
- The *time series models* based on historical data can be classified into a few families
- Historically, exponential smoothing has been viewed as an algorithmic approach (without explicit expression for error distribution, required to measure CHANCE)
- Box Jenkins methodology for ARIMA models are generally too complex for beginning forecasters to comprehend. However, they have a sound theoretical foundation for modeling ‘change and chance’ (cf. Box, Jenkins, and Reinsel: **Time Series Analysis: Forecasting and Control** (1994)).
- Since the mid 1990s, publications on State Space Forecasting have unified the exponential smoothing family and univariate ARIMA models into a single theoretical framework, including multiplicative error terms (cf. Hyndman, Koehler, Ord and Snyder: **Forecasting with Exponential Smoothing – The State Space Approach** (2008)).
- More recently, neural nets has an active following among academics and researchers, but has not proven itself yet among demand forecasting practitioners
- Note: Some methods like moving averages and double exponential smoothing are outdated and outmoded.

None of these methodologies can work without the active involvement of the demand forecaster in a practical environment using informed judgment.



The variability in monthly retail sales in a region over a five year period:

1. Consumer/Customer Habit (Seasonality) 49%
2. Consumer/Customer Demographics (Trend) 49%
3. Other (including Uncertainty) 2%

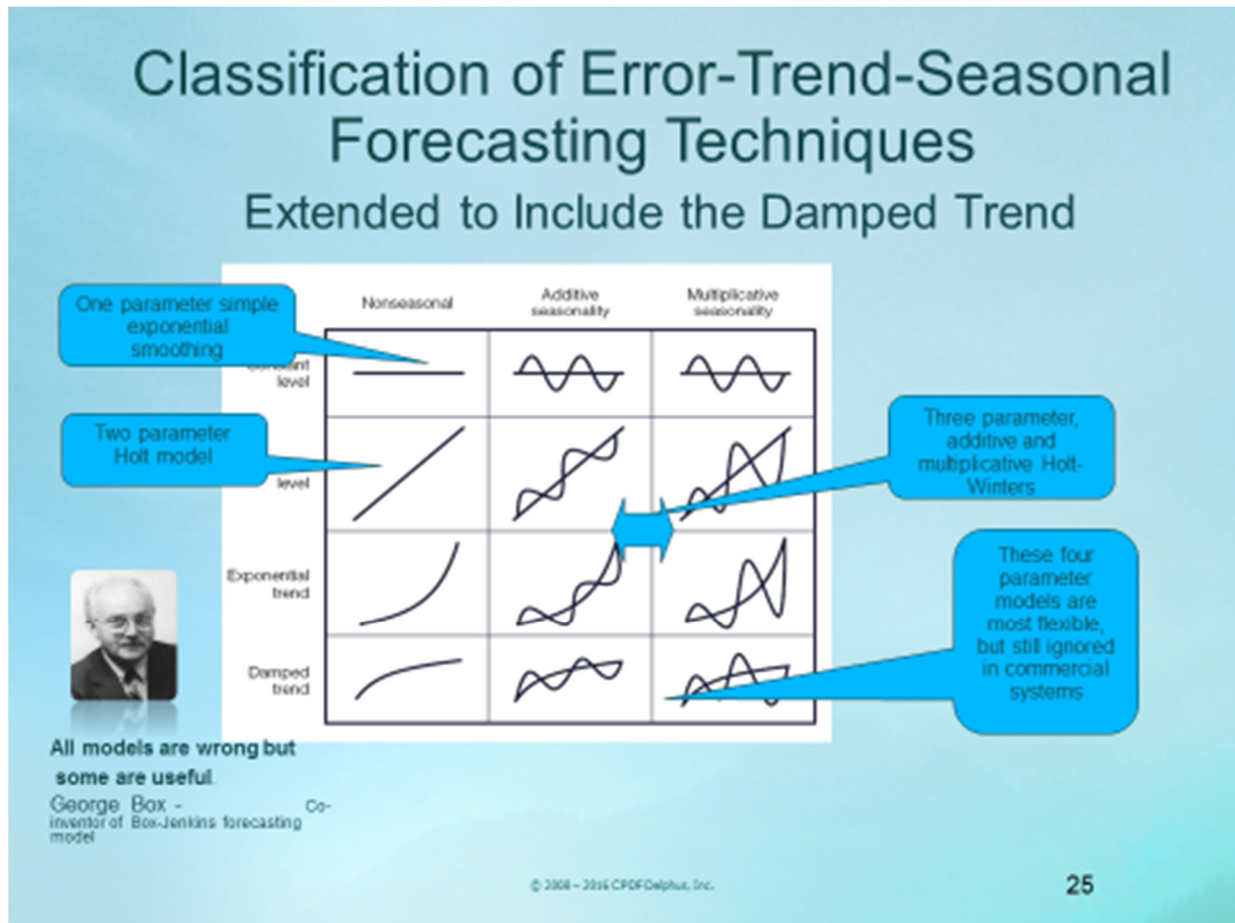


What are the components of demand variability and how can you measure their contribution to the total variability in the data?

- Understanding variability in data and error distributions is what we need for modeling **CHANGE** and measuring **CHANCE**
- Models should be developed sequentially, starting with the basic variability in trend and seasonality
- Typically in consumer-driven supply chains, trend and seasonality frequently constitutes more than 50% of the variability in historical data
- Demand modeling is like peeling an onion, one layer at a time
- Only after we identify and model the essential variables, will we be able to properly deal with model promotions, strikes, etc. – these are a lower layer of the onion
- There will always be an unknown portion – this will drive the error inherent in all forecasting.

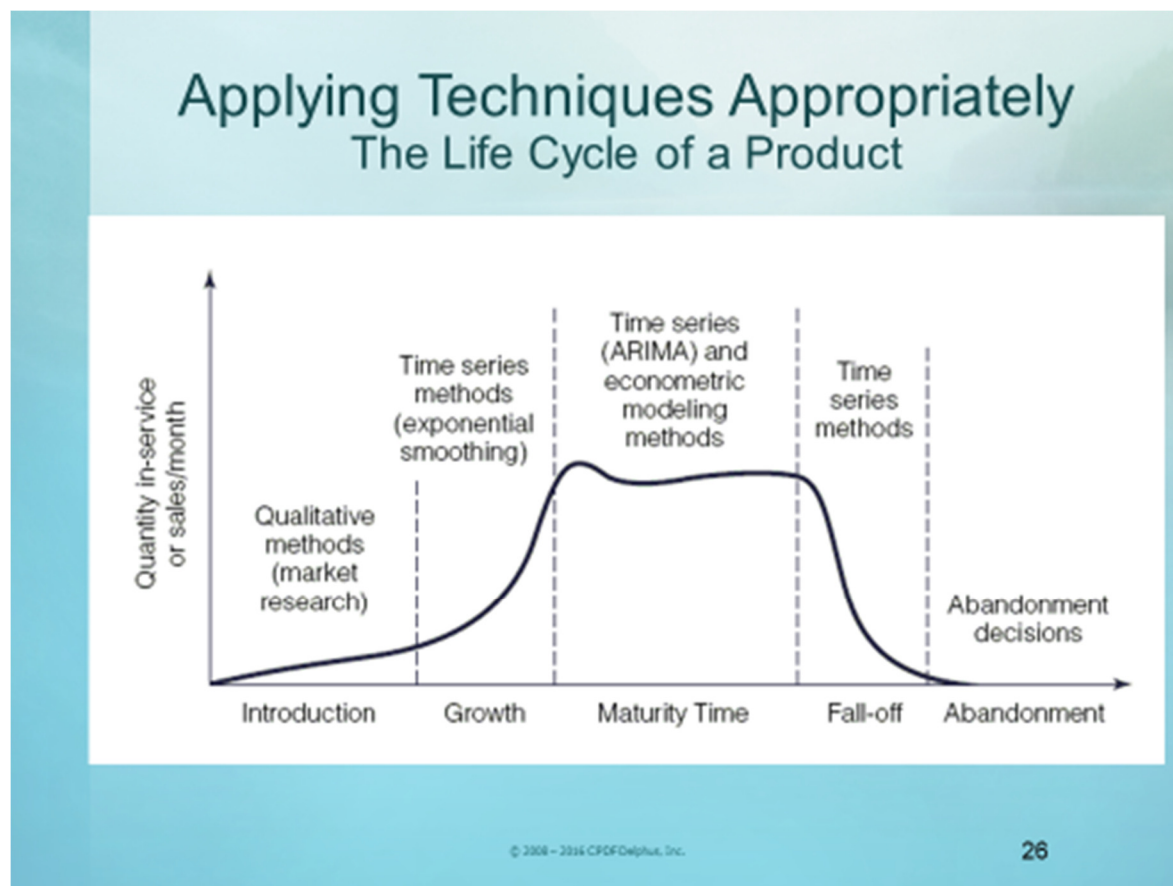


Perfect accuracy is unattainable in an uncertain environment : it is a perfect myth!



What is Error-Trend-Seasonal (ETS) Classification of exponential smoothing and ARIMA models?

- ETS is a classification of exponential smoothing models in an array breaking down trend, non-seasonal, additive/multiplicative seasonal forecast profiles.
 - The simple exponential smoothing model (SES) produces a horizontal, non-seasonal profile (cell 1,1)
 - The Holt model (Linear Trend, Non-seasonal) produces a straight line, non-seasonal forecast profile
 - The Holt-Winters produces a linear trend, additive or multiplicative seasonal profile
- These models also include a non-additive error model structure providing asymmetric (i.e. not symmetrical like the normal distribution) prediction limits.
- The ARIMA models can also be classified by looking at their forecast profiles (they are deterministic)
- It is generally not beneficial to understand forecast profiles and forecast performance through manipulation of parameter settings.

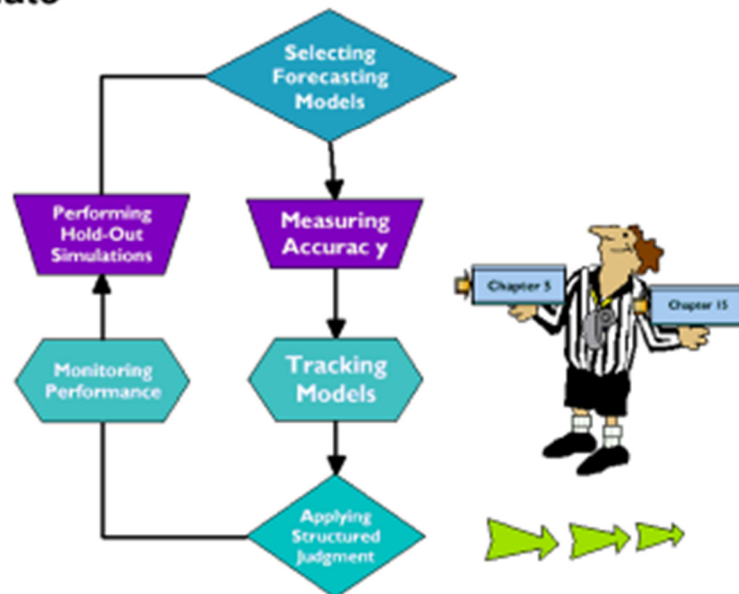


How can you use the lifecycle of a product as a means of selecting the most appropriate model?

- It is sometimes useful to link a forecasting technique to the lifecycle curve of a product or service
- During the introductory phase, limited or no data are available, so qualitative techniques or market research are most appropriate
- During the growth phase, univariate models such as exponential smoothing work the best
- In the mature phase, there are explanatory (driver) variables to help strengthen the modeling approach, such as regression analyses and econometrics
- While a product falls off in sales, again a univariate approach is most useful
- Lastly, as the product phases out, it becomes a management decision to terminate or abandon the product.
- At times, the damped trend exponential smoothing models can also supplement this phase with a modeling approach to abandonment.

Step 3: The Evaluation phase of the PEER process

Phase III: Evaluate

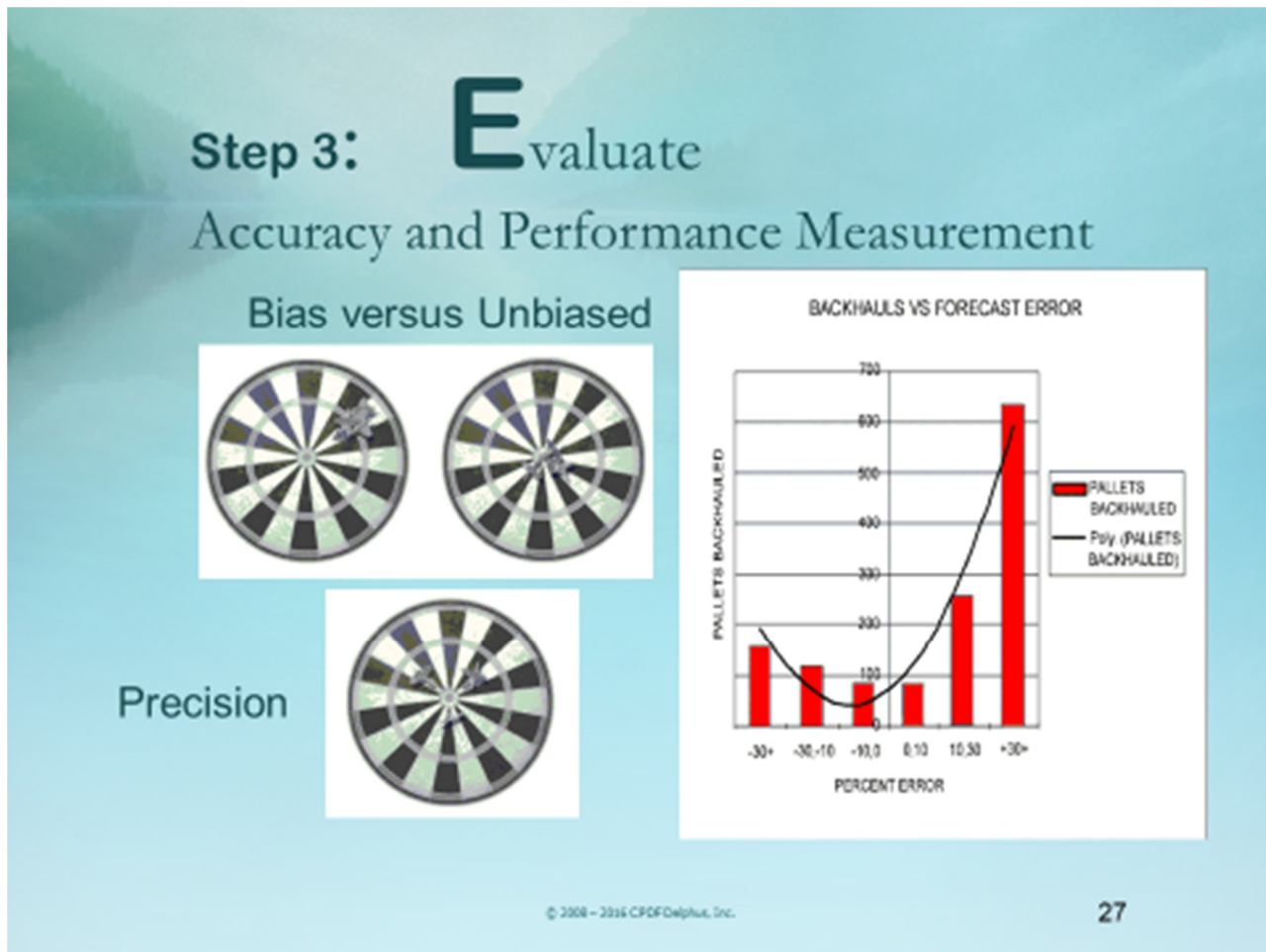


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Step 3: What is the Evaluation phase of the PEER process?

The forecasting cycle is typically an iterative process. Once the forecasting models are built, we still need to turn our attention to the evaluation stage. How well have the models performed in the past? The process of forecasting focuses attention on *evaluating* forecasts and using the right methodology for a given forecast. For example, do not use short-term methods for long-term forecasts.



What is meant by forecast accuracy and how do you maintain performance measurements of forecasts and models?



Case: Confectionary Manufacturer (CPG)
Focuses on Process Improvement Along With Error Reduction

Objective: Identify the main objectives of measuring accuracy:

- COST OPTIMIZATION
- CUSTOMER SERVICE
- LONG TERM CAPITAL PLANNING
- ANNUAL BUDGETS
- **FORECASTER PERFORMANCE**
- VALUE OF FORECASTING
- OPERATIONAL EFFICIENCY IMPROVEMENTS
- VALUE ADDED FEATURE FOR YOUR CUSTOMERS
- CONTINUOUS IMPROVEMENT WITHIN THE ORGANIZATION

Definition of accuracy: How close was the forecast to actual sales?

- AT THE TOTAL PRODUCT LEVEL
- AT THE PRODUCT LEVEL
- AT THE SUB_PRODUCT LEVEL
- AT ALL CUSTOMERS LEVELS
- 80 % OF CUSTOMERS



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Case: FMCG products

- A FMCG distributor was shipping the wrong amount to the wrong locations (stores), resulting in having to make transshipments between locations
- Transshipments of materials are expensive
- Hence the cost of over and underforecasting is not the same
- This may necessitate the treatment of asymmetric (not symmetric) forecast error measurement for determining forecast accuracy – not commonly available in commercial software systems

Cost Of Inaccurate Forecasts

- Customer service – below target line item fill rates
- Finance – excess inventory carrying costs
- Production - schedule disruptions
- Inventory management – Misalignment of supply and demand
- Sales & Marketing - Lost sales opportunities
- Transportation - Unbalanced shipment volumes and sizes
- Warehousing - Excess space and storage costs



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Measuring Forecast Accuracy

Defining forecasting accuracy: Which calculation best represents your business, but defines it without ambiguity

Measures of Bias:

- % ERROR: $(A-F)/A \times 100\%$
- % VARIANCE: $(F-A)/F \times 100\%$



- ABSOLUTE % ERROR: This Measures Accuracy Regardless Of Over/Under Forecast: $|A - F| / A$

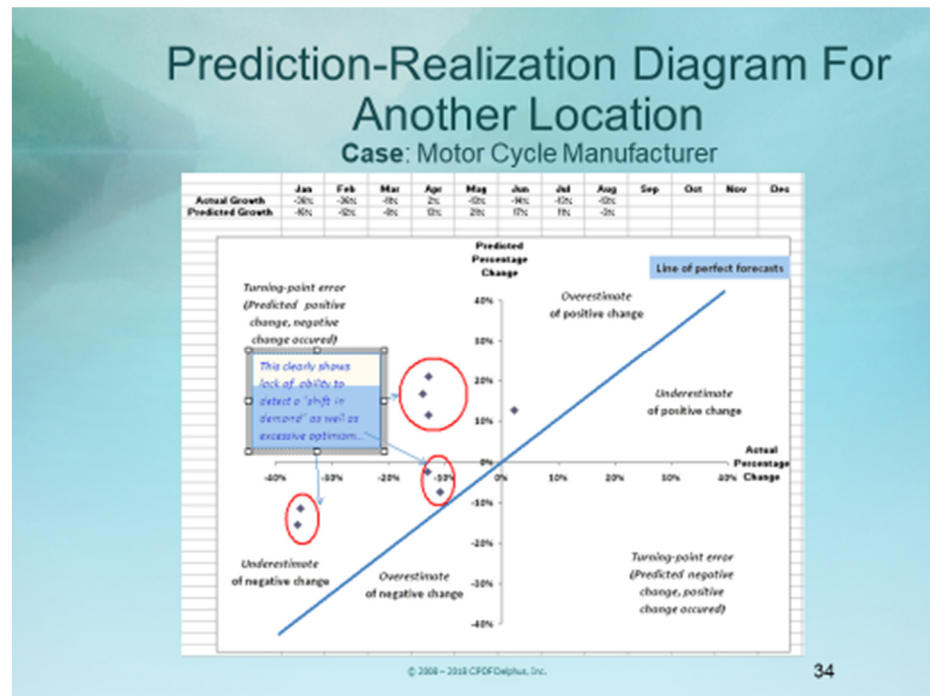
Measures of Precision:

- Mean Absolute Deviation (MAD): $1/n \sum |A-F|$, n # of periods
– But add an outlier resistant check: Median AD (MdAD)
- Mean Absolute Percentage Error (MAPE): $1/n \sum |A-F| / A \times 100$
– But add an outlier resistant check: Median APE (MdAPE)

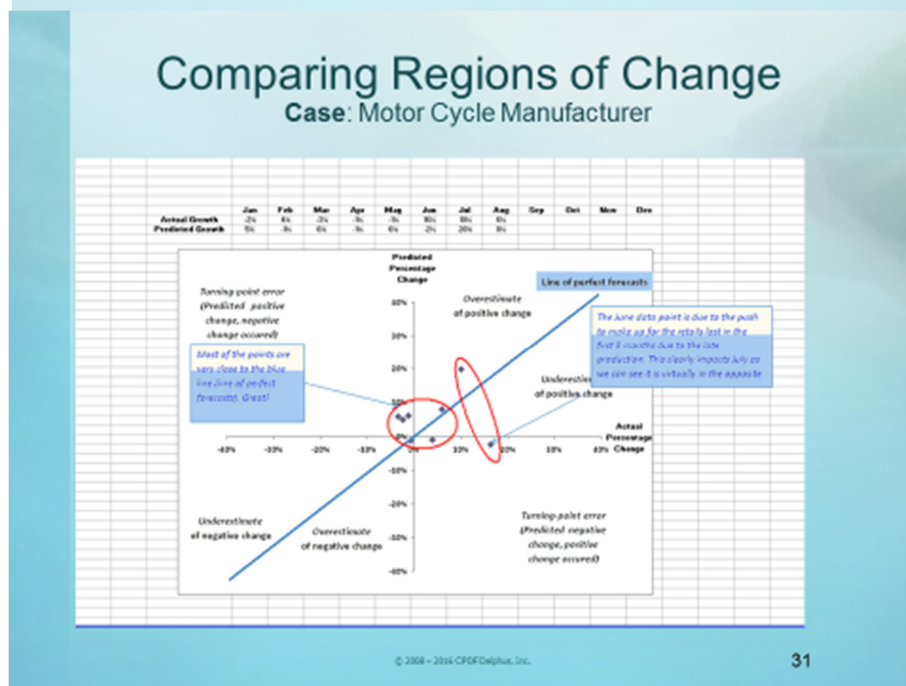
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Predictive Visualization – Depicting forward looking evaluations graphically

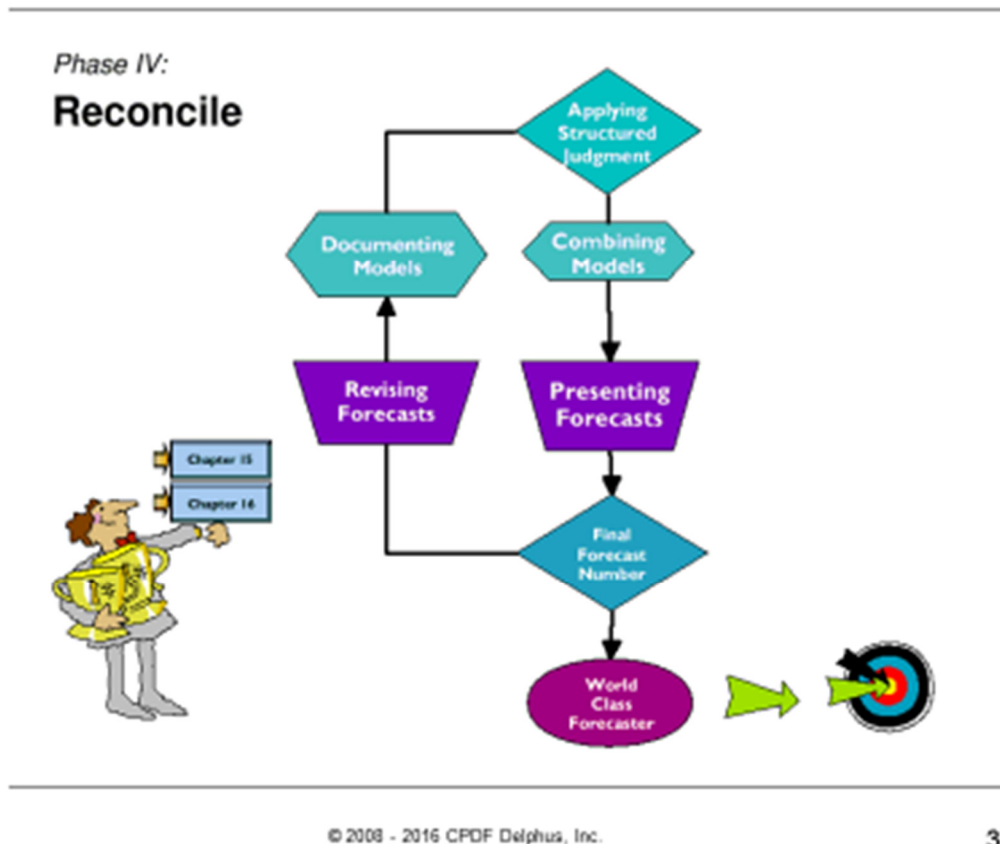


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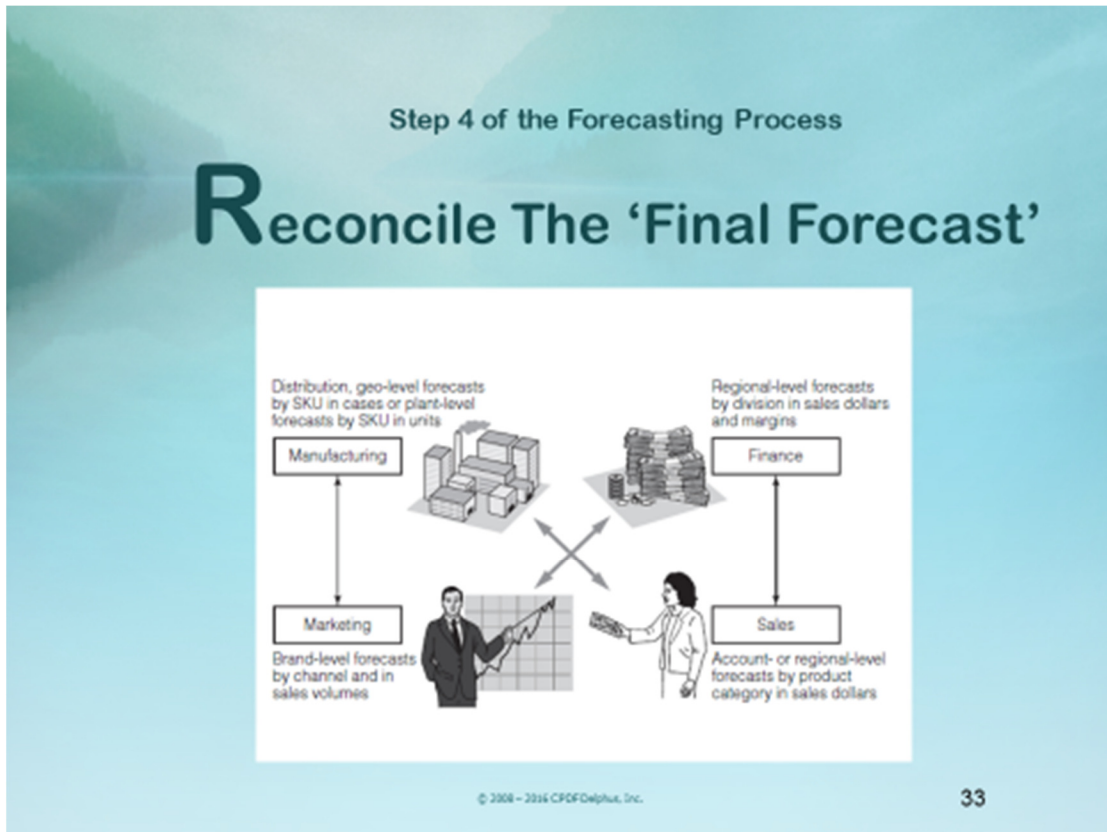
Step 4: The Reconcile step of the PEER process



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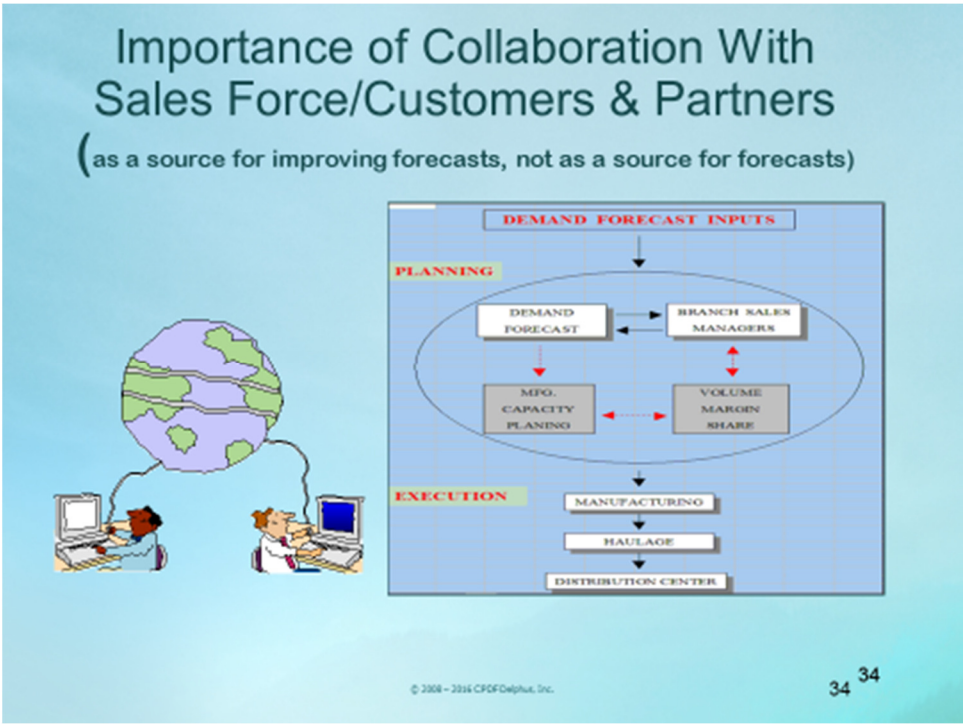
Step 4: What is the Reconcile step of the PEER process?

During the forecasting cycle, we could be making changes to the models, projections, and assumptions behind our forecasts. But in the end we need to come up with a final forecast, essentially a number or set of numbers on which the company can make its future plans. Instead of focusing first on the numbers they hope will result from a forecast, forecast managers and users must *reconcile* their planning approaches so that the most likely methodology will produce accurate forecasts. Selecting the right forecasting methodology is the focus of the next chapter.



Why do you reconcile the 'final' forecast?

- This is where communication, collaboration and cooperation is most needed – the reconciliation of inputs, forecasts, and requirements from all the organizations in the company
- The demand forecaster/planner organization is vital in this scheme, though it is very inter-dependent with other 'silos' in the company
- All organizations have their favorite biases and will want to 'game' whatever system is in place
- To mitigate inevitable biases, a forecasting organization must be neutral and be fully supported by management and peers to retain its independence
- Only then can an organization produce an unbiased demand forecast
- The final forecast (with expression of uncertainty) then feeds into the planning
- Unless assumptions change significantly, unbiased demand forecasts (baseline) should never be changed – only the plans need to be changed and separately measured for accuracy from the baseline accuracy measurements



How does field sales/customer collaboration work as a source for improving forecasts?

- Since the sales force is closest to the customer, variation in customer demand can greatly influence the demand forecast
- The field sales input is needed as a collaboration between demand forecaster and sales force, since central forecasting may not have adequate and current visibility to changing customer needs

Collaborative Planning, Forecasting and Replenishment (CPFR, a trademark of the Voluntary Interindustry Commerce Standards) (VICS) Association), is a concept that aims to enhance supply chain integration by supporting and assisting joint practices. CPFR seeks cooperative management of inventory through joint visibility and replenishment of products throughout the supply chain. Information shared between suppliers and retailers aids in planning and satisfying customer demands through a supportive system of shared information. This allows for continuous updating of inventory and upcoming requirements, making the end-to-end supply chain process more efficient. Efficiency is created through the decrease expenditures for merchandising, inventory, logistics, and transportation across all trading partners.


Collaborative forecasting allows sales teams to generate sales forecasts and track quota attainment.

Pipeline	Amount	Quantity	Opportunity	Close Date

Achieving Agility in the Demand Forecasting Workflow Cycle

- Grasp of economics, statistics and mathematics will NOT ensure success
- Apply judgment within a sound framework – A health demand forecasting process
- Create checklists to reduce chances of inadvertently overlooking a key step
- Omission of key steps can jeopardize a forecaster's credibility, and

CREDIBILITY IS A FORECASTER'S LIVELIHOOD!



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How does the PEER Model streamline the work forecasting cycle?

In the end,

- Grasp of economics, statistics and mathematics will not ensure success
- Apply knowledge within a sound framework – A forecasting process
- Reduce chances of inadvertently overlooking a key step
- The PEER model structures the forecasting work cycle into four standardized process steps
- Omission of key steps can jeopardize a forecaster's credibility, and

CREDIBILITY IS A FORECASTER'S LIVELIHOOD!

Take-Aways To Think About

(before you reach for the stars)

- Anticipate Data Proliferation
Establish an Integrated
Data Framework
- Break Down Silos
Promote Unconstrained
Collaborative
Forecasting
- Manage Complexity
Implement Checklists

And Remember:

Uncertainty is a Certain Factor!!



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Things to think about

- Data Proliferation – Integrated Data Framework
- Breaking Down Silos – Collaborative Forecasting
- Managing Complexity – Use Checklists (see next page for an example of a Demand Forecasting Principles
- Checklist – there are many more offered as take-away in other workshops

Remember! – Uncertainty is a Certain Factor!!

A Demand Forecasting Principles Checklist

Source: <http://www.vtex.lt/informatica/pdf/INFO685.pdf>

Example of forecasting principles checklist in medical research:

Checklist of the Ten Principles (To be completed for each Forecast)

- ☐ Have I identified the principal customers/decision-makers of the forecast and do I clearly understand their needs?
- ☐ Have I understood and clearly communicated the purpose of the forecast and the decisions that will be affected by the forecast?
- ☐ Have I created a forecasting process that is independent of plans and targets?
- ☐ Have I understood the political considerations and taken measures to protect the process from political interference? Is my process transparent?
- ☐ Have I understood the broader environment in which the forecasting process is occurring? Have I created the forecast in the context of market and policy trends, portfolio of investments, and new product developments by suppliers? Have I clearly communicated this context?
- ☐ Have I created a dynamic forecasting process that incorporates and will reflect changes in the market and in public policy as they occur?
- ☐ Have I selected the methods that are most appropriate for the forecast problem and data available? Do I understand how to apply the various methods that are most suitable? Have I obtained decision-makers' agreement on the methods?
- ☐ Does my methodology reflect the appropriate level of accuracy and detail that is needed for the forecast? Have I explicitly identified confidence intervals in the forecast?
- ☐ Have I made my forecast assumptions clear and explicitly defined them for those who will use the forecast?
- ☐ Do I understand the data and their limitations? Have I searched for data from multiple sources and gathered both qualitative and quantitative data? Am I using these different types of data appropriately?

Workshop A

Targeting the Environment: How to Uncover Drivers of Demand for New Products/Services

What You Should Be Able To Do After completing this workshop, you should be able to:

- Define factors affecting demand for a product or service – new or existing
- Quantify the impact of a factor over time
- Evaluate the overall impact of the environment on demand
- Identify collaborative partners in the forecasting process

Resources

- Example of forecasting principles checklist in medical research:
<http://www.vtex.lt/informatica/pdf/INFO685.pdf>

Key Words

Factor – a **measurable influence** relating the demand for a product or service to its sources of variation. For purposes of forecasting, a factor is a driver to help explain past, current, and future patterns of demand.

Good Factor - objective, reliable structure that is fully disclosed and empirically based.

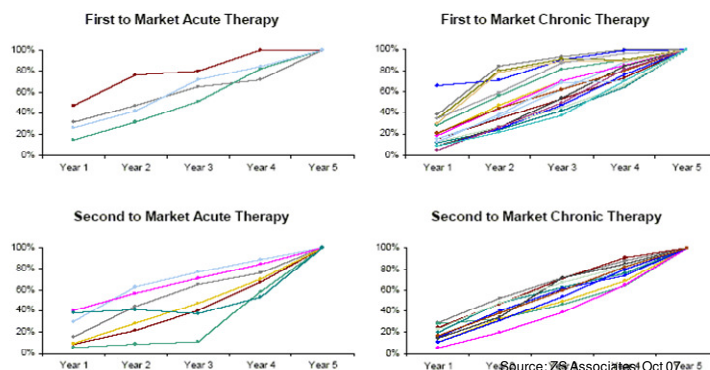
Ongoing Factor – a factor existing over a longer term, creating momentum in demand

Unique Factor – a factor that does not last a long time, like an exception or very short-term event.

Impact Matrix – displays the factors in order of importance along with past changes, current impact, change in upcoming periods and the maximum influence that the factor can have on demand. These are usually guestimates, but they begin to quantify the assumptions and rationale about a forecast.

New Product Introductions – Visual Comparisons

Using similar variability in analogues to find models



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Source: A.G. Cook, ZS Associates 2008

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How to analyze and compare new product introductions visually

- By grouping similar products, you can examine the homogeneity of the group: how much alike they are in trend and volatility
- The higher the volatility the more difficult to forecast
- The closer the patterns are, the more similar the variability and the more likely it is to obtain early growth estimates for the product
- When the variability in a new product can be compared to an existing product, its early growth may also show similar patterns. The new product is like an analogue of the existing product or family of products



11 Fascinating Sights Most Washington DC Visitors Miss

<http://www.youtube.com/watch?v=Pfq4XKT2PCA>

CASE: Demand for Tourism in a Major Metropolitan Area

The tourism industry is a significant contributor to the economy of most countries. It is estimated that travel and tourism directly and indirectly contributes over 10% of the gross world product, the most comprehensive measure of the total value of the goods and services the world's economies produce.

As one example, the demand for commercial lodging in the Washington, DC area in the USA is one such case. Tourism demand is a measure of the visitors' use of a good or service. To forecast tourism demand one needs to establish measures of tourism activity. For the following activities, suggest an appropriate unit of measure of demand.

1. Define four factors of demand a tourism director might want to investigate, related to weather, price, income, demographics, advertising, and government regulation, etc.. Are there others?
2. Quantify the impact of your choice of the top factor over time
3. Define a measure of demand related to each of the activities below
4. Who are the potential users of your forecast?

Activity Measured	Measure of Demand
Number of people traveling away from home	
Groups of people traveling away from home together	
Total nights visitors spend away from home	
Distance traveled while away from home	
Total money spent purchasing goods and services related to the trip	

Source: Frechtling, D.C. (1996). **Practical Tourism Forecasting**. Oxford: Butterworth-Heinemann.

The Historical Impact Over The Past Few Periods

Factor (examples)	Direction (+/-)	Intensity (1-5)
1.		
2.		
3.		
4.		
5.		

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How to assess (*quantitatively*) the past impact of a factor on demand over the past few periods?

- Assess the effect of the factors on demand over the past few periods (say several quarters)
- For each factor, assess the pressure (plus or minus)
- In addition, we assess whether the factor's impact on demand has changed positively or negatively in the **recent past**
- For example, Factors 1 and 2 both represent positive pressure on demand that remained constant at 3 from the recent past to present. Factor 3 represents a negative pressure increasing from 4 to 5. Factor 4 (business partner inventory) represents a negative pressure decreasing from 4 historically to 3 currently.

The Factor's Effect on Demand in the Current Period

Factor (examples)	Direction (+/-)	Intensity (1-5)
1.		
2.		
3.		
4.		
5.		

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How do you quantitatively assess the impact of a factor on demand in the current period?

- The impact of a factor on demand is measured in terms of direction and intensity.
 - **Direction** can be positive, negative or neutral
 - **Intensity** is a pressure measurement from low to high on a 1 to 5 scale
 - **Impact** is expressed on a five-point scale:
 - 1 = low, 2 = Medium/Low, 3 = Medium, 4 = Medium/High, 5 = High
- Create a grid with 3 columns:
 - The factor
 - Its pressure on demand, either positive, negative or neutral
 - Its estimates impact on demand on a numerical scale from 1 to 5.
- Initially, this assessment is based on the forecaster's judgment and experience
- Over time, these assessments should be substantiated through a formal review process with users and subject matter experts
- For example, Factor 1 (new application growth) is expected to have a medium, but positive impact on projected demand. Factor 3 (predicted competitor value/price), on the other hand, is expected to have a strong negative impact on projected demand.

The Expected Future Impact of a Factor on Demand

Factor (examples)	Direction (+/-)	Intensity (1-5)
1.		
2.		
3.		
4.		
5.		

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How do you quantitatively assess the expected impact of a factor on demand in a future period?

- Assess, for each factor, the expected pressure on demand in the future
- Assess whether the factor's impact on demand is likely to change in a positive or negative direction in upcoming periods
- For example:
 - Factor 1 has a constant (+3) impact that is expected to decrease.
 - Factor 2 has a constant (+4) impact that is expected to decrease.
 - Factor 3 has an increasing impact (-5) that is expected to further increase.
 - Factor 4 has a decreasing impact (-3) that is expected to remain constant.

How to summarize the intensity of the top factor's impact on demand?

The Overall Impact of the Top Factors

Factor	Category	Past changes	Current impact	Change in upcoming periods	Maximum influence that the factor can have (+/-%)
1.					%
2.					%
3.					
4.					%
5.					%

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More issues to consider:

- For one top factor, summarize the factor category, past, current and future impacts and changes
- Specify a maximum influence that the factor can have on projected demand (in isolation), if other factors did not change
- If each factor acts independently on demand, the overall maximum influence of these top factors would be the sum of the individual influences
- There is always some correlation between the factors that will result in a somewhat different level of demand.

Workshop Takeaway

- Use ratios, flowcharts, and graphical methods to quantify factors
- Establish consistent factor forecasts
- Employ analytical methods that meet stringent quality standards
- Interview industry experts, peers and end-users
- Research proprietary databases that include trade publications, government reports and corporate literature

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Example: Micro-trends in the Pharmaceutical Industry

Industry Macro-trends

Impact on P&L	
● Good	
● Uncertain/neutral	
● Bad	

- ❑ Scientific & technology choices ☹
- ❑ NPD attrition rates ☹ then ☺, possibly then ☹
- ❑ Unit development costs ☹☹ then ☺, possibly then ☹
- ❑ Importance of inward licensing to big pharma ☹
- ❑ NPD sales uptake curves ☹ with demand ☹ & new product prices ☺ or ☹
- ❑ Tougher pricing environment for established products ☹
- ❑ Shift to biologicals ☹
- ❑ Shift to chronic therapy, prevention & earlier diagnosis ☹
- ❑ Complexity of relationship with stakeholders ☹
- ❑ “Personalisation of Medicine” ☹ but over time
- ❑ Company cost containment measures ☹☹ (varies by situation) but changing mix

Source: Graham Clarke, CEO, Immunobiology Ltd, UK

Immunobiology Ltd

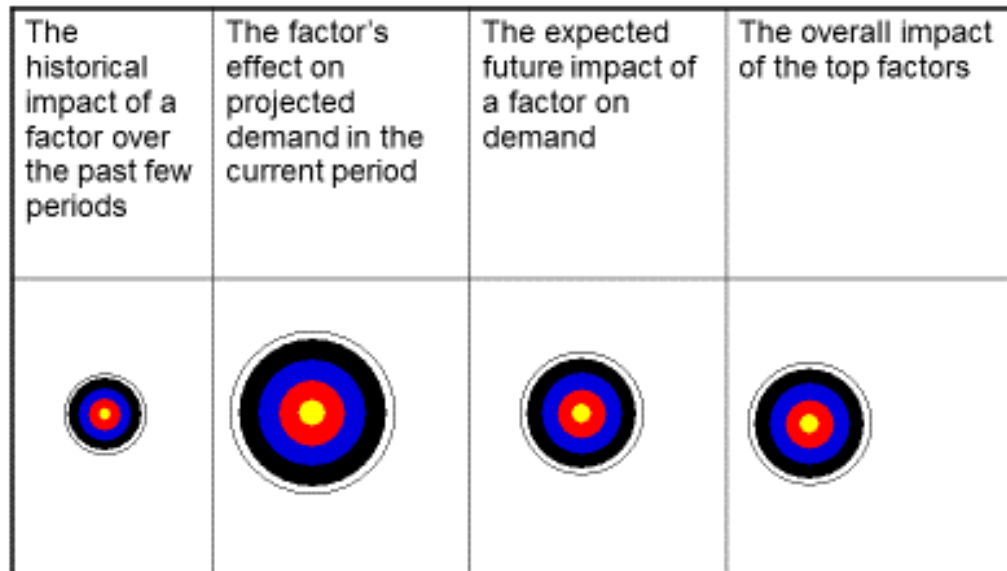
What are some of the checklist questions a demand forecaster need to be able to answer?

- How do you identify factors that can affect demand?
- How do you quantify the impact of a factor on demand?
- How do you use structured judgment to assign numerical values to positive and negative impacts
- How do you assess the impact over time

How to display the impact of factors graphically

- Review a factor's impact on demand by assessing its impact historically
- Review a factor's impact on demand by assessing its impact currently
- Review a factor's impact on demand by assessing its anticipated impact in the future.
- Then, review the overall impact of the top factors.

Predictive Visualization: The Impact of the Best Factors



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To summarize the impact of a driver on demand, we create a **predictive visualization** of the driver or factor by relating the score to the size of a dartboard surface. Use the relationship of $\text{Area} = \pi (\text{radius})^2$ to determine the size of the circles shown. For instance, for a score of 5, the circle should appear five times larger than the one with a score of 1.

To get the correct visual effect, you can accomplish this as follows: Score 1 → radius 1, Score 2 → radius $\sqrt{2}$, Score 3 → radius $\sqrt{3}$, Score 4 → radius 2 and Score 5 → $\sqrt{5}$. If you have deeper domain knowledge, you can extend the scale to 7 or 11.

Supplementary Material to Workshop A

Dealing With Multiple Interacting Factors

- Generally, the factors' influence on demand do not occur in isolation.
- If factors serve as proxies for one another, positive influences may cancel negative ones.
- Two positive factors do not necessarily re-enforce each other and impact on demand may not be additive.

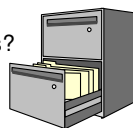
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How you can deal with multiple interacting factors

- While factors can have positive and negative influences on demand, their impacts do not occur in isolation
- Negative and positive influences can offset each other if factors serve as proxies for each other
- Two factors may not necessarily reinforce each other, and their impact on demand would not be additive.
- Seek factors that act as independently of each other as possible
- There will never be many that act independently on demand. These are top factors

Document Top Factors

- Information sources for factors – where are they coming from?
- What are the ratings of factors?
- Summarize rationale and assumptions about ratings
- Develop a revision schedule for factors



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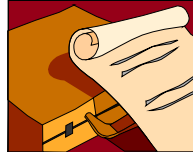
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Why document top factors?

- In order to efficiently transfer information to a “new” forecaster, and not waste time duplicating past work, it is essential to document the analysis that went into the development of the top factors
- Describe the sources of the factors as well as successful and unsuccessful factors
- When maintained in a Critical Factors file, the forecaster will minimize the need for making revisions and will save time when reviewing previous work done by others.

Update and Maintain Top Factors On An Ongoing Basis

- Present results of current performance of top factors
- Summarize executions of model performance
- Evaluate past performance in relation to current performance
- Reconcile results with standards for future performance



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What should be in a CHECKLIST for updating and maintaining top factors?

- A. Presentation of current performance
 - Make available historical tables and plots
 - Provide adjustments made to the data
 - Provide supporting detail for special events affecting current demand
 - Provide forecast versus actual performance
- B. Execution of model performance
 - Present assumptions for model creation involving factors
 - Present model summaries involving factors
 - Present forecast scenarios from selected model(s) involving factors
- C. Evaluation of past performance
 - Explain differences from past performance
 - Indicate amount or rate of impact of factors on demand
 - Indicate the timing of impact of factors on demand
- D. Reconciling standards for future performance
 - Describe changes in basic assumptions for factors and models
 - Establish rationale statements for each change in assumptions
 - Identify sources for new factors, models, assumptions
 - Provide time-integration of factors (short versus long term)
 - Provide item-integration of factors (hierarchies)
 - Provide functional integration of factors (units versus revenues)
 - Provide model-integration of factors (objective versus subjective)
 - Provide user-integration of factors (marketing versus production)



Part II

Improving Data Quality through Data Exploration and Visualization

Workshop A – Review: How do you assess the qualities of a good factor?

Quantifying Factors Affecting Population Health Demand Case: Metropolitan Hospital

The Historical Impact Over The Past Few Periods

Factor (examples)	Direction (+/-)	Intensity (1-5)
1.		
2.		
3.		
4.		
5.		

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Assessing the Impact of the Best Factors

The historical impact of a factor over the past few periods	The factor's effect on projected demand in the current period	The expected future impact of a factor on demand	The overall impact of the top factors

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Workshop 01 Review: Assessing Qualities of a Good Factor

- Objective — avoid 'guessing'
- Reliable — use dependable sources
- Fully disclosed — avoid poor research
- Empirically based — quantifiable and practical



And you can measure performance against standard benchmarks
and is quantifiable


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A good factor should be:

- Objective – avoid factors that are subjective, based on a person's opinion, and biased.
- Reliable – the source of the factor is dependable; WHERE is the data coming from?
- Fully disclosed – avoid incomplete, poorly researched and inadequately documented factors, HOW is the data collected?
- Empirically based – seek first hand, practical data that is quantifiable
- Measurable - performance against standard benchmarks, rather than the benchmark that makes you look best, and is quantifiable

Learning Objectives



- Data exploration - learning from actual examples
- Judging the quality of data
- Dealing with unusual events and outliers
- Distinguishing between quantitative (mostly data) and qualitative (mostly judgment) approaches
- Selecting forecasting models from forecast profiles
- Evaluating forecasts and forecasting models
- Integrating and reconciling the final forecast for an integrated business planning process

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What You Should Be Able To Do

After completing this topic, you should be able to:

Recognize data quality issues

- Interpret data patterns for forecasting use
- Identify unusual events and outliers in data
- Define what a forecasting model is
- Understand what quantitative and qualitative methods are
- Recognize the need for demand integration into the supply chain

How You Will Check Your Progress

Develop a procedure manual for your job, incorporating

- A framework for demand forecasting in the supply chain.
- Specific methods and techniques are defined within the context of the overall process.
- A four-step process for streamlining the forecasting cycle. In doing so, you will end up with the PEER model that unifies techniques while simplifying the role of data, models and forecast presentations in the forecasting cycle.

Resources

Levenbach, C&C, Chapter 2

Step 1: Create data framework for demand forecasting

A Guide To Creating Database
Forecasters Need to Use

	Description	Common Pitfalls
Objective (quantified info)		
Reliable (reliable properties)		
Fully Disclosed (no unresolved issues)		
Empirically Based (sound data gathering process)		
Can be Measured (validated data)		

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What criteria should good data gathering process have?


- Determine the needs of the user of the forecast
- Define parameters that will govern the forecast
- Obtain information about the products/services and the business environment
- Find sources of data about the items to be forecast
- Make preliminary choices of alternative forecasting techniques

Create a table in which you list the characteristics of good data:

- **Objective** – refers to type of information based on quantifiable data
- **Reliable** – guarantees that data have reliable properties
- **Fully disclosed** – there are no unresolved issues surrounding its existence
- **Empirically based** – supported by evidence and is supported by a sound data gathering process
- **Measurable** – data that can be validated as observations

How Healthy Are Your Data?

- **Consistency** – data that retains the same significance for demand over time
- **Accuracy** – the extent that data are free from significant error
- **Conformity** – corresponds with business cycles?
- **Timeliness** – the committed availability time frame meets the forecaster's schedule
- **Reliable** – can be depended on when and as promised
- **Affordable** – cost of data acquisition is within budget
- **Ease of use** – how readily users can access data



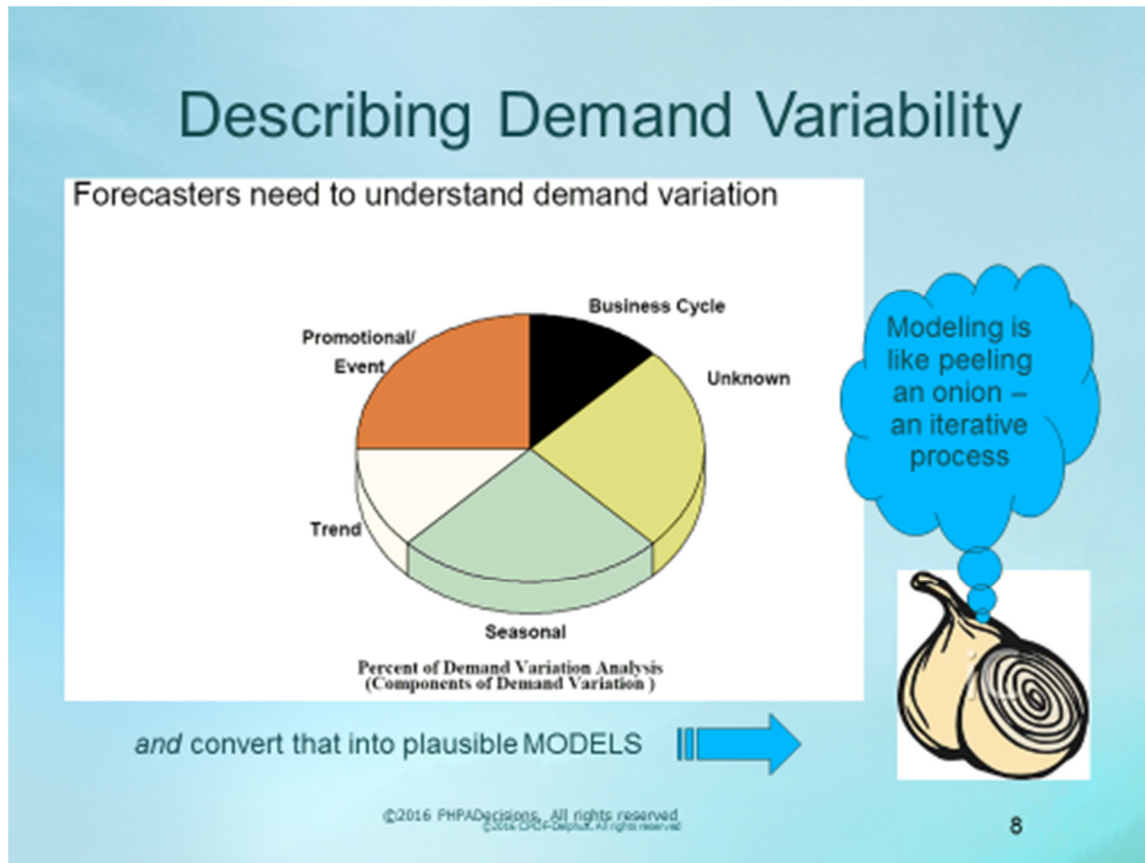
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How can you judge the quality of data?

Data quality is important in modeling, because a model based on historical data will be no better than the quality of its source. Paraphrasing a statement made about the usefulness of models, we can say: "All data are wrong, some are useful"

- **Accuracy** – reflects whether data is collected from a reliable source. Examples of such data are government survey data and indexes, such as an economic or consumer confidence index
- **Conformity** – must adequately represent the phenomenon for which it is being used. With economic data, one expects to see it correspond to the ups and downs of business cycles.
- **Timeliness** – data collected, summarized, and published on a timely basis are of greatest value to the forecaster.
- **Consistency** – must be consistent throughout the period of their use. When definitions change, adjustments need to be made in order to retain the logical consistency in the historical patterns
-



Describing demand variability

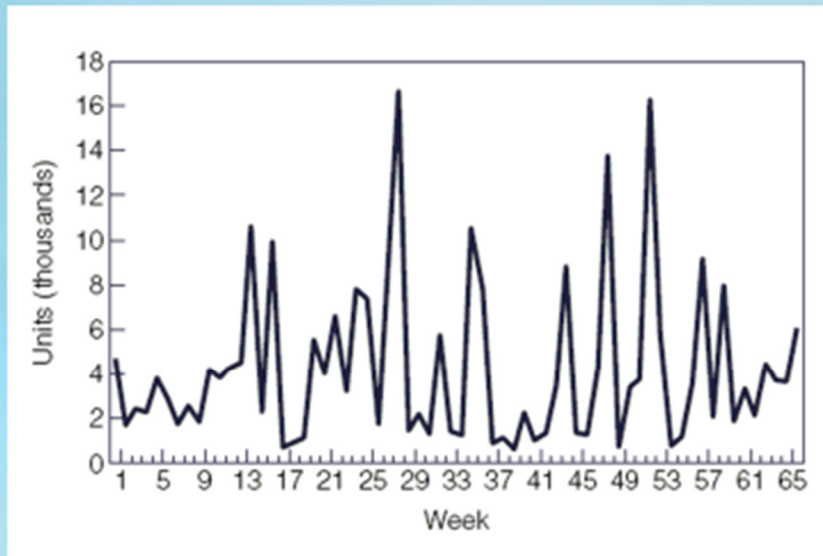
- Variation in demand can be depicted as a pie in which each slice represents a component of variation, such as seasonality, trend or tend-cycle, promotion and an unknown (random) component
- In turning this into models, the forecaster needs to take modeling steps. Each step is like peeling a layer off the onion
- Start with the most prominent effects, like trend and seasonality.
- With a characterization of seasonality removed from the data, the forecaster can get a clearer view and model for remaining components of variation.



Usually, this takes two or three steps to reach a satisfactory model

Caution! - Avoid 'all-in-one', automatic approaches that will only hide the real data insights you need to forecast (*'uncover the heart of the onion'*)

Time Variability of Weekly Sales (Promotions??)

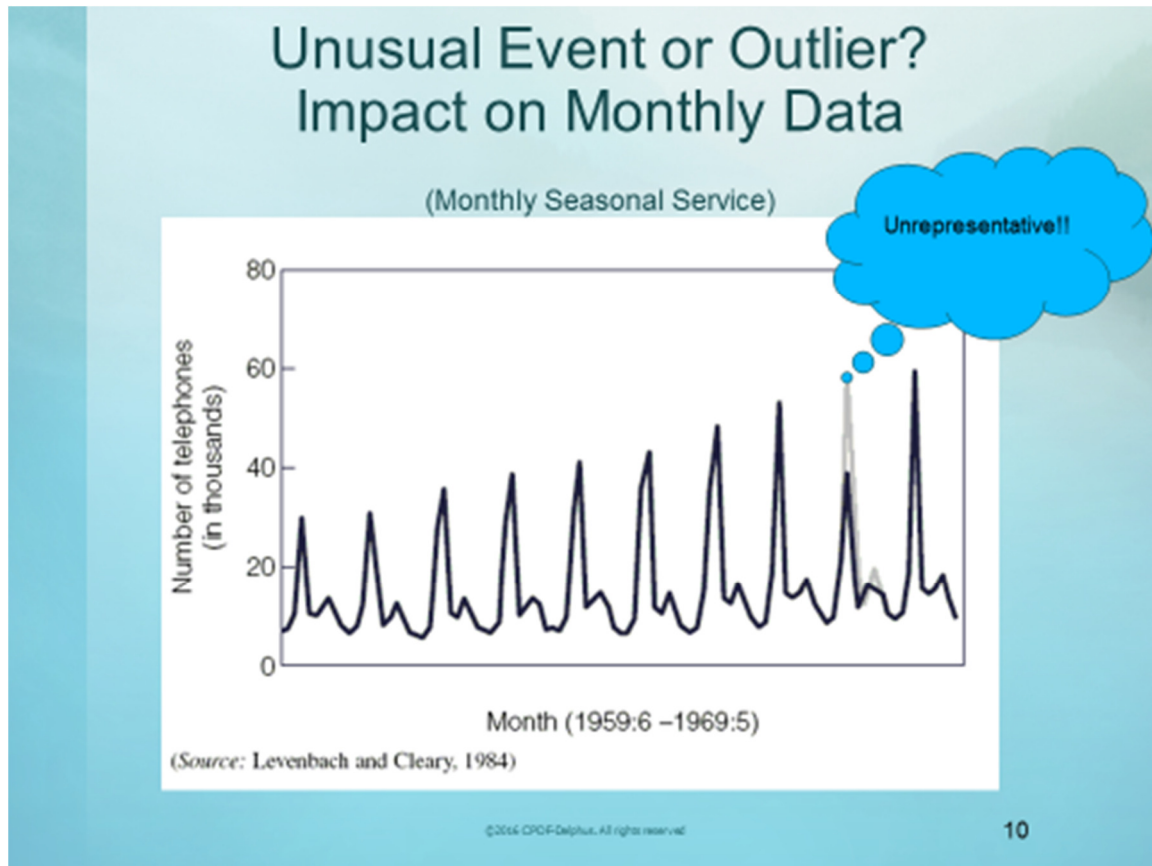


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What are some other common data patterns? Example, time plot of weekly shipments with seasonality and promotions

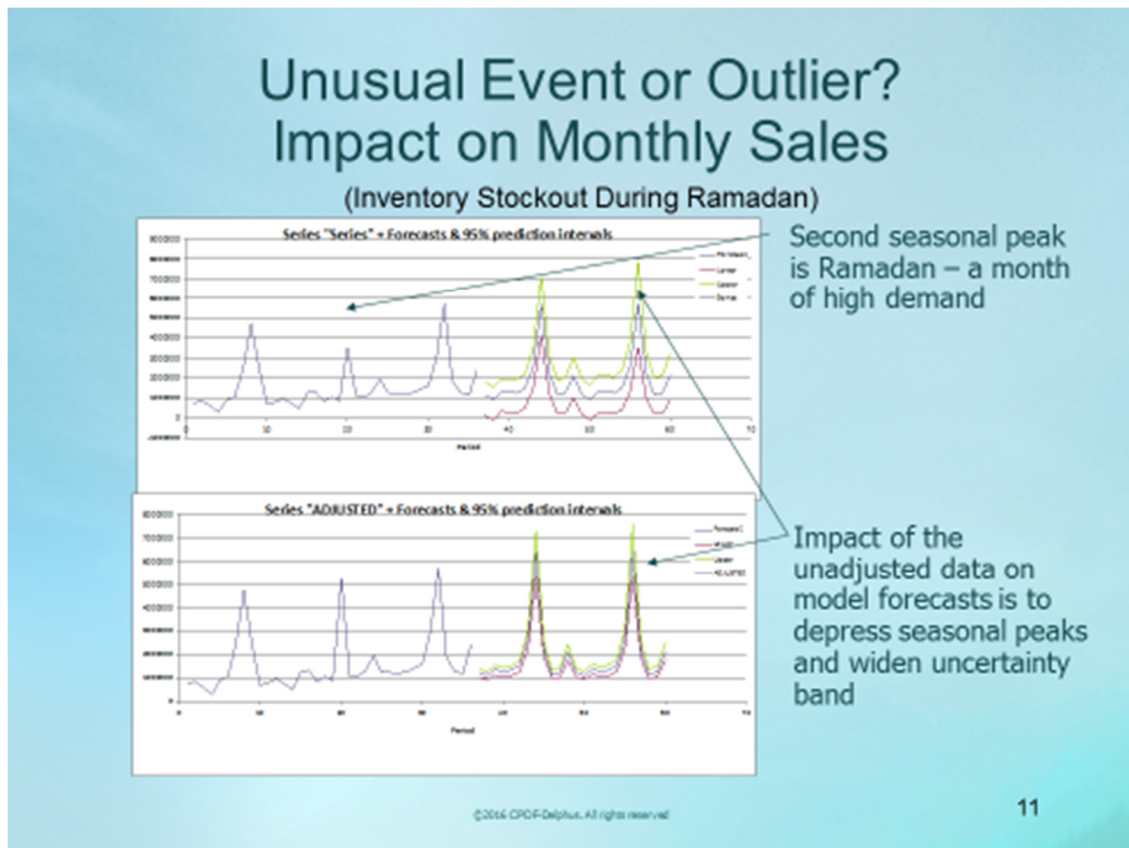
- How do you separate monthly periodicity from repeated promotional patterns?
- It would be difficult to argue that the peak in week X is regularly repeated same week every year, so seasonality in weekly data needs to be put in monthly terms
- To adequately separate seasonal and weekly variation, you should first remove the seasonal pattern in monthly aggregations (4-4-5, for example) and then analyze the residuals for promotional variations. This adjustment process is known as seasonal adjustment and there are a number of techniques for doing that.



Is an unusual event always an outlier?

If you have a seasonal product or service an unusual event can create an outlier in the seasonal pattern, which can subsequently affect forecast patterns in the future

Most product data are seasonal, irrespective of the industry it comes from. Seasonal data commonly also show evidence of outliers and unusual events, like tsunamis, hurricanes, and weather). Such data needs to be adjusted before modeling, because it will adversely affect forecast profiles and hence credibility of the forecast numbers.



How can seasonal forecasts be affected by special events?

- Ramadan is high season for acquiring new refrigerators in Islam communities
- Second seasonal peak in the history was attributed to a stock out situation
- Seasonal models using unadjusted data can yield below expected levels in the seasonal peaks
- When adjusting the historical low judgmentally (half-way between the first and third season), yields more credible forecasts, given the increasing trending data.
- If you have a seasonal product or service an unusual event can create an outlier in the seasonal pattern, which can subsequently affect forecast patterns in the future
- Most product data are seasonal, irrespective of the industry it comes from. Seasonal data commonly also show evidence of outliers and unusual events, like tsunamis, hurricanes, and weather). Such data needs to be adjusted before modeling, because it will adversely affect forecast profiles and hence credibility of the forecast numbers.

Month of Year by Day of Week Table Daily Volumes of Bank Transactions

	Monday	Tuesday	Wednesday	Thursday	Friday	Row Average
Jan	477,917	409,518	379,047	393,664	452,449	418,000
Feb	636,680	432,902	394,166	408,315	498,308	464,222
Mar	706,768	420,468	340,188	369,720	538,977	478,260
Apr	682,889	438,742	362,521	413,258	497,603	476,059
May	705,511	411,623	372,164	391,595	577,121	478,848
Jun	695,630	404,631	332,660	375,995	521,897	466,163
Jul	658,762	369,258	357,572	338,208	469,491	445,289
Aug	669,210	364,905	317,892	369,743	528,029	449,859
Sep	680,885	380,473	360,015	371,994	509,277	464,742
Oct	669,066	382,439	361,079	392,102	522,753	447,327
Nov	714,527	401,480	392,144	385,208	545,422	485,524
Dec	666,161	400,921	361,410	384,294	518,274	461,053
Results:						
Day of week	91%					
Time of year	3%					
Irregular	6%					

(Exhibit 4.14)



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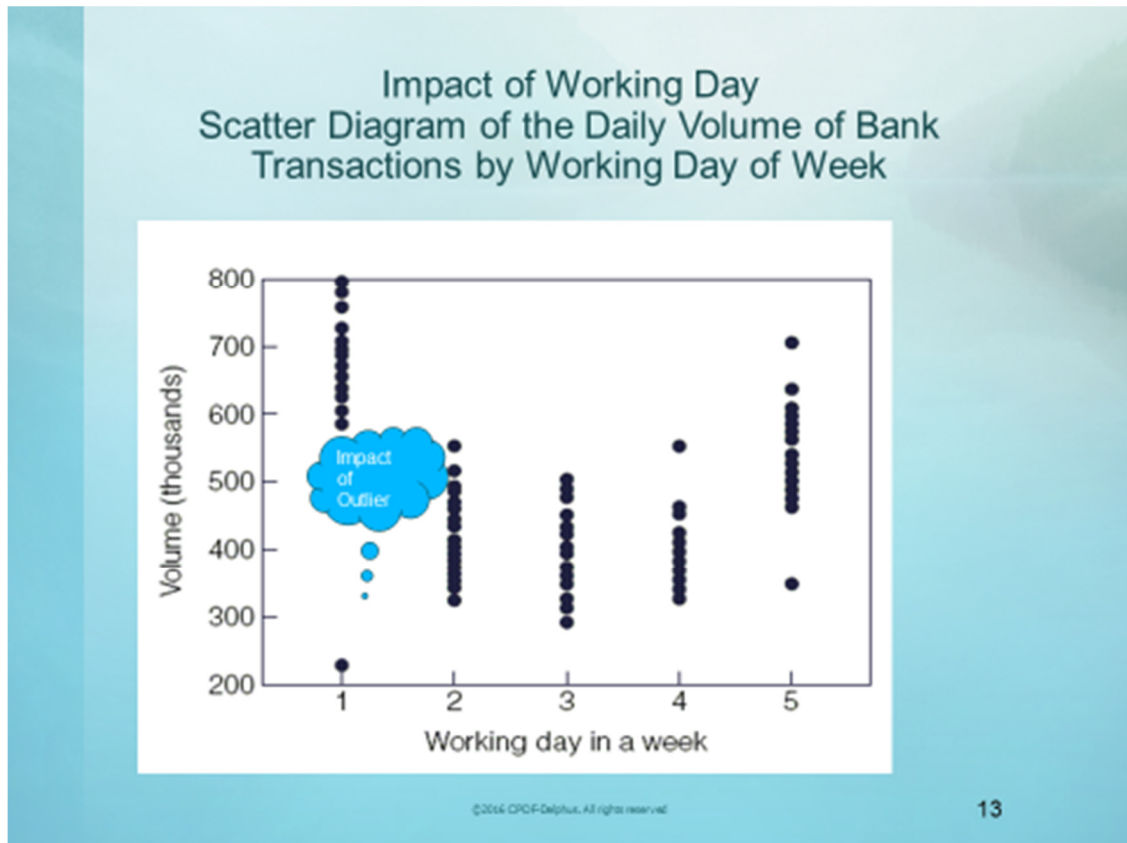
12

How can you analyze variability in a two-way table analysis?

Example: Variability in month of year by day of week for bank transactions

- ANOVA decomposition shows that Day of the week accounts for 91% of the variation in bank transactions.
- Time of year accounts for 3% of the variation
- Irregular accounts for 6% of the variation
- What is impact of Day 1 outlier on typical Monday transactions?

See also: Pre-course Workshop and Workshop B



What other data patterns can be analyzed?

Example: Time plot of the impact of working days on the daily volume of bank transactions

- This example shows the working day impact on bank transactions, which peak on Mondays and is lowest on Wednesdays.
- Can you detect this pattern in the table on the next page with the original data?
- How does Day 1 outlier impact estimating a typical Monday?


What is Time Series Analysis?

TSA is used

- Like peeling an onion, to identify essential components of variability in historical data
- To reveal our understanding of the core of the data

Is it accurate and if necessary, adjusted for extreme values?

- To seek a credible **forecast profile**
- To determine if a causal model is appropriate



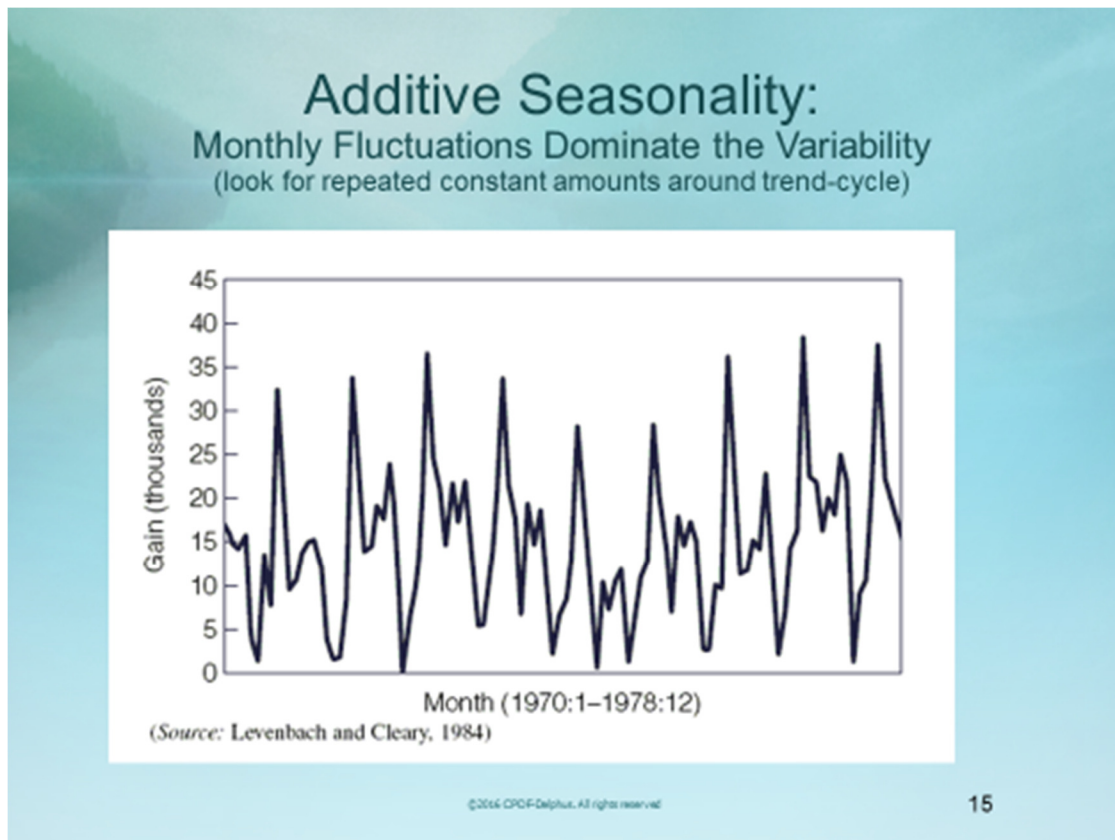
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What is time series analysis?

- We can determine the type of series we are dealing with. This leads to the selection of starting models. We will see, that different exponential smoothing models apply for trend, seasonal and damped data
- Time series analysis is an effective way to gain an understanding of the data that are typical or representative of the problem. It can also pinpoint extreme values that may be transcription errors or unusual events that can distort the forecast if not taken into account or adjusted.
- Each univariate forecasting technique produces a unique *forecast profile*. Suppose you believe that the demand for a product will taper off based on a market analysis. You would want to consider a damped trend exponential smoothing model rather than a linear or exponentially growing model.
- The pattern in the residuals may suggest the need to add one or more variables to help explain the remaining variation, e.g., trend or cycle, leading to a causal regression model.

There may also be a need to transform variables to create a linear relationship between dependent and independent variables. Time series analysis helps determine if this is the case



What does additive seasonality look like?

Seasonality refers to

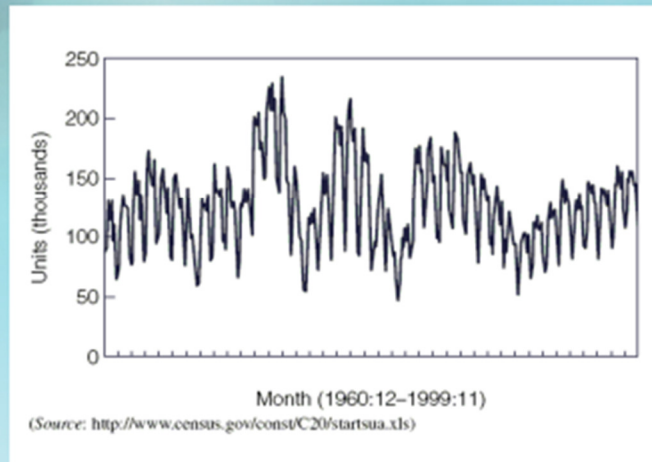
- Refers to regular periodic fluctuations that recur every year with about the same timing and intensity. Can also occur as fluctuations that recur during months, weeks or days.
- Many economic series show seasonal variation.
- When seasonality is removed, trend-cycle patterns become apparent.

Note that

- The time plot shows the monthly fluctuations in telephone line access over a 9-year period
- While the seasonal pattern is dominant, there is evidence of a cyclical fluctuation, possible related to economic upturns and downturns
- The series is said to be additive because the highs and lows appear to be a constant amount away from the middle of the data (the underlying 'cycle')

What is *Additive* Seasonality?

Monthly Housing Starts over a 40-Year Period



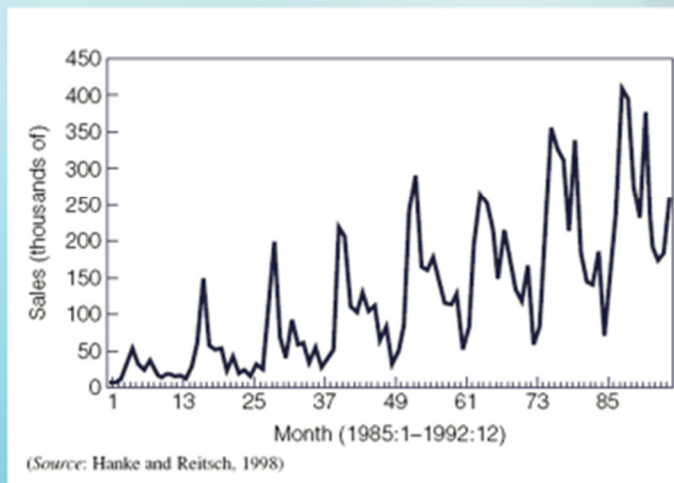
(Source: <http://www.census.gov/const/C20/startsua.xls>)

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What is *Multiplicative* Seasonality?

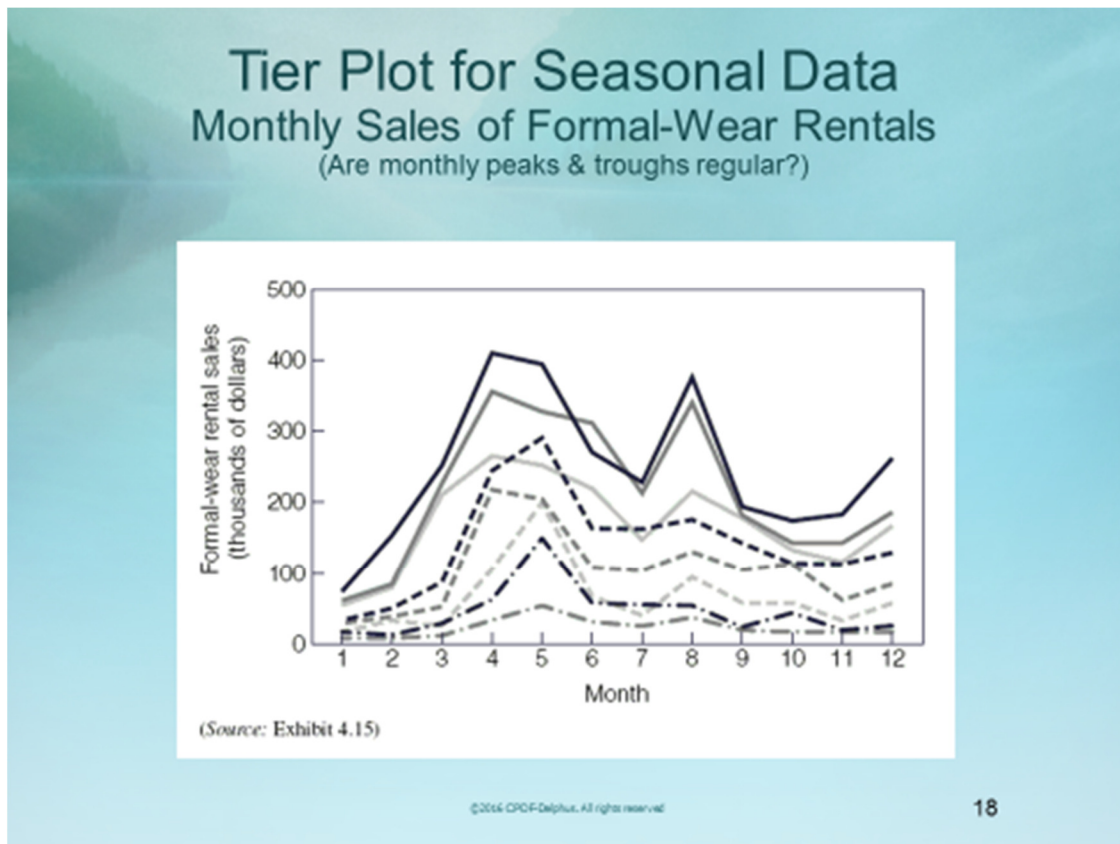
Monthly Sales of Formal-Wear Rentals
(look for repeated constant percentage or ratio around trend)



(Source: Hanke and Reitsch, 1998)

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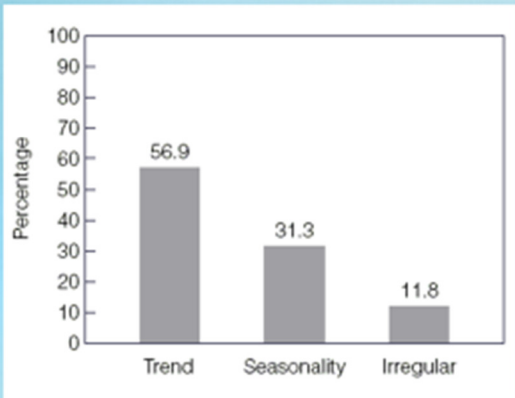


Is the seasonality constant (i.e. has same pattern year after year)? Visualize the Tier Plot

- This data is monthly sales of formal-wear rentals over an 8-year period
- A time series with multiplicative seasonality shows an increase in dispersion with increasing values. The seasonal impact is increasing in magnitude over time
- A series with multiplicative seasonality is typically trending as well. Hence, the seasonality may be a constant *percentage* of the underlying trend
- This is in contrast with additive seasonality which is characterized by a constant *amount* above or below trend
- A **monthly tier plot** shows all the Januaries, and then all the Februaries ... up through December.
- The seasonal pattern is evident with high rentals in April and August and low rentals in January

Trend/Seasonal Contributions to the Total Variability

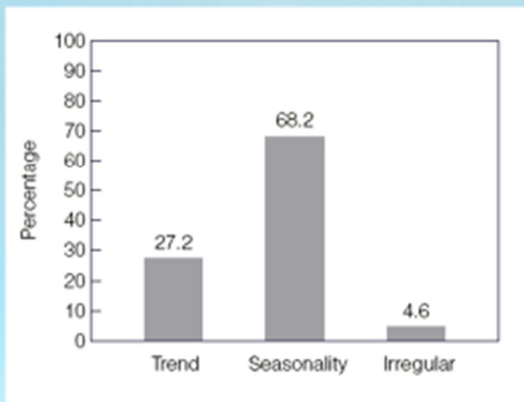
A Visual Decomposition of Monthly Sales of Formal-Wear Rentals



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Trend/Seasonal Contribution: Visual Decomposition of Quarterly Automobile Sales





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Step 2 **E**xecute Models
Using Clean Data with Models

- Exponential Smoothing
 - Quantitative: time series data
- BJ ARIMA /Transfer
 - Now part of a E-T-S State Space Formulation
- Neural Nets
 - promising possibilities
- Best Practices: Blend with qualitative (judgmental) approaches

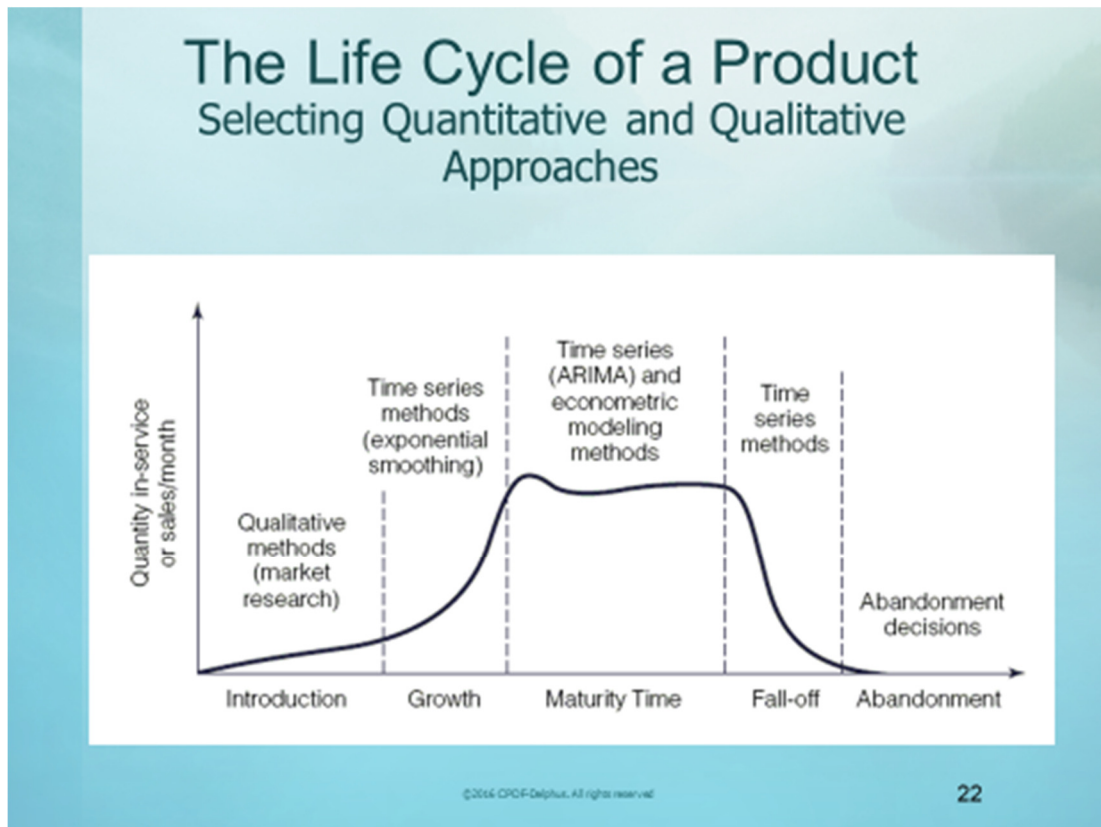
The 'B' in 'BJ'
Box & Jenkins



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What are the most useful models for forecasting historical demand patterns?

- The *time series models* based on historical data can be classified into a few families
- Historically, exponential smoothing has been viewed as an algorithmic approach (without explicit expression for error distribution, required to measure CHANCE)
- Box Jenkins methodology for ARIMA models are generally too complex for beginning forecasters to comprehend. However, they have a sound theoretical foundation for modeling 'change and chance' (cf. Box, Jenkins, and Reinsel: **Time Series Analysis: Forecasting and Control** (1994)).
- Since the mid 90s, publications on State Space Forecasting have unified the exponential smoothing family and univariate ARIMA models into a single theoretical framework, including multiplicative error terms (cf. Hyndman, Koehler, Ord and Snyder: **Forecasting with Exponential Smoothing – The State Space Approach** (2008)).
- More recently, neural nets has an active following among academics and researchers, but has not proven itself yet among demand forecasting practitioners
- Note: Some methods like moving averages and double exponential smoothing are outdated and outmoded.
None of these methodologies can work without the active involvement of the demand forecaster in a practical environment using structured judgment.

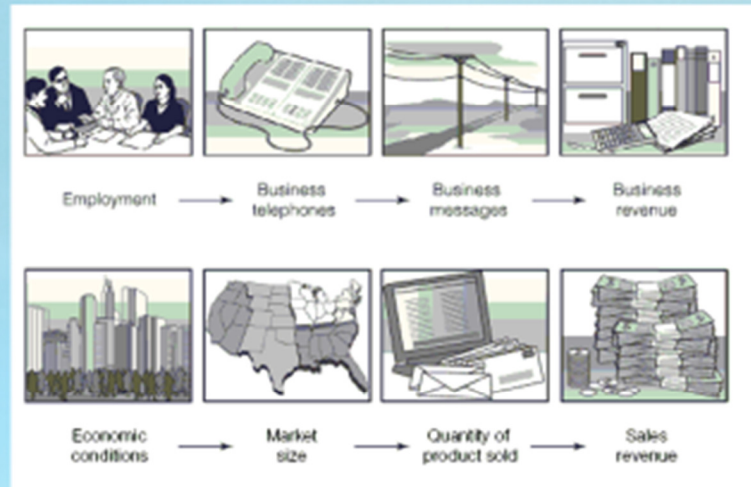


***In 1979 George E. P. Box, a world renowned statistician, stated in a paper:
“All models are wrong, but some are useful”***



How Do We Learn From Actual Examples?

A Volume-Revenue Forecasting Relationship



The nice thing about the forecasting discipline is that the nouns may change, but the verbs stay the same – (paraphrasing Prof Carl Marshall, Oklahoma State U)

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How do we learn from actual examples of forecasting?

- Forecasting problems are derived from the requirement for accurate, timely, and reliable forecasts of demand, sales, revenues, product shipments and services
- In this telecom example, the market that generates telephone toll revenues may be viewed, in part, as the number of business telephones from which calls can be made. Toll messages (calls) are regarded as the quantity of service rendered (or product sold)
- In the FMCG industry, the economic and demographic environment can generate demand for consumer products and services
- The correspondence between revenues and messages is not one to one because additional factors cause variation in the revenues.
- Paraphrasing Prof Carl Marshall, Oklahoma State University :

The nice thing about the forecasting discipline is that the nouns may change, but the verbs stay the same.

A Forecasting Model As an Abstraction of Reality:

Example: Service Demand for a Major Metropolitan Area

Albert Einstein once said
"Things should be made as simple as they are, but not simpler"

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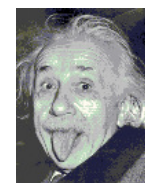
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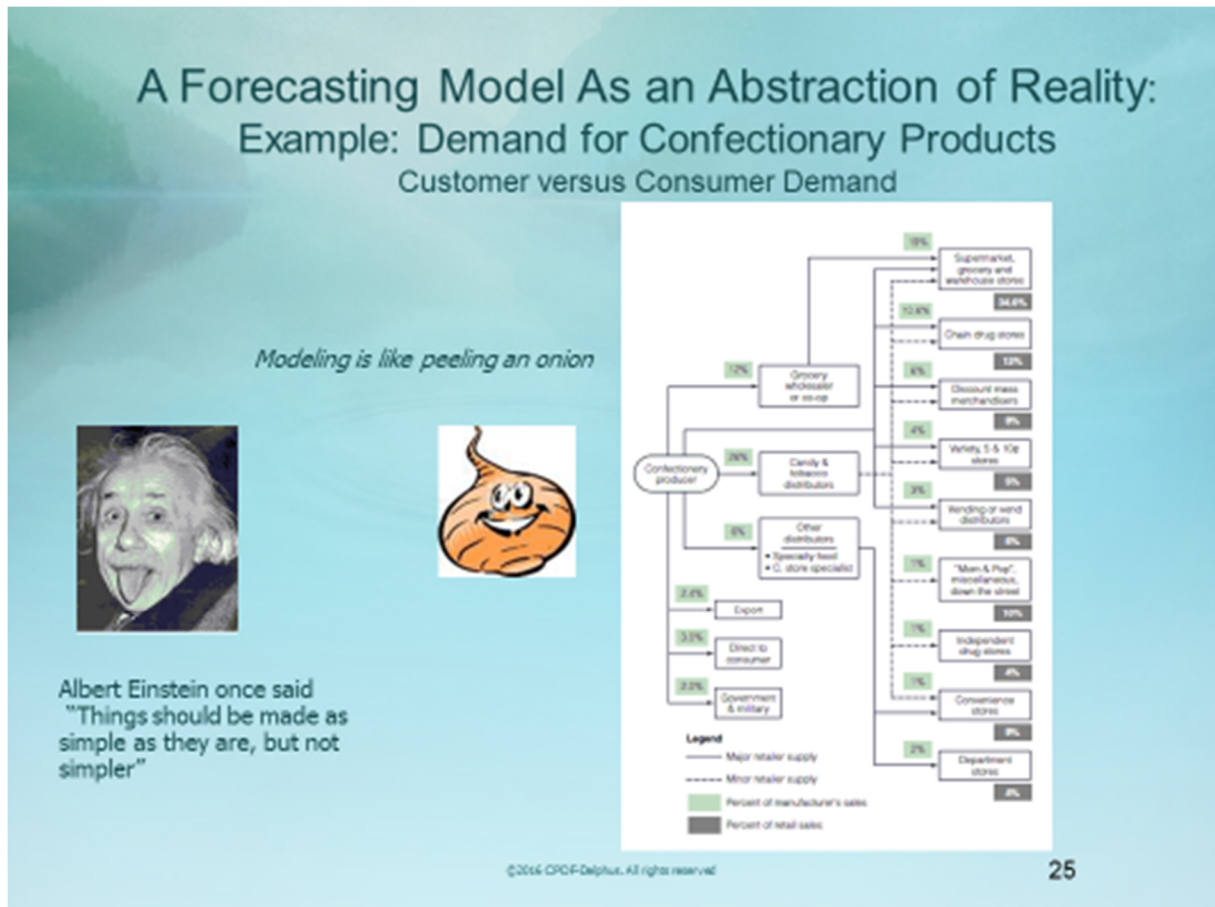
What are forecasting models?

- Get a picture first. A forecasting model is a simplified representation of reality for making projections. It is a job aid for forecasters
- In the telecom industry, there are numerous reasons why subscribers want their services connected or disconnected or why they place calls over a network
- A forecaster attempts to distill these many influences down to a limited number of the most pertinent factors
- This model of the demand for telephone service in a major metropolitan area assumes that the automobile industry creates jobs for people, who then buy homes or rent apartments and want telecommunication services
- The forecaster's job is to determine the relationships among employment levels, household growth, land use and telephone demand.

Albert Einstein once said

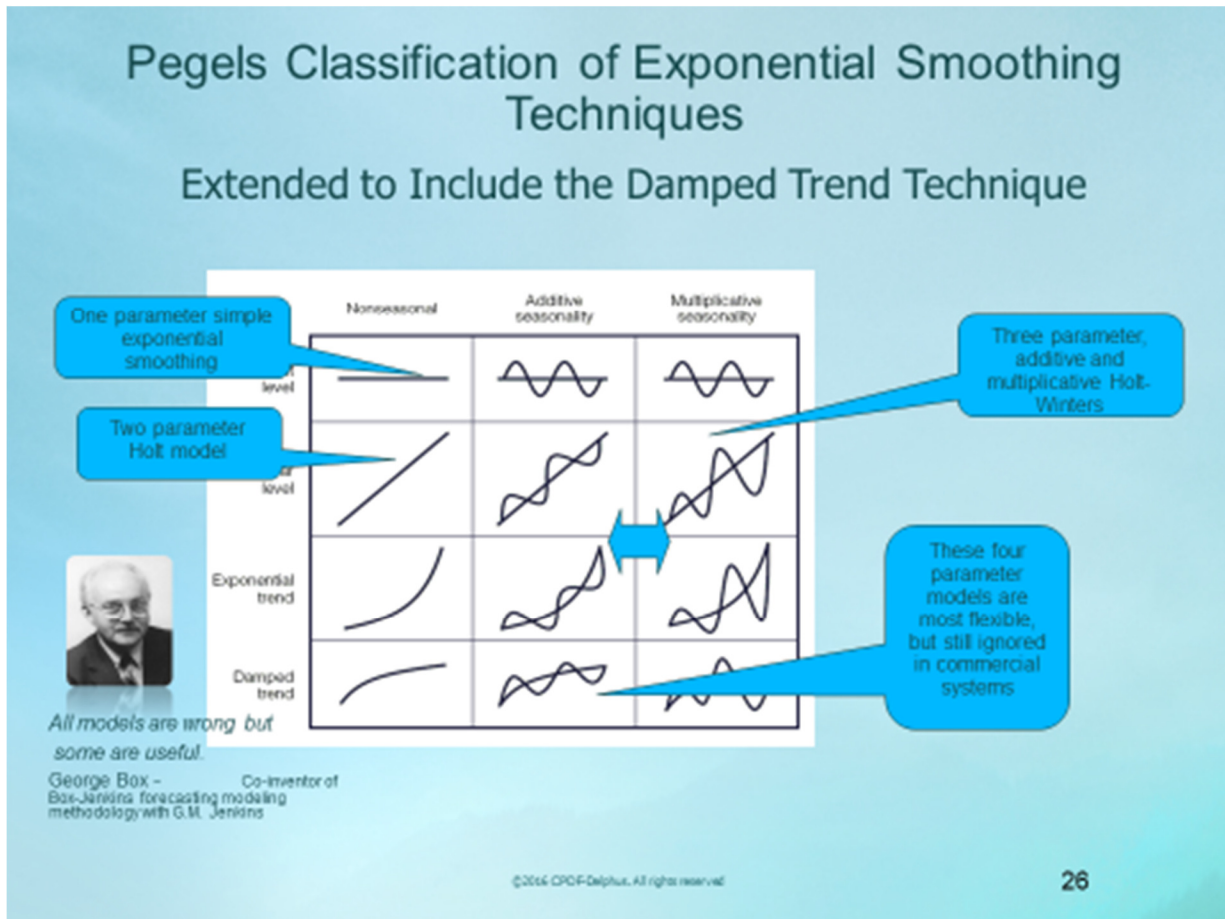
"Things should be made as simple as they are, but not simpler"





What are forecasting models?

- Get a picture first. A forecasting model is a simplified representation of reality for making projections. It is a job aid for forecasters
- In the FMCG industry, there are numerous reasons why consumers want products and services
- A forecaster attempts to distill these many influences down to a limited number of the most pertinent factors
- The forecaster's job is to determine the relationships among economic, demographic and regulatory policy variables.





What is PEGELS' CLASSIFICATION for exponential smoothing models?

Pegels classified exponential smoothing models in an array breaking down trend, nonseasonal, additive/multiplicative seasonal *forecast profiles*.

- The simple exponential smoothing model (SES) produces a horizontal, nonseasonal profile (cell 1,1)
- The Holt model (Linear Trend, Nonseasonal) produces a straight line, nonseasonal forecast profile
- The Holt-Winters produces a linear trend, additive or multiplicative seasonal profile
- These models also include a non-additive error model structure providing asymmetric (i.e. not symmetrical like the normal distribution) prediction limits. These are NEW and generally not available in commercial forecasting software
- The ARIMA models can also be classified by looking at their forecast profiles (they are deterministic)
- It is generally not beneficial to understand forecast profiles and forecast performance through manipulation of parameter settings in computer systems.

Documenting Data Validation Steps

- Identify outliers and extreme values
 - Data analysis – plots, tables, % changes, ratios to other series, seasonal adjustment
 - Compare to alternative robust methods and outlier resistant statistics
- Investigate possible causes of outliers, such as
 - Transcription errors
 - Strikes, weather, changes in seasonality
 - Temporary changes in geographic boundaries
 - Changes in customer segments/product groups
 - And BLACK SWANS
<http://www.youtube.com/watch?v=BDbuJtAiABA>



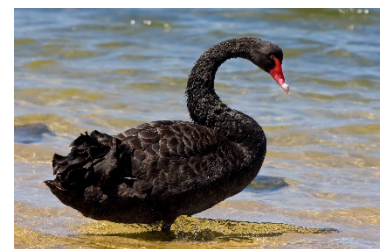
Nassim Taleb

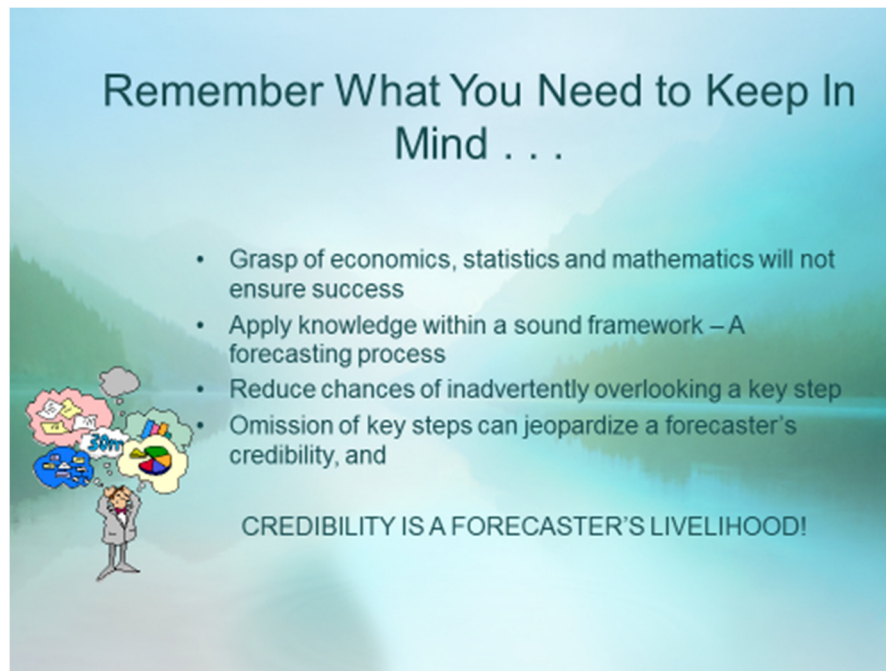
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Why document what you are doing? The data validation steps

- Identify outliers and extreme values
 - Data analysis – plots, tables, % changes, ratios to other series, seasonal adjustment
 - Compare to alternative robust methods and outlier resistant statistics
- Investigate possible causes of outliers, such as
 - Transcription errors
 - Strikes, weather, changes in seasonality
 - Temporary changes in geographic boundaries
 - Changes in customer segments/product groups
- **Beware of Black Swans!** A **black swan** is an event, positive or negative, that is deemed improbable yet causes massive consequences. In this groundbreaking and prophetic book by Nassim Taleb - **The Black Swan: A Highly Improbable Event with High Impact.**

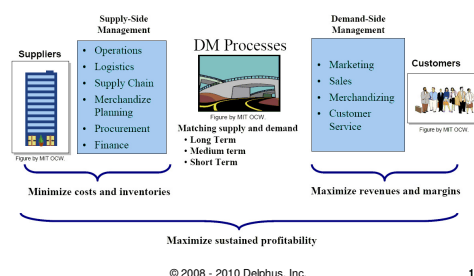




Remember what do you need to keep in mind in the demand-forecasting job?

- A grasp of economics, statistics and mathematics, including psychology and computer science, although necessary for the forecaster, will not in itself ensure successful forecasting
- For the best results, apply such knowledge within a sound framework – a forecasting process
- Following a sound process, which describes the sequence of activities to be followed, can reduce the chances of inadvertently overlooking a key step
- The omission of a key step, whether deliberate or inadvertent, can jeopardize a forecaster's credibility, and credibility is a forecaster's livelihood.

Need To Integrate Demand and Supply Management Processes



Computer Workshop B (02): Exploring Trend and Seasonal Variation

Computer Workshop B Take-Away:



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What You Should Be Able To Do

Computer Workshop B (02) Exploring Trend and Seasonal Variation

1. Use a two-way decomposition analysis to determine the relative contribution of the trend, seasonal, and irregular components in historical data. Construct a pie or bar chart.
2. Create a time plot of the original data and of the logarithms of the data. Comment on the variability of the seasonal fluctuations in the data.
3. Is the seasonality additive or multiplicative, in your opinion?

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After completing this workshop, you should be able to:

- Construct several kinds of time plots used in demand forecasting for trending and seasonal data
- Understand the motivation behind showing sources of variation
- Create an ANOVA decomposition of a time series and its interpretation for seasonal and trend analysis
- Interpret the row and column effects in terms of seasonal and trend variations
- Create an exploratory time series decomposition (RMA) into trend-cycle, seasonal and irregular components..

Resources

- L&C, Chapters 3 & 4
- China Ice Cream: <http://chinatownicecreamfactory.com/>
- China Tourism: <http://www.chinatour.com/data/data.htm>

Key Words

Time plot – a graph in which the data values are shown sequentially in time

Trend – basic tendency of a measured variable to grow or decline over a long period

Seasonality – regularly recurring or systematic yearly variation in a time series

Irregular – unusual or rare events arising in a time series

Analysis of Variance (ANOVA) – a technique in which the total variation of a dataset is assumed to be influenced by different causes and the variation due to each cause is separated from the total variation and measured. For business data, ANOVA is used to decompose the time series into trend, seasonal, and irregular components

Forecast profile – set of m-period ahead forecast produced by a forecasting technique

ECO BIZ: Ben & Jerry's - YouTube



www.youtube.com/watch?v=yQyGinvNrww

May 17, 2007 - 4 min - Uploaded by sundancechannel

Top Comments. Thumbs up if you were eating Ben 'N Jerry's when you watched this video. TheRStard 1 year ago ...



Workshop CASE 1: Demand for Ice Cream - Data name: ICECREAM

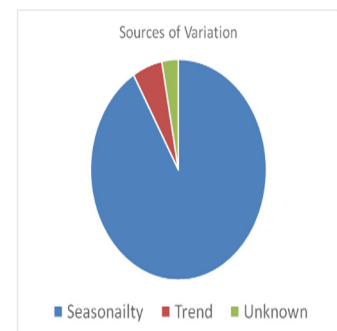
1. Create a time plot of the original data and of the logarithms of the data. Comment on the variability of the seasonal fluctuations in the two plots.
2. Use a two-way decomposition analysis to determine the relative contribution of the trend, seasonal, and irregular components in the two situations. Construct a pie chart or bar diagram for these.
3. Is the seasonality additive or multiplicative, in your opinion?





CASE 2: Demand for Tourism - Data Name: DCTOUR

4. Create a time plot of the original data and of the logarithms of the data. Comment on the variability of the seasonal fluctuations in the two plots.
5. Use a two-way decomposition analysis to determine the relative contribution of the trend, seasonal, and irregular components in the two situations. Construct a bar diagram for these.
6. Is the seasonality additive or multiplicative, in your opinion?




Alternative CASE: Demand for Product - Data file: Supplied by workshop participant



Part III

How to Use Components of a Time Series

Learning Objectives



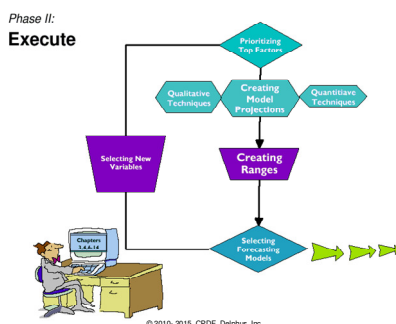
- Characterizing components of a time series
- Using moving averages for smoothing kinks out of time series data
- Contrasting between *centered* and *un-centered* moving averages
- What is the Ratio-to-Moving Average (RMA) method?
- Creating additive and multiplicative seasonal factors
- Creating exploratory projections with the RMA decomposition method

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What this topic is about

- Using moving averages to smooth unwanted variation in time series
- Contrasting between centered and un-centered moving averages
- Using the 'ratio-to-moving average' (RMA) method for decomposing a time series into trend, seasonal and irregular components
- Determining seasonal indices (seasonal factors) from the RMA method
- Creating projections with the RMA decomposition method

Resources: Levenbach, H. C&C, Chapter 5



RMA is a
quantitative
analysis METHOD,
not a Forecasting
MODEL!!

What Is A Time Series?

A Time Series is a chronologically ordered set of data

Examples

- Hourly demand for electricity
- Daily stock prices
- Weekly shipments
- Monthly sales
- Quarterly index of an economic variable
- Annual profit



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What is a time series?

- A time series is a chronologically (time-ordered) set of data
- A time plot is a plot of the values of the time series against a time scale
- Examples of commonly occurring time scales range from hourly, daily, weekly, monthly, quarterly to annually
- These time scales are referred to as the period of the data.


Remember Time Series Analysis?

TSA is used

- Like peeling an onion, to identify essential components of variability in historical data
- To reveal our understanding of the core of the data

Is it accurate and if necessary, adjusted for extreme values?

- To seek a credible **forecast profile**
- To determine if a causal model is appropriate



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What is time series analysis?

- We can determine the type of series we are dealing with. This leads to the selection of starting models. We will see, that different exponential smoothing models apply for trend, seasonal and damped data
- Time series analysis is an effective way to gain an understanding of the data that are typical or representative of the problem. It can also pinpoints extreme values that may be transcription errors or unusual events that can distort the forecast if not taken into account or adjusted.
- Each univariate forecasting technique produces a unique *forecast profile*. Suppose you believe that the demand for a product will taper off based on a market analysis. You would want to consider a damped trend exponential smoothing model rather than a linear or exponentially growing model.
- The pattern in the residuals may suggest the need to add one or more variables to help explain the remaining variation, e.g., trend or cycle, leading to a causal regression model.

There may also be a need to transform variables to create a linear relationship between dependent and independent variables. Time series analysis helps determine if this is the case

Trend

- The tendency for the same pattern to be predominantly upward or downward over time
- Trending data are often modeled with exponential smoothing methods and linear regression models



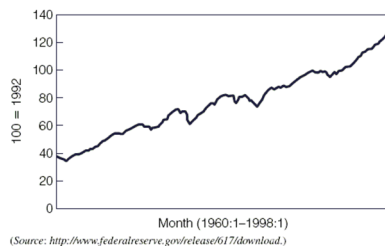
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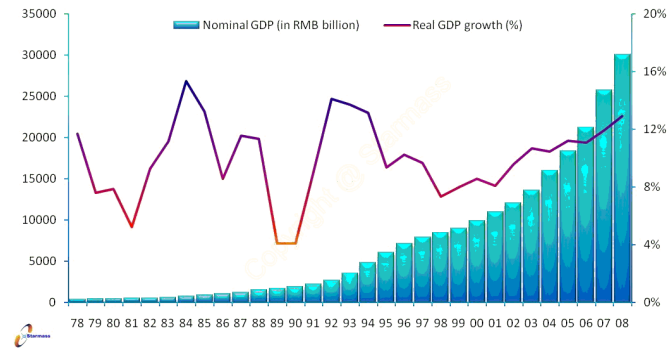
What is meant by Trend?

- This is the tendency of the same pattern to be continuing upward or downward over the duration of the time series. Trends do not imply a straight line pattern.
- Trending data are often modeled with exponential smoothing and linear regression models

Time Plot of a Trending Series - FRB Index of Industrial Production (INDPROD)



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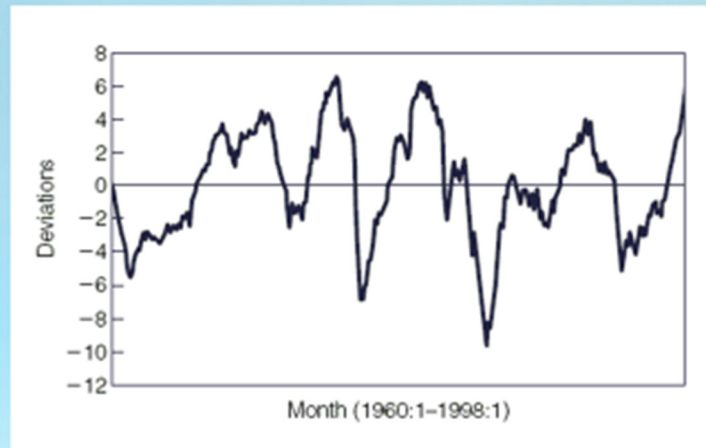
Time plot of a trending series – US Federal Reserve Board Index of Industrial Production

- Notice the tendency of the series to head in one direction
- Trends can be down or up
- There are disruptions in the trend due to economic contractions and expansions
- A trend does not have to follow a straight line

Time plot of a trending series - China GDP trends

- Over the years, Chinese economy growth transition brings about improvement in Chinese people's standard of living and upgrades consumption spending. According to experts from China Machinery Industry Federation, car begun to enter into families when the country's GDP per-capita reaches US\$1000; private car purchase will become common when the figure reaches US\$3000. Such example is large cities such as Beijing and Guangzhou.
- Furthermore, upgrades in consumer spending promote fast growing industries such as electronic telecommunications, auto and housing as the main driving forces of China. In addition, it develops service sector rapidly and the elevation of the level of service industry will be an evitable trend. Such revolution will bring about changes in China's business economy as investors move along with China's economic development.

Cycle – Irregular in Depth and Duration- Deviations from a Straight-Line Trend of the FRB Index of Industrial Production – 37 year period

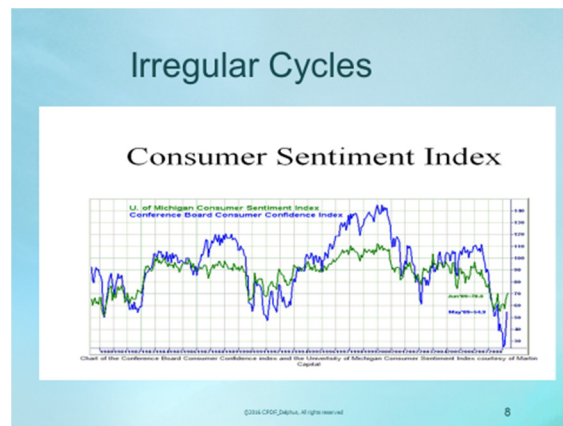


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Cycle- Irregular in depth and duration

- This time plot was created by plotting *deviations from a straight line* fitted through the original INDPROD data, thereby removing the trend
- This emphasizes the cyclical variation around the trend
- The 'cycles' are irregular in duration (how long they last) and depth (highs and lows)



From Wikipedia, the free encyclopedia

The **University of Michigan Consumer Sentiment Index** is a consumer confidence index published monthly by the University of Michigan. The index is normalized to have a value of 100 in December 1964. At least 500 telephone interviews are conducted each month of a United States sample which excludes Alaska and Hawaii. 50 core questions are asked.

The consumer confidence measures were devised in the late 1940's by George Katona at the University of Michigan. They have now developed into an ongoing, nationally representative survey based on telephonic household interviews. The Index of Consumer Sentiment (ICS) is developed from these interviews. The Index of Consumer Expectations (a sub-index of ICS) is included in the Leading Indicator Composite Index published by the U.S. Department of Commerce, Bureau of Economic Analysis.

Objectives

The Index was created and still is published with the following objectives:

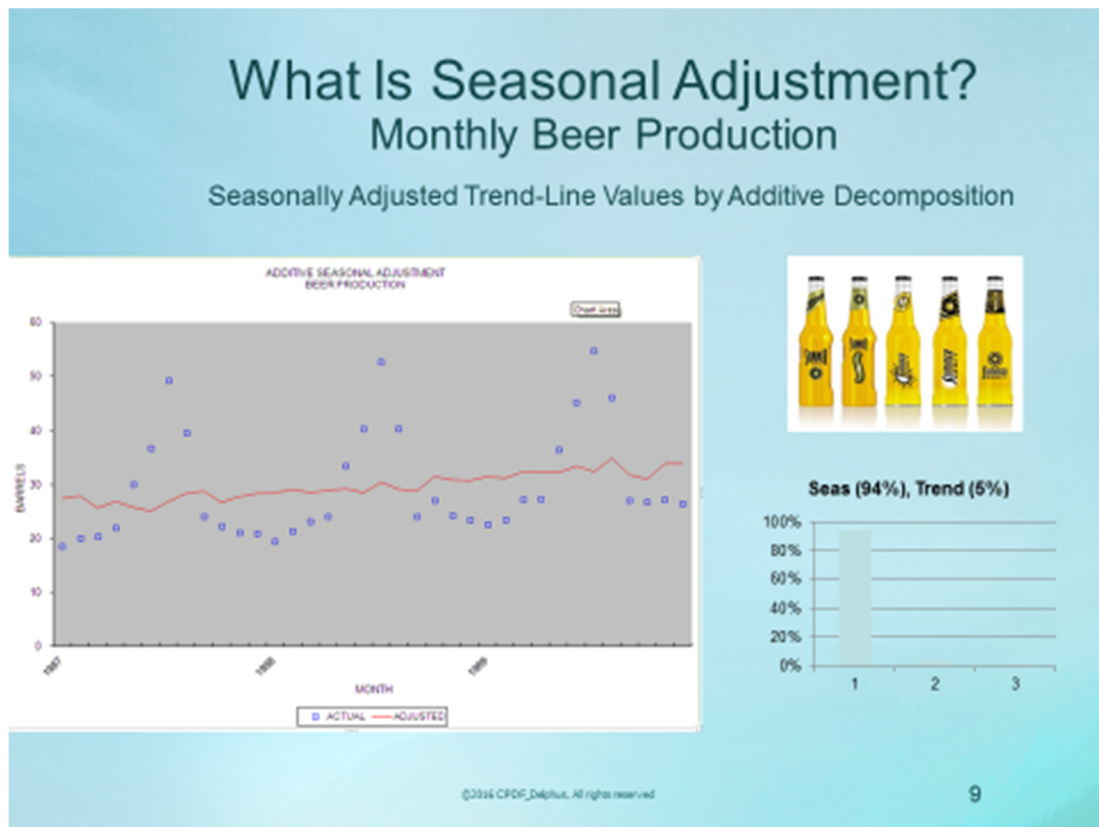
- Near time assessment of consumer attitudes on the business climate, personal finance, and spending
- To create capability for understanding and forecasting changes in the national economy
- To provide means to directly incorporate empirical measures of consumer expectations into models of spending and saving behavior
- To forecast the economic expectations and the future spending behavior of the consumer
- To judge the level of optimism/pessimism in the consumer's mind

Inputs

The Index of Consumer Expectations focuses on three broad areas:

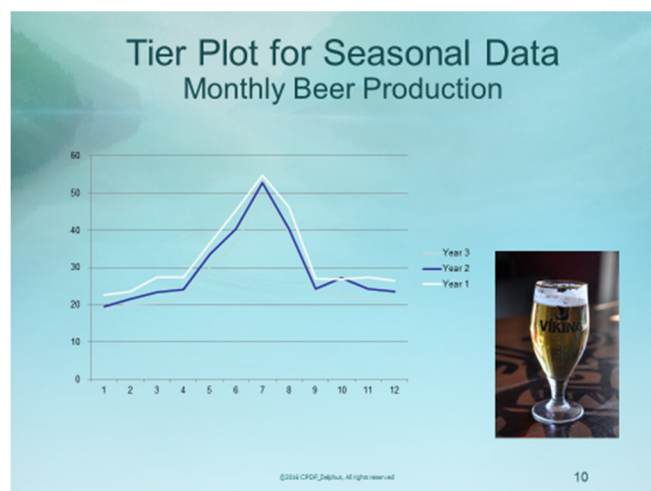
- How consumers view prospects for their own financial situation
- How they view prospects for the general economy over the near term
- Their view of prospects for the economy over the long term

Consumer sentiment indexes from around the world
(<http://marshallplace.com.au/consumer-confidence>)




What does a decomposition of seasonal data look like in terms of trend line determination?

- Tier plot of monthly beer production over a three-year period.
- Solid line are seasonally adjusted values by the additive ratio-to-moving average method
- RMA method is the result of using 'centered' moving averages
- Tier plot shows three lines, one for each year of beer production



What Is The Decomposition Method?

- A decomposition method is an *intuitive* approach to forecasting
- Regards a time series in terms of a number of *unobservable* components, such as Trend, Cycle, Seasonal and Irregular
- Helpful to visualize trend, seasonality and cycle as *abstractions of reality* that provides structure to data and models for forecasting
- Use visualization tools – time plot, tier plot and ANOVA pie/bar chart



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What is the decomposition method?

- It is helpful to think about a time series in terms of *unobservable* components, which are referred to as trend, cycle, seasonal and irregular
- While these components are abstractions of reality, they help to think about the structure of the data and models for them.

Why do we perform time series decompositions?

- To identify essential components in historical data
- To enhance our understanding of data (accurate, adjusted, if necessary, for extreme values)
- To suggest a unique forecast profile for modeling
- To determine if a causal model is needed

Time Series Decomposition - Definitions

	Characteristic Pattern	Type of Data
Trend	Tendency of same pattern to prevail	Revenue Growth
Cycle	Peaks and troughs of similar duration and amplitude	Economic indicators
Seasonal	Regular repeating fluctuations recurring every year	Sales of consumer products
Irregular	Nontypical, unusual or special events	Strikes, factory closings, promotions



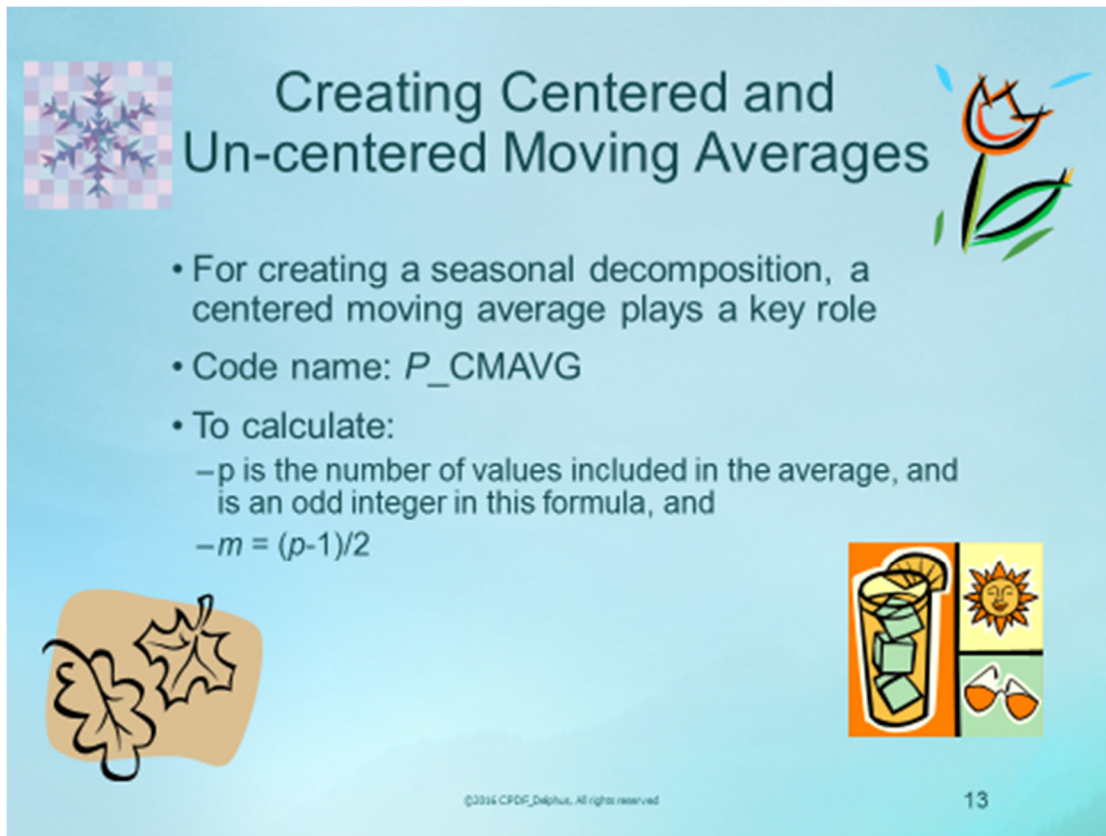
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What are the uses of time series decompositions?

These are examples of series that show patterns typical of trend, cycle, seasonal and irregular:

- Trending series are seen in revenue growth
- Cyclical series occur in economic indicators
- Seasonal series are represented in sales of consumer products
- Irregular series appear in data with strikes and factory closings



Creating Centered and Un-centered Moving Averages

- For creating a seasonal decomposition, a centered moving average plays a key role
- Code name: P_CMAVG
- To calculate:
 - p is the number of values included in the average, and is an odd integer in this formula, and
 - $m = (p-1)/2$

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How do you create centered and un-centered moving averages?

- Excel uses *right* moving average (last value is average of previous values) P_MAVG
- When the average is placed in the center of the data, it is called a *centered* moving average
- For creating a seasonal decomposition, a centered moving average plays a key role.
- The p -term centered moving average P_CMAVG is given by:

$$P_CMAVG_t = (Y_{t-m} + Y_{t-m+1} + \dots + Y_{t-1} + Y_t + Y_{t+1} + \dots + Y_{(t+m)/p})$$

- where Y_t denotes the actual values
- p is the number of values included in the average, and is an odd integer in this formula, and $m = (p-1)/2$

Example: 3-Term Centered Moving Average Calculation

A 3-term centered moving average is given by:

$$3_CMAVG_t = (Y_{t-1} + Y_t + Y_{t+1}) / 3$$

If p is even, as in monthly or quarterly data, there is no middle position to place the smoothed value

Place it to the right of the observed value or take another centered two-period moving average



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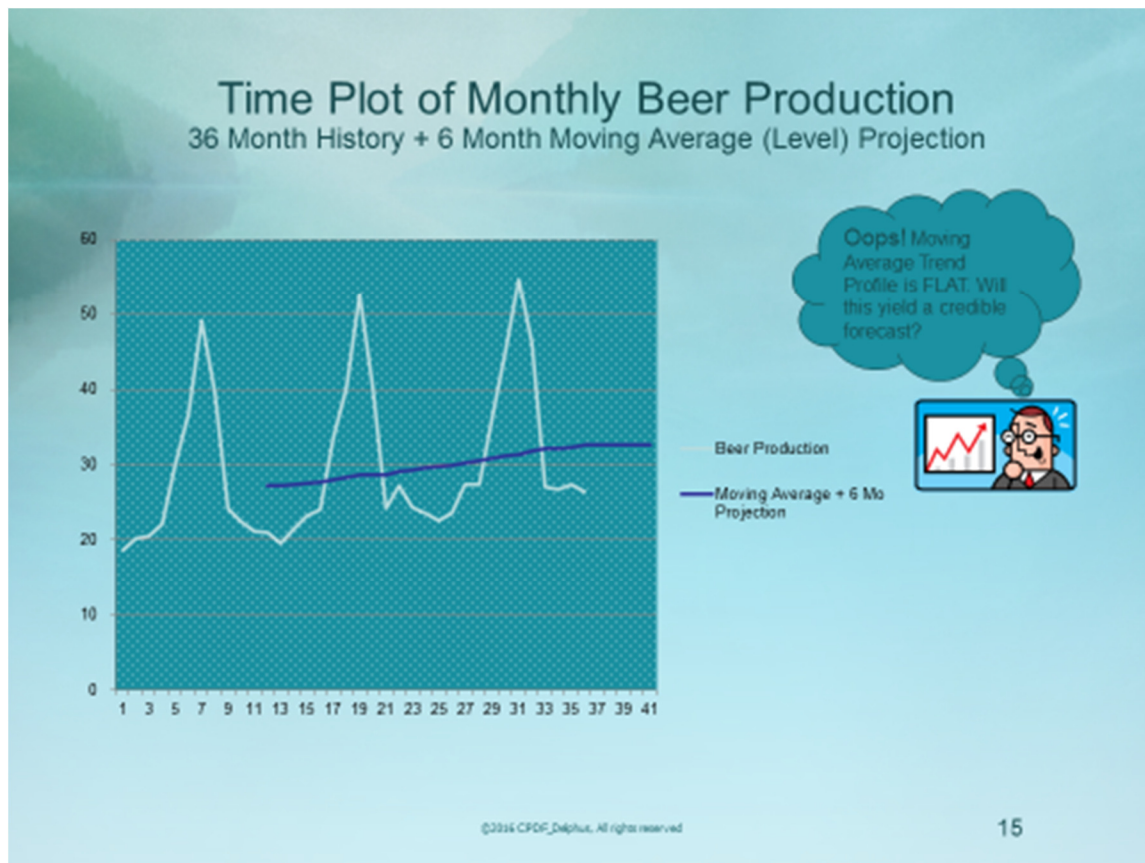
14

What is an example of a three-term centered moving average?

- First step in the RMA method is to create a centered moving average
- Formula is given by

$$3_CMAVG_t = (Y_{t-1} + Y_t + Y_{t+1}) / 3$$

- If p is even, as in monthly or quarterly data, there is no middle position to place the smoothed value
 - Place it to the right of the observed value or take another centered two-period moving average
- When p is an even integer, take a p -term moving average followed by a 2 term moving average (same result as taking a 2-term followed by a p -term moving average)



What is an example of a moving average trend projection?

- $P (= 12)$ is even
- Note how much easier it is to identify the trend-cycle once the seasonality is removed from the data.
- Taking the moving averages in reverse order does not impact the results. That is, the 12-term of a 2-term moving average gives the same results
- The moving average projection is a level line (always, even if the historical data is trending)

The Ratio-To-Moving-Average Method

- Remove trading day variation first from the data by dividing the number of trading days for a given month by the average number of trading days over time
- Then, divide the original data Y_t by the TD adjustment ratio
- Seasonal factors S are found from using a multiplicative form

$$Y_t = TC \times S \times TD \times I$$

Or additive form

$$Y_t = TC + S + TD + I$$

- TC is trend-cycle and I is Irregular (other)



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What is the RMA (ratio to moving average) method?

- Remove trading day variation first from the data by dividing the number of trading days for a given month by the average number of trading days over time
- Then, divide the original data by the TD adjustment ratio
- Seasonal factors S are found from using a multiplicative form

“

$$Y_t = TC \times S \times TD \times I$$

where TC denoted Trend-Cycle, S is for Seasonal, TD is Trading Adjustment and I represent the Irregular

In a series with multiplicative seasonality, the seasonal factor is the symbolic ratio.


$$S = Y_t / TC \times TD$$

- The seasonally adjusted series is given by

$$Y_t / S$$

Determining Seasonal Factors with the RMA Method

The objective of a seasonal
decomposition is to measure typical or
average seasonal movements in
monthly or quarterly data
Seasonal decomposition is
categorized as either additive or
multiplicative

$$\text{Data} = \text{Trend-cycle} + \text{Seasonal} + \text{Irregular}$$
$$\text{Data} = \text{Trend-cycle} * \text{Seasonal Factor} * \text{Irregular factor}$$


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How do you determine additive or multiplicative seasonal factors?

- The objective of a seasonal decomposition is to measure typical or average seasonal movements in monthly or quarterly data
- Seasonal decomposition is categorized as either additive or multiplicative


$$\text{Data} = \text{Trend-cycle} + \text{Seasonal} + \text{Irregular}$$

or

$$\text{Data} = \text{Trend-cycle} * \text{Seasonal Factor} * \text{Irregular factor}$$

Completing The Seasonal Factor Calculation

- Divide the data value by the centered moving average to create a ratio
- Total the ratios for each month/quarter separately
- Divide the total by the number of ratios
- Normalize the ratios to sum to 12 for monthly data or 4 for quarterly data
- Spreadsheet calculations automated in PEERForecaster Add-in



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How do you complete the seasonal factor calculations?

- Because seasonal variation often is a significant component of the variation about the mean value of the data series, it is helpful to remove the seasonal influence to understand the underlying trend-cycle pattern in the data
- The seasonal pattern can be added back if the goal is to forecast the series including the seasonal factor.
- In calculating seasonal factors, the notion of a centered moving average comes into play. With a p point centered moving average, where p is the number of values in the average, you go back $(t-m)$ values and forward $(t+m)$ values, where $m = (p - 1)/2$.
- The moving average is then centered at Y_t (For example, a twelve point moving average contains the six months before and after the midpoint. Since p is an even integer, we take a two point moving average of the twelve point moving average to center the moving average calculation

Uses Of Seasonal Adjustment Factors

- To identify turning points not apparent in historical time series data
- Remove seasonality from data for forecasting techniques that cannot handle seasonal data
 - $\text{Data} - \text{Seasonal factor} = \text{Trend-cycle} + \text{Irregular}$
 - $\text{Data} / \text{Seasonal factor} = \text{Trend-cycle} * \text{Irregular}$



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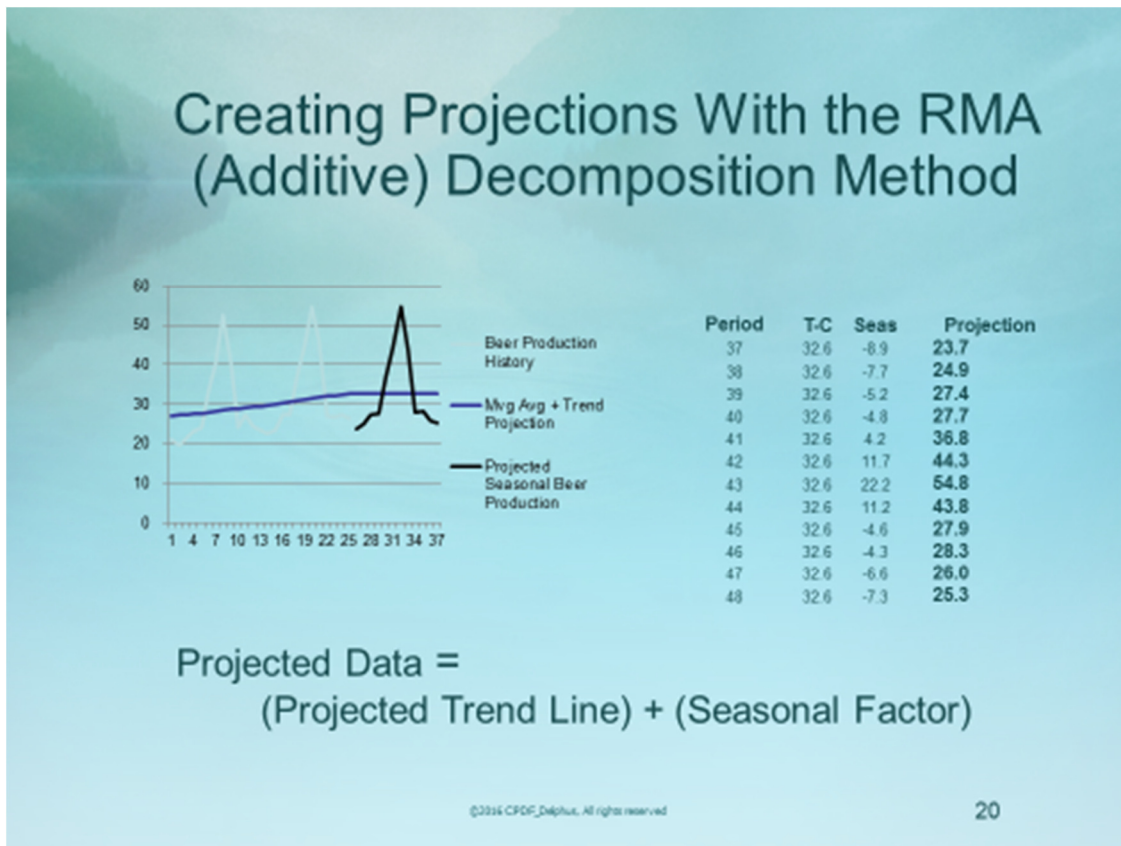
How do you make a seasonal adjustment?

- To identify turning points not apparent in raw data
- Adjust seasonality out of data for forecasting techniques that cannot handle seasonal data
- *Additive* seasonal adjustment with RMA method

$\text{Data} - \text{Seasonal factor} = \text{Trend-cycle} + \text{Irregular}$

- *Multiplicative* seasonal adjustment with RMA method

$\text{Data} / \text{Seasonal factor} = \text{Trend-cycle} * \text{Irregular}$



How do you create projections with the RMA decomposition method?

$$\text{Projected Data} = (\text{Projected Trend Line}) * (\text{Seasonal Factor})$$

or

$$\text{Projected Data} = (\text{Projected Trend Line}) + (\text{Seasonal Factor})$$

Workshop C (03)

Creating Projections and Seasonal Adjustments with RMA Decomposition Technique

Ben & Jerry's Factory Tour and Flavor Graveyard

<http://www.roadsideamerica.com/story/8545>



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Workshop C, Question 1

Interpreting seasonal factors

1. → Based on past data, your firm's sales show a seasonal pattern. The seasonal index for November is 1.08; for December 1.38; and for January 0.84. Sales for November were \$285,167.
 - a. → Would you ordinarily expect an increase in sales from November to December in a typical year? How do you know?
 - b. → Find November's sales on a seasonally adjusted basis.
 - c. → Take the seasonally adjusted November figure in (b) and seasonalize it using the December index to find the expected sales level for December.
 - d. → Sales for December have just been reported as \$430,106. Is this higher or lower than expected, based on November's sales?
 - e. → Find December's sales on a seasonally adjusted basis.
 - f. → On a seasonally adjusted basis, were sales up or down from November to December? What does this tell you?

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Part IV

Baseline Forecasting With State Space Forecasting Models

Learning Objectives



- Understanding what a naïve forecasting technique is
- Understanding smoothing weights and forecast profiles for exponential smoothing
- Applying univariate forecasting models to trend/seasonal time series
- Recognizing forecasting profiles for exponential smoothing models
- Using models to find exceptions in data
- Understanding the distinction between forecasting **Methods** and forecasting **Models**

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What You Should Be Able To Do

After completing this topic, you should be able to

- Understand what a naïve forecasting technique is
- Understand the basic concepts of smoothing weights and exponential smoothing
- Distinguish between types of forecasting profiles for an exponential smoothing model
- Recognize forecasting profiles for exponential smoothing models

How You Will Check Your Progress

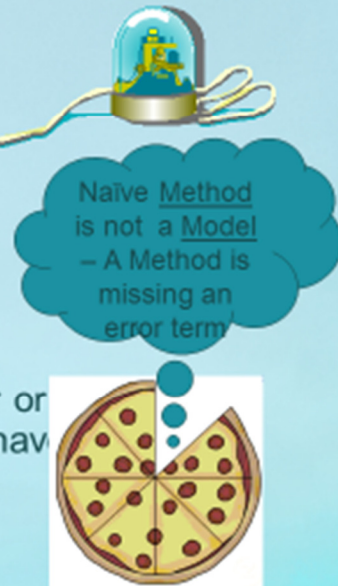
- Create checklist with steps to follow in creating time series forecasts

Resources

- Levenbach: C&C, Chapter 8 - Big Data: Baseline Forecasting with Exponential Smoothing Models.
- Spreadsheet software tools: www.usfca.edu/bps/spreadsheet-analytics

What is a Naïve Forecasting Technique?

- The simplest technique is known as Naïve_1 or NF1
- NF1 is also referred to as a “random walk” or stock market “stock price model”
- The *naïve forecast* serves as a benchmark for level forecast profiles
- If a forecasting technique is no better or worse than the naïve technique, we have not accomplished very much



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What is a naïve forecasting technique?

- The simplest technique is known as Naïve_1 or NF1 and it uses the current period's actual value for next period's forecast
- This is also referred to as a “random walk” or Wall Street's “stock price model”
- The naïve forecast serves as a benchmark for level forecast profiles
- If a forecasting technique is no better or worse than the naïve technique, we have not accomplished very much

What is Exponential Smoothing?

- A univariate forecasting technique that extrapolates historical patterns into the future
- There is a large family of exponential smoothing techniques, each appropriate for a particular pattern and forecast profile
- Can forecast a wide variety of data having trend and seasonal patterns



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What is exponential smoothing?

Exponential smoothing is a family of techniques that

- are widely used in the areas of sales, inventory, logistics, and production planning as well as in quality control, process control, financial planning and marketing planning
- can be described in terms of a state-space modeling framework that provides prediction intervals and procedures for model selection
- are well-suited for large-scale, automated forecasting applications, because they **require** little forecaster intervention, thereby releasing the time of the demand forecaster to concentrate on the few problem cases
- are based on the mathematical extrapolation of past patterns into the future, accomplished by using forecasting equations that are simple to update and require relatively small number of calculations
- capture level (a starting point for the forecasts), trend (a factor for growth or decline) and seasonal factors (for adjustment of seasonal variation) in data patterns

What Are Smoothing Weights?

- An equally weighted average gives the same weight to each value
- The value of the weights in simple exponential smoothing decline exponentially, placing more weight on more recent data



Week	Weights	Equal	Naïve_1	Linear Decay	Exponential Decay	Adjusted Weights
$T-3$	w_4	0.25	0	0.1	0.0625	0.0667
$T-2$	w_3	0.25	0	0.2	0.125	0.1333
$T-1$	w_2	0.25	0	0.3	0.25	0.2667
T	w_1	0.25	1	0.4	0.5	0.5333
Sum		1.00	1.00	1.00	0.9375	1.0000

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What are smoothing weights?

- An equally weighted average gives the same weight to each value
- The value of the weights decline exponentially, placing more weight on more recent data
- The smoothing weight is usually selected by a criteria that minimizes the mean squared error of the one-step-ahead forecasts

What are weighting schemes?

Chart provides examples of alternative weighting schemes for smoothing including:

- Equal – every data value gets the same weight
- Naïve – last data point gets weight =1, all the rest have zero weight
- Linear Decay – the weights decline linearly (as in a straight line) with the latest data value given the highest weight and the earliest data value gets the lowest weight
- Exponential decay – the weights decline in an exponential pattern with the latest data value given the highest weight and the earliest data value gets the lowest weight
- The weights must sum to 1.

What Are Smoothing Weights?

- An equally weighted average gives the same weight to each value
- The value of the weights in simple exponential smoothing decline exponentially, placing more weight on more recent data



Week	Weights	Equal	Naïve_1	Linear Decay	Exponential Decay	Adjusted Weights
$T-3$	w_4	0.25	0	0.1	0.0625	0.0667
$T-2$	w_3	0.25	0	0.2	0.125	0.1333
$T-1$	w_2	0.25	0	0.3	0.25	0.2667
T	w_1	0.25	1	0.4	0.5	0.5333
Sum		1.00	1.00	1.00	0.9375	1.0000

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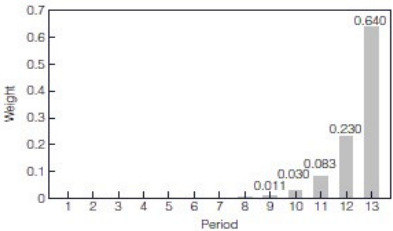
How do you compute weights?

This example illustrates the weighted average of all past data, with recent data receiving more weight than older data. The most recent data is at the bottom of the spreadsheet. The weight on each data value is shown in Figure 8.3.

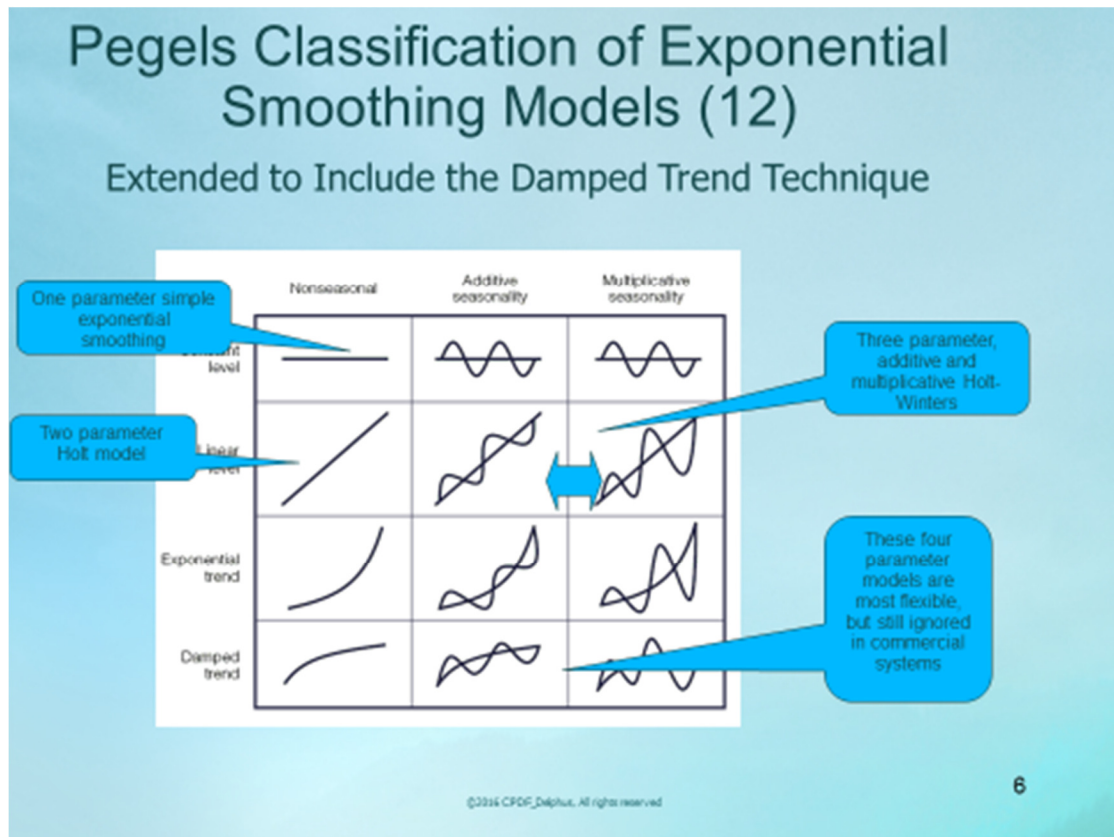
The weights decline exponentially with time, a feature that gives exponential smoothing its name.

ANALYSIS OF WEIGHTS ON PAST DATA					
TITLE1:	WEIGHTS ON PAST DATA			SMOOTHING WEIGHT =	0.64
TITLE2:	SIMPLE EXPONENTIAL SMOOTHING			NBR. OF PERIODS =	12
X-AXIS:	PERIOD				
Y-AXIS:	WEIGHT				
Year	Month	Per	Data	Weight	Data*Weight
1989		0	14	0.000005	0.000066
	1	1	14	0.000008	0.000118
	2	2	11	0.000023	0.000257
	3	3	12	0.000065	0.000780
	4	4	14	0.000181	0.002528
	5	5	12	0.000502	0.006018
	6	6	14	0.001393	0.019504
	7	7	18	0.003870	0.069657
	8	8	17	0.010750	0.182742
	9	9	19	0.029860	0.567337
	10	10	16	0.082944	1.327104
	11	11	18	0.230400	4.147200
	12	12	16	0.640000	10.240000
SUM				1.000000	16.563312

Computation of weights on historical data



Exponentially decaying weights



Why use the Pegels classification of exponential smoothing Models?

- 12 basic formulations resulting in distinct **forecast profiles**:
 - 4 non-seasonal
 - 8 seasonal
 - 4 additive seasonal
 - 4 multiplicative seasonal
- Constant level, non-seasonal is simple exponential smoothing
- Holt models are linear trend, non-seasonal
- Holt-Winters models are linear trend, additive seasonal
- Damped trend models give additional flexibility to damped unusually high fluctuations in trend
- Damped trend models have led to superior overall forecasting performance among univariate techniques
- Simple smoothing is used when there is no trend or seasonal pattern in the data
- Holt is used for linear trend and no seasonality
- Holt-Winters is used for linear trend and additive or multiplicative seasonality

New State Space Classification for Exponential Smoothing Models (15)

	Trend Component		Seasonal	Component
		N (None)	A (Additive)	M (Multiplicative)
One parameter simple exponential smoothing	N (None)	N,N	N,A	
Two parameter Holt model	A (Additive)	A,N	A,A	A,M
	Ad Additive damped	Ad,N	Ad,A	Ad,M
	M Multiplicative	M,N	M,A	M,M
	Md Multiplicative damped	Md,N	Md,A	Md,M

Three parameter, additive and multiplicative Holt-Winters

The damped four parameter models are most flexible, but may not be available yet in commercial systems

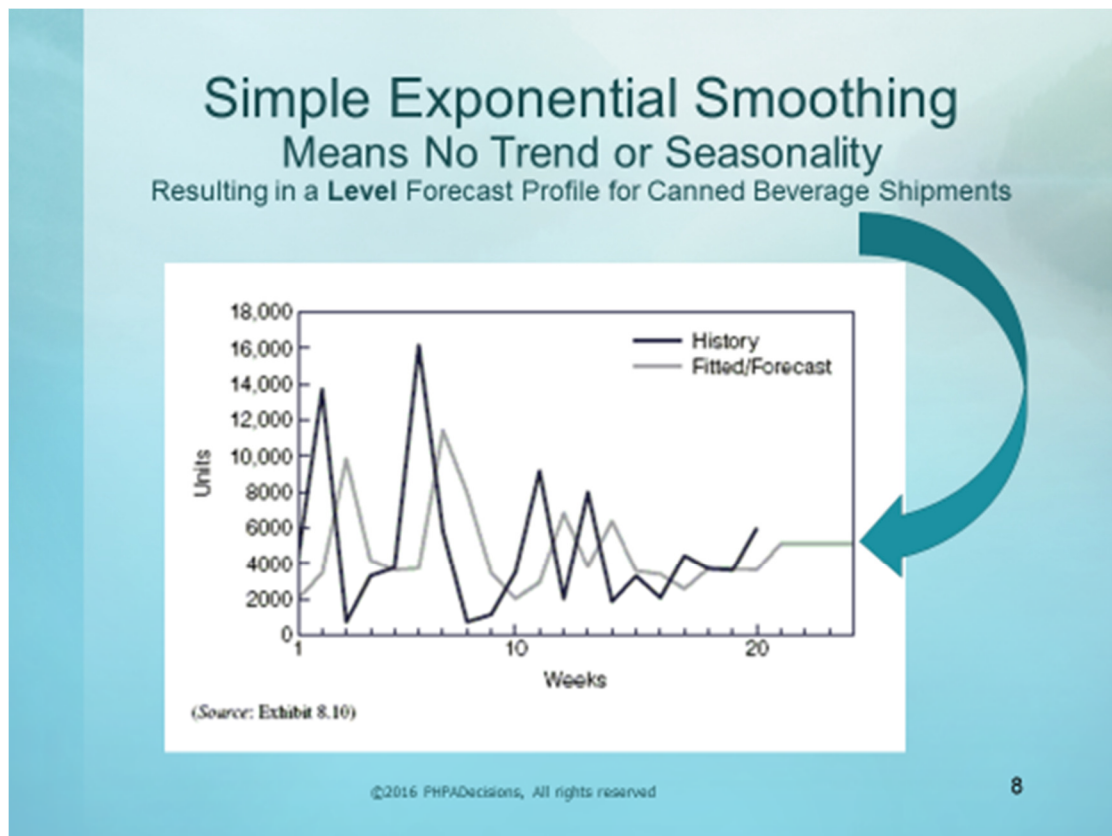
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Additive and multiplicative error models gave identical forecast profiles, but prediction limits are different: symmetrical for additive error and asymmetrical for multiplicative error

State Space Classification of Exponential Smoothing Models

(PEERForecaster.xla Excel Add-in; KFAS: Exponential Family State Space Models in R)

- 15 basic formulations resulting in distinct forecast profiles:
 - 5 non-seasonal
 - 10 seasonal
 - 5 additive seasonal
 - 3 non-damped
 - 2 damped
 - 5 multiplicative seasonal
 - 3 non-damped
 - 2 damped
- It includes additive and multiplicative (NEW!) error → 30 models
- Most commercial systems assume additive error only



What is simple exponential smoothing?

Example: No Trend or Seasonality - Forecast Model for Canned Beverage Shipments

A simple exponential smoothing model is fit to 66 weeks of historical data and a forecast is made for 4 weeks. The optimal estimate (based on the MSE criterion) of the smoothing parameter is 0.62 with $MSE = 1669$. The multi-period forecasts are a constant level ($= 5129$). Thus, it represents a “typical” level. The figure displays the most recent 20 weeks of historical shipments, 20 weeks of fitted values, and the four (level) forecasts.


Because simple exponential smoothing views the future of the time series as lacking both trend and seasonality, the forecasting equation does not contain these terms, leaving the current level as the sole component.

- Note that the fitted values follow the pattern of the historical data (dark line)
- When the historical data ends, the forecasts are level. This means that the forecast profile for simple exponential smoothing is always a horizontal line
- The values of the estimated parameters in the model determine at what level the *horizontal forecast profile*.

Exponential Smoothing Models For Trending Data

- Double exponential smoothing is an
 - Obsolete method, yet still found in software systems
- Holt's Linear Trend exponential smoothing
- Nonlinear (exponential) trend
- Damped trend

Explicit error term is included in *models*



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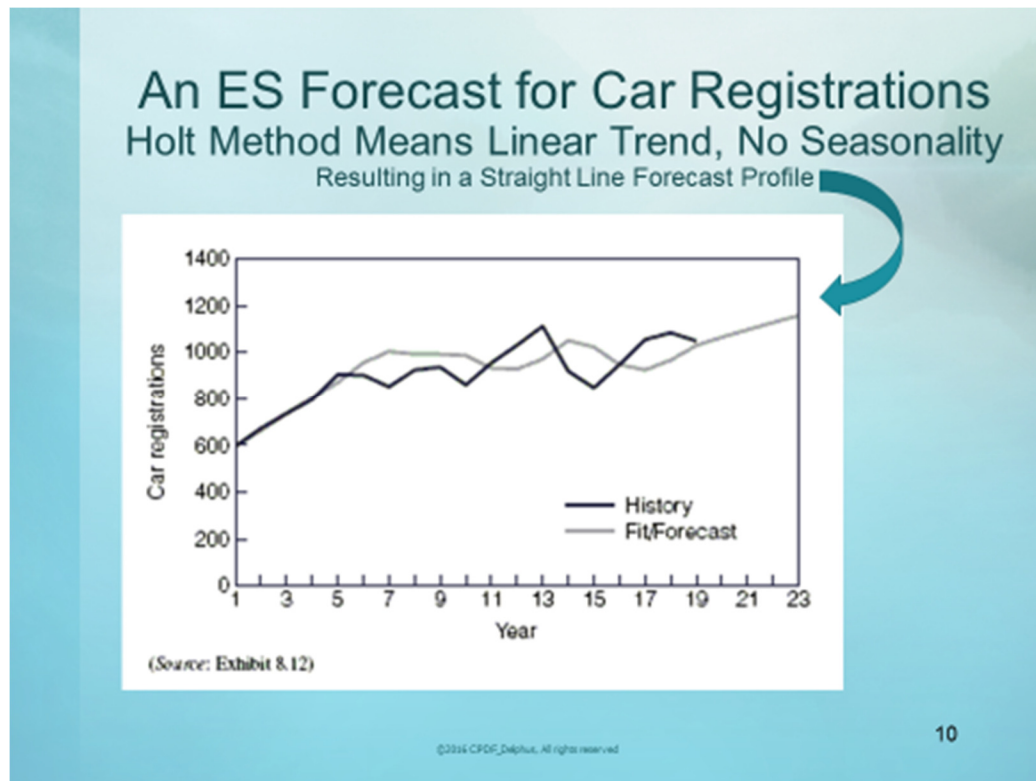
9

What are exponential smoothing models for trending data?

- Holt's Linear Trend exponential smoothing
- Exponential trend
- Damped trend

What is a 'model' versus what is a 'method'?

- Double exponential smoothing (DES) is an outdated method but still widely found in commercial systems
- Performs simple smoothing twice – it is an algorithm
- Capable of smoothing changes in level of the series to produce a linear projection
- But, incapable of measuring uncertainty because it is not a model.
- Holt's model supersedes DES - shown to give better accuracy as well as measured uncertainty
- Methods are like pizza pies with a missing slice (measured uncertainty)



What is the Holt exponential smoothing model for car registrations data?

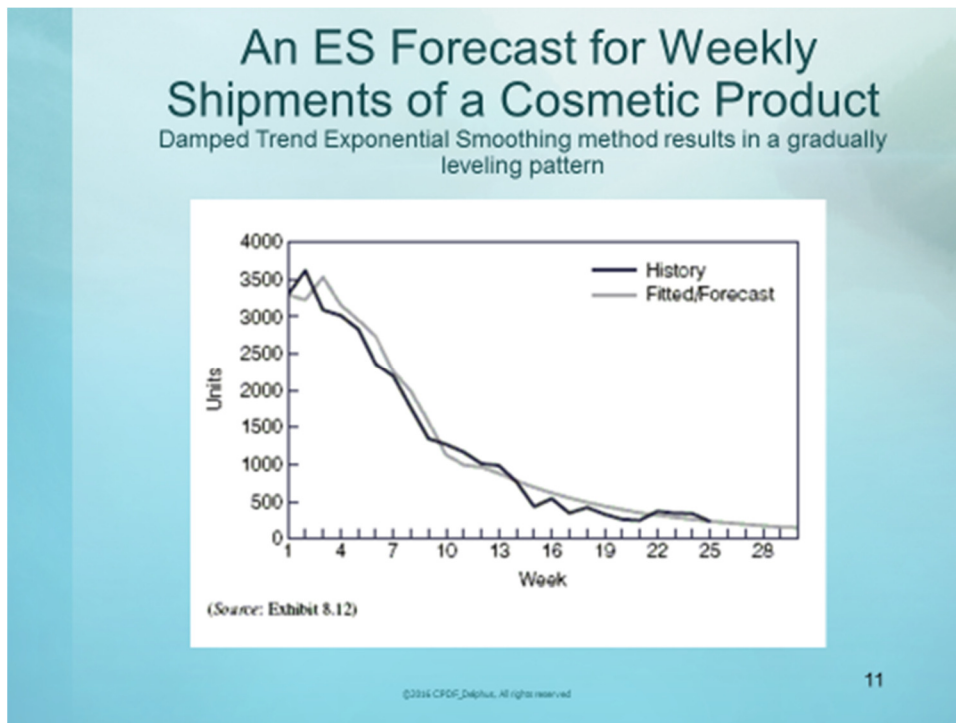
The figure shows a time plot of annual car registration data for a 19-year period. Because the data are annual, the time series is necessarily nonseasonal. The global trend appears to be linear, although there are a number of local variations on the trend. The graph shows the output from the Holt model (A, N) – linear trend, no seasonality. We see that from the vantage point of Year 19, the current level of car registrations is estimated to be 1034 and the current trend is estimated to be an increase of 31 registrations per year. For nonseasonal data, the seasonal index terms are not present in the forecasting equations. What remains in the Holt method, however, is the forecasting equation for a linear trend:

$$Y_T(m) = [L_t + m \times T_t]$$

The forecast for year 22 is 1126, based on calculating a 3-year-ahead projection from the base year $T = 19$:

Source: C&C, Chapter 8, Figure 8.11; Equations: C&C, Chapter 8, page 207

- Trending, irregular pattern in history, forecast profile is a straight line with positive slope
- Note that the fitted values follow the pattern of the historical data (dark line)
- When the historical data ends, the forecasts are a linear (straight line) trend. This means that the forecast profile for the Holt exponential smoothing model is a linear trend line
- The values of the estimated parameters in the model determine at what level and slope the forecast profile is drawn



What is a damped trend exponential smoothing model for weekly shipments?

- In the case of a downward trend, the damped and exponential patterns are similar. During a phase out or decline under adverse market conditions, a forecast profile will be decaying without becoming negative. We may refer to the pattern of shipments of a cosmetic product either as a downwardly damped trend or as exponential decay. Source C&C, Chapter 8, Figure 8.12; Equations: C&C, Chapter 8,

Both damped and exponential trends can be represented in a single forecasting equation, given by

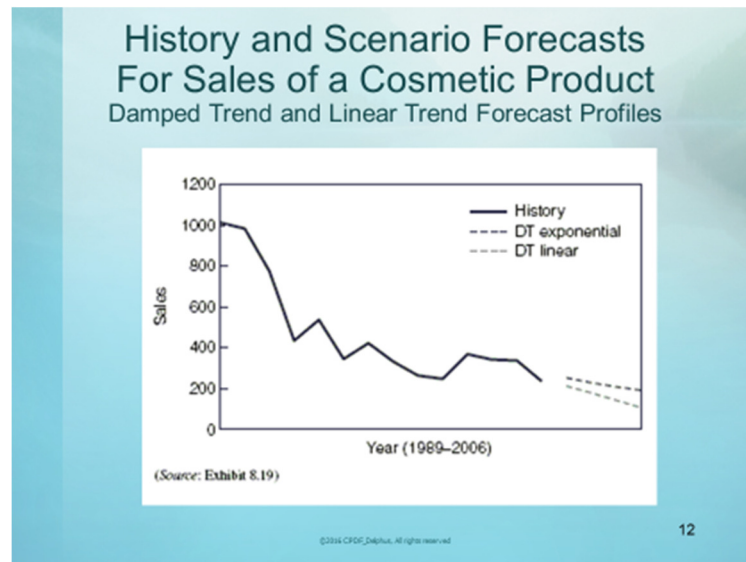
$$Y_T(m) = L_t + \sum \phi^i \times T_t$$

where m is the length of the forecast horizon. The symbol ϕ is called the trend-modification parameter. Depending on the value of ϕ , the forecast profile can be an exponential trend, linear trend, damped trend, or constant level. Here are the cases.

If $\phi > 1$ trend is *exponential*; If $\phi = 1$ trend is *linear*.

If $\phi < 1$ trend is *damped*; If $\phi = 0$ there is *no trend*.

- Exponential series have a constant % growth which becomes harder to achieve as the base grows or declines
- Damped trends may be appropriate when growth is reaching a saturation level
- Declining damped trends may be appropriate when a product is being phased out or replaced by a new product



What are the forecast profiles for damped trend and linear trend exponential smoothing for the sales of a cosmetic product?

- The sales for this cosmetic product, for the period 1978 - 2002, show a declining trend. The forecasts decline exponentially, modeled by a nonlinear trend exponential smoothing model. The figure presents a comparison of a linear trend and damped exponential trend model for the cosmetic product. Note that minimizing MSE should not be the only criterion for selecting a model; the forecast profile should also be considered. In this case, the linear trend model with the lowest MSE also yields much lower forecasts over the forecast period than the damped trend model. It may require informed judgment on the part of the forecaster to determine the most appropriate profile for the data at hand. Source: C&C, Chapter 8, Figure 8.19; Equations: C&C, Chapter 8, Appendix 8, page 319

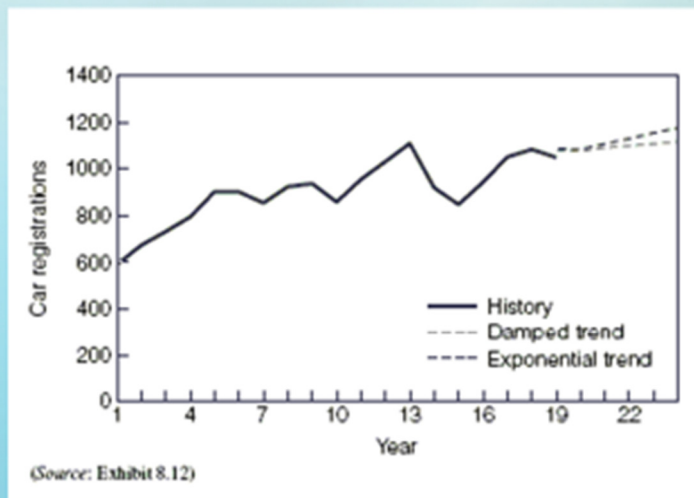
The damped exponential trend forecast was obtained for the year 2005 ($= T + 3$), we set $m = 3$ and $T = 2002$:

$$Y_{2005}(3) = L_t + (\phi_1 + \phi_2 + \phi_3) \times T_t = 279.85 + (0.88 + 0.882 + 0.883) \times (-29.86) = 210.1$$

The difference in the forecast profiles for the linear trend and damped trend arises from the value of the trend modification parameter, which is below unity ($\phi = 0.88$) for the damped trend model. This value of ϕ leads to a decrease over prior year's forecast and is characteristic of an exponential decline. On the other hand, the damped exponential trend model, for which the trend modification parameter is constrained to $\phi = 1$, gives rise to a linear trend forecast profile.

- Because an exponentially growing series can produce excessively high forecasts, extra care should be taken in using them. For example, as companies grow in size, it is difficult to maintain the growth rate
- Many companies acquire other companies in an attempt to maintain their growth rate
- Avoid blind acceptance of optimal parameter estimates and best MSE values

Projecting Car Registration Data With Two Scenario Forecasts



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Projecting car registration data with two exponential smoothing forecasts

The figure shows the historical and forecast values for a damped trend and exponential trend model of the annual car registration data. The growth in the forecasts, the change from the prior year's forecast, has dampened. With $\phi = 0.83$, the forecasted trend is slowing by $1 - 0.83 = 0.17$ or 17% per period. The estimates of level and trend weights are 0.6 and 0.2, respectively,

- This is an example of an Exponential Trend and a Damped Trend profile.
- Note that the damped trend begins to become asymptotic while the exponential trend continues to grow.

This is how the forecast was obtained for Year 20 ($= T + 1$); the fitted value for year 19 is 1078.55, $L_t = 1060.86$, and $T_t = 18.75$. Setting $m = 1$,

$$Y_{19}(1) = L_t + \phi \times T_t = 1060.86 + 0.83^1 \times (18.75) = 1076.42$$

The Year 21 forecasts are calculated as follows:


$$\begin{aligned} Y_{19}(2) &= L_t + (\phi^1 + \phi^2) \times T_t \\ &= 1060.86 + (0.831 + 0.832) \times (18.75) = 1089.34 \end{aligned}$$

Alternatively, we can obtain the forecast for $T + 2$ by calculating $Y_T(2) = Y_T(1) + \phi^2 \times T_t$

Seasonal Exponential Smoothing

Referred to as the Holt-Winters Method

- Allows for additive or multiplicative seasonality
- Creates forecasts by
 - Starting at the current level
 - Adding the product of the current trend by the number of periods ahead we are projecting
 - Adjusting the resulting sum of level and trend for seasonality with an additive or multiplicative seasonal index
 - Adding prediction limits (additive or multiplicative)



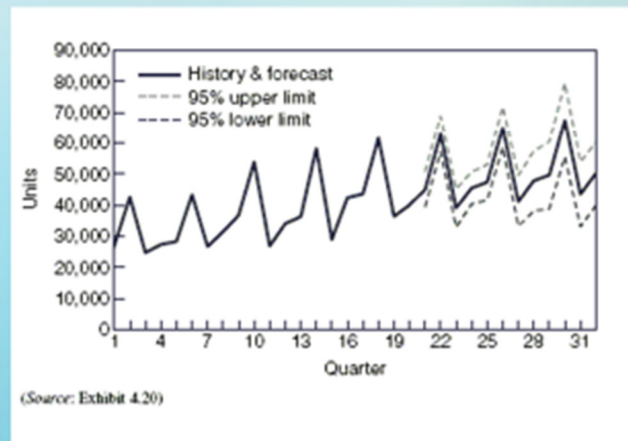
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Seasonal exponential smoothing models

- Referred to as Holt-Winters method
- Allows for additive or multiplicative seasonality
- Method works by
 - Starting at the current level
 - Adding the product of the current trend by the number of periods ahead we are projecting
 - Adjusting the resulting sum of level and trend for seasonality with an additive or multiplicative seasonal index
- Referred to as Holt-Winters method
- Allows for additive or multiplicative seasonality
 - Additive : Use with none or slightly trending data
 - Multiplicative: Use with strongly trending data
- Cannot handle zeroes or negative numbers

Time Plot with 95% Prediction Limits of Quarterly Automobile Sales Using the ETS Holt-Winters Model



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Time plot of quarterly automobile sales with seasonal forecast profile

- Source: C&C, Chapter 8, Figure 8.24; Equations: C&C, Chapter 8, page 218
- Note the prediction limits widen as you go further out to the future, but the annual pattern has a constant seasonal fluctuation

The 95% prediction limits indicate that we are 95% sure that the true (in the sense that the model is correct) forecasts will lie within these limits. If the prediction limits do not appear symmetrical around the forecast, it suggests that the model errors are multiplicative. The forecasts are more likely to be high than low, which makes sense with the consistent upward trend in the historical data. Starting from spring Q2 of Year 6, the automobile sales forecast for Q3 is (setting $m = 1$):

$$Y_T(m) = [L_t + m \times T_t] + \text{Seasonal index}$$

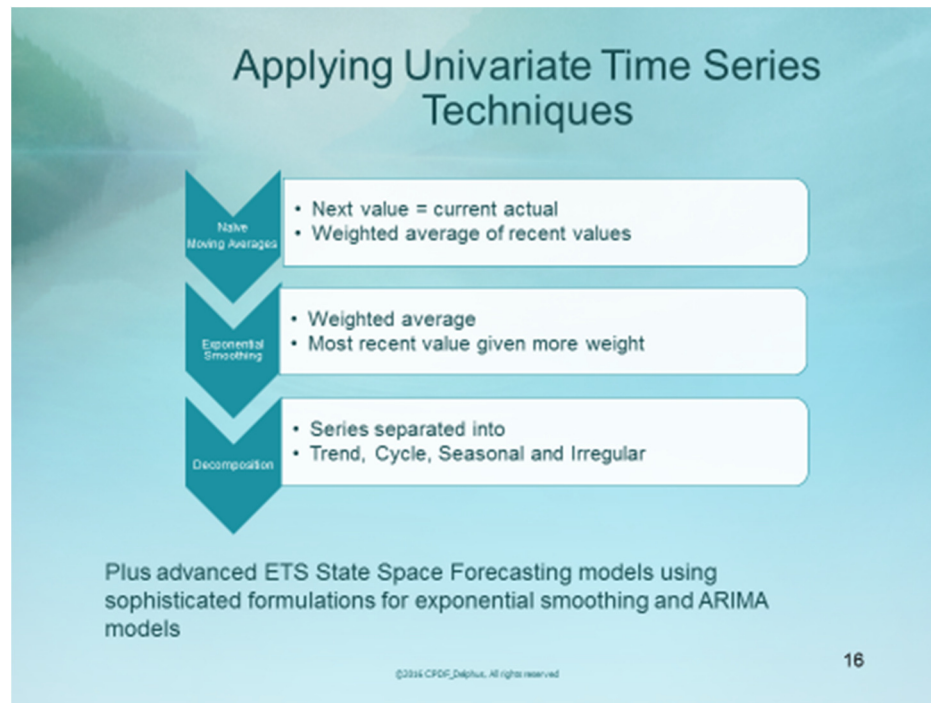
$$Y_T(1) = [46,841 + 561.8] + (-2225.8) = 45,177 \text{ units}$$

To forecast three periods ahead to winter Q1 of Year 7, we set $m = 3$ and use the seasonal index for Q1:

$$Y_T(3) = [L_t + 3 \times T_t] + \text{Seasonal index} = [46,841 + 3 \times 561.8] + (-9602.5) = 38,924 \text{ units}$$

The forecast for the winter of Year 7 is lower than that for the previous summer for two reasons. First, the trend is only growing by approximately 562 units per quarter. Second, and more substantially, the seasonal index for winter is 7377 units lower than in summer. The multiplicative seasonal model produces the following forecast for the winter quarter of Year 7:

$$Y_T(3) = [L_t + 3 \times T_t] \times \text{Seasonal index}$$



Applying univariate time series techniques

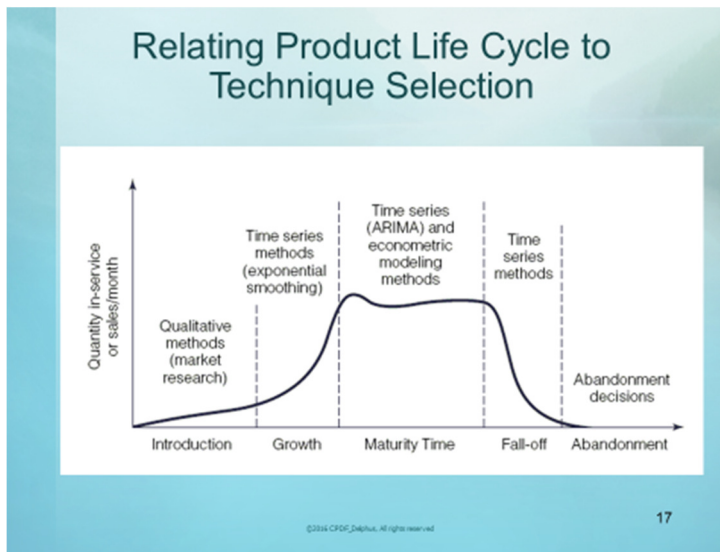
- Exponential smoothing is not the only or necessarily the best approach
- However, has in the past decade become a stable, reliable method and has a sound theoretical framework (State-space models)

The **family** of exponential smoothing models is useful for forecasting trending and seasonal data with prediction limits:

- The components can describe a current level, trend, and seasonal index
- The current level is the starting point, the trend is the growth or decline factor, and seasonal index is the adjustment for seasonality
- All three components are exponentially weighted averages, rather than equally weighted averages, of the historical data. In calculating the current level, an exponentially weighted average is taken of the past data. The current trend is an exponentially weighted average of the past changes in the level and each seasonal index is an exponentially weighted average of the past ratios of data to level.

Parameter estimation and manipulation of parameter estimates for exponential smoothing algorithms are not emphasized, because:

- In practical situations, estimates can vary widely without significantly affecting the forecast profile created by the algorithm
- Optimal or near optimal parameter settings are readily derived with automated software tools
- Combinations of multiple parameter values can limit an intuitive feel for their impact on the forecast profile
- In large database applications, a demand forecaster needs to be able to rely on the automatic forecasting features of modern software because of the very large volumes of data involved.



What is the lifecycle of a product or service?

How does model selection relate to the lifecycle of a product or service?

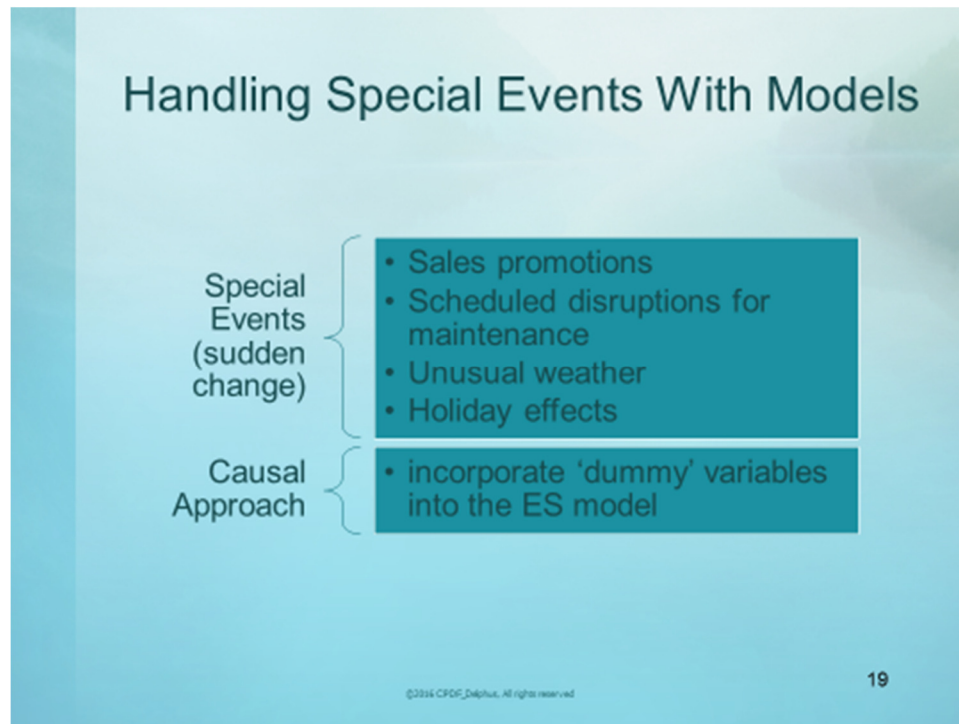
- Forecasting techniques can be related to the appropriate stage of a product's lifecycle.
- Exponential smoothing models are often used in the growth, maturity and fall-off stages.
- Introduction – rely on qualitative techniques because of scarcity of data. Exponential smoothing models generally require a minimum of seven data points
- Growth period – The best time to use exponential smoothing
- Maturity phase – The more stable the period, the better for regression methods in which factors (drivers of demand) can be used. Econometric (multi-equation) models are also frequently applied during this phase of the product/service lifecycle
- Fall-off – similar to growth period but with trend reversed
- Abandonment – qualitative methods and management decisions as far as timing for dropping the product/service

Stage 1: Introduction - New products are introduced to meet local (i.e., national) needs, and new products are first exported to similar countries, countries with similar needs, preferences, and incomes.

Stage 2: Growth - A copy product is produced elsewhere and introduced in the home country (and elsewhere) to capture growth in the home market. This moves production to other countries, usually on the basis of cost of production. (E.g., the clones of the early IBM PCs were not produced in the US.)

Stage 3: Maturity - The industry contracts and concentrates -- the lowest cost producer wins here. (E.g., the many clones of the PC are made almost entirely in lowest cost locations.)

Stage 4: Decline - Poor countries constitute the only markets for the product. Therefore almost all declining products are produced in developing countries. (E.g., PCs are a very poor example here, mainly because there is weak demand for computers in developing countries. A better example is textiles.)

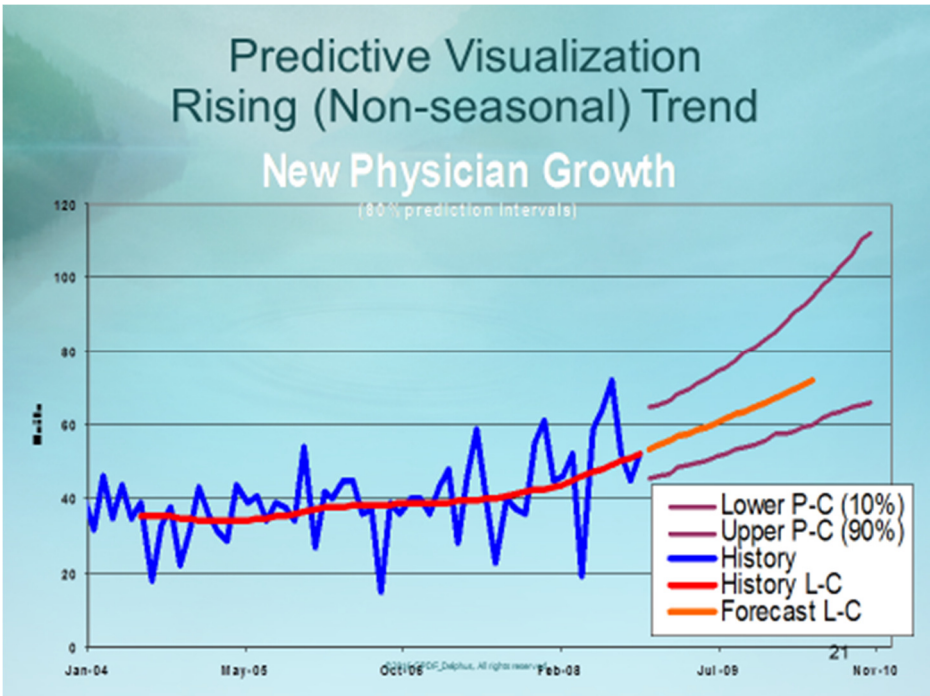
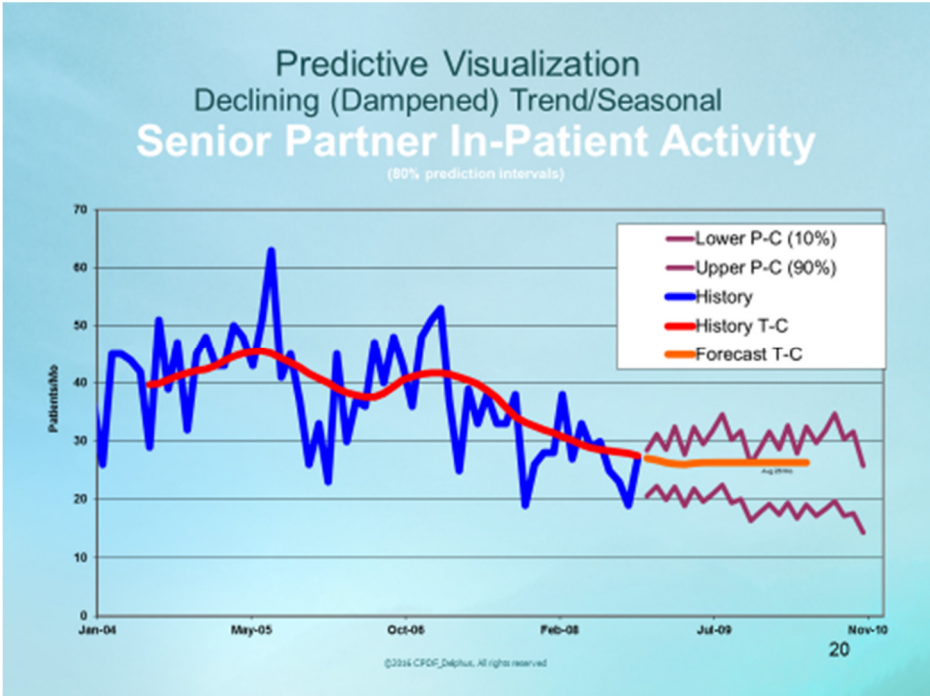


How can you handle special events with exponential smoothing models?

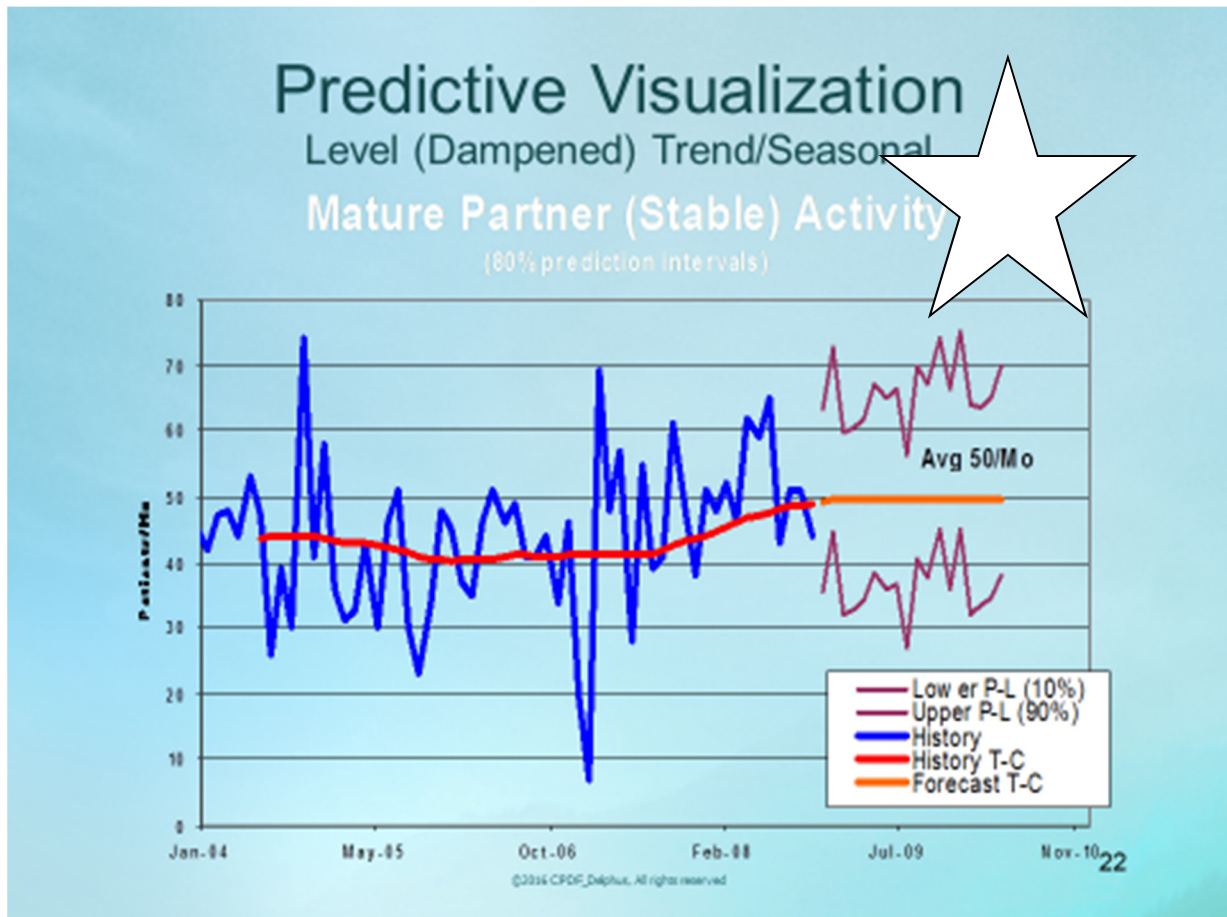
How do you find exceptions in data? This is an alternative, nontraditional method to the conventional “mean plus or minus 3 standard deviations” approach. It is resistant to outliers, which the conventional approach is not! It has the same purpose, to identify exceptional values like outliers and unusual events. The nontraditional approach can identify values that are unrepresentative of the data distribution.

The Interquartile difference (IQD) is the difference between the 75th and 25th percentile in the data distribution. Way to use it;

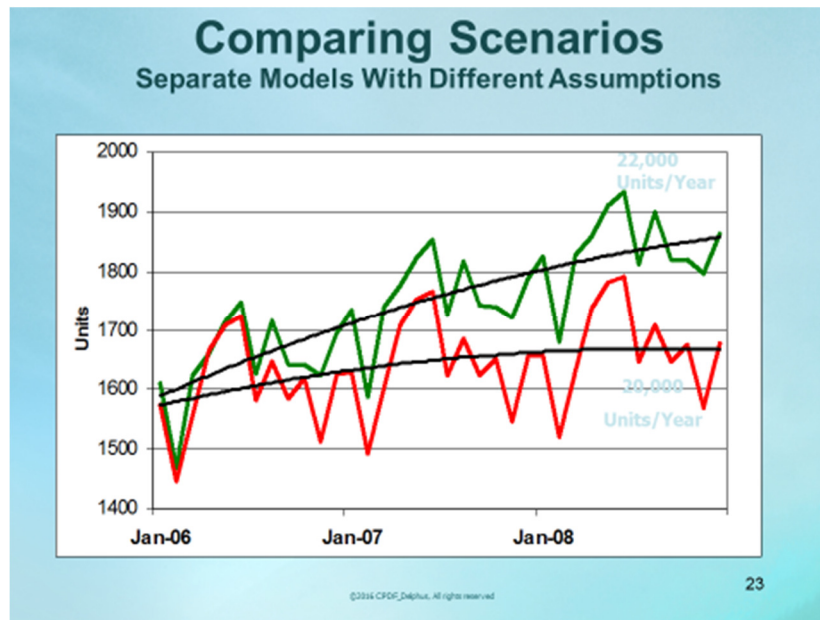
1. Also calculate conventional metric
 2. If both are close, use conventional approach. Managers will understand that better
 3. If sufficiently different by your judgment, then scrutinize data more closely and look for outliers in the dataset.
- Special events → Sudden change in level that are not seasonal
 - Sales promotions
 - Scheduled disruptions for maintenance
 - Unusual weather
 - Holiday effects
 - Causal approach through incorporation of 'dummy' variables into the ES model



Predictive Visualization - **Presenting historical data, forecast prediction limits and underlying trend. Note the presence of seasonality.**



Predictive Visualization - *Presenting historical data, forecast prediction limits and underlying trend. Note the presence of seasonality in the top frame, but not in the bottom frame. The bottom frame is also missing the prediction limits (not a best practice)*



Visualizing Scenarios?

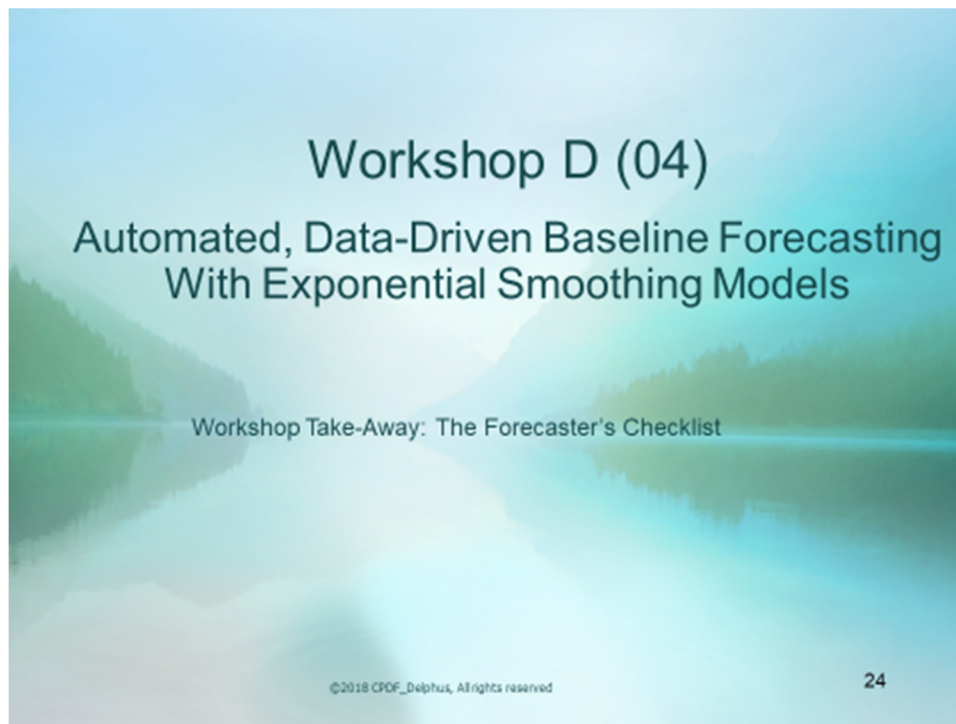
From Wikipedia, the free encyclopedia

Scenario analysis is a process of analyzing possible future events by considering alternative possible outcomes (scenarios).

The analysis is designed to allow improved decision-making by allowing consideration of outcomes and their implications. Scenario analysis can also be used to illuminate "wild cards." For example, analysis of the possibility of the earth being struck by a large celestial object (a meteor) suggests that whilst the probability is low, the damage inflicted is so high that the event is much more important (threatening) than the low probability (in any one year) alone would suggest. However, this possibility is usually disregarded by organizations using scenario analysis to develop a strategic plan since it has such overarching repercussions.

Scenario planning, also called scenario thinking or scenario analysis, is a strategic planning method that some organizations use to make flexible long-term plans. It is in large part an adaptation and generalization of classic methods used by military intelligence. The original method was that a group of analysts would generate simulation games for policy makers. The games combine known facts about the future, such as demographics, geography, military, political, industrial information, and mineral reserves, with plausible alternative social, technical, economic, environmental, educational, political and aesthetic (STEEPA) trends which are key driving forces.

In business applications, the emphasis on gaming the behavior of opponents was reduced (shifting more toward a game against nature). At Royal Dutch/Shell for example, scenario planning was viewed as changing mindsets about the exogenous part of the world, prior to formulating specific strategies.



Workshop D

Having performed a thorough preliminary data analysis looking for the important patterns, a food entrepreneur feels prepared to build some models on monthly shipments data.


- (1) Review the Pegels diagram and select three of the most appropriate model formulations for the ice cream data (ICECREAM.DAT)
- (2) Run the models, using the first 5 years (60 months) and project the remaining 8 months
- (3) Summarize and interpret the performance measures over the forecast period
- (4) Summarize your results and make a recommendation as to what model(s) should be retained for forecasting in the future
- (5) With your choice of a best model(s), create projections for the 16 months following the last data period
- (6) If possible, create a time plot of the history, forecasts, and upper and lower prediction limits for presentation to management.



Part V

Big Data: Data Mining, Exploration and Quality Management

Learning Objectives



- Understanding methodologies best suited for large-scale data exploration
- Recognizing data mining and analysis methods used in predictive analytics
- Identifying criteria for correcting data quality issues
- Creating a database architecture and decision support reporting framework for large datasets
- Creating a checklist for a data process framework for demand forecasting

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What You Should Be Able To Do

After completing this topic, you should be able to:

- Select the most appropriate forecasting methodologies for large volume forecasting
- Recognize data mining and analysis methods for forecasting and planning data
- Create a database architecture and reporting framework for forecasting large data sets

How You Will Check Your Progress

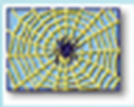
Develop a data repository and analysis checklist for your job, incorporating such issues as

- What are the appropriate data-driven methodologies?
- How can we best make necessary data adjustments?
- What are the requirements of an effective forecast decision support system?

Resources

1. Levenbach. **C&C**, . Chapters 2 and 3.
2. A data mining/analysis checklist is provided in <http://stemed.unm.edu/PDFs/TEACHER%20RESOURCE%20CD-ROM/ISEF%20RULES-FORMS-RESOURCES/Data%20Mining%20Project%20Checklist.pdf>
3. Hoaglin, D.C., F. Mosteller and J.W. Tukey (1983). **Understanding Robust and Exploratory Data Analysis**, New York. John Wiley & Sons,

Predictive Analytics – Something Really New?



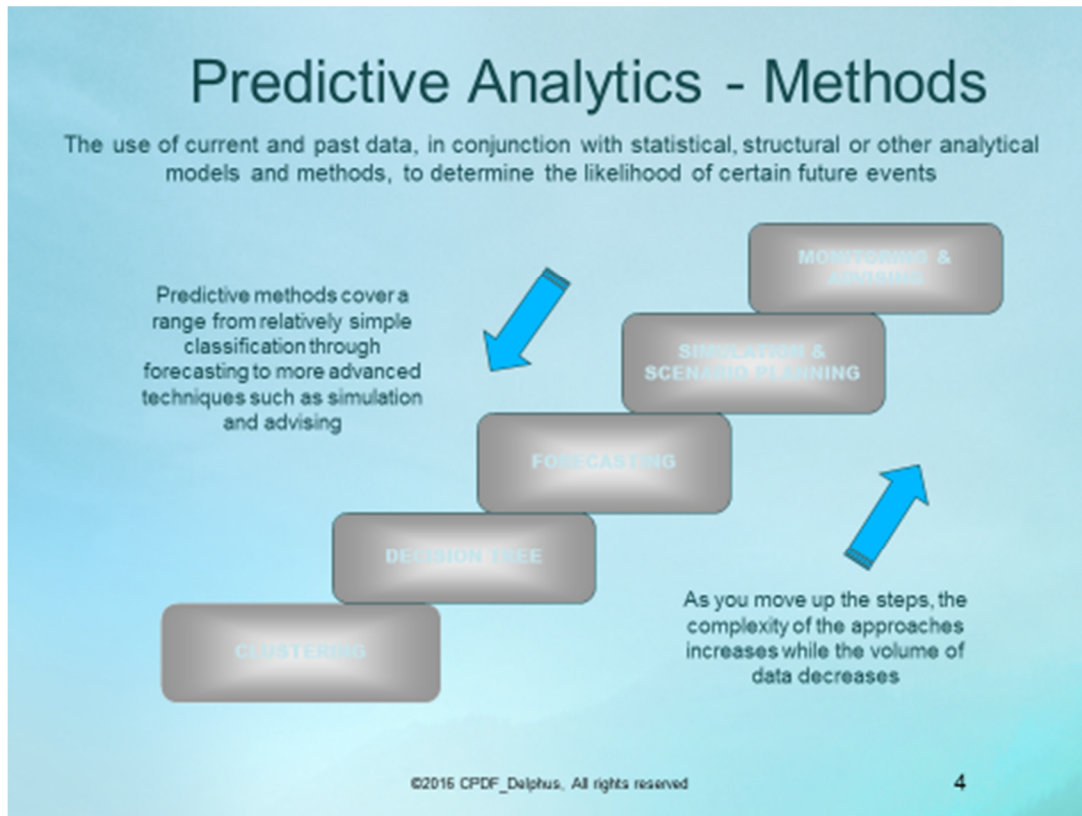
According to Wikipedia:

Rather than
game theory,
Operations
Research is
better choice?

Predictive analytics encompasses a variety of techniques from statistics, data mining and game theory that analyze current and historical facts to make predictions about future events.

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Is predictive analytics really something new?

- Predictive analytics encompasses a variety of techniques from statistics, data mining and game theory that analyze current and historical facts to make predictions about future events.
- Rather than 'game theory', we would have preferred to use 'operations research' in the definition

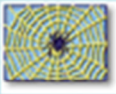
What are predictive analytic methods?

There is a hierarchy of methodologies so that

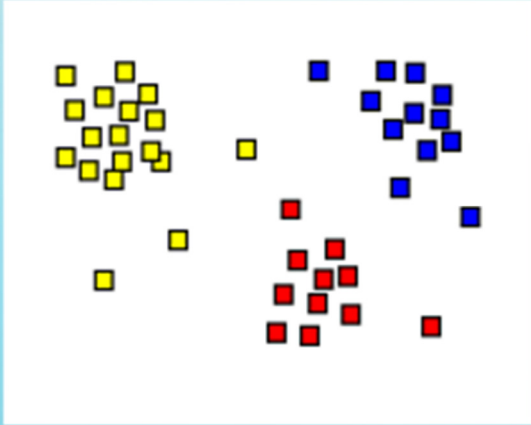
- Predictive methods cover a range from relatively simple classification through forecasting to more advanced techniques such as simulation and advising
- As you move up the steps, the complexity of the approaches increases while the volume of data decreases

The methods use current and historical data, in conjunction with statistical, structural or other analytical models and methods, to determine the likelihood of certain future event

Clustering



Cluster analysis or clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics.

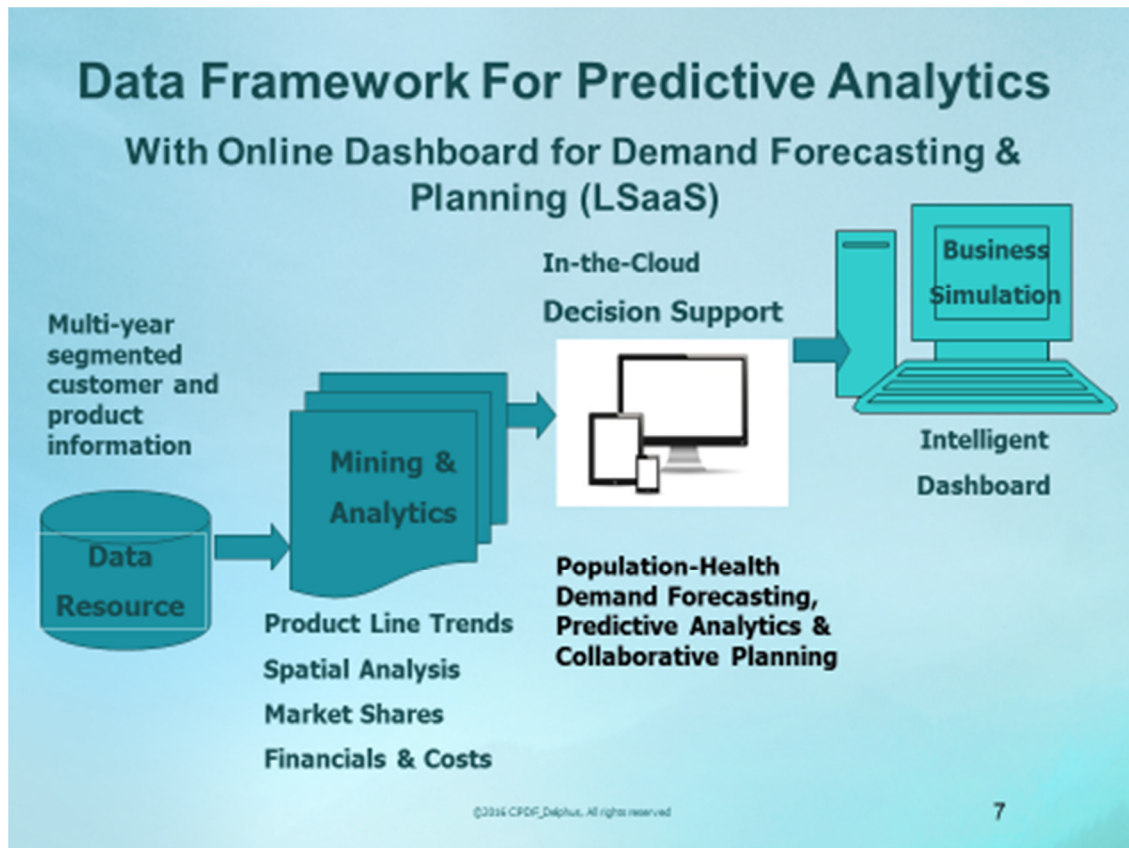


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What is the clustering method?

Cluster analysis or clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics.

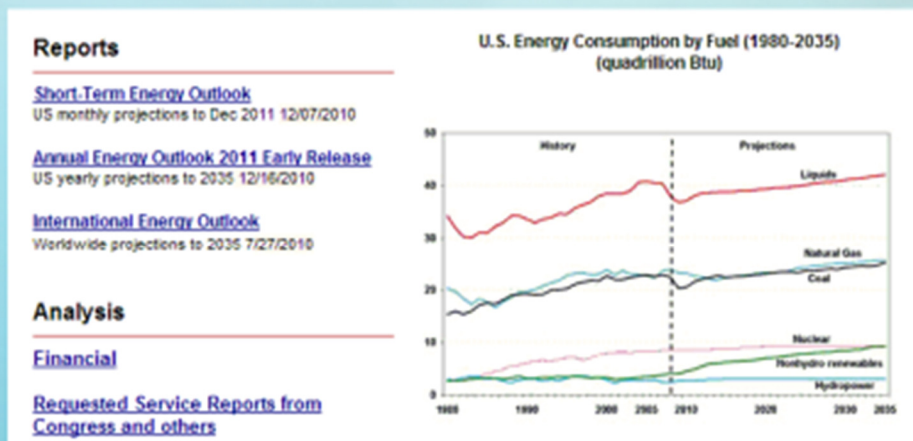


What is a data framework for demand forecasting and planning?

- At the top is a repository or data server containing the forecast data required for data mining, analysis and forecasting. Nowadays, this could represent terabytes of data to be analyzed
- Next, data base tools (queries in SQL, for example) organize and manipulate records for performing data mining or exploratory analyses
- When data is appropriately sliced and diced , segmented and organized in data tables, then higher level tools and languages allow for forecasting and planning functions. For instance when forecasting several hundred products (stock keeping units) for several thousand customers, accounts or locations, you will end up with hundreds of thousands of records to analyze. This is usually beyond the capabilities of a spreadsheet program
- Through a dashboard capability, extracts can be created for budgeting, simulation and strategic planning applications

Free and Easy Access to Monthly Forecasts – Case: Energy Industry

Source: US Energy Information Administration (EIA)
(www.eia.doe.gov/oiaf/forecasting.html)



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How can you access monthly forecasts?

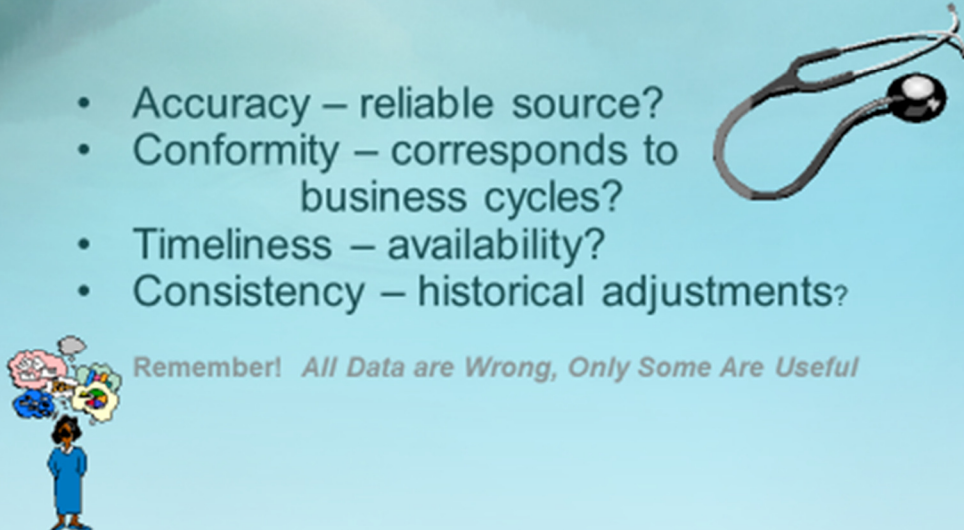
Reports:

- Short-term energy outlook
- Annual energy outlook
- International energy outlook Analysis
- Financial
- Requested service reports from customers

How Healthy Are Your Data?

- Accuracy – reliable source?
- Conformity – corresponds to business cycles?
- Timeliness – availability?
- Consistency – historical adjustments?

Remember! *All Data are Wrong, Only Some Are Useful*



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Making improvements in data quality

- Remember, 'all data are wrong, only some are useful'
- The most important ingredient in developing accurate and credible forecasts is DATA.
- Large datasets have lots of DIRTY DATA, business as usual if you are a practitioner.
- These are the main issues. They are generally treated lightly in business forecasting textbooks, software implementations and forecasting process implementations in companies.
- How seriously are gaps in data quality being addressed by practitioners? Have researchers been able to influence practitioners with best practices in dealing with data, especially large data sets?
- Data mining techniques with predictive analytics are just coming into their own, but in achieving quality in data, there is still a big data quality challenge to overcome.
- Timeliness is becoming less of an issue as it was before the computer age. We are much better off today, but the lesson to remember is that: DATA, DATA, DATA is the foremost obstacle to accurate and credible forecasting.

No forecasts have credibility if based on BAD DATA.

Basic Statistical Analysis Tools For Summarizing Large Data Sets

- Measures of central tendency
 - Mean, Median, IQD
- Measures of variability
 - Standard deviation, MdAD
- Data summary displays
 - Box plots
- Exceptions in datasets
- Scatter plot, Probability plot (Q-Q)



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What are the basic statistical tools for summarizing data?

- Measures of central tendency – mean, median, midmean, trimean
- Measures of variability – standard deviation, mean absolute deviation
- Data summary displays – box plots, scatter diagrams, histograms
- Exceptions in datasets - outliers, strikes, ramps, jumps
- Scatter plot – XY pl
- Probability plot (Q-Q) – Scatter plot of quantiles of the sample vs. quantiles of a standard distribution, like the normal

All these tools can be readily demonstrated with the DataAnalysis Add-in in Excel

Defining Measures Of Central Tendency

- Central tendency - middle, typical value in a data set
- Most familiar and commonly used typical value – arithmetic mean
- But outliers (unusual or atypical) - not typical and distort meaning and interpretation of arithmetic mean & standard deviation measure
- Median – middle value in a data set arranged from lowest to highest. Gives better protection against outliers for describing central tendency
- Trimmed mean is a *nonconventional* measure of central tendency as a way to make a mean less sensitive to outliers



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What is a measures of central tendency

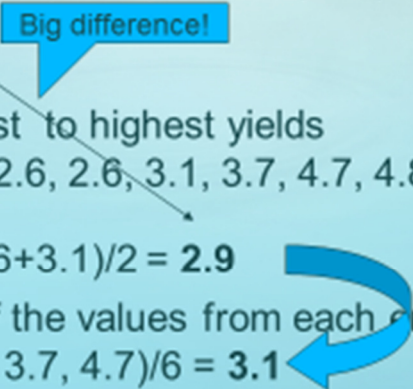
- The conventional measure for the average in a symmetrical (e.g. normally distributed data) is the *arithmetic mean*
- The median is another measure of central tendency that works better when a distribution is skewed. For example, incomes are highly skewed, so one uses the median income as the appropriate measure of central tendency
- Central tendency is a middle or typical value in a distribution
- A distribution becomes skewed when a proportion of the values in a distribution are either high or low.
- An **outlier** is therefore an *atypical* or unusual value in a dataset
- One way to reduce the influence of skewness and outliers while trying to capture a central tendency, you can use the **trimmed mean**

Trimmed Mean

Example of *nonconventional* measure of central tendency

- Consider set of numbers
 - 1.1, 1.6, 4.7, 2.1, 3.1, 32.7, 5.8, 2.6, 4.8, 1.9, 3.7, 2.6.
 - The *mean* is 5.6
- Ranking from smallest to highest yields
 - 1.1, 1.6, 1.9, 2.1, 2.6, 2.6, 3.1, 3.7, 4.7, 4.8, 5.8, 32.7.
 - The *median* is $(2.6+3.1)/2 = 2.9$
- Trimming* say 25% of the values from each end yields
 - $(2.1, 2.6, 2.6, 3.1, 3.7, 4.7)/6 = 3.1$

Big difference!



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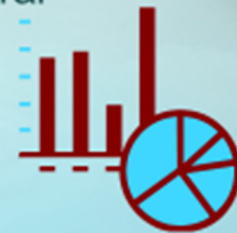
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What is the trimmed mean?

- When calculating a trimmed mean, you remove a fixed percentage of the data from the low and high end of the distribution
- For the example, the arithmetic mean or average is 5.6. This is the sum of the 12 values divided by 12
- Next, rank the data from low to high
- The median is the middle value. If the number of values is even, you may have to take a simple average of the middle two values to determine the median
- By trimming 3 values (i.e. 25%) from the high and low ends, respectively, calculate the arithmetic mean of the remaining six (6) values. This gives 3.1 as the 25% trimmed mean
- Notice this is lower than 5.6, which has been influenced by the skewness in the data towards higher values. The trimmed mean is also closer to the median and hence is a better representation of central tendency than the arithmetic mean (i.e. average)

A Conventional Measure Of Variability

- Variability measures spread or dispersion about the measure of central tendency
- *Sample Standard Deviation (SD)* is a conventional measure of spread = square root of sample variance = sum of squared deviations from mean divided by $n-1$, where n is the number of deviations.



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Why is the standard deviation a conventional measure of variability?

- The sample standard deviation is the familiar measure of variability in data.
- It is calculated by measuring spread from a measure of central tendency, in this case the arithmetic mean. This suggests that skewness in data as well as outliers can distort the results.
- These deviations are squared and averaged. Squaring will highlight large deviations, like outliers, which may have unintended consequences in interpreting the result.
- By taking the square root, the standard deviations will be in the same units as the original data.
- When data are symmetrical, like normally distributed data, the results will be meaningful.

Like measures of central tendency, measures of variability also need to be handled differently in the presence of outliers to avoid misinterpretation

Non-Conventional Measures of Variability: (Resistant To Outliers)

Key difference: Deviations are not squared, so large deviations are not over-emphasized

Examples

- MAD: Mean absolute deviation
- MdAD: Median absolute {deviation from the median}



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What measures of variability are more resistant to outliers?

1. Measures that are not too adversely affected by outliers are called *resistant*
2. The mean absolute deviation are simple absolute values of the deviations from a measure of central tendency, typically the mean.
3. A more resistant version of that is the median absolute deviation from the mean, or better yet the median of the absolute deviations from the median. This is the MdAD.
4. Clearly, there are many variations of this, but these measures have been found to be most useful in practice.

Calculation of the Median Absolute Deviation (MAD)

Data (n)	Data (sorted)	Deviations from the Median	Absolute Deviations from the Median
1.1	1.1	-1.75	0.25
1.6	1.6	-1.25	0.25
4.7	1.9	-0.95	0.25
2.1	2.1	-0.75	0.75
3.1	2.6	-0.25	0.85
32.7	2.6	-0.25	0.95
5.8	3.1	0.25	1.25
2.6	3.7	0.85	1.75
4.8	4.7	1.85	1.85
1.9	4.8	1.95	1.95
3.7	5.8	2.95	2.95
2.6	32.7	29.85	29.85

$$\text{1st quartile} = \frac{1}{4}(n + 1) = 13/4 = 3.25$$

$$\text{Median} = (2.6 + 3.1)/2 = 2.85$$

$$\text{Midmean} = (2.1 + 2.6 + 2.6 + 3.1 + 3.7 + 4.7)/6 = 3.13$$

$$\text{3rd quartile} = \frac{3}{4}(n + 1) = 39/4 = 9.75$$

MdAD = 1.1

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Calculation of MdAD

5. Several definitions – not consistently used, so watch out!!
 - Central tendency is the arithmetic MEAN
 - a. Calculate deviation from the mean: Data minus Mean
 - b. Calculate the absolute values of the deviations
 - c. Calculate Median of the absolute deviations
6. Instead of Median in step c, use the Mean
 - Central tendency is MEDIAN
 - d. Calculate deviation from the mean: Data minus Mean
 - e. Calculate the absolute values of the deviations
 - f. Calculate Median of the absolute deviations
 - Instead of Median in step c, use the Mean

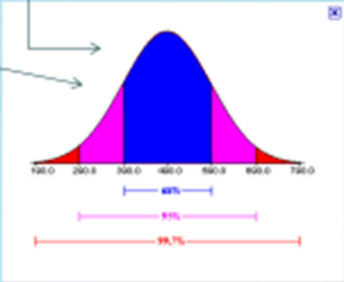
If data are not normally distributed and outliers are possible, then use the second calculation, using MEDIAN as central tendency, and MEDIAN of the absolute deviations (from the median). Best protection against outliers.

Some Refinements ...

Non-typical Values and Variability

For normally distributed data:

- UMdAD - an 'unbiased', empirically derived measure of spread comparable to a standard deviation, if data were normal
 $= \text{MdAD} / 0.6745$
- Unbiased IQD — Interquartile difference is an unbiased measure of spread
 $= \text{IQD} / 1.349$
- An *extreme value* might be found outside the range
 $= \text{Median} \pm 1.5 \times \text{UMdAD}$



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What are nonconventional measures of variability and how do you use them to find outliers or extreme values?

- For normally distributed data, UMdAD is an unbiased measure of spread comparable to a standard deviation =

$$\text{MdAD} / 0.6745$$

- Unbiased IQD (Interquartile difference) is an unbiased measure of spread =

$$\text{IQD} / 1.349$$

- The IQD is the difference between the 75th and 25th percentiles. Unusual values are data outside the range =

$$\text{Median} \pm 2 \text{ UMdAD}$$

Finding Exceptions In Datasets

- The *Interquartile difference* is the difference between the 75th and 25th percentile in an ordered data set
- Unusual values can be detected by considering 'outlier cutoffs' or fences
- Lower cutoff = 25th percentile – 1.5 IQD
- Upper cutoff = 75th percentile + 1.5 IQD



- Alternatively, use Median +/- 1.5 UMdAD

where UMdAD = Median { Absolute Deviations from Median } divided by 0.6745

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How do you find exceptions in datasets?

- The Interquartile difference is the difference between the 75th and 25th percentile in an ordered data set. Unusual values can be detected by considering outlier cutoffs or fences. Using the service order travel data
-

$$\text{Lower cutoff} = 25\text{th percentile} - 1.5 \text{ IQD} = -15.5$$

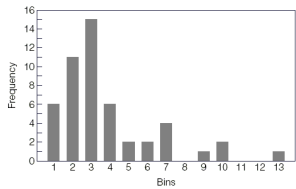
$$\text{Upper cutoff} = 75\text{th percentile} + 1.5 \text{ IQD} = 29.5$$

- Potential outliers = 30,32 and 40.

Alternatively, using

$$\text{Median} \pm 3 \text{ UMdAD} (=10 \pm 16. \text{ Same outliers plus 27 value.})$$

A Histogram Plot of the Frequency Distribution for 50
Service-Order Travel Data



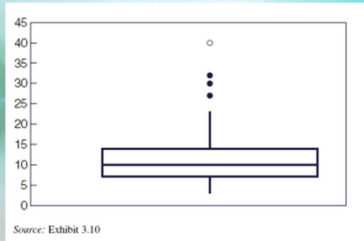
(Source: Exhibit 3.10)

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What is a Box Plot Used For?

A display based on a five-number summary of a frequency distribution: median, upper and lower quartiles, and two extreme values in a data set



Source: Exhibit 3.10

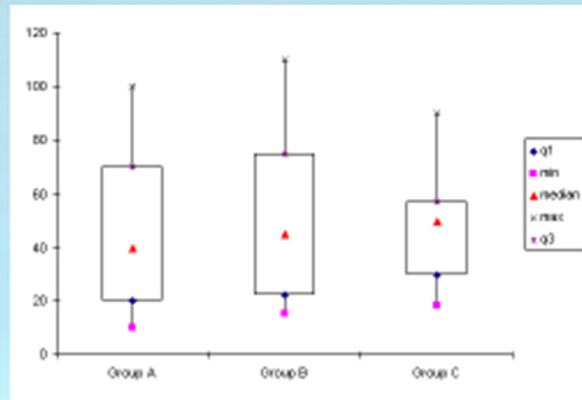
What is the difference between a (traditional) histogram and a (nonconventional) box plot?
Example: service order travel data

Interval (min)	Number of Service Orders	Relative Percentage of Orders	Cumulative Percentage of Orders
3-5	6	12	12
6-8	11	22	34
9-11	15	30	64
12-14	6	12	76
15-17	2	4	80
18-20	2	4	84
21-23	4	8	92
24-26	0	0	92
27-29	1	2	94
30-32	2	4	98
33-35	0	0	98
36-38	0	0	98
39-41	1	2	100
Total = 50			

Box Plot

A display based on a five-number summary of a frequency distribution (median, upper and lower quartiles, and two extreme values in a data set)

Statistic	Group A	Group B	Group C
q1	20	22	30
min	10	15	18
median	40	45	50
max	100	110	90
q3	70	75	57



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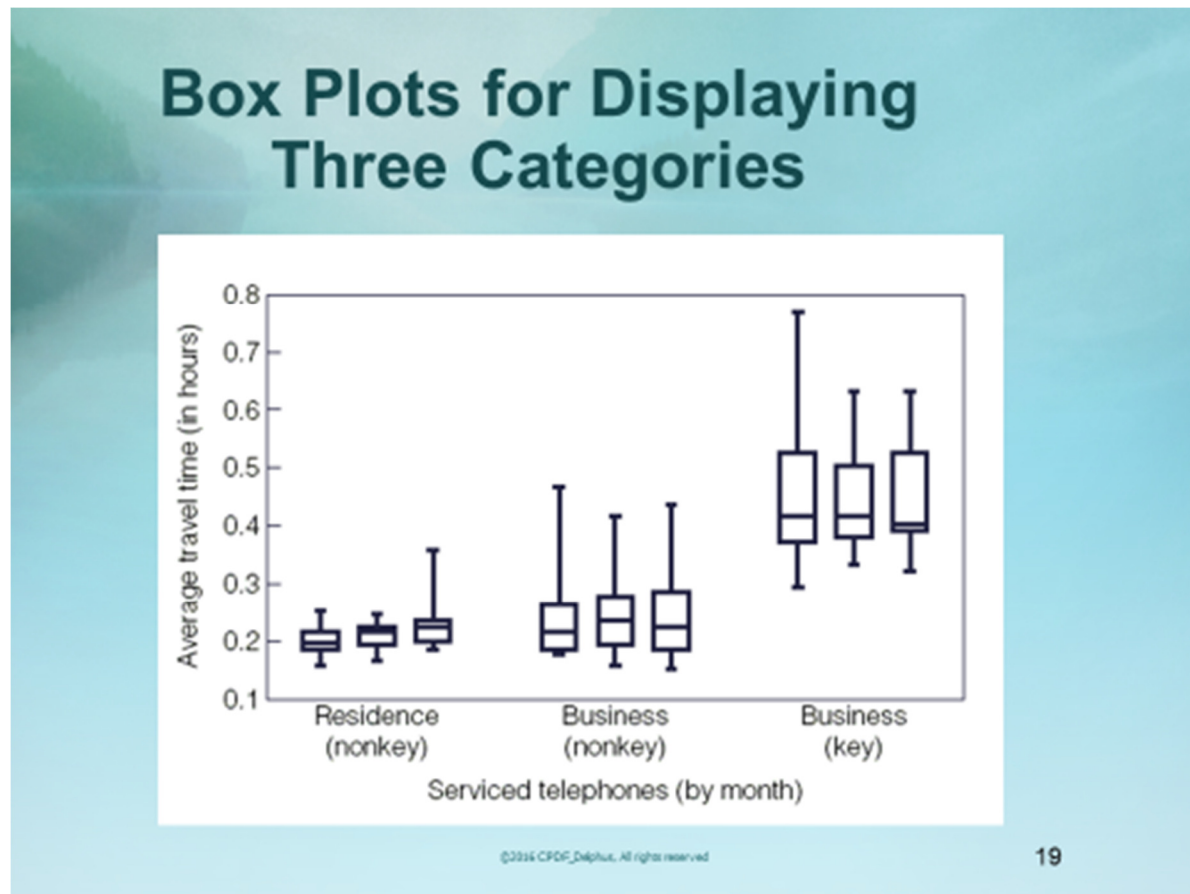
18

How do you create a box plot?

A box plot, or box and whisker diagram, provides a simple graphical summary of a set of data. It shows a measure of central location (the median), two measures of dispersion (the range and inter-quartile range), the skewness (from the orientation of the median relative to the quartiles) and potential outliers (marked individually).

Statistic	Group A	Group B	Group C
q1	20	22	30
min	10	15	18
median	40	45	50
max	100	110	90
q3	70	75	57

To make box plots in Excel, you cannot do it directly, but visit <http://www.coventry.ac.uk/ec/~nhunt/boxplot.htm> for instructions for all versions of Excel.



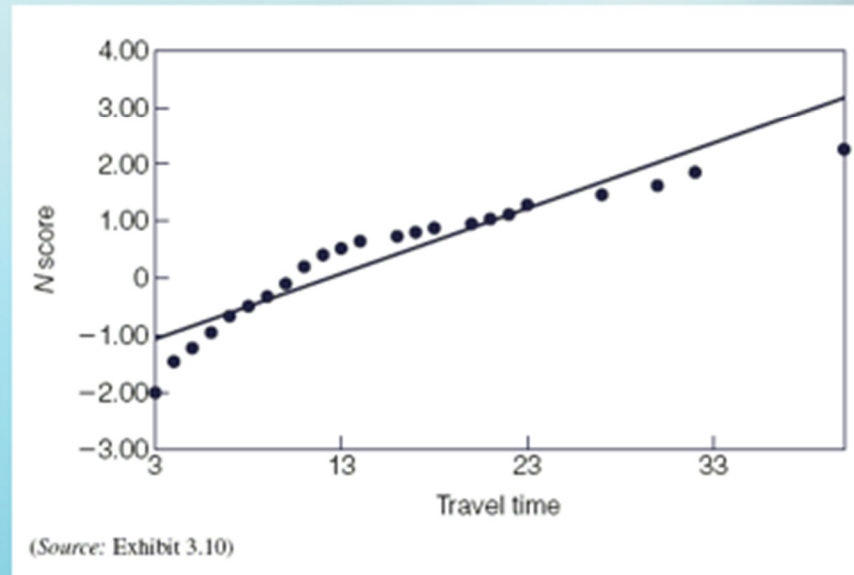
19

How do you use box plots for comparing multiple groups in a single diagram?

Box plots are especially useful when comparing two or more sets of data. The simple box plot summarizes the distribution in terms of five quantities. In addition, the distance between the quartiles is the interquartile distance (IQD), a measure of dispersion. Missing from this plot is the number of values in the distribution, which affects the reliability of the estimate of the median

A single comprehensive box plot may not be enough by itself. One weakness is its inability to identify or discern data from two different populations. This plot shows box plots for the service-order travel times for three categories of telephones. It shows that there are really two distributions; orders for nonkey telephone sets and orders for key telephone sets (a key telephone set is linked to multiple telephone numbers). A single box plot would mask these differences.

Normal Probability Plot



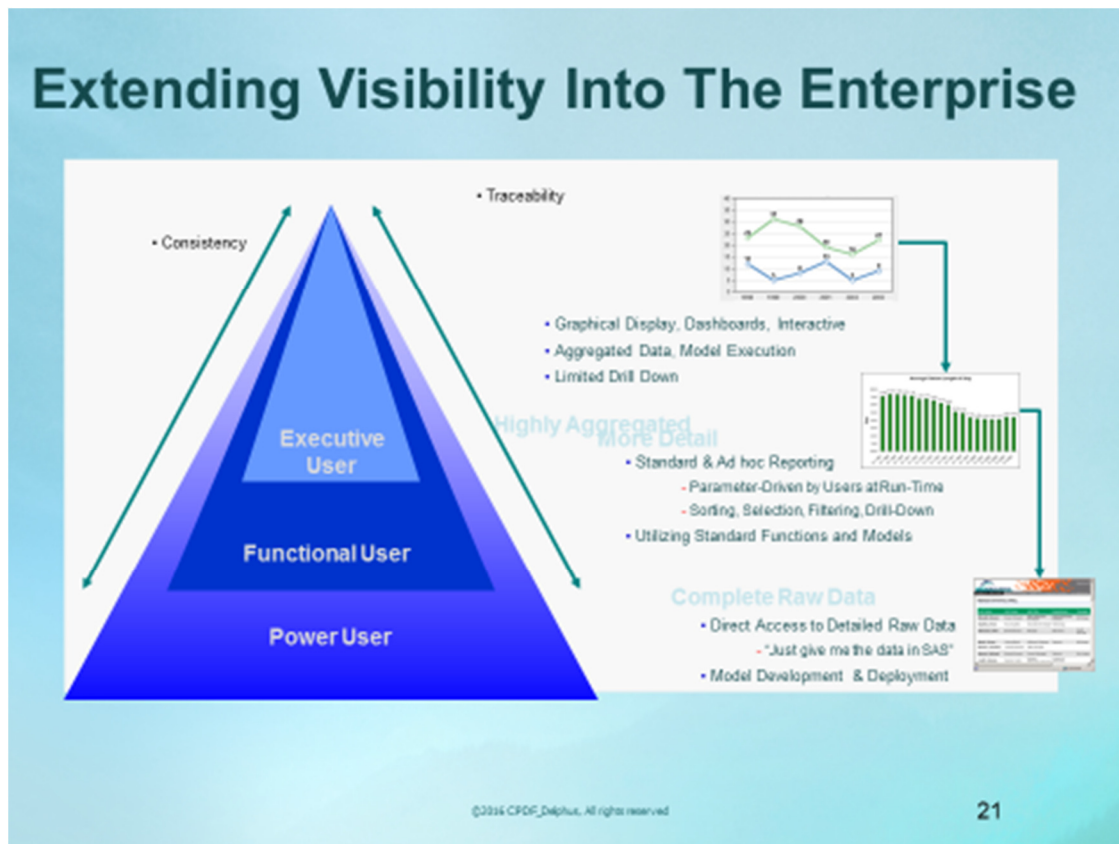
(Source: Exhibit 3.10)

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What are probability plots or quantile-quantile plots (Q-Q)?

- Used to determine if two data sets have the same probability distribution
- When the quantiles (or percentiles) of one distribution are plotted in a scatter diagram against the quantiles of the second distribution, we get a *quantile-quantile (Q-Q) plot*
- If two data sets have the same probability distribution, the Q-Q plot is linear. For example, the quantiles of an empirical data set can be compared to the quantiles of the *standard* normal distribution ($\mu = 0$, $\sigma = 1$) to test for normality. Such a display is known as a *normal probability plot*.
- The plot shows a normal probability plot for a situation in which the data is clearly NOT normally distributed. It appears that the highest and lowest data value exceed the expected normal deviates. This plot shows an upper tail in the empirical distribution that is much longer than that of the normal distribution.



How does the data framework extend visibility into the entire business?

- With a structured data framework at a one's disposal, the forecaster then has complete visibility into the entire enterprise and can therefore fully support and provide forecasting information to all departments within the company.
- Spreadsheets now become a component of the data framework and no longer needs to be the central core of operation for a planner.
- It is the forecaster's control of the database framework that makes the forecaster relevant to the entire company, not just an organization or two – an essential and powerful position to be in.
- Because of the analytics and decision support tools embedded in this data framework, this is not an application that can be supported in its entirety by an IT organization.
- For 'best-in-class' operations, the demand forecaster/planner needs to be the PIC (Person-in-charge) of this environment

Intelligent Dashboard Environment For Summarized and Cleansed Data



- Enhances demand planning
- Monitors competitive environment
- Manages strategic opportunities
- Provides a visual reporting capability

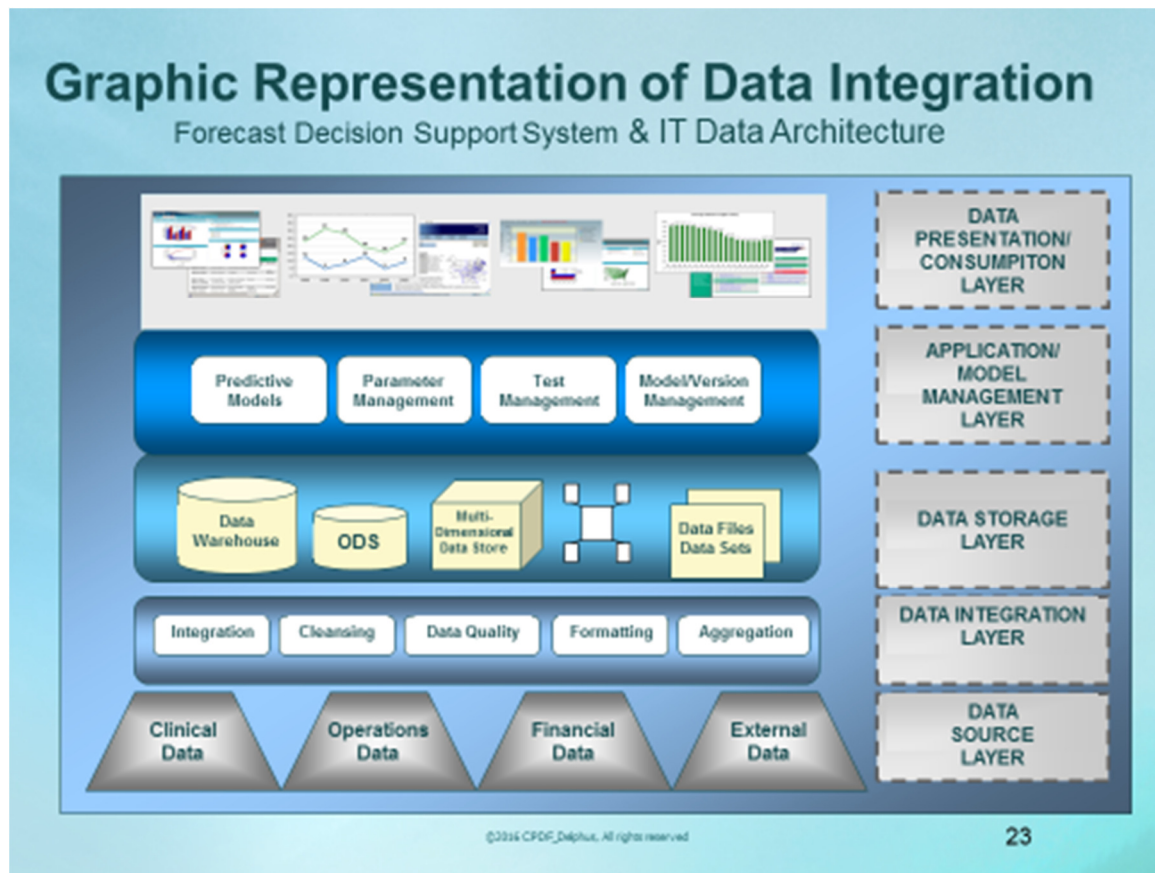
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What is a dashboard display of customer/locations, products, forecasts and historical data?

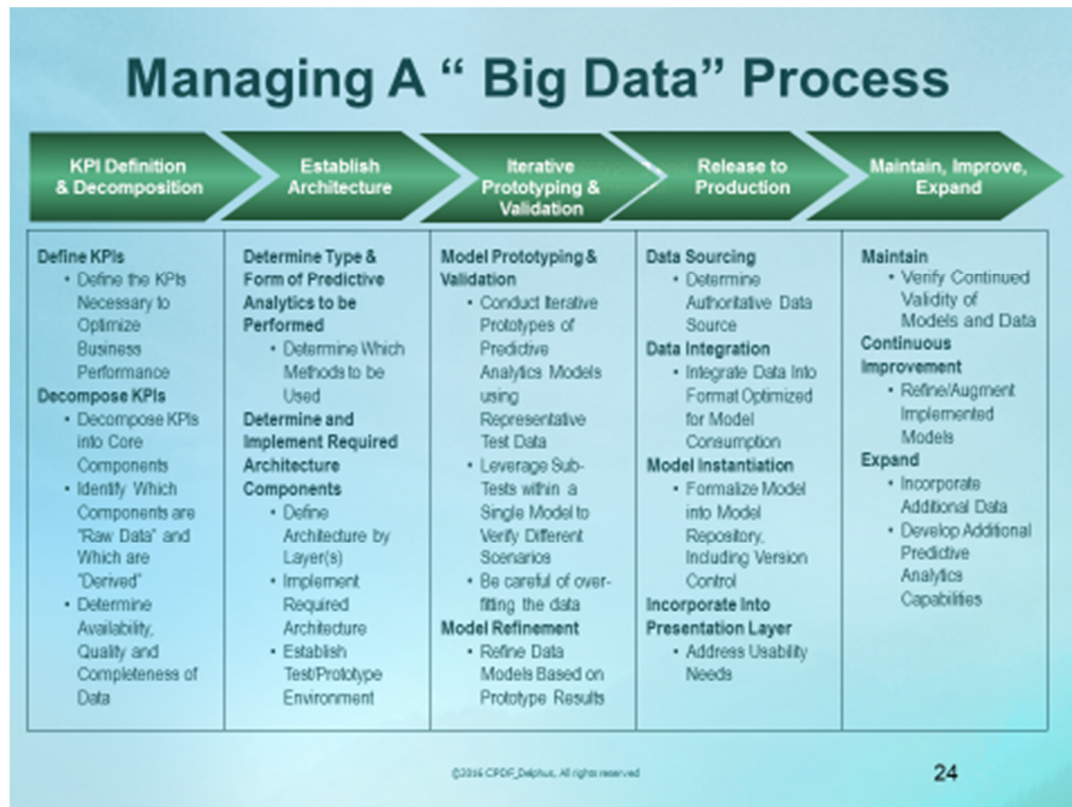
In an intelligent dashboard environment you should be able to

- Manages strategic opportunities
- Monitors competitive environment
- Enhances demand planning



How to integrate the Forecast Decision Support System (FDSS) into the enterprise data architecture

- When the forecast data framework gets integrated with the forecasting software, this yields a **Forecast Decision Support System** or FDSS.
- When the forecast data framework is used for creating baseline forecasts and allowing for the judgmental override of forecasts, often lacking a comprehensive database structure, it is called a Forecast Support System (FSS)
- This structure cannot be supported solely by spreadsheet software, flat file statistical forecasting package or hierarchical databases – in essence these basic, but widely used tools are not scalable and thus clearly inadequate
- Likewise, an IT-developed or acquired transaction-oriented ERP database system may also lack the decision support functionality required for forecast decision support.



How do you create a data process framework and checklist?

- **EXAMPLES OF PUBLIC DOMAIN DATA:** Information from research journals, magazines, newspapers, TV and radio broadcasts, commercial or government pamphlets – essentially, anything produced for the general public’s use, without expressed restrictions.
- **EXAMPLES OF NON-PUBLIC DOMAIN DATA:** Medical files, personal information (date of birth, SSN, etc.), school records and information, other people’s or institutions’ research not published.
 - You need to list all of the specific sources from where the data will be obtained. You can’t say you’ll find it later. It must be determined beforehand. (List bibliographic info, websites, broadcast info, etc.)
 - If the data is not public domain data, then written and signed permission from the owner needs to be attached to the study design.
 - If it is unclear if your data is public domain data or not, it must either be clarified that the data is public domain or written and signed permission from the owner needs to be included.
 - If the data is of a confidential nature, it requires informed consent from each subject before it can be used in the analysis.
 - Be sure the data analysis is present and valid for this project.
 - The study design needs to list the inferential statistics that will be used in supporting/refuting your hypothesis. They must be appropriate for the data and project type.

Workshop E (05)

Data Exploration, Outlier Correction and Predictive Visualization



- Run the trend-seasonal Exponential Smoothing model (automatic option) from the PEERForecaster Add-in
- Do you suspect any outlying or unusual data in the residuals? Detect them (a) visually from a time plot of the residuals and (b) by the traditional rule: mean \pm 3 Std. Deviation, and (c) by a nonconventional outlier-resistant method.



- Use the RMA Decomposition method (Time Series Decomposition available in the PeerForecaster Add-in) as an exploratory tool to estimate replacement values
- In the historical data, replace the two most significant outliers with the fitted values (from the RMA method) and rerun the exponential smoothing model with PEERForecaster Add-in
- Visually contrast the forecasts, prediction limits and seasonal factors. What has changed in the output? (Use RMA as a benchmark method in lieu of expert judgment)

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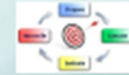
25



Part VI

Forecasting Short-term Trends with ETS State Space Forecasting Models

Learning Objectives



- Creating a flexible model building strategy for short-term trending models
- Recognizing various forms of stationary (level) and non-stationary (trending and seasonal) behavior in time series
- Identifying criteria for 'best' model selection
- Producing short-term trend forecasts from historical data
- Comparing forecasts with prediction limits to visualize measured uncertainty around forecasts
- Creating a trend modeling checklist

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What You Should Be Able To Do

After completing this topic, you should be able to:

- Understand the model building strategy for building ARIMA models
- Identify criteria for best model selection
- Interpret forecasts and create prediction limits with ARIMA models
- Recognize advantages and disadvantages of the ARIMA approach
- Create a time series modelling checklist based on the BJ Methodology

How You Will Check Your Progress

Develop a model-building checklist for ARIMA models, incorporating such issues as

How do you identify an appropriate ARIMA model?

What are the data requirements?

What diagnostic tools should be examined for ARIMA models?

Resources


1. Levenbach, H., (2017). **C&C**. Chapter 9.
2. A sample ARIMA model checklist can be found in Chapters 9 and 14.
3. Ord, K., Fildes, R. and Kourentzes, N. (2017). **Principles of Business Forecasting**, Wessex Pub


Defining an *Iterative* Model-Building Strategy

This is also known as the Box-Jenkins methodology

Because of the relative complexity of building these kinds of models, creating a model building strategy is essential. It consists of three stages:

- Identification
- Estimation
- Diagnostic checking



 George Box, who knew how to build useful time series models, said:
"All models are wrong, Some are useful"

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What is the Box-Jenkins (BJ) model-building strategy?

The modeling procedure consists of the following three stages:

1. *Identification* consists of using the data and any other knowledge that will tentatively indicate whether the forecast variable can be adequately described with a simple or rudimentary model.
2. *Estimation* consists of using the data to make inferences about the parameters that will be needed for the tentatively identified model and to estimate their values.
3. *Diagnostic checking* involves the examination of residuals from fitted models, which can result in either no indication of model inadequacy, or a determination of model inadequacy together with information on how the series may be better described.
4. The procedure is iterative. After each iteration, we examine the residuals for any lack of randomness and, if residuals are found to be serially correlated (a common problem of nonrandomness in time series), we use this information to modify a tentative model. The modified model is then fitted and subjected to diagnostic checking again until an adequate model is obtained. This may take two or three iterations.

What is an *Iterative* Modeling Process?

- ❑ The procedure is iterative when after each iteration (once through each stage), we review the residuals (*actuals minus fit*) for lack of randomness to determine what steps to take next . . .
- ❑ We can then
 - Correct for outliers
 - Detect and compensate for serial correlation in the residuals, and
 - Transform variables to make them more useful



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What is an iterative process?

The procedure is iterative when

- After each iteration, we review the residuals for lack of randomness to determine what steps to take next
- We can detect and compensate for serial correlation in residuals
- Transformation of variables may become necessary

Why Use a Model Building Strategy?

- ❑ The Box-Jenkins strategy is an integral part of a forecast modeling process
- ❑ Provides a systematic framework for incorporating quantitative techniques
- ❑ Reduces arbitrary selection of final forecast numbers
- ❑ Incorporates key variables into the decision-making process
- ❑ Enhances credibility with users and management



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Why use a model building strategy?

- Is an integral part of a forecast modeling process
- Provides a systematic framework for incorporating quantitative techniques
- Reduces arbitrary selection of final forecast numbers
- Incorporates key variables into the decision-making process
- Enhances credibility with users and management

A well-executed modeling strategy gives you the whole 'pizza pie', but not omitting the essential ingredient of measured uncertainty



Detecting Short-Term Memory or Autocorrelation



- ❑ In autocorrelation analysis, a time series is related to *lagged* versions of itself.
- ❑ Autocorrelation coefficients are similar to ordinary correlation coefficients.
- ❑ An ordinary *correlogram* is a display of the sample autocorrelation coefficients.
- ❑ 95% confidence limits are at ± 1.96 times the square root of n (assuming normal distribution and large n)

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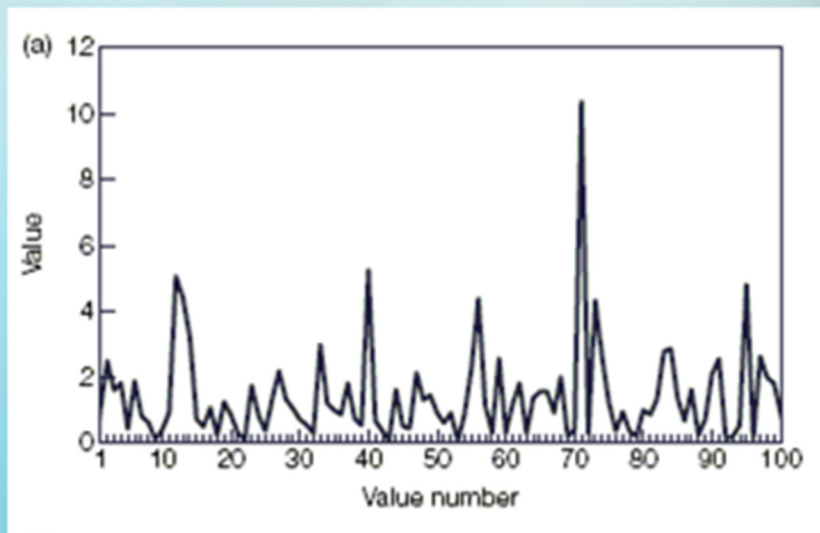
Detecting autocorrelation in time series

- An objective of *autocorrelation analysis* is to develop tools for describing correlation in time series.
- In autocorrelation analysis, a time series is related to lagged versions of itself.
- Autocorrelation coefficients are similar to product moment correlation coefficients.
- An ordinary correlogram is a display of the sample autocorrelation coefficients.

95% confidence limits are at ± 1.96 times the square root of n (assuming normal distribution and large n).

Time Plot of Data Without Any Pattern

Source: 100 Random Values Generated from a
Random (Lognormal) Series



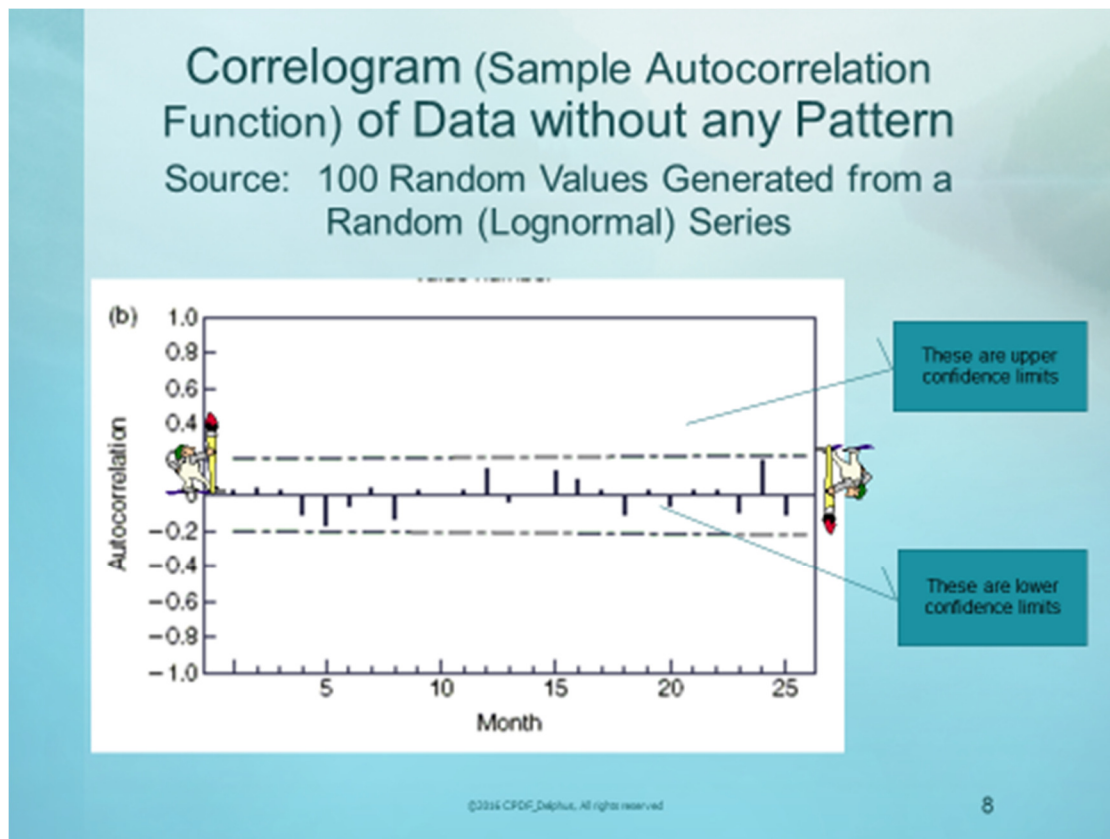
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How do you recognize a time plot that has no pattern?

- The quickest way to acquire the expertise necessary to identify ARIMA models is by looking at examples.
- What does random data look like when plotted as a time series? A purely *random* time series is one in which there is no time dependence between values any number of time periods (lags) apart and thus no systematic pattern that can be exploited for forecasting.
- The correlation coefficients measured at all lags for a purely random time series should be 0 at all lags, except at lag 0. At lag 0, the time series is perfectly related to itself and has the maximum value 1.
- In a spreadsheet, create two columns with the same data and then start shifting one of the columns down a step at a time. That creates the 'lag' effect.

A scatter diagram of the two columns will display the effect of correlation.

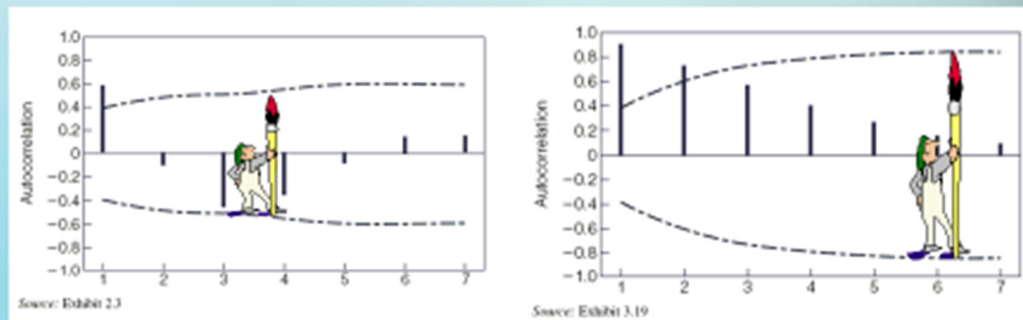


How do you recognize a correlogram of data that has no pattern?

- One hundred random values were generated from a random (lognormal) series
- A random series is not necessarily normally distributed. In this example the randomness comes from a log-normal distribution.
- Autocorrelation coefficients for a purely random time series should be 0 at all lags, except at lag 0.
- At lag 0, the time series is perfectly related to itself and has the maximum value 1
- For a sampled random series, a correlogram shows sample estimates of autocorrelations of the data. Hence, the correlogram of a random series is 1 at lag 0 and nearly 0 for all lags different from lag 0.
- The correlogram shown above is unity at lag 0 and very close to 0 for all nonzero values k of the lag (there are 15 of these plotted on the abscissa.)

Low Order Autocorrelation

For a series with low order autocorrelation, a decaying pattern is evident



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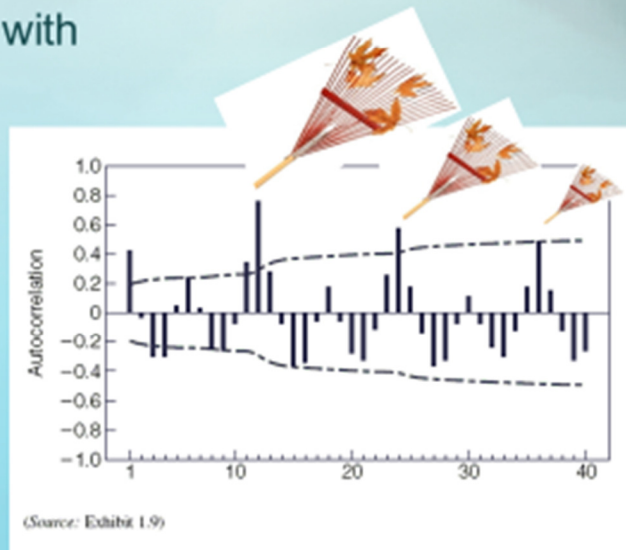
How do you identify low-order autocorrelation?

- Many time series, even after a certain amount of differencing, exhibit short-term correlations (or memory) in their pattern. Thus, autocorrelation at shorter lags is greater than autocorrelation at longer lags.
- For a time series having low-order dependence, a correlogram shows a decaying pattern.
- The diagram on the left shows a correlogram of the annual housing starts data, and on the right is a correlogram of the annual mortgage rate series
- Note that the spikes tend to get progressively smaller
- Once inside the bounds (roughly, $2/\sqrt{n}$, $n = 29$, the spikes cannot be interpreted as significant. In this case, the trending in the data induces a memory pattern, and the correlogram corroborates this. Thus, a correlogram can help identify structure in the data, but the pattern is not unique to the individual time series.

A practical example is an *index of consumer sentiment*

Seasonal Autocorrelation

A seasonal or cyclical series
has a correlogram with
a repeating spike
at the seasonality



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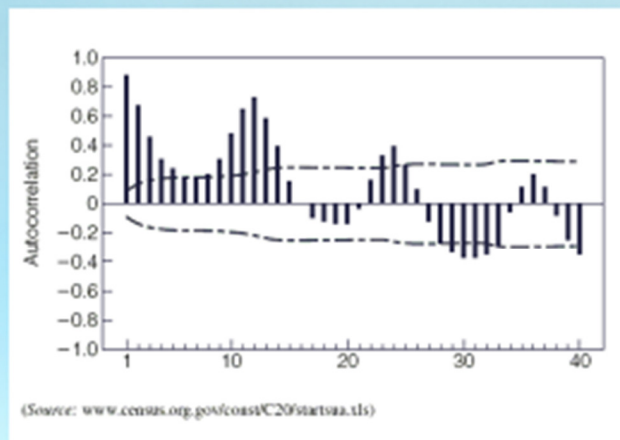
10

How do you identify seasonal autocorrelation?

- A seasonal or cyclical series has a correlogram with a spike at the seasonality
- At multiples of the seasonal period, there are spikes of decreasing magnitude

Combined Low Order And Seasonal Autocorrelation

Shows a pattern of decay and spikes at the seasonal periods



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How do you identify low order and seasonal autocorrelation?


- In practice, most monthly time series are both seasonal and have trend
- The autocorrelation then shows a pattern of spikes at the seasonal period ($=12$), but with decaying patterns in between and overall due to the trending (low autocorrelation) nature of the data

Identifying Short-Term Trending (Non-Seasonal) Models

You can use this for trending or with deseasonalized data

Procedure:

- ☐ Detrend data by taking differences ($Y_t - Y_{t-1}$) once or (at most) twice
- ☐ Run model (in default mode)
- ☐ Create *correlograms* of the residuals and look for new patterns breaking through the limits




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How do you identify non-seasonal ARIMA models?

- It is simpler to start (peeling the onion) for the simplest case – non-seasonal data
- You can use this for deseasonalized data or trending data
- Procedure steps:
 - Detrend data by taking differences ($Y_t - Y_{t-1}$) once or twice ($d=2$, at most)
 - Select $d = 1$. Run model (in default mode)
 - Create correlograms of the residuals and look for new patterns breaking through the limits
 - Ignore patterns or spikes within the limits. These are due to the fact that we had a sample of 100 values.





Look at Plots to Choose ARIMA(p,d,q) Model

(d = # diff, p = AR, q = MA)

There is only one rule to remember:

- If the *correlogram* cuts off at some point, say $k=q$, then the appropriate model is MA (q)
- If the *partial correlogram* cuts off at some point, say $k=p$, then the appropriate model is AR(p)
- If neither diagram cuts off at some point, but does decay gradually to zero, the appropriate model is ARMA (p' , q') for some p' , q' .



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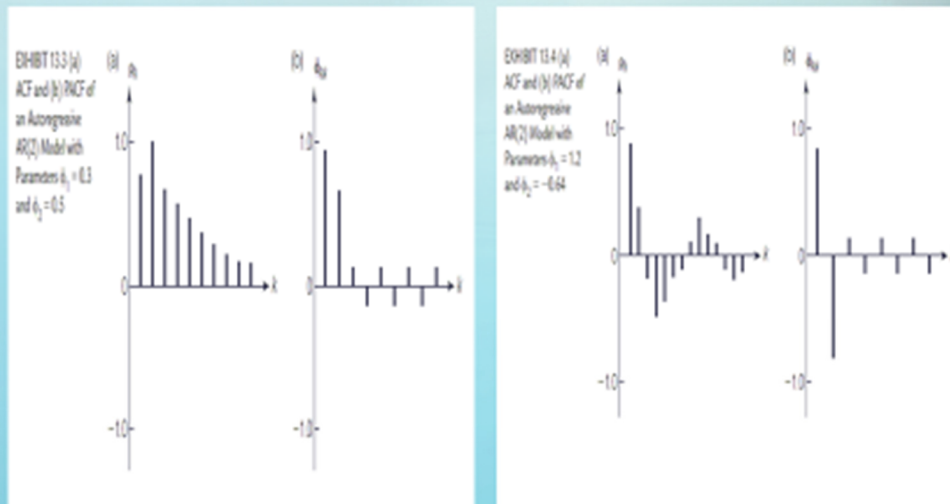
13

How do you use plots to choose ARIMA (p,d,q) model?

- The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are widely used in identifying ARIMA models. When estimated using data, the corresponding *ordinary correlogram* and *partial correlogram* are the estimates of the ACF and PACF
- ACF and PACF play an important theoretical role in the identification phase of the Box-Jenkins methodology for forecasting and control applications
- (d = number of differencing steps, p = order of AR, q = order of MA)
- If the *ordinary correlogram* cuts off at some point, say $k=q$, then the appropriate model is MA (q)
- If the *partial correlogram* cuts off at some point, say $k=p$, then the appropriate model is AR(p)
- If neither diagram cuts off at some point, but does decay gradually to zero, the appropriate model is ARMA (p' , q') for some p' , q' .

This is the most important and only useful rule to follow!!

Examine Plots to Identify ARIMA(2,0,0) Model ($p = 2, d=0, q = 0$)



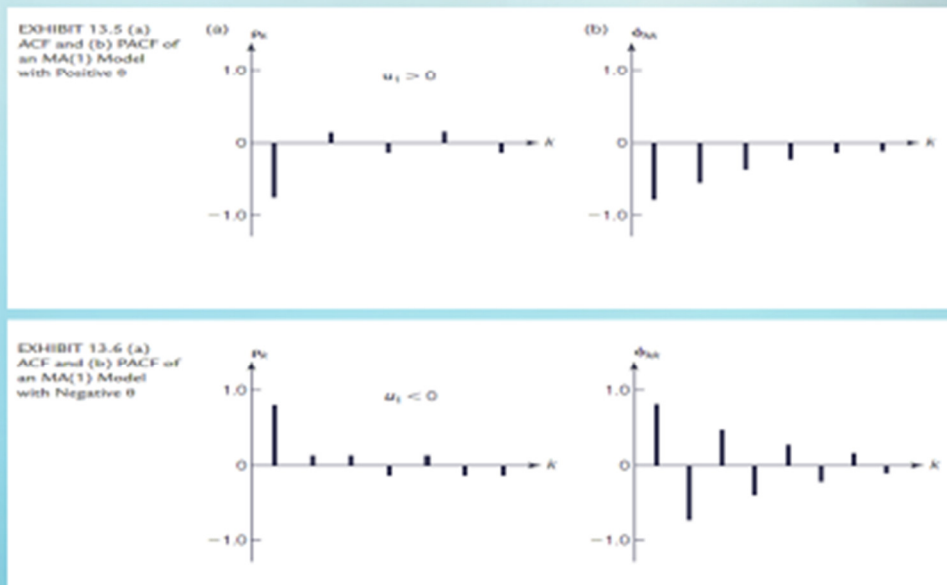
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How do you look at ACF and PACF plots to choose an ARIMA model?

-
- A common process that occurs fairly often in practice is the AR(2) process. In this case there are two autoregressive coefficients ϕ_1 and ϕ_2
- The left display shows the ACF and PACF of an AR(2) model with $\phi_1 = 0.3$ and $\phi_2 = 0.5$.
- The PACF shows positive values at lags 1 and 2 only
- The PACF is very helpful because it suggests that the process is autoregressive and, more importantly, that it is second-order autoregressive.
- If $\phi_1 = 1.2$ and $\phi_2 = -0.64$, the ACF and PACF have the patterns shown in the right display
- The values in the ACF decay in a *sinusoidal* pattern; the PACF has a positive value at lag 1 and a negative value at lag 2.

Examine Plots to Identify ARIMA(0,0,1) Model ($p = 0, d = 0, q = 1$)



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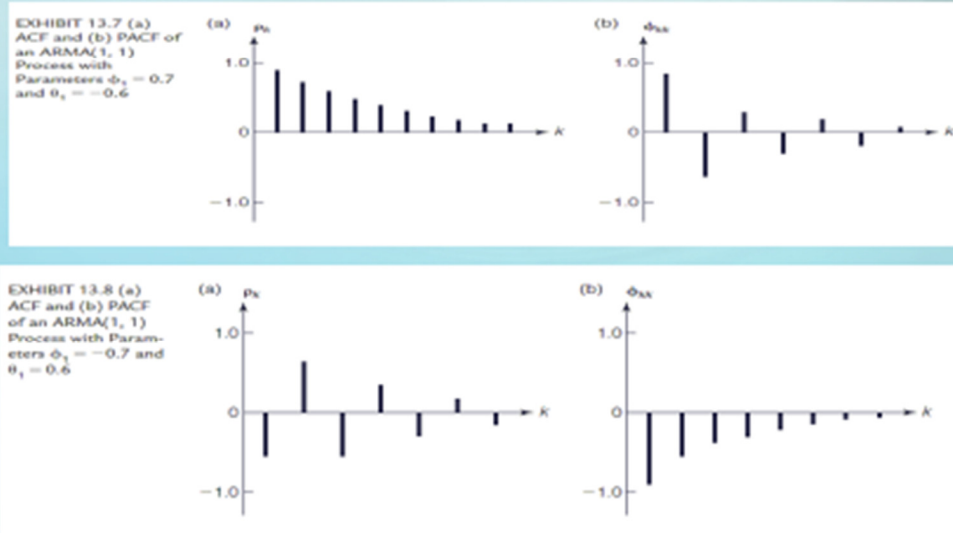
15

How do you choose the MA (1) or ARIMA (0,0,1) model?

- The ACF of a MA(q) process is 0, beyond the order q of the process (i.e., it has a cutoff after lag q). For example, the ACF of a MA(1) process has one spike at lag 1, the others are 0
- The PACF of the MA process is complicated, It has a complicated formula
- The ACF and PACF of an MA(1) model with positive θ are depicted in the top diagram
- There is a single negative spike at the lag 1 in the ACF. There is a decaying pattern in the PACF
- The ACF of an MA(1) process with negative θ (bottom display) shows a single positive spike, but the PACF shows a decaying pattern with spikes alternating above and below the zero line
- One important consequence of the theory is that the ACF of an AR process behaves like the PACF of an MA process and vice versa.

This aspect is known as a duality property of the AR and MA processes. If both the ACF and the PACF attenuate, then a mixed model is called for.

Examine Plots to Identify ARIMA(1,0,1) Model ($p = 1, d = 0, q = 1$)

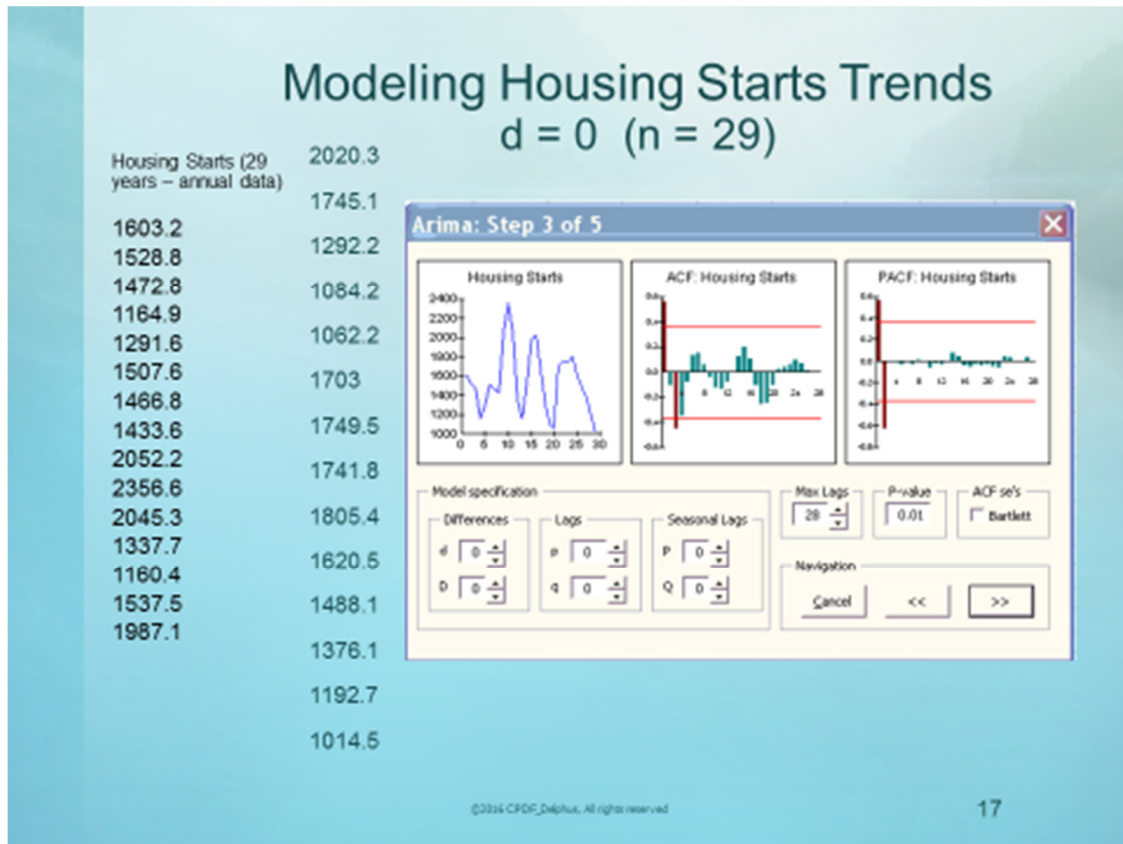


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16

How do you choose the mixed ARMA model? ARIMA (p, d, q) or ARIMA (1,0,1) model?

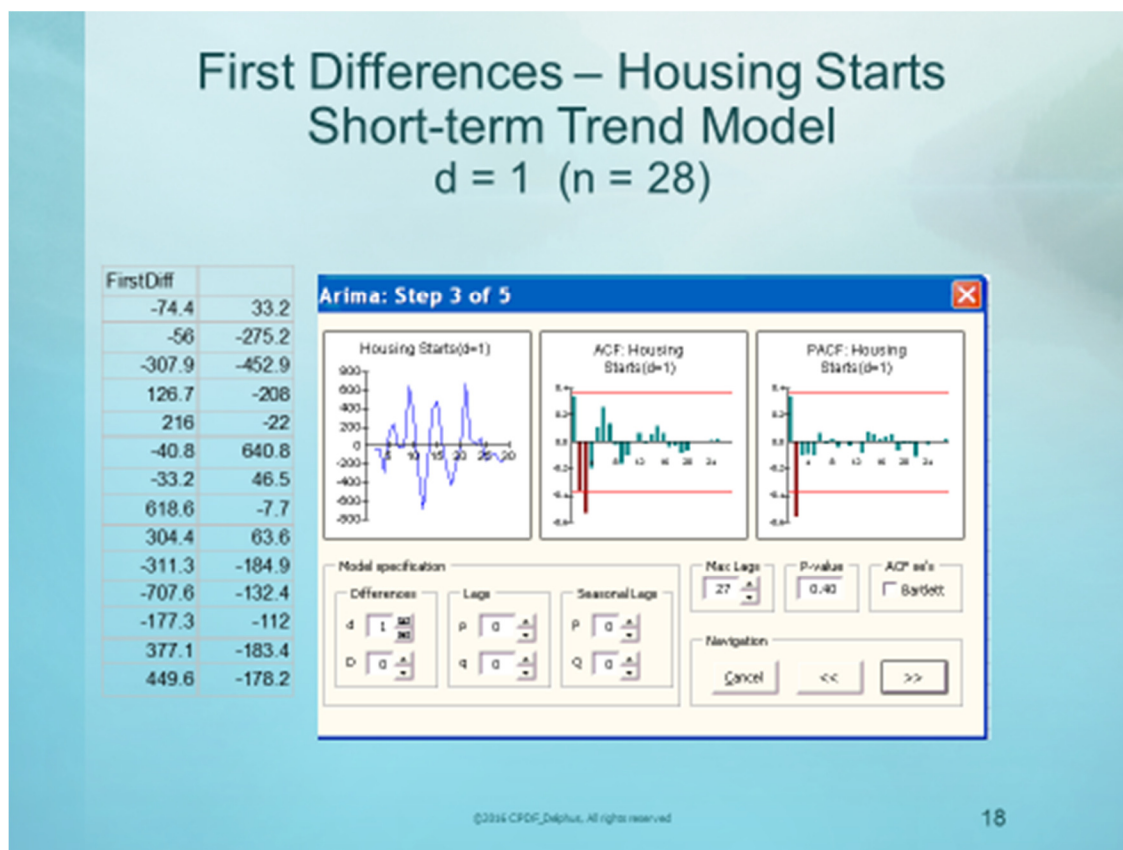
- It turns out that the ACF of the pure MA (q) process truncates, becoming 0 after lag q , whereas that for the pure AR (p) process is of infinite extent. MA processes are thus characterized by *truncation* (spikes ending) of the ACF, whereas AR processes are characterized by *attenuation* (gradual decay) of the ACF
- The best way to identify an ARMA process initially is to look for decay or a tail in both the ACFs and PACFs
- In practice, it is sufficient to recognize the basic structure of the ACF and PACF for values of $p = 1, 2$ and $q = 1, 2$.
- The ACF and PACF of an ARMA (1,1) process with $\phi_1 = 0.7$ and $\theta_1 = -0.6$ are shown in the upper display
- The ACF and PACF of the same ARMA(1, 1) process, but with the signs of ϕ_1 and θ_1 reversed, shows alternating decaying values in the ACF (lower display)
- In practice, it can be challenging to identify the process just by looking at empirical ACF and PACF based on real data. There are many possible parameter values to choose from that result in similar-looking patterns in the ACF and PACF. Even when performed on a computer, the range of permissible values for the coefficients is limited.



How to choose an ARIMA (p,d,q) model for forecasting annual housing starts

- The first frame of the three charts shows the historical 29 years of housing starts. The data is cyclical (not seasonal!), likely related to economic cycles
- The second frame is the ordinary correlogram (estimate of ACF) for these data. This shows lag 1 and 3 outside the confidence limits
- The third frame is the partial correlogram. This shows lags 1 and 2. Truncation of spikes at lag 2 suggests an ARIMA (2, 0, 0).
- Clearly, this is a mixed model with no clear signals of what parameters to use. It is practical to consider AR and MA lags 1 and 2, such as ARIMA (2,0,2) or ARIMA (2, 0, 0) and then make comparisons based on hold-out samples or relative widths of prediction limits.

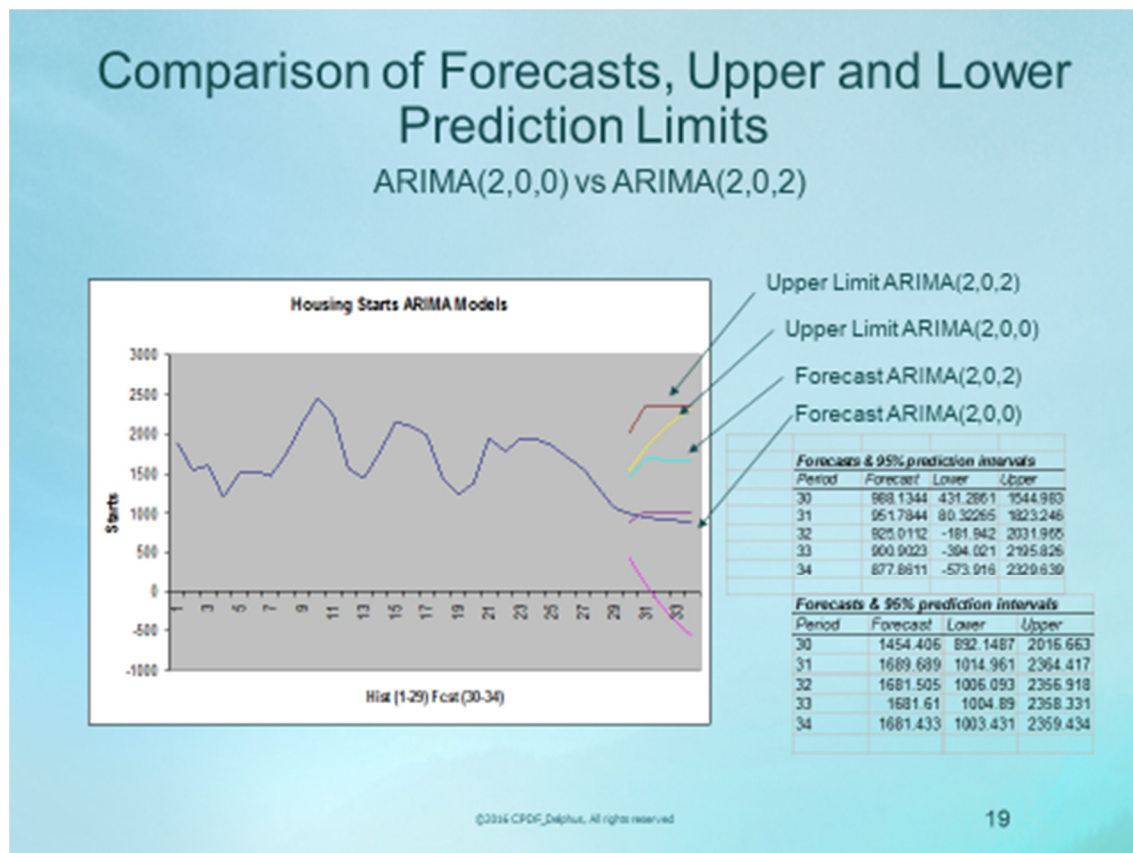
The forecast profile is a trending line for this specification



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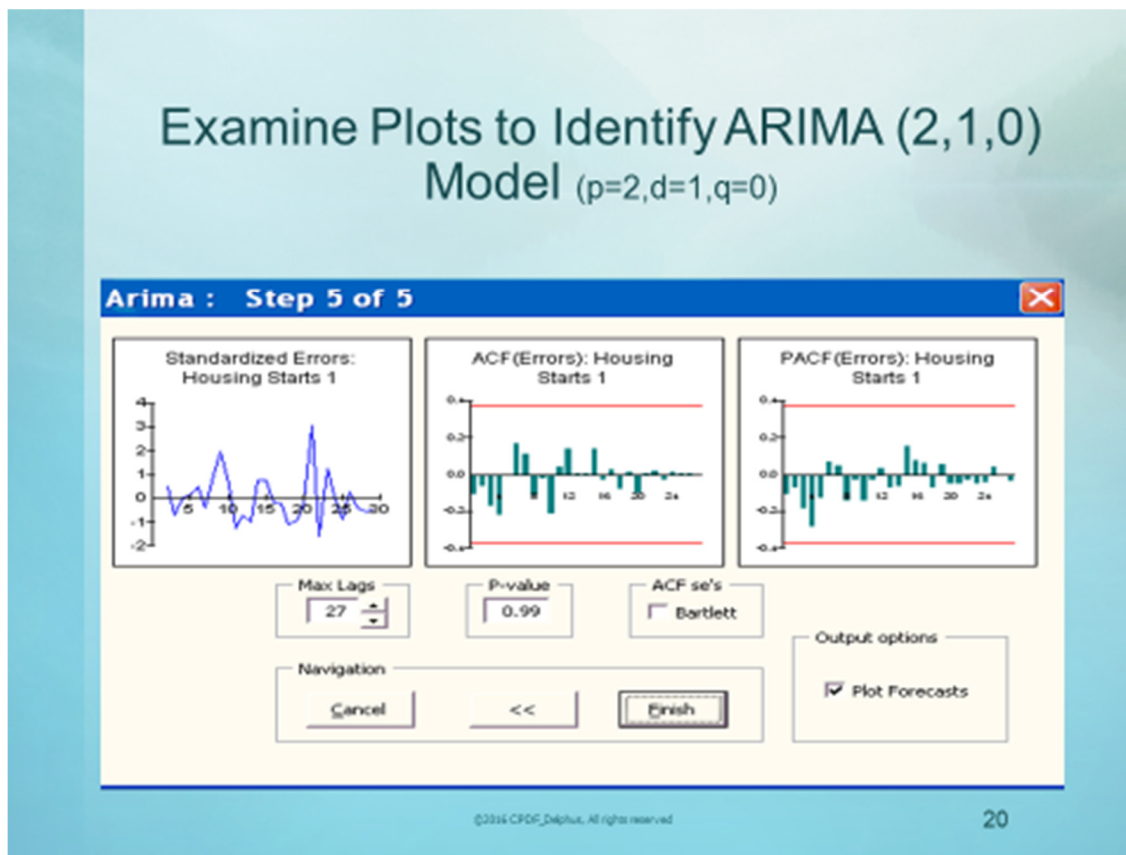
Why take first differences ($d = 1$) of annual housing starts data?

- Taking a first difference is recommended because most annual data is trending and hence differencing will level the data (a step towards *stationarity*)
- The first display on the left shows the first difference of the housing starts. After differencing, there are only 28 data values (Why?)
- Both correlograms have not changed much, so there is no additional benefit seen in differencing. Housing starts is more cyclical than trending.



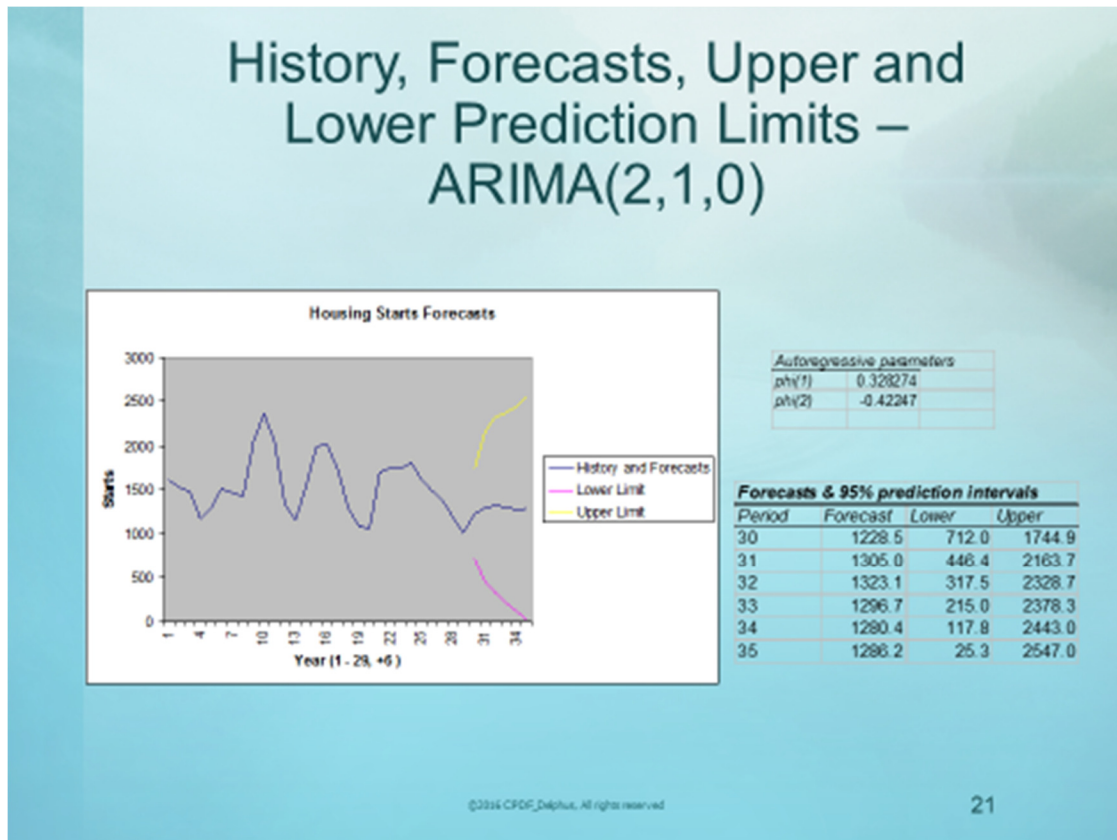
How do you compare forecasts with upper and lower 95% prediction limits?

- Two alternatives are selected: ARIMA(2.0.0) and ARIMA(2.0.2)
- To compare two of the models, the preferred step is to make forecasts based on a hold-out sample and examine the distribution of forecast errors (compared to the actuals in the hold-out sample).
- Then create some summary measures of forecast accuracy and make a structured judgment, keeping in mind the context and 'downstream' or eventual use of this forecast
- The width and placement of the prediction limits suggest how much uncertainty is reflected in the model. This can also be useful in selecting the most appropriate model. There is no one measure or statistic that should be used in all situations
-
-
-
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-



How do you compare the ARIMA (p,d,q) or ARIMA (2,1,0) model (incorporating a first difference $d=1$) ?

- The left frame depicts the differenced data – level and volatile
- Both the empirical ACF and PACF show no patterns outside the confidence limits
- This would be another viable model, but it needs to be evaluated in terms of forecast performance.




How do you display history, forecasts and prediction limits for the ARIMA (p,d,q) or ARIMA(2,1,0) model for housing starts?

- Prediction limits appear very wide, suggesting wide uncertainty in the forecast horizon
- This is an example of a predictive visualization. It is made up of history, forecasts and prediction limits.

Implementing Trending (Nonseasonal) ARIMA Models

Checklist for implementing ARIMA models

- ☐ Create time plots to establish what data adjustments and transformations may be needed
- ☐ Inspect empirical ACF (*correlogram*) for pure AR or MA structures
- ☐ Inspect *partial correlogram* to confirm or supplement the information derived from a correlogram.



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How do you create a checklist to implement nonseasonal ARIMA models?

- Create time plots to establish what data adjustments and transformations may be needed
- Inspect empirical ACF (correlogram) for pure AR or MA structures
- Inspect partial correlogram to confirm or supplement the information derived from a correlogram
- The inspection of the ordinary and partial correlograms together should suggest a preliminary model to be fitted in the first iteration of the model-building process.
- The most significant patterns in the correlograms should be documented for future reference.

If the ACF and PACF both decay, we recommend using an ARIMA (p, 0, q) model. If the ACF and PACF both truncate, try the simpler AR (p) and MA (q) models, especially if one cuts off more quickly.

Partial Autocorrelation	Autocorrelation Function Pattern	
	Decays	Truncates
Truncates	AR	Mixed (ARMA)
Decays	Mixed (ARMA)	MA




Part VII

Taming Uncertainty: What You Need to Understand About Measuring Forecast Accuracy

Learning Objectives

- Identifying accuracy measures appropriate for evaluating demand forecasts
- Interpreting these measures in the context of predictive analytics (forecasting)
- Recognizing the costs of inaccurate forecasts
- Recommending the use of non-conventional metrics when there are outliers or non-normality.
- Suggest relative error measures to improve the understanding of accuracy in forecasting applications

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What You Should Be Able To Do

After completing this topic, you should be able to:

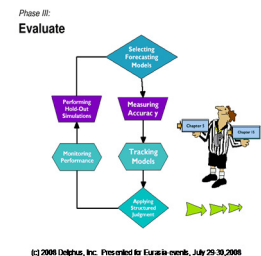
- Identify accuracy measures appropriate for evaluating demand forecasts
- Interpret these measures in the context of univariate time series data
- Note the sensitivity of conventional measures with non-normal data and outliers
- Recommend the use of relative error measures to improve the understanding of accuracy in forecasting applications.

How You Will Check Your Progress

- Establishing standards of forecasting performance in terms of customer service and cost metrics for downstream users of the forecast
- Creating a checklist of forecast measures appropriate for the levels and groupings where forecasts have meaningful use

Resources


- Levenbach, C&C, Chapter 4



Case: Confectionary Manufacturer (CPG)
Focuses on Process Improvement Along With Error Reduction

Objective: Identify the main objectives of measuring accuracy:

- COST OPTIMIZATION
- CUSTOMER SERVICE
- LONG TERM CAPITAL PLANNING
- ANNUAL BUDGETS
- **FORECASTER PERFORMANCE**
- VALUE OF FORECASTING
- OPERATIONAL EFFICIENCY IMPROVEMENTS
- VALUE ADDED FEATURE FOR YOUR CUSTOMERS
- CONTINUOUS IMPROVEMENT WITHIN THE ORGANIZATION



Definition of accuracy: How close was the forecast to actual sales?

- AT THE TOTAL PRODUCT LEVEL
- AT THE PRODUCT LEVEL
- AT THE SUB_PRODUCT LEVEL
- AT ALL CUSTOMERS LEVELS
- 80 % OF CUSTOMERS

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OBJECTIVE: IDENTIFY THE MAIN OBJECTIVE (S) FOR MEASURING ACCURACY:

- COST OPTIMIZATION
- CUSTOMER SERVICE
- LONG TERM CAPITAL PLANNING
- ANNUAL BUDGETS
- FORECASTER PERFORMANCE
- VALUE OF FORECASTING
- OPERATIONAL EFFICIENCY IMPROVEMENTS
- VALUE ADDED FEATURE FOR YOUR CUSTOMERS
- CONTINUOUS IMPROVEMENT WITHIN THE ORGANIZATION

DEFINITION OF ACCURACY: HOW CLOSE WAS THE FORECAST TO ACTUAL SALES


- AT THE TOTAL PRODUCT LEVEL
- AT THE PRODUCT LEVEL
- AT THE SUB_PRODUCT LEVEL
- AT ALL CUSTOMERS LEVELS
- 80 % OF CUSTOMERS
- CUSTOMERS OF "x" AMOUNT OF POUNDS
- CUSTOMERS OF "X" AMOUNT OF REVENUE
- AT FORM LEVEL
- BY PLANT

CALCULATING FORECASTING ACCURACY: WHICH CALCULATION BEST REPRESENTS YOUR BUSINESS

- % ERROR: $A-F / A$
- % VARIANCE: $F-A / F$
- ABSOLUTE % ERROR: THIS MEASURES ACCURACY REGARDLESS OF OVER/UNDER FORECAST: $| A-F | / F$
- MEAN ABSOLUTE DEVIATION (MAD): $| A-F | / n \text{ \# of periods}$
- MEAN ABSOLUTE PERCENTAGE ERROR (MAPE): $| A-F | / n \text{ \# of periods} \times 100$

Measuring Forecast Accuracy

Defining forecasting accuracy: Which calculation
Best represents your business, but define it
without ambiguity



- % ERROR: $(A-F)/A \times 100\%$
- % VARIANCE: $(F-A)/F \times 100\%$
- MEAN ABSOLUTE DEVIATION (MAD): $\sum |A-F| / n$ ($n = \#$ of periods)
- ABSOLUTE % ERROR (APE): $100\% \times |A-F| / A$
– THIS MEASURES ACCURACY REGARDLESS OF OVER/UNDER FORECAST
- MEAN ABSOLUTE PERCENTAGE ERROR (MAPE):
 $100\% \times 1/n \sum |A-F| / A$, ($n = \#$ of periods)

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How is forecast accuracy measured?

Case: Consumer Package Goods (CPG) Industry

- There are numerous metrics that can be considered to measure 'accuracy'
- Fundamentally, they are numbers based on the distribution of forecast error
- What functions of forecast error do we calculate and how do we interpret and use them in practice?
- For a start, there is %Error and %Variance – similar formulae but different denominators
- Looking at it in terms of absolute values helps interpretation when we do not need to distinguish between 'good and bad' over- and underforecasting. It is either 'good' or 'bad'
- But there is always a cost associated with 'bad' forecasts
- Understanding and predicting customer demand is vital to manufacturers and distributors to avoid stock-outs and maintain adequate inventory levels. While forecasts are never perfect, they are necessary to prepare for actual demand. In order to maintain an optimized inventory and effective supply chain, accurate demand forecasts are imperative.

Cost Of Inaccurate Forecasts

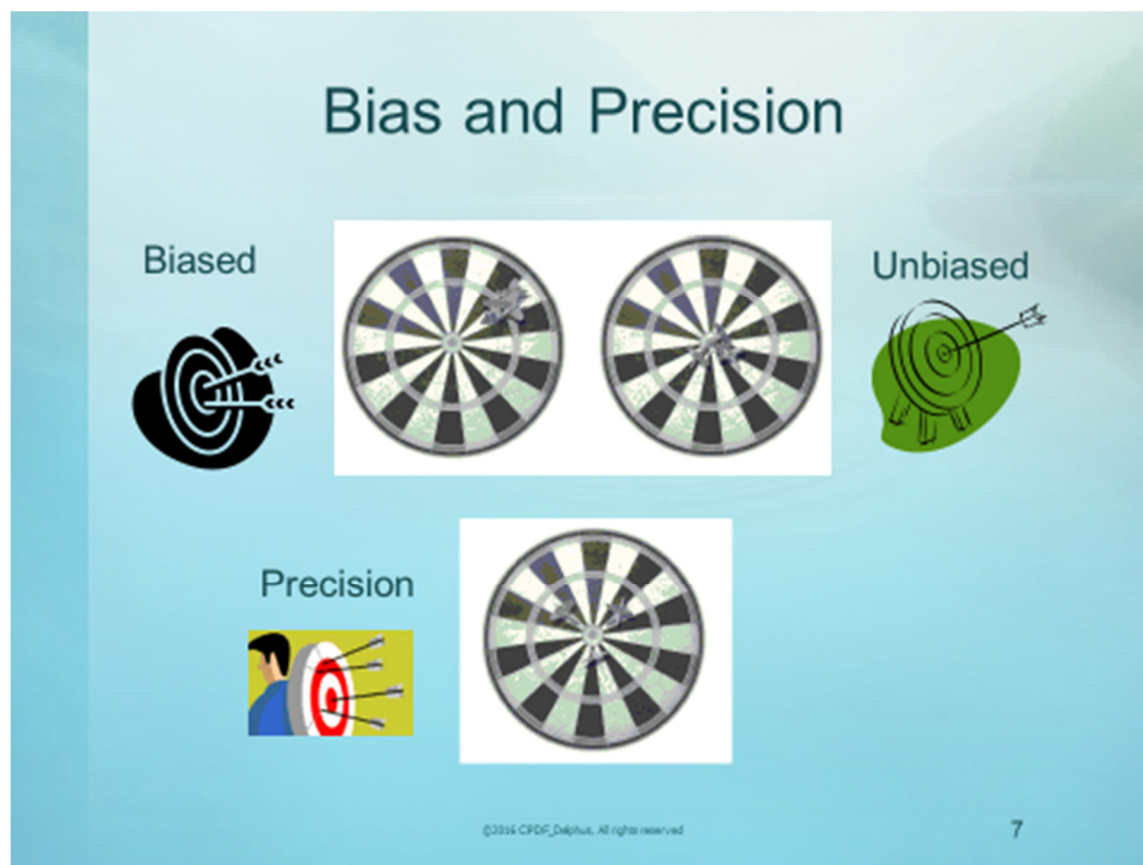
- Customer service – below target line item fill rates
- Finance – excess inventory carrying costs
- Production - schedule disruptions
- Inventory management – Misalignment of supply and demand
- Sales & Marketing - Lost sales opportunities
- Transportation - Unbalanced shipment volumes and sizes
- Warehousing - Excess space and storage costs



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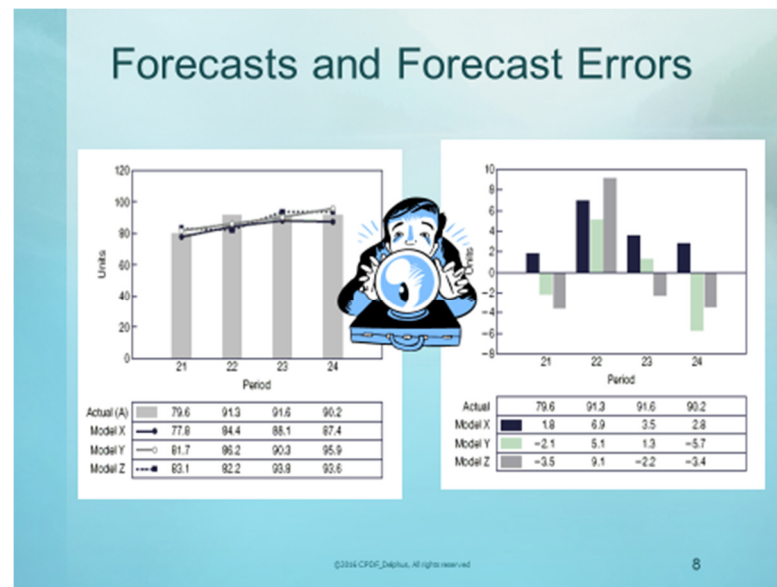
What are the costs of inaccurate forecasts?

- Customer service
 - below target line item fill rate
 - large number of backorders
- Finance
 - excess inventory carrying costs
- Production
 - schedule disruptions
 - increased overtime
- Inventory management
 - misalignment of supply and demand
 - inadequate turns and high obsolescence
- Sales and marketing
 - lost sales opportunities
 - loss of consumer loyalty
- Transportation
 - unbalanced shipment volumes and sizes
 - unusual amount of expediting freight
- Warehousing
 - excess space and storage costs
 - inconsistent shipping/receiving patterns



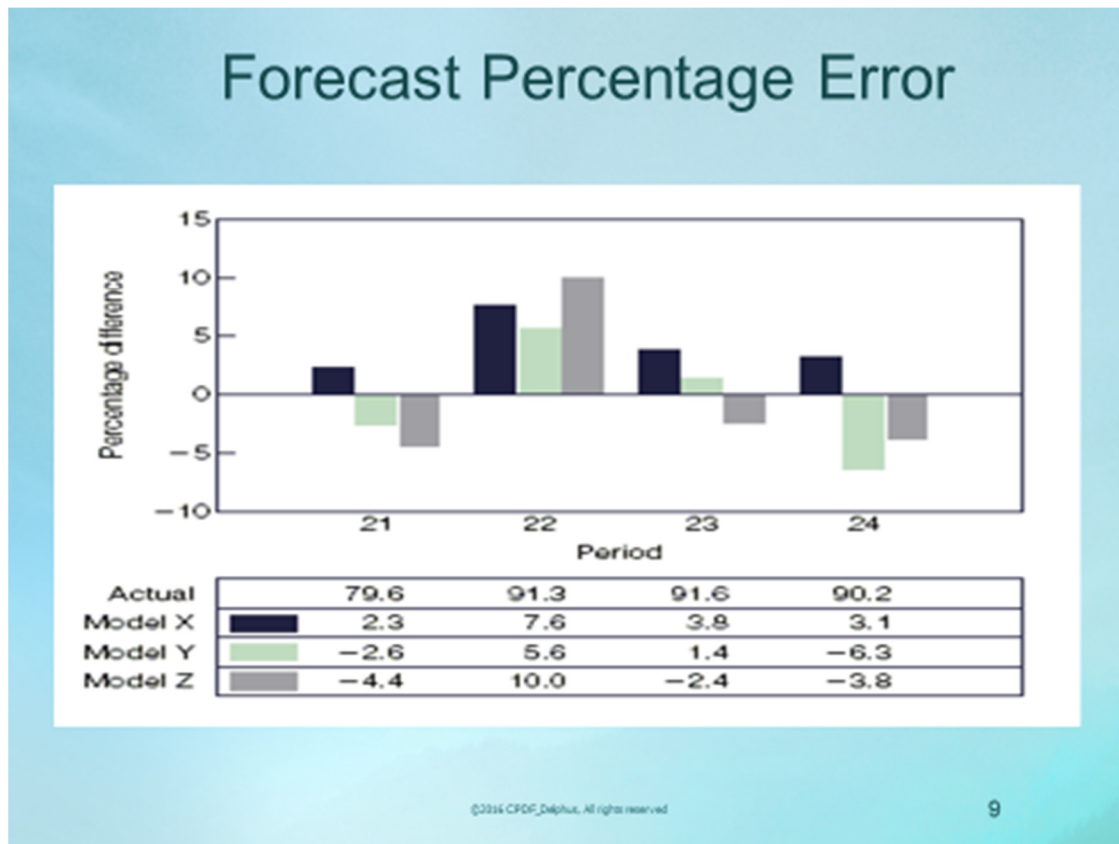
What is meant by bias and precision?

- **Bias is a problem of direction:** Forecasts are typically too low (downward bias) or typically too high (upward bias)
- If we think of forecasting as aiming at a target, then a bias implies that the aim is off-center, so that the darts land repeatedly toward the same side of the target. In contrast, if the forecasts are unbiased, that is, evenly distributed around the target.
- **Precision is an issue of magnitudes:** Forecast errors can be too large (in either direction) using a particular forecasting technique
- Precision refers to the distance between the forecasts as a result of using a particular forecasting technique and the corresponding actual values.



What are forecasts and forecast errors?

- Consider the measurement of bias and precision for three hypothetical forecasting techniques. In each case, the fit period is periods 1 – 20
- The deviations are the differences between the actuals and their forecasts
- Each deviation represents a *forecast error* (or forecast miss) for the associated period: Forecast error (**E**) = Actual (**A**) - Forecast (**F**)
- Contrast this with a *fitting error* (or residual) of a model over a fit period, which is: Fitting error = Actual (**A**) - Model fit
- When we *overforecast*, we must make a *negative* adjustment to reach the actual value. Note that if the forecast is less than the actual value, the miss is a positive number; if the forecast is more than the actual value, the miss is a negative number
- The forecast error shown for technique X is 1.8 in period 21. This represents the deviation between the actual value in forecast period 21 (= 79.6) and the forecast using technique X (= 77.8)
- In forecast period 22, the forecast using technique X was lower than actual value for that period resulting in a forecast error of 6.9
- The period 24 forecast using technique Z was higher than that period's actual value; hence, the forecast error is *negative* (- 3.4)
- Technique X underforecasts in all four periods, indicative of a persistent (downward) bias
- Technique Y underforecasts and overforecasts with equal frequency; therefore, it exhibits no evidence of bias in either direction
- Technique Z is biased slightly toward overforecasting.



What are forecast percentage errors

- As one measure of forecast accuracy, we calculate a percentage error, given by $PE = 100\% * (A - F)/A$
- We can take either reject any technique that projects with serious bias in favor of a less-biased alternative (after we have first compared the precision and complexity of the methods under consideration) or
- We investigate the pattern of bias in the hope of devising a bias adjustment
- For example, we might take the forecasts from method X and adjust them upward to try to offset the tendency of this method to underforecast.

Fit Period vs. Forecast Period

Some commonly misunderstood notions

$(I_t, t=1, 2, \dots, T)$ the historical dataset up to and including period $t = T$

$(\hat{I}_t, t=1, 2, \dots, T)$ the data set of fitted values that result from fitting a model to historical data


I_{T+m} the future value of I_t , m periods after $t = T$

$(I_T(1), I_T(2), \dots, I_T(m))$, the one- to m -period ahead-forecasts made from $t = T$

Consequently, we see that forecast errors and fit errors (*residuals*) refer to:

$I_1 - \hat{I}_1, I_2 - \hat{I}_2, \dots, I_T - \hat{I}_T$ the fit errors or residuals from a fit

$I_{T+1} - Y_T(1), I_{T+2} - Y_T(2), \dots, I_{T+m} - Y_T(m)$ the forecast errors (*not to be confused with the residuals from a fit*)



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What is the difference between fit period and forecast period?

- In measuring forecast accuracy, a portion of the historical data is withheld, and reserved for evaluating forecast accuracy
- The historical data are first divided into two parts: an initial segment (the *fit period*) and a later segment (the *holdout sample*). The fit period is used to develop a forecasting model
- A fit period is called the *within-sample* training, initialization, or calibration period
- Model forecasts are made for the forecast period (*holdout sample*)
- The accuracy of these forecasts is determined by comparing the projected values with the data in the holdout sample
- A forecast accuracy test should always be performed with data from a holdout sample
- Notation: $Y_t(1)$ as the a *one-period-ahead* forecast of Y_t , and $Y_t(m)$ as the *m-period-ahead* forecast
- $Y_{T+1} - Y_T(1), Y_{T+2} - Y_T(2), \dots, Y_{T+m} - Y_T(m)$ the forecast errors (*not to be confused with the residuals from a fit*)
- In dealing with forecast accuracy, it is important to distinguish between forecast errors and fitting errors.

Goodness of Fit versus Forecast Accuracy

- Goodness of fit statistic → Fit period
- Accuracy measure → Forecast period
- Model fit is designed to model historical patterns → May not necessarily translate into accurate forecasts
- Model fit may add complexity → May not be beneficial to forecast periods

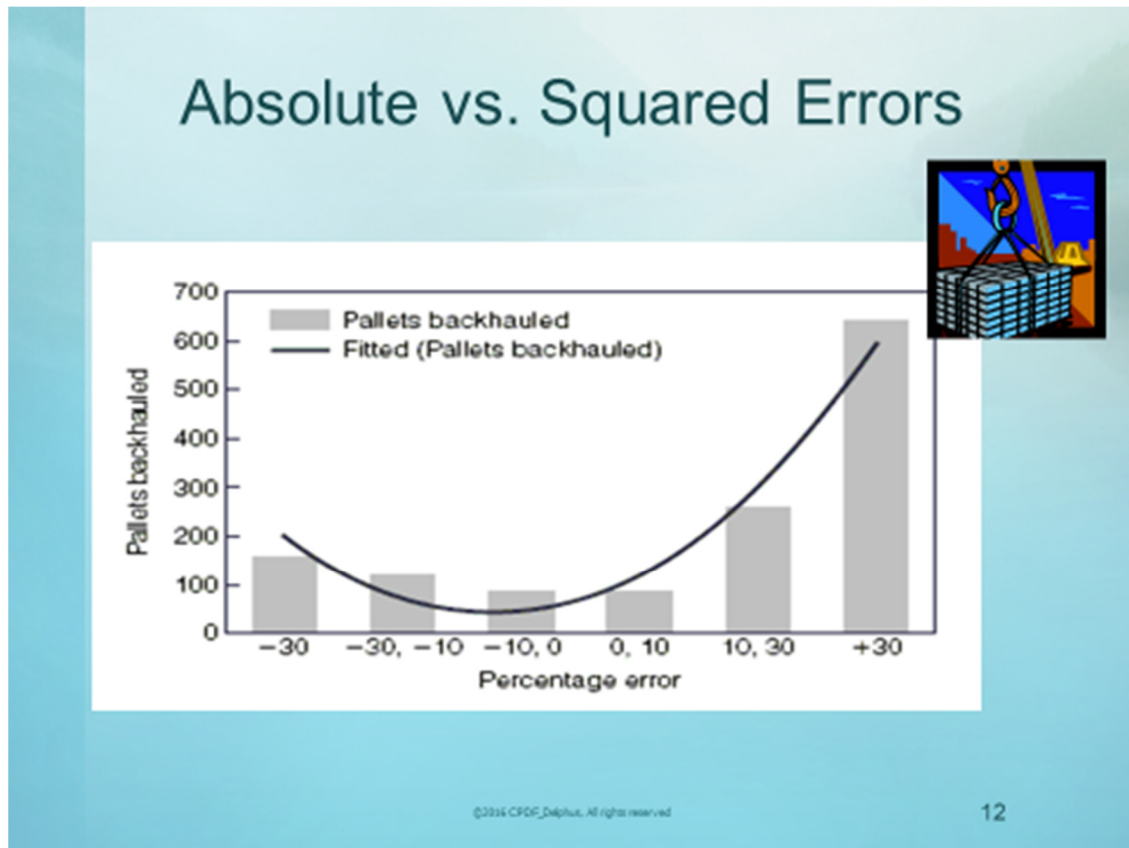


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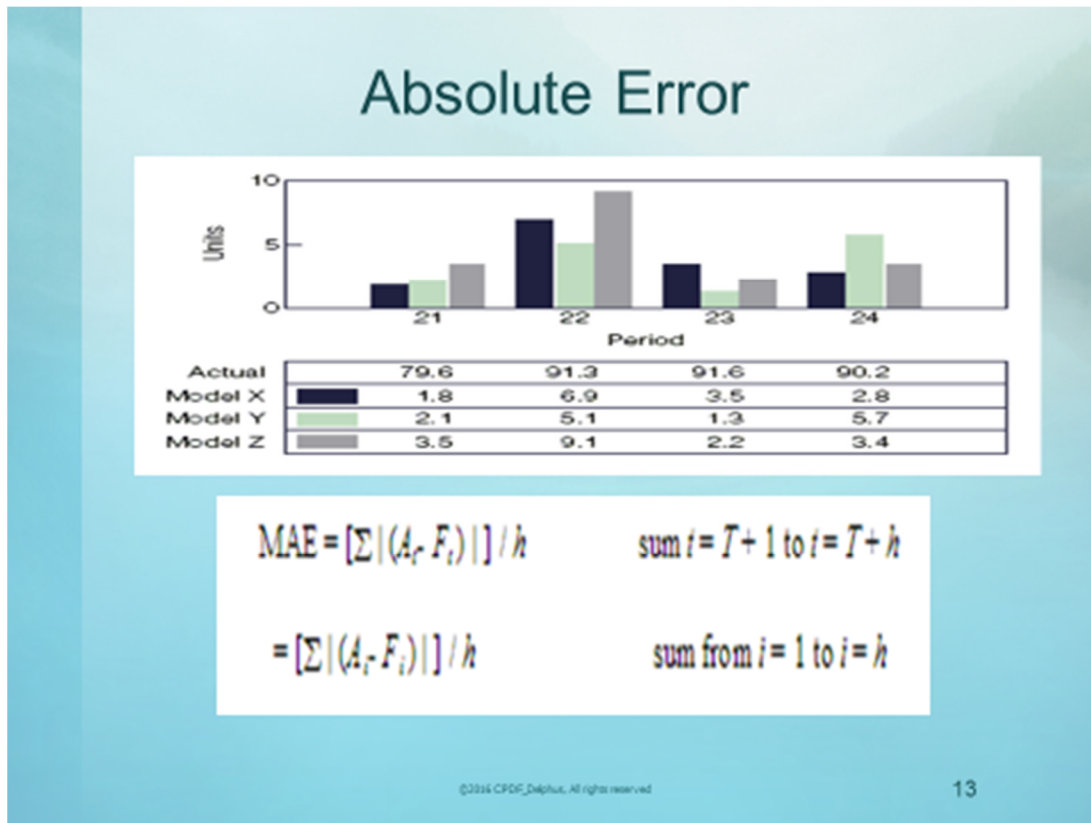
What is the difference between goodness-of-fit and forecast accuracy?

- *Goodness-of-fit* statistics may appear to give better results than a forecasting-based calculation, but goodness-of-fit statistics measure model adequacy over a fitting period that may not be representative of the forecasting period
- When a model is fit, it is designed to reproduce the historical patterns as closely as possible. This may create complexities in the model that capture insignificant patterns in the historical data, which may lead to overfitting
- By adding complexity, we may not realize that insignificant patterns in the past are unlikely to persist into the future. More important, the subtle patterns of the future are unlikely to have revealed themselves in the past
- When assessing forecast accuracy, we may want to know about likely errors in forecasting more than one period-ahead.



What is the difference between absolute and squared errors?

- Costs or losses due to forecast errors may be in direct proportion to the size of the error - double the error leads to double the cost
- For example, when a soft drink distributor realized that the costs of shipping its product between distribution centers was becoming prohibitive, it made a study of the relationship between *underforecasting* (not enough of the right product at the right place, thus requiring a transshipment, or backhaul, from another distribution center) and the cost of those backhauls
- Overforecasts of 25% or higher appeared strongly related to an increase in the backhaul of pallets of product. In this case, the measures based on absolute errors are more appropriate
- In other cases, small forecast errors do not cause much harm and large errors may be devastating
- We need to stress the importance of (avoidance of) large errors, which is what squared-error measures accomplish.



What is the absolute error?

- The most common averages of absolute values are mean absolute error (MAE), mean absolute percentage error (MAPE), and median absolute percentage error (MdAPE)

$$MAE = \frac{\sum |A_t - F_t|}{h} \quad \text{sum } t = T+1 \text{ to } t = T+h$$

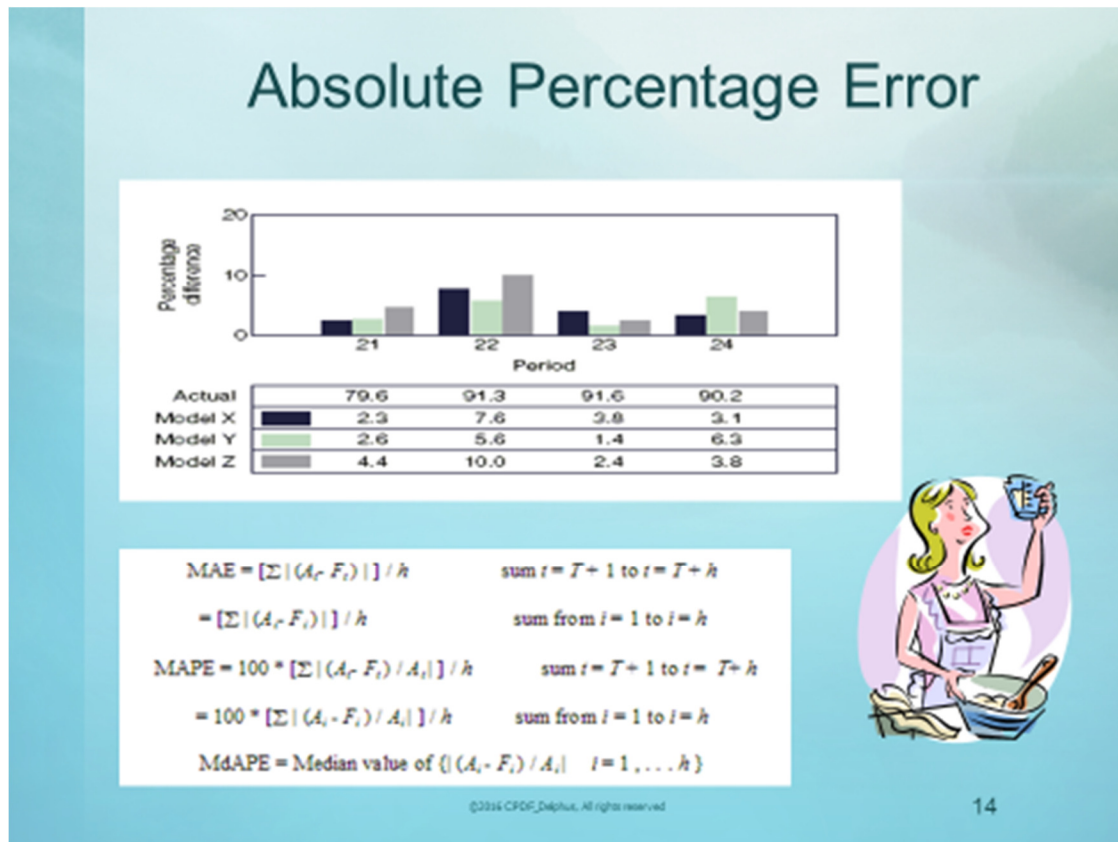
$$= \frac{\sum |A_i - F_i|}{h} \quad \text{sum from } i = 1 \text{ to } i = h$$

$$MAPE = 100 * \frac{\sum |A_t - F_t| / A_t}{h} \quad \text{sum } t = T+1 \text{ to } t = T+h$$

$$= 100 * \frac{\sum |A_i - F_i| / A_i}{h} \quad \text{sum from } i = 1 \text{ to } i = h$$

$$MdAPE = \text{Median value of } \{ |A_i - F_i| / A_i \mid i = 1, \dots, h \}$$

- By taking an absolute value, we eliminate the possibility that underforecasts and overforecasts negate one another
- An average of the absolute forecast errors reveals simply how far apart the forecasts are from the actual values. It does not tell us if the forecasts are biased
- The MAE is 4.6 for technique Z, from which we can conclude that the forecast errors from this technique average 4.6 per period.



What is absolute percentage error?

- The MAPE is 5.2%, which tells us that the period forecast errors average 5.2%
- The MdAPE for technique Z is approximately 4.1% (the average of the two middle values: 4.4 and 3.8). Thus, half the time the forecast errors exceeded 4.1%, and half the time they were smaller than 4.1%
- When there is a serious outlier among the forecast errors, as with technique Z, it is useful to know the MdAPE in addition to the MAPE because medians are less sensitive than mean values to distortion from outliers
- The MdAPE is a full percentage point below the MAPE for technique Z. Sometimes, as with technique Y, the MdAPE and the MAPE are virtually identical. In this case, we can report the MAPE because it is the far more common measure.

TAPE Measures
Typical Absolute Percentage Error

APE set {1.1%, 1.6%, 4.7%, 2.1%, 3.1%,
32.7%, 5.8%, 2.6%, 4.8%, 1.9%, 3.7%,
2.6%}

MAPE = 5.6%
MdAPE = $[2.6 + 3.1]/2 = 2.9\%$

Is there a better way? Avoid the MYTH of
the MAPE:
[http://www.cpdftraining.org/downloads/Levenbach_AccuracyTAP
E2015.pdf](http://www.cpdftraining.org/downloads/Levenbach_AccuracyTAP E2015.pdf)

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To find out about Typical Absolute Percentage Error (TAPE), download the White Paper:

http://cpdftraining.org/downloads/Levenbach_AccuracyTAPE2015.pdf

Outliers in forecast errors and other sources of unusual data values should never be ignored in the accuracy measurement process. With the simplest measure of bias, for example, the calculation of the mean forecast error ME (the arithmetic mean of Actual (A) minus Forecast (F)) will drive the estimate towards the outlier. An otherwise unbiased pattern of performance can be distorted by just a single unusual value. The outlier-resistant measures introduced here operate to reduce their impact on the calculation of measures involving the arithmetic mean. This includes the Mean Absolute Error (MAE), the Mean Absolute Deviation from the Mean (MAD), and the Mean Absolute Percentage Error (MAPE), which is a commonly used measure of precision for reporting forecast accuracy. When we deal with forecast accuracy in practice, a demand forecaster typically reports averages of quantities based on forecast errors (squared errors, absolute errors, percentage errors, etc.). To properly interpret a measure of forecast accuracy, we must also be sensitive to the role of unusual values in these calculations.

Comparing Performance With Naïve Techniques

Period	Actual	NAIVE_1
21	79.6	73.5
22	91.3	79.6
23	91.6	91.3
24	90.2	91.6
MAE	3.6	4.9
MAPE	4	5.60%
RMSE	4	6.6
RMSPE	4.5	7.50%



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Why make comparisons with naïve techniques?

- Based on the evidence of bias and precision, we may want to select technique Y as the best of the three candidates
- Technique Y's forecast for periods 21 - 24 shows no indication of bias - two underforecasts and two overforecasts - and proves slightly more precise than the other two techniques, no matter which measure of precision is used
- The MAE for technique Y reveals that the forecast errors over periods 21 - 24 average approximately 3.5 per period, and the MAPE indicates that these errors come to just under 4% on average
- Contrast technique Y's forecasting record with that of a very simplistic procedure, one requiring little or no thought or effort. Such procedures are often called **naïve techniques**
- If the forecasting performance of technique Y is no better or is worse than that of a naïve technique, it suggests that in developing technique Y we have not accomplished very much.
- For data that are yearly or otherwise lack seasonality; it is called a NAIVE_1 or *Naive Forecast1* (NF1)
- A NAIVE_1 is called a no change forecasting technique, because its forecasted value is unchanged from the previously observed value.

Measures Based on Relative Errors

Leading Edge Practice!!

Let r_t = ratio of forecast error / naïve forecast error

- Mean Relative Absolute Error MRAE

$$= \text{mean } |r_t|$$

- Median Relative Absolute Error MdRAE)

$$= \text{median } |r_t|$$



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What are measures based on relative errors?

- Disadvantage is that relative error can be small
- Suggestion to trim extreme values (both large and small) by winsorizing.

MASE, A Scaled Error Measure (a promising new good practice)

Mean Absolute Scaled Error (MASE)

= Mean (absolute value of scaled error)

Scaled Error = ratio of forecast error divided by *in-sample* MAE



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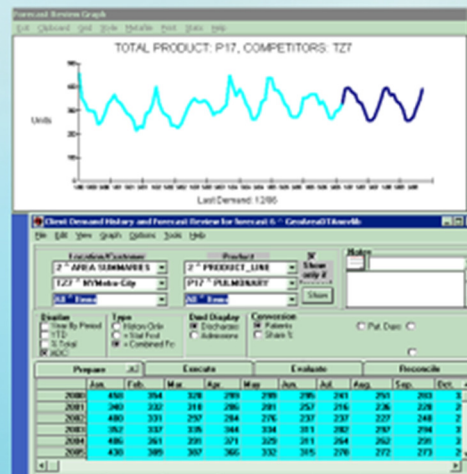
18

What are scaled error measures?

- Recently developed and lacking undesirable properties of 'old measures'
- Removes the scale of the data, so can be used with both large and small values in data
- A scaled error is less than one (unity) if it arises from a better forecast than the average one-step ahead naïve forecast computed in-sample.
- A scaled error is greater than one if the forecast is worse than the average one-step naïve forecast computed in-sample.

Creating a Waterfall Chart

Step 1 – Select hold-out sample



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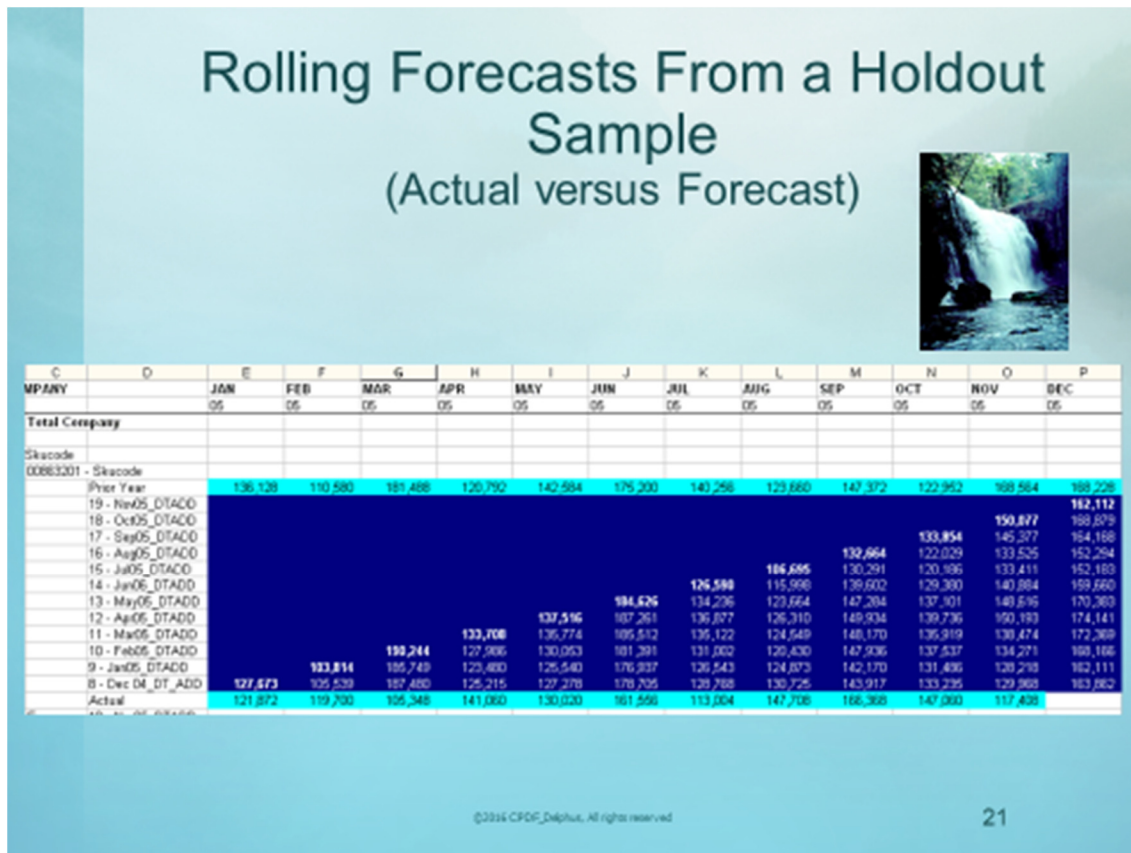
Creating a Rolling Forecast

- ❑ Step 1 – Create Hold-out samples (or use stored forecasts)
- ❑ Step 2 – Make forecasts with hold-out sample
- ❑ Step 3 – Create table of forecasts, actuals, forecast errors, percentage errors, etc. (This will look like an upside down waterfall.



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How to create rolling forecasts from a hold-out sample (used in budgeting)

- Step 1:** Hold out a sample twelve periods, say January through December. The actual values are depicted on the last line of the table (light blue). See the line labeled Actual
- Step 2:** Run twelve consecutive forecasts with end dates December of the previous year through November of the holdout year. The forecasts are labeled 8 – 19 in reverse order.
- Step 3:** Calculate one-step, two-step and three-step ahead forecasts. The one-step ahead forecasts lie on the first diagonal. The two-step ahead forecasts lie on the second diagonal, etc.
- Step 4:** Note that there are many different forecasts that can be evaluated, depending on the forecast horizon (lead-time), forecast start period and accumulation (e.g. three month sums). Rolling averages can be used to smooth forecast errors.




The top table shows a waterfall chart for forecast errors (actual minus forecast)

The bottom table shows a waterfall chart for the **Absolute Percentage Error (APE)**:

$$APE = 100 * |(Actual - Forecast)| / Actual$$

Workshop G (07)

Improve Forecast Accuracy Through Gap Analysis and Exception Reporting



Uncertainty Is a Certain Factor II

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Workshop G (07)

- Calculate the Mean Error (ME), Median Error (MdE), Mean Absolute Error (MAE), Median Absolute Error (MdAE), Mean Percent Error (MPE), Median Percent Error (MdPE), Mean Absolute Percent Error (MAPE), Median Absolute Percent Error (MdAPE), Mean Absolute Scaled Error (MASE), Median Absolute Scaled Error (MdASE), and the Root Mean-Square Error (RMSE). Use the forecasts from Case D
- Identify the bias and precision measures
- Consider the LHHB TAPE measure
 - New Levenbach Huber Huber Bisquare Typical Absolute Percentage Error
- Contrast and interpret these multiple measures of accuracy
- Compare the forecasts with the Naïve_12 forecasts (Actual same period one year previous). Do the Naïve_12 forecasts fall within the 95% prediction intervals?

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Part VIII

Graphical Tools for Forecast Process Improvement

Learning Objectives



- Tracking provides a perspective on forecast bias
- Introduces the ladder chart for monitoring forecast results
- Introduces the prediction-realization chart for monitoring turning points
- Recommends prediction intervals as a way of expressing uncertainty in future values
- Use of tracking signals to indicate successions of overruns and underruns

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What You Should Be Able To Do

After completing this topic, you should be able to:

- Identify forecasting bias
- Monitor forecasts with a ladder chart
- Create a prediction-realization diagram
- Create prediction intervals on forecasts
- Effectively create tracking signals for monitoring model performance

How You Will Check Your Progress

- Checkpoint questions
- Relate the material to your current forecasting efforts
- Work problems in L&C, Chapter 5

Resources

Levenbach, H. (2017). **C&C**. Chapter 11.

Yikang Li, Mike Lange and Cody Stocks (2012) *Monitoring Forecasting Systems – Revisit Trigg’s Tracking Signal*
(http://www.webmeets.com/files/papers/ISF/2012/154/Li_Yikang_ISF2012.pdf)

Know What to Monitor

A demand forecaster should be able to monitor

- Composites or groups of items
- Comparisons of sum of components of a forecast to the whole
- Ratios or relationships between different items
- Similar forecasts in different regions or locations
- Time relationships – changes or percentage changes
- Both on monthly and cumulative basis
- External factors and user needs

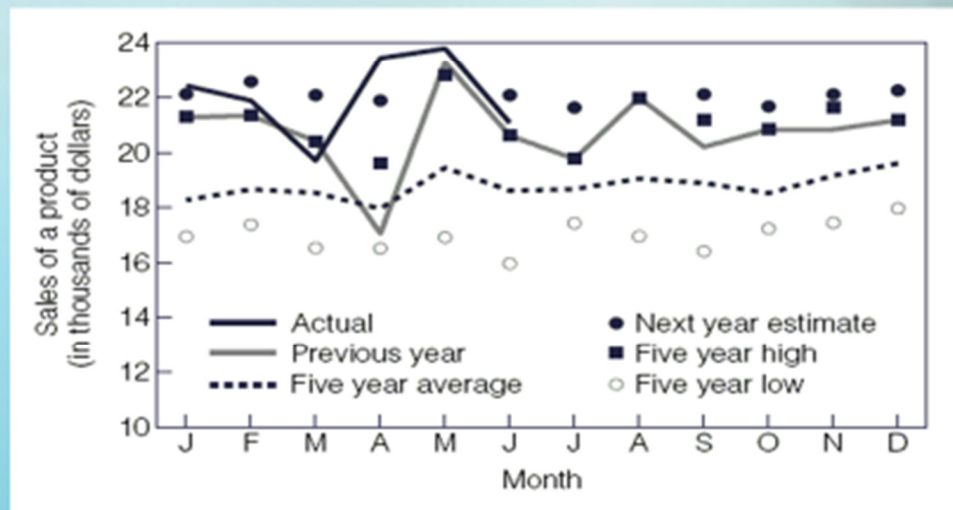
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What do you need to monitor?

- Composites serve as indicators of overall forecast quality and are frequently used a basis for decision making. For example, a forecast of total revenues might on target, although forecasts of revenues accruing from the commercial sector might grow quite differently than the residential market
- Sum of individual product forecasts should be compared to the sum of a total product-line forecast
- The ratio of a given geographic area's sales to the total corporate sales is an example of this approach
- Forecasts in several geographic regions usually perform differently due to different environments and economic conditions.
- Forecaster should consider monitoring time relationships. It may be appropriate to monitor changes or percentage changes over time.
- The sum of actuals since the beginning of the year should be compared to the sum of the forecasts, which will smooth out irregular, random, month-to-month variation
- The external factors monitor key assumptions about business conditions or the economic outlook
- User need changes occur with budgetary or organizational changes, new or discontinued products, or changes in management.

Ladder Chart For Monitoring Forecast Results



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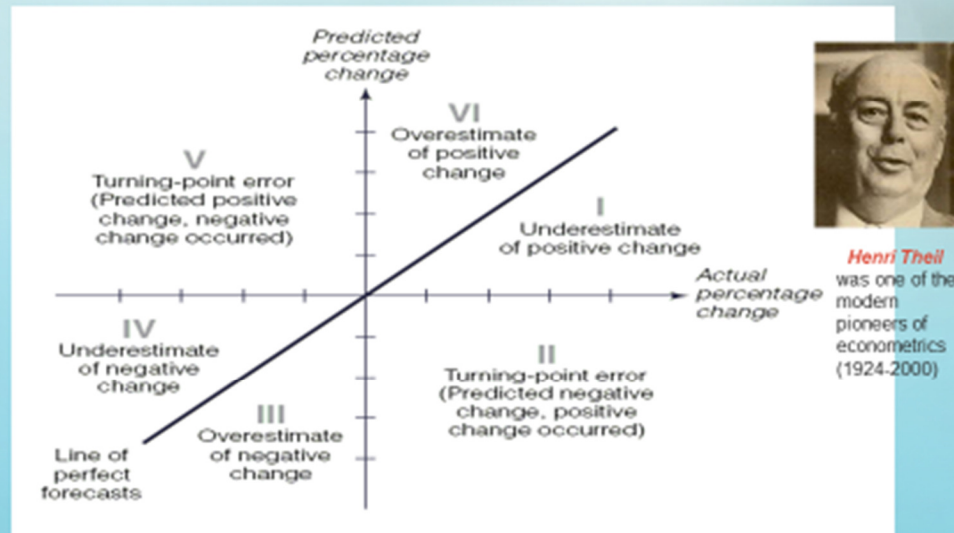
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What is a ladder chart for monitoring forecast results?

A ladder chart displays historical patterns year-by-year in a chart or on separate frames on a chart. Look for similarities and differences among years.

- The five year average smoothes out the seasonality when compared to the actual data.
- The previous year had a trough (seasonal?) compared to the current year.

What is a Prediction-Realization Diagram?



Source: http://cpdftraining.org/downloads/Levenbach_Accuracy2015.pdf

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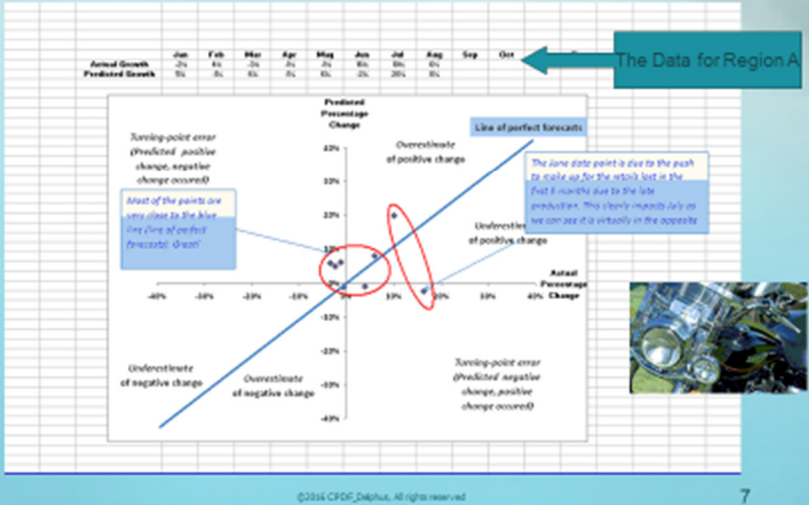
What is a prediction-realization (P-R) diagram?

The prediction-realization diagram indicates how well a model or forecaster has predicted turning points and also how well the magnitude of change has been predicted given that the proper direction or change has been forecast. The diagram has six sections:

- Points falling in sections II and V are the result of turning points
- In Section V, a positive change was predicted, but the actual change was negative
- In Section II, a negative change was predicted, but positive change occurred.
- Remaining sections involve predictions that were correct in sign but wrong in magnitude
- Points above the line of perfect forecasts reflect actual changes that were less than predicted
- Points below the line of perfect forecasts represent actual change that were greater than predicted.

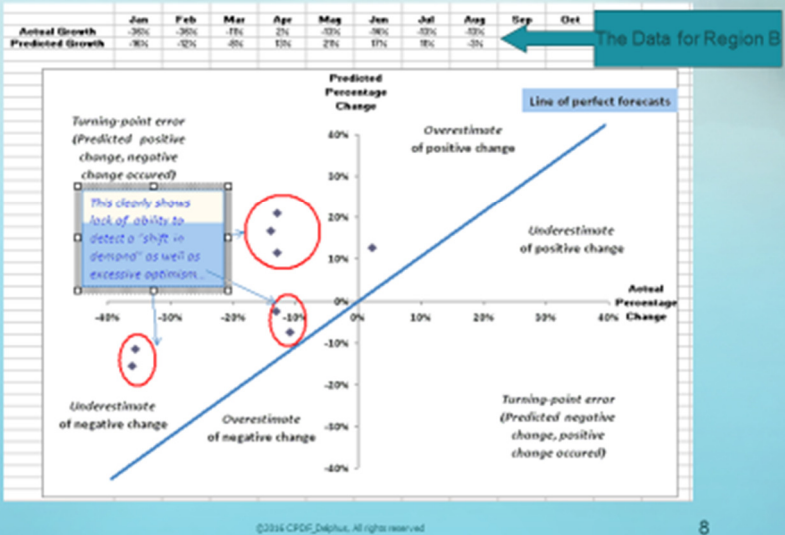
Comparing Performance in Two Regions

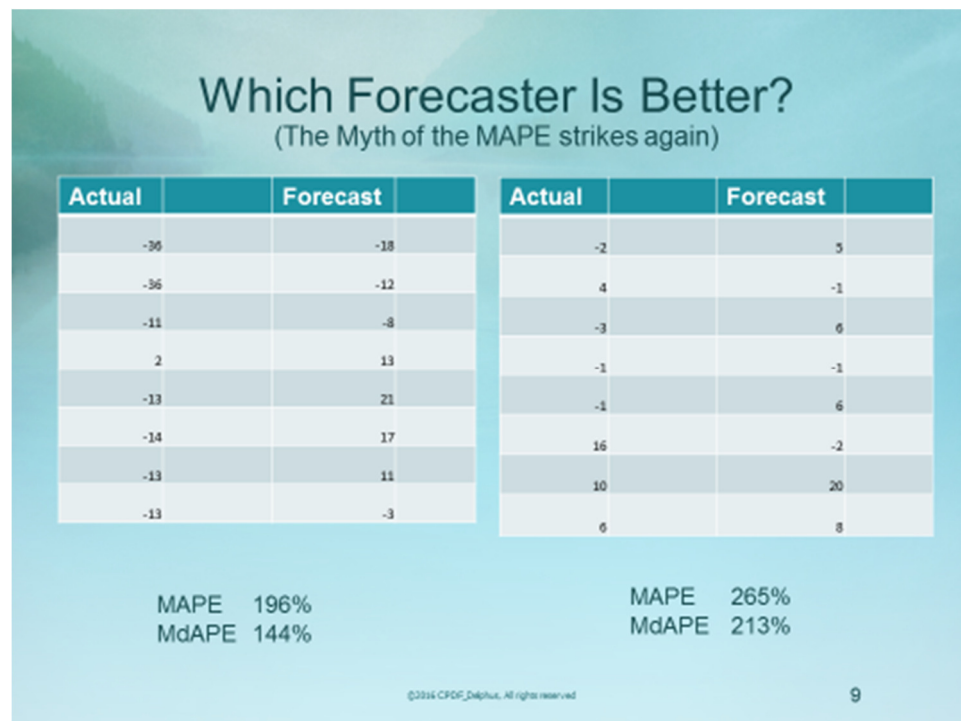
Case: Motorcycle Manufacturer



A Prediction-Realization Diagram For Region II

Case: Motorcycle Manufacturer

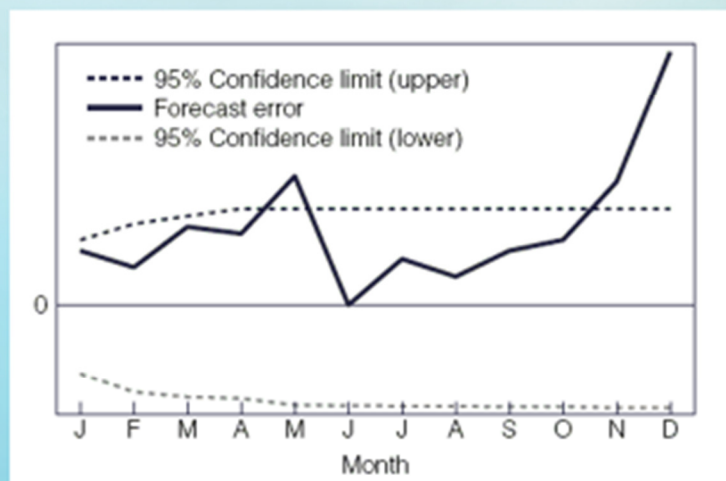




Is the MAPE the right accuracy measure

http://cpdftraining.org/downloads/Levenbach_AccuracyTAPE2015.pdf

Prediction Intervals for Time Series Forecasts



Source: http://cpdfttraining.org/downloads/Levenbach_Accuracy2015.pdf

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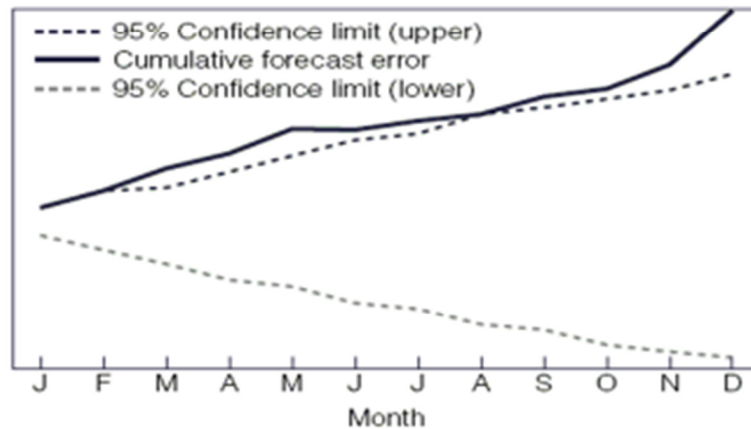
10

What are prediction intervals for time series forecasts?

An early warning signal is a succession of overruns and under runs

It can be seen in this chart that the monthly errors are well within the 95% prediction interval for 9 of the 12 months with two of the three exceptions occurring in November and December. This suggests that the individual forecast errors lie within their respective prediction intervals. However, it is apparent that none of the errors are negative. Hence, there appears to be a bias.

Dealing With Bias CUSUM Forecasts With Prediction Intervals



Source: http://cpdfttraining.org/downloads/Levenbach_Accuracy2015.pdf

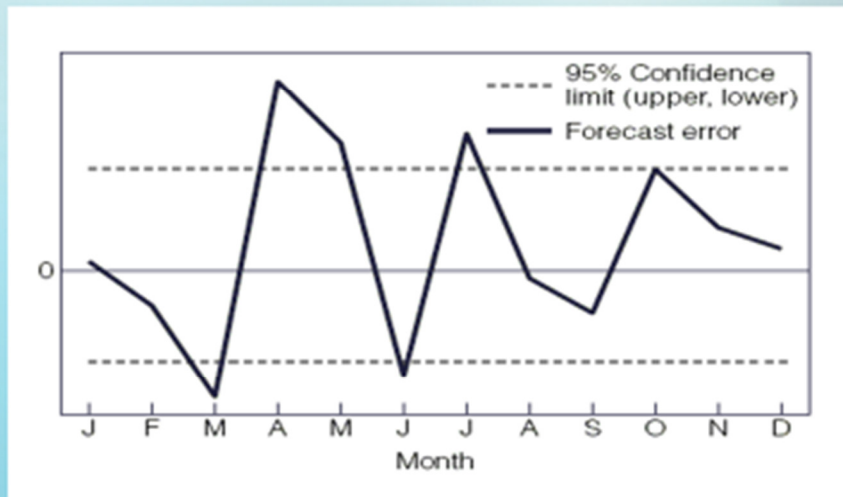
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What are Cusum forecasts with prediction intervals?

- To determine whether the bias in the forecast is significant, we review the prediction intervals for cumulative sums of forecast errors.
- The cumulative prediction intervals confirm the problem with the forecast bias. The cumulative forecast errors fall on the outside of the prediction interval for all twelve periods. The model is clearly underforecasting.
- Using these two plots, a forecaster should be inclined to make upward revisions in the forecast after several months. It should not be necessary to wait until November to recognize the problem.

Dealing with Precision Monthly Forecast Errors and Prediction Limits



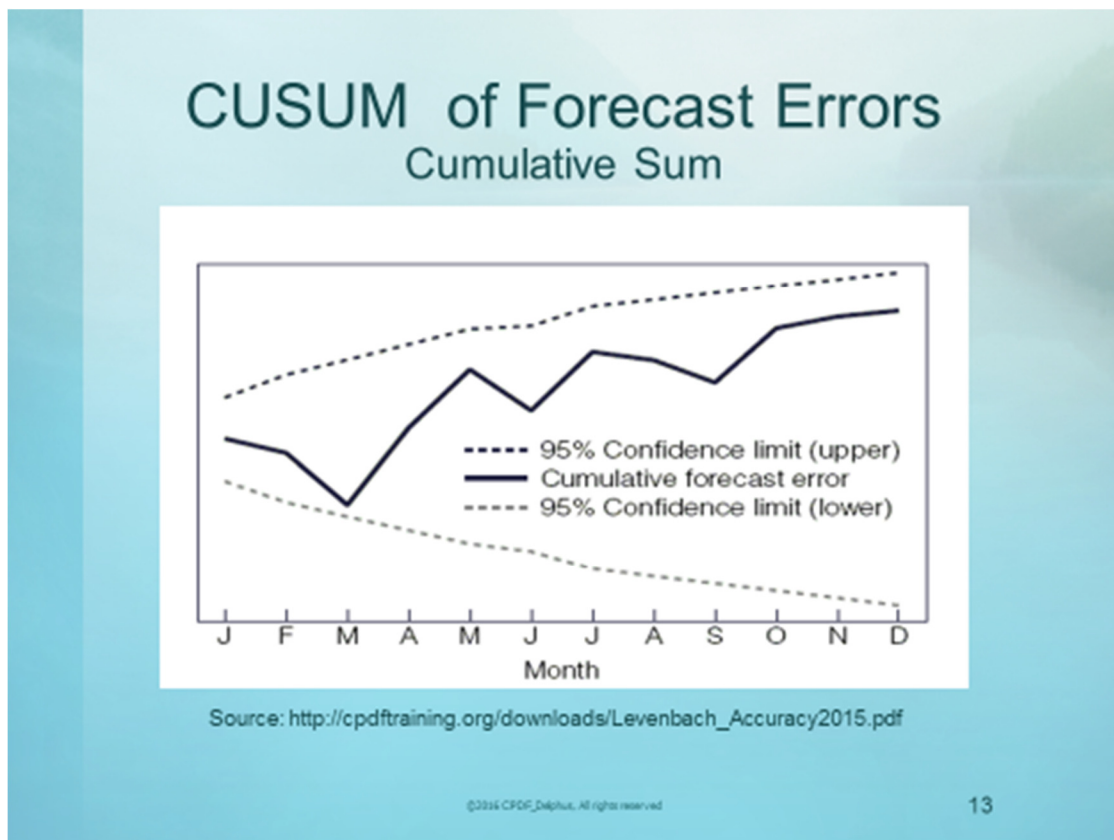
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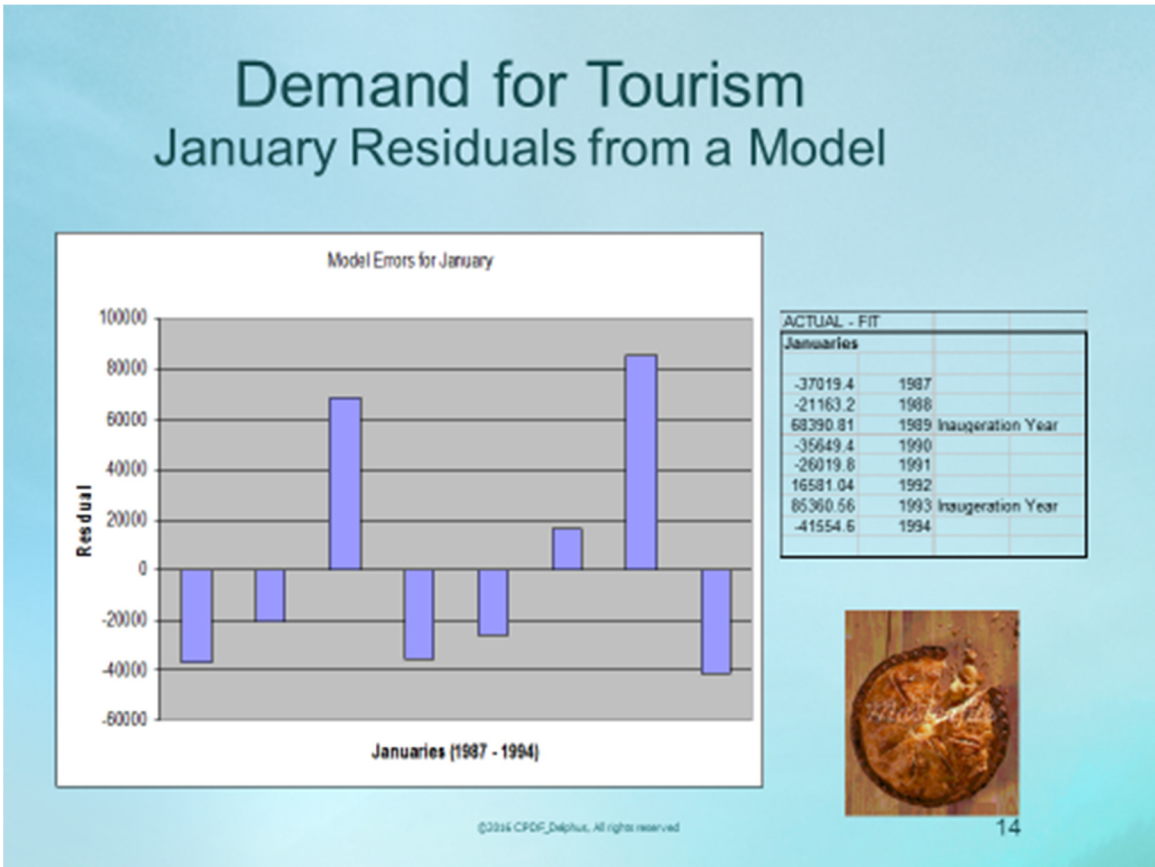
How do you use prediction limits with monthly forecast errors

- Another kind of warning signal occurs when too many forecast errors fall outside the prediction intervals. For example, with a 90% prediction interval, we expect only 10% (approximately one month per year) of the forecast errors to fall outside prediction interval.
- This exhibit shows a plot of the monthly forecast errors for a time series model. In this case, five of the twelve errors lie outside the 95% interval.
- Clearly, this model appears unacceptable as a predictor of monthly values.



What are Cusum forecast errors?

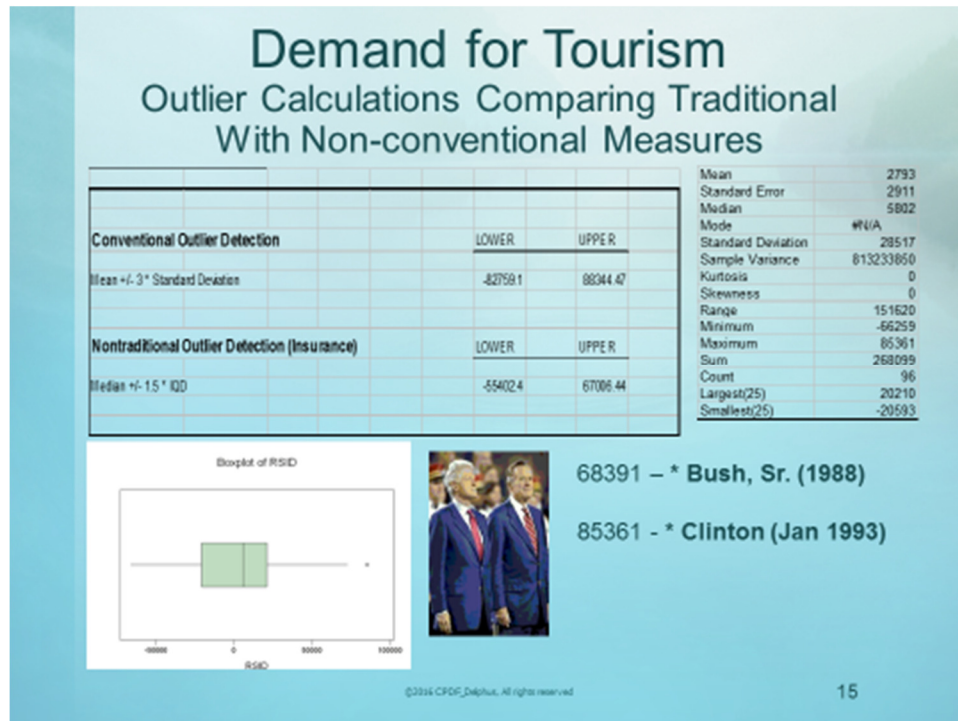
- On the other hand, the monthly error patterns appear without bias, so the annual forecast (cumulative sum of twelve months) might be acceptable.
- The exhibit shows the cumulative forecast errors and the cumulative prediction intervals. It appears that the annual forecast lies within the 95% prediction interval and is acceptable.



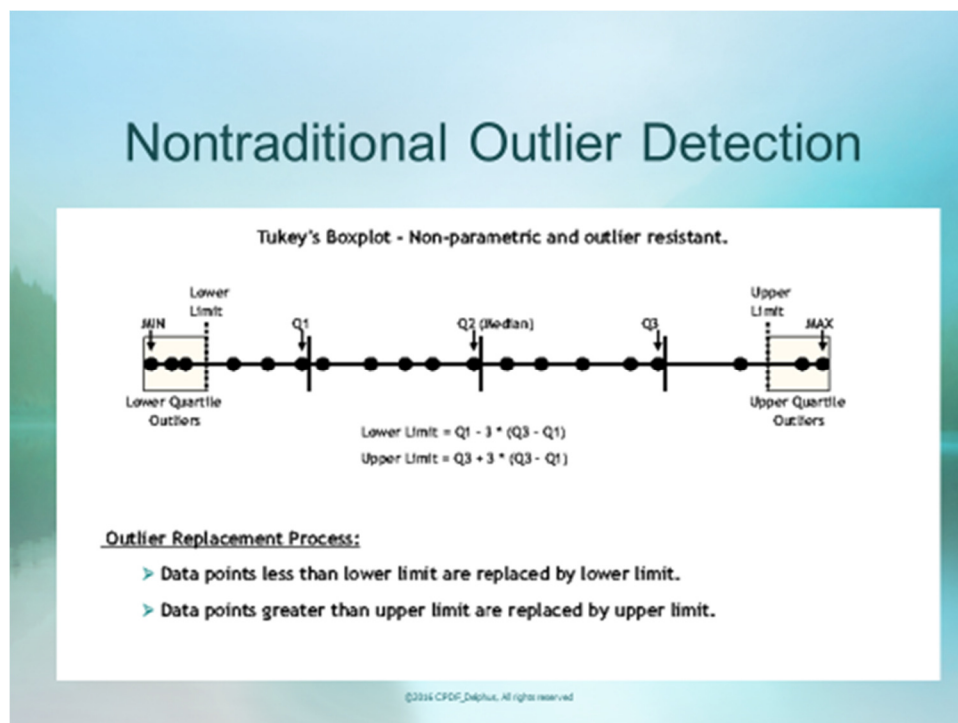
Monitoring residuals from a model for Tourism Demand in Washington DC?

- Presidential elections are held every four years in the US
- During January following the election, there are celebrations in Washington, DC, the capital city
- There is extra demand for room nights during those celebrations
- It is of interest to determine the incremental demand for January every four years
- The chart shows the January residuals from a monthly model of Room nights in Washington DC





How do you compare outlier detection techniques for the Tourism Demand model



Trigg's Tracking Signal
(1964)

Trigg's tracking signal checks whether the chosen forecast model is suitable for a certain location product, or whether it would be better to choose a new forecast model.

Time	Error	Smoothed Error	Smoothed Absolute Error	Tracking Signal
1	-1.58	-1.17	1.68	-0.70*
2	2.54	-0.53	2.04	-0.26
3	5.24	-0.53	1.89	-0.28
4	-0.51	-0.42	1.76	-0.24
5	0.59	-0.15	1.81	-0.08
6	2.26	0.01	1.78	0.01
7	1.49	-0.14	1.73	0.08
8	1.31	0.17	1.6	0.11
9	0.43	-0.62	2.21	-0.28
10	-7.73	0.6	3.15	0.19
11	11.57	1.44	3.73	0.39
12	8.98	1.68	3.74	0.45
13	3.82	1.93	3.78	0.51
14	4.17	1.84	3.51	0.53†
15	1.06			

* Starting value—ignore.
† Exceeds 0.51—warning!

Source: http://cpdfraining.org/downloads/Levenbach_Accuracy2015.pdf

How do you calculate Trigg's tracking signal?

- The tracking signal, proposed by Trigg in 1964, indicates the presence of nonrandom errors; it is the ratio of two smoothed errors E_t and M_t . The numerator E_t is a simple exponential smooth of the errors and the denominator M_t is a simple exponential smooth of the absolute values of the errors. (See L&C, Chapter 5, p. 183).
- Trigg shows that when this tracking signal ratio exceeds 0.51 (smoothing parameter = 0.1) or 0.74 (smoothing parameter = 0.2), the errors are nonrandom at the 95% significance level.
- The table shows a sample calculation for an adaptive smoothing model of seasonally adjusted airline data. The tracking signal correctly provides a warning at period 15 after five consecutive periods in which the actual exceeded the forecast.
- Period 11 has the largest error, but no warning is provided because the sign of the error became reversed.
- The model errors can increase substantially above prior experience without warning being signaled as long as the errors change sign. Once a pattern of over- or underforecasting is evident, a warning is issued.

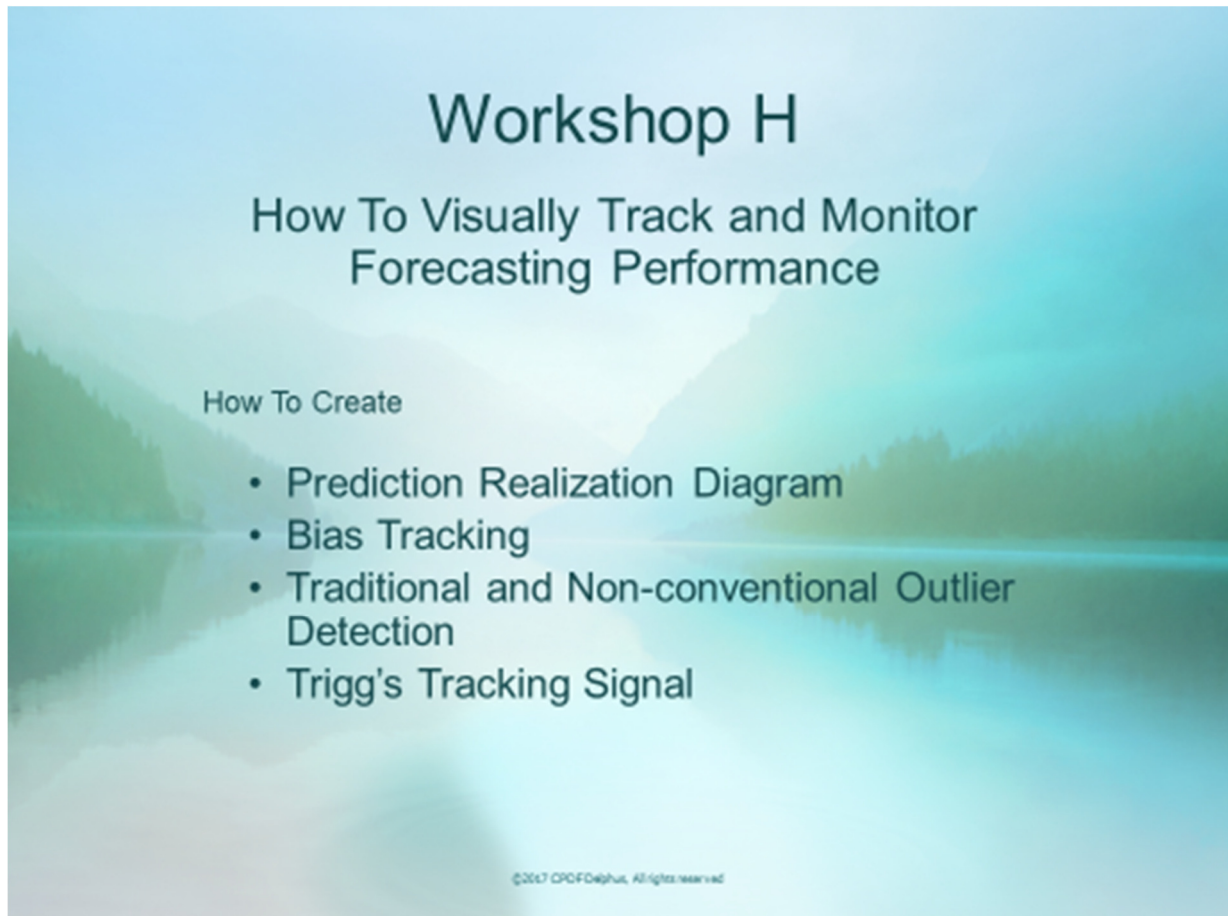
Trigg's tracking signal calculates the quotient of the smoothed sum of absolute deviation (SAD) and the smoothed mean absolute deviation (MAD).

The system calculates the smoothed sum of absolute deviation according to the following formula:

$$SAD(t) = \alpha \times (Demand(t) - Forecast(t)) + (1 - \alpha) \times SAD(t-1)$$

The system calculates the mean absolute deviation (MAD) according to the following formula:

$$MAD(t) = \alpha \times (|Demand(t) - Forecast(t)|) + (1 - \alpha) \times MAD(t-1)$$





Part IX

Implementing Demand Forecasting With an Integrated Business Planning Process

Learning Objectives



- Recognizing the importance of demand forecasting in a *consumer-driven* integrated business planning process (IBP)
- Identifying the steps for a successful implementation of a demand forecasting process
- Embracing best-in-breed demand management
- Using a checklist to identify gaps in the implementation processes needing ongoing improvement

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What You Should Be Able To Do

After completing this topic, you should be able to:

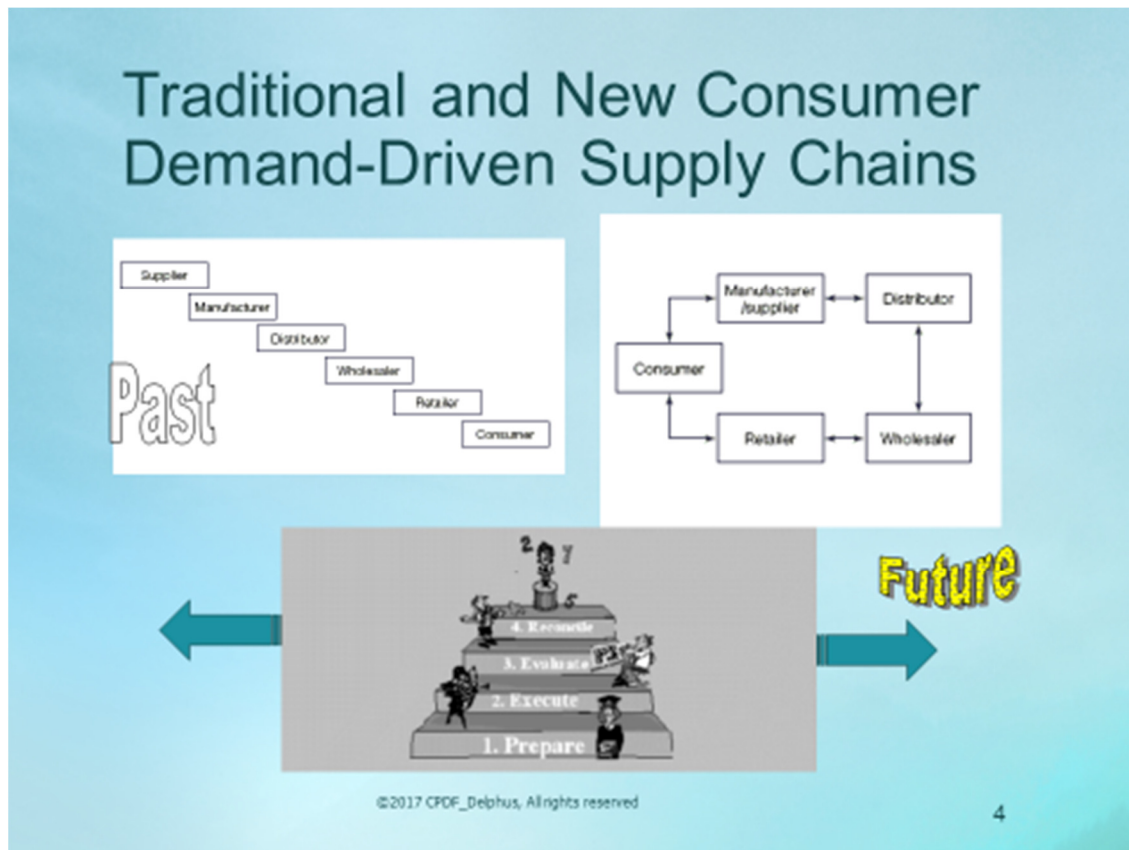
- Recognize the importance of demand forecasting in a consumer-driven demand planning process
- Identify the steps for a successful implementation of the forecasting process leading to the efficient completion of the forecasting cycle
- Recognize the role of demand forecasting in the Sales and Operations planning process (S&OP)
- Use checklists to identify gaps in the implementation processes needing continuous improvement.

How You Will Check Your Progress

- Checkpoint questions
- Relate the material to your current forecasting efforts
- Complete and periodically review the appropriate checklists

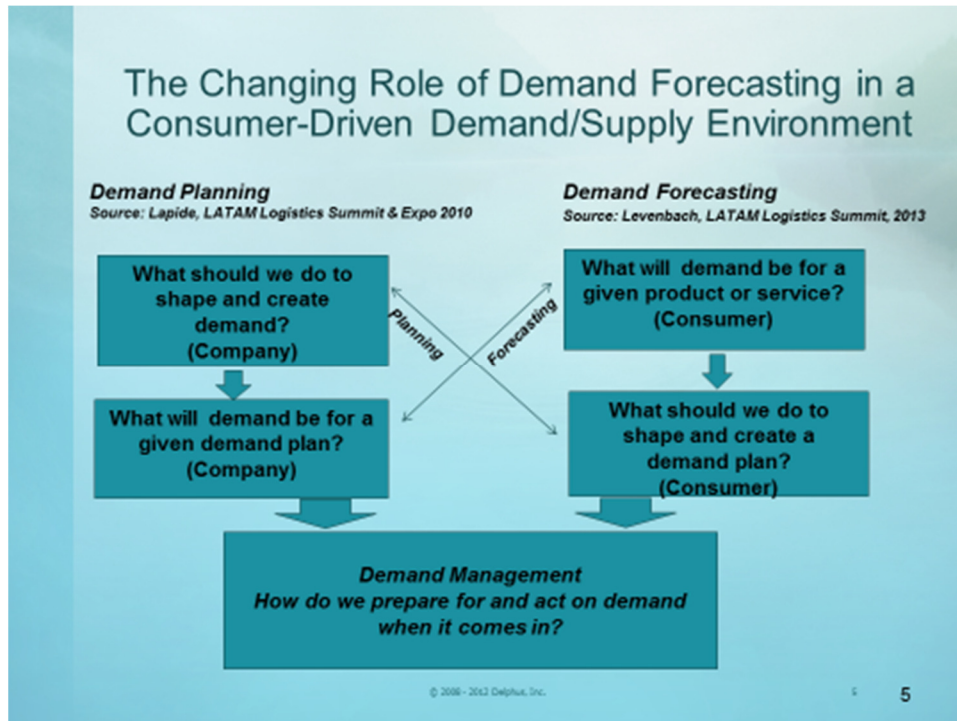
Resources

- ✓ Levenbach (2017) C&C, Chapter 1, 13 & 14



The PUSH vs PULL paradigm. What is the difference between a traditional (*push*) and the modern (*pull*) consumer demand-driven supply chain?

- Traditional supply chains are linear - a 'push' philosophy driven by manufacturing
- Example, 100 years ago, the first automobiles were manufactured. The choices the consumer had at the time was a black model-T, no matter what you may have 'demanded' in a different color with a willingness to pay for it. It was black
- Likewise, with the early telephones manufactured by Western Electric. All phones were the same - black, with rotary dialing.
- In modern times, companies have learned to respond to the consumer - a push philosophy resulting in a circular supply chain. Products flow in the clockwise direction, while demand, expressed as 'information for manufacturers and suppliers' flows in the counter-clockwise direction
- Because of the internet, consumers can now get directly supplied by manufacturers, hence the link is closed
- At all the links, there is a crucial need for forecasts, resulting in a complex job for demand forecasters.



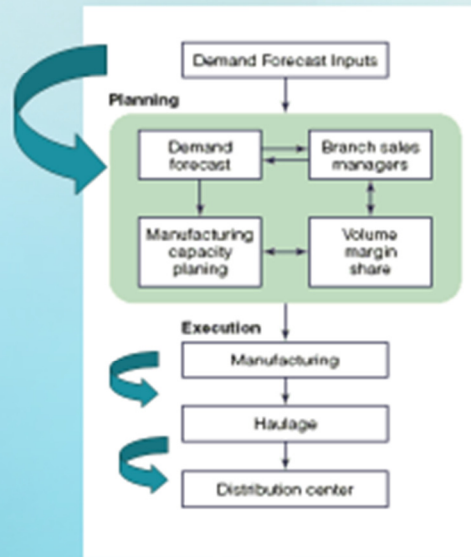
Demand Forecasting And Demand Planning Are Separate Disciplines!!

- **Demand Forecasting** is all about CHANGE and CHANCE, by creating an objective, unbiased view of what consumers desire (and are willing to purchase) in products and services
- **Demand Planning** is about actions to sense and shape demand for the business and
- **Demand Management** is about preparing for and providing of the *right* amount of the *right* product to be in the *right* place at the *right* time at the *right* price

Plans are what we can 'feel we can do' while forecasts are statistical estimates of what is most likely

Video Clip: I Love Lucy Candy Factory
<http://www.youtube.com/watch?v=HnbNcQIzV-4>

How Demand Forecasting Has Become a Crucial Link in the Supply Chain



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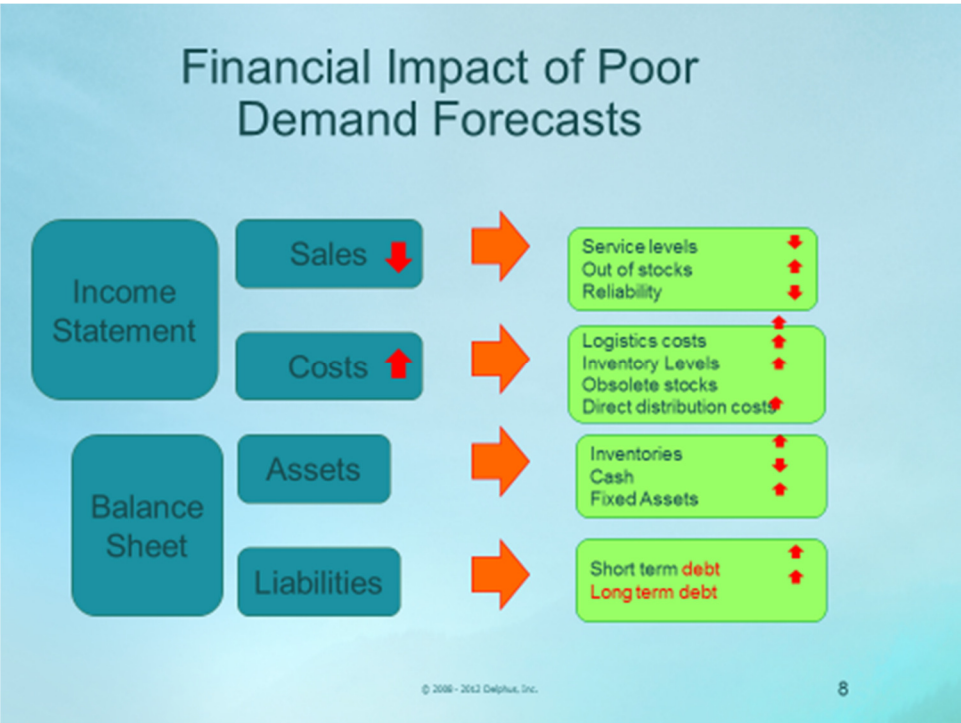
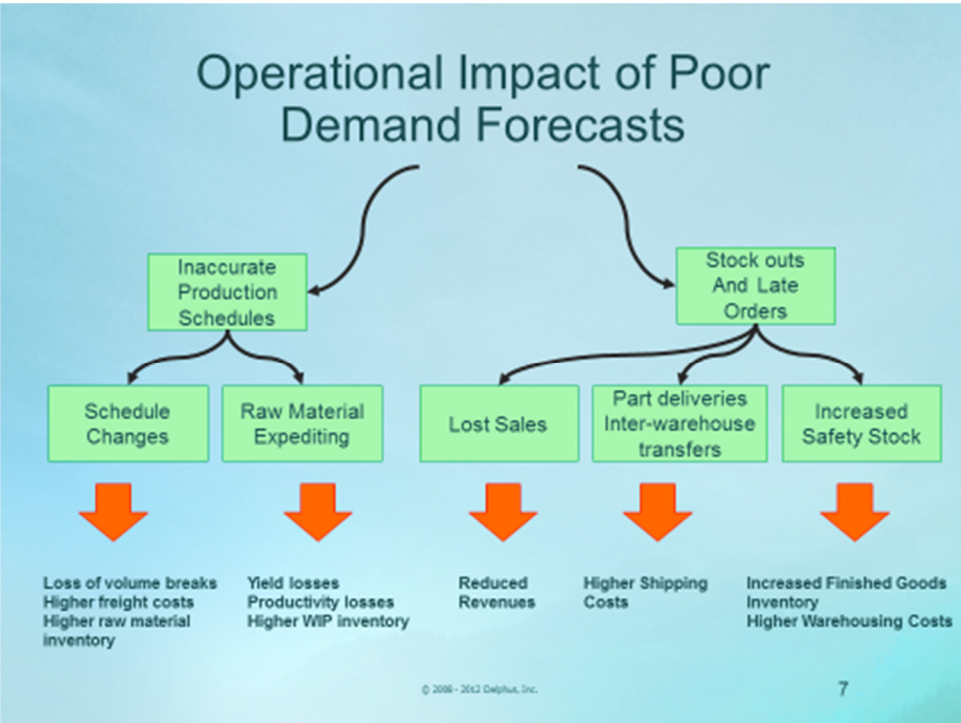
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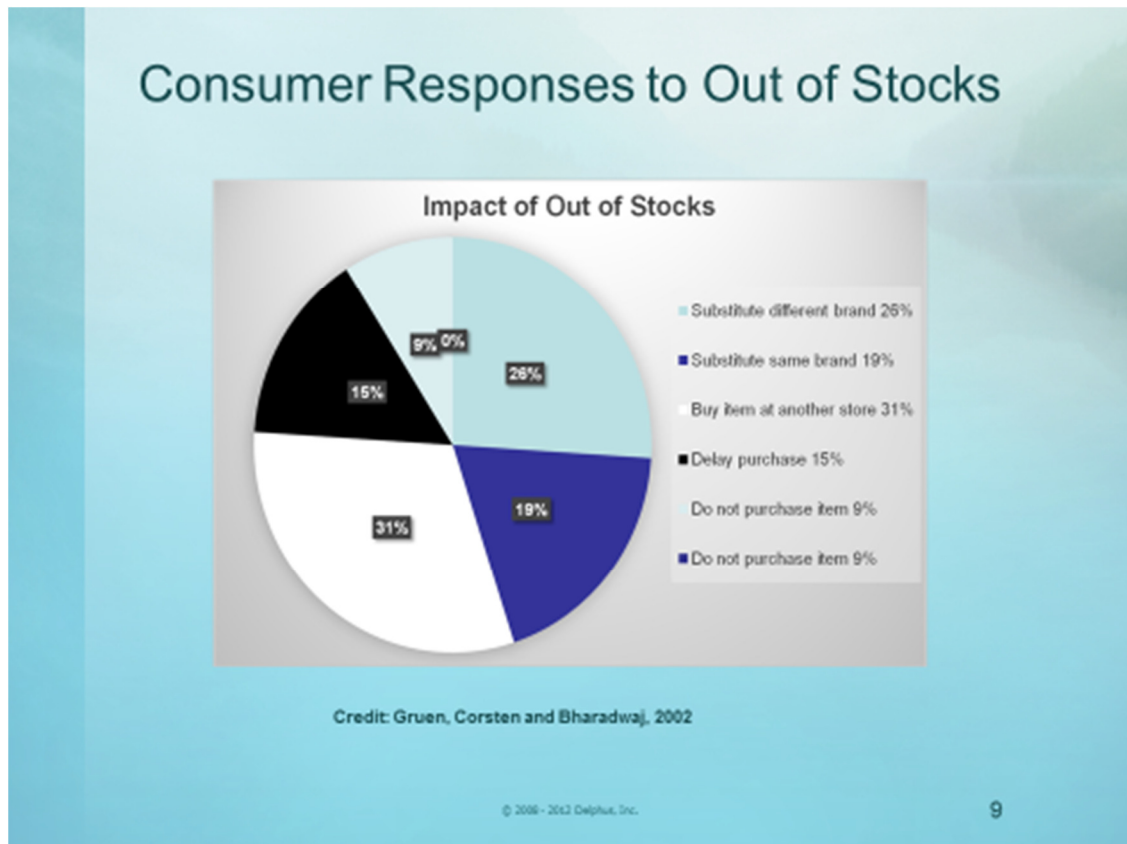
Why is demand forecasting plays an important role in the modern supply chain

Manufacturing companies generally use forecasting systems to help synchronize production schedules and finished-goods inventory with actual customer/consumer sales. Therefore, they are more likely to feed forecast information to the Materials Resource Planning (MRP) module of an Enterprise Resource Planning (ERP) system or even to an Advanced Planning system (APS). In addition, demand forecast data are becoming part of the **Sales and Operations Planning (S&OP)** process, which brings people from different functional areas together to agree on a “final forecast” that drives the activities of the entire enterprise.

The sales and operations planning (S&OP) process brings people from different functional areas in the organization together to agree on a single planning forecast.

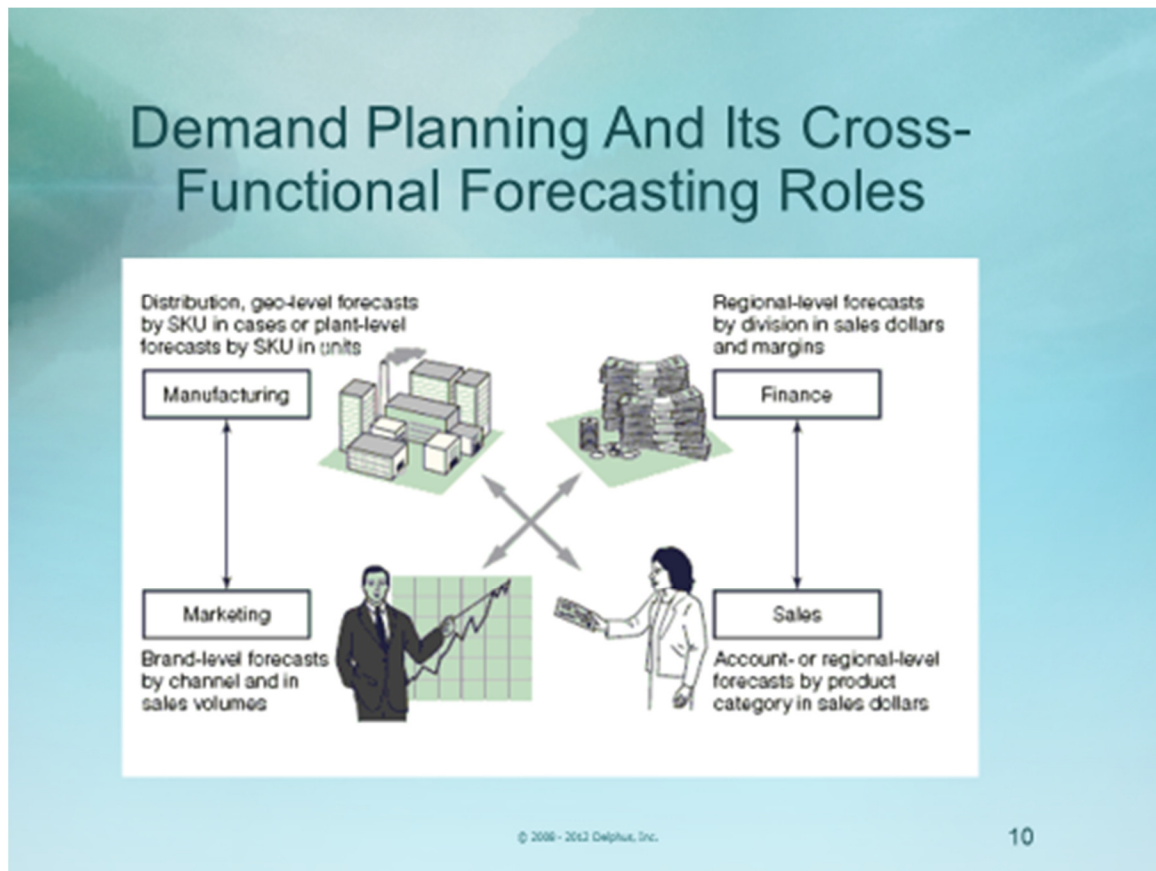
Each industry has its own production and distribution needs. Systems designed to manage the supply chain are focused on vertical markets in process manufacturing or discrete/repetitive/to-order **manufacturing**. Process manufacturers, which are predominantly batch-processing operations, include companies in the energy/petrochemical, chemical, and pharmaceutical industries. Electronics, fabricated metals, and automotive supplies are examples of discrete manufacturing markets.





Forecast Inaccuracy impact on out-of-stocks

- In today's global market place, companies must achieve both in-stock levels and high *inventory turns*. In addition to competitive pressures, many companies have found it necessary to share information and forecasts with their business partners.
- Retailers, in particular, frequently share forecasting information with their supply chain partners. Manufacturers have also recognized the importance of data-based demand forecasting and top-down planning along with joint collaborations in forecasting with suppliers and customers.
- Because of the high volume of items involved and the uncertain nature in variability (see C&C, Chapter 3), data-driven analytics (see C&C, Chapter 2) and statistical forecasting techniques (see C&C, Chapter 5) are increasingly being adopted by demand planners.



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How does demand management relate to its cross-functional roles?

- There are several reasons why the forecasting job has become much more complex in the modern supply chain:
- Manufacturing requires unit demand at the lowest level (by Stock-keeping Unit, usually) in order to be able to produce the products
- Marketing requires forecasts at brand level in revenues for market and promotion planning
- Finance needs units and revenues, so they can calculate margins and manage the budget. Typically forecasts are needed by division (location) several times a year.
- Sales require a baseline forecast by customer for the products they are responsible for. As field sales reps, they may be required to submit overrides to these forecasts as they see a need in the market or with their customer base.
- There may be other organizations in the company that periodically require forecast to reconcile with their planning function. Organizations such as purchasing and warehousing have periodic needs, as well.

Case: Demand Planning at a Midsize Medical Equipment Manufacturer

- ◆ **Company Overview**
- ◆ **Complex Supply and Demand Structure**
- ◆ **Demand Planning**
- ◆ **Forecasting Process Steps**
 - Data Preparation
 -  Statistical Forecast
 - Forecast Consensus Tool
 - Forecast Consensus Meeting
- ◆ **Post Consensus Meeting Activities**
- ◆ **Demand Management Scorecard: Metrics**
- ◆ **What the Metrics Say**
- ◆ **Next Steps**



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Case example – Demand planning at a midsize medical equipment manufacturer

Agenda


- ☐ Company Overview
- ☐ Complex Supply and Demand Structure
- ☐ Demand Planning at mid-size Medical Device Manufacturer
- ☐ Process Steps
 - Data Preparation
 - Statistical Forecast
 - Forecast Consensus Tool
 - Forecast Consensus Meeting
- ☐ Post Consensus Meeting Activities
- ☐ Demand Management Scorecard: Metrics
- ☐ What the Metrics Say
- ☐ Next Steps

Medical Equipment Products

- The Company offers an array of automated collection devices to help alleviate blood shortages. The devices are sold or placed in donor centers and hospitals and the machines process blood with the use of disposable products sold to the centers and hospitals.

Donor Products:

- Blood is generally collected as whole blood, but is usually transfused as blood components (red blood cells, plasma or platelets), according to the patient's specific need. Our systems make it possible to collect multiple units of selected blood components from one donor, thereby enabling blood collectors to get more usable blood from a smaller donor base.



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What are the products? - Donor products

- The Company offers an array of automated collection devices to help alleviate blood shortages. The devices are sold or placed in donor centers and hospitals and the machines process blood with the use of disposable products sold to the centers and hospitals.

Donor Products:

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Products (Continued)

Surgical Products

The Company also offers products for surgical blood salvage - also known as auto transfusion.

Blood lost by a surgical patient is collected, cleaned, and made available for reinfusion to that patient.

This process is used in close to a million surgeries each year, and has become an integral part of blood management and conservation programs of hospitals, saving money and preserving hospital blood inventories.



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What are the products? (Cont'd) - Surgical products

- The Company also offers products for surgical blood salvage - also known as auto transfusion.
- Blood lost by a surgical patient is collected, cleaned, and made available for reinfusion to that patient.
- This process is used in close to a million surgeries each year, and has become an integral part of blood management and conservation programs of hospitals, saving money and preserving hospital blood inventories.

Complex Supply and Demand Structure

- ◆ 7 Manufacturing Facilities in 5 Different Countries
- ◆ 5 Global Distribution Centers on 4 Continents
- ◆ 15 Local Warehouses
- ◆ 48 Forecasting Entities (Management Organizations)
- ◆ Customer Base includes direct sales and distributor sales, generating \$450M net revenue
- ◆ Equipment is placed and sold in low and high volumes
- ◆ Disposable product types range from simple ancillary sets to complex bowl sets. Volumes vary significantly.
- ◆ Seasonal and non-seasonal demand patterns

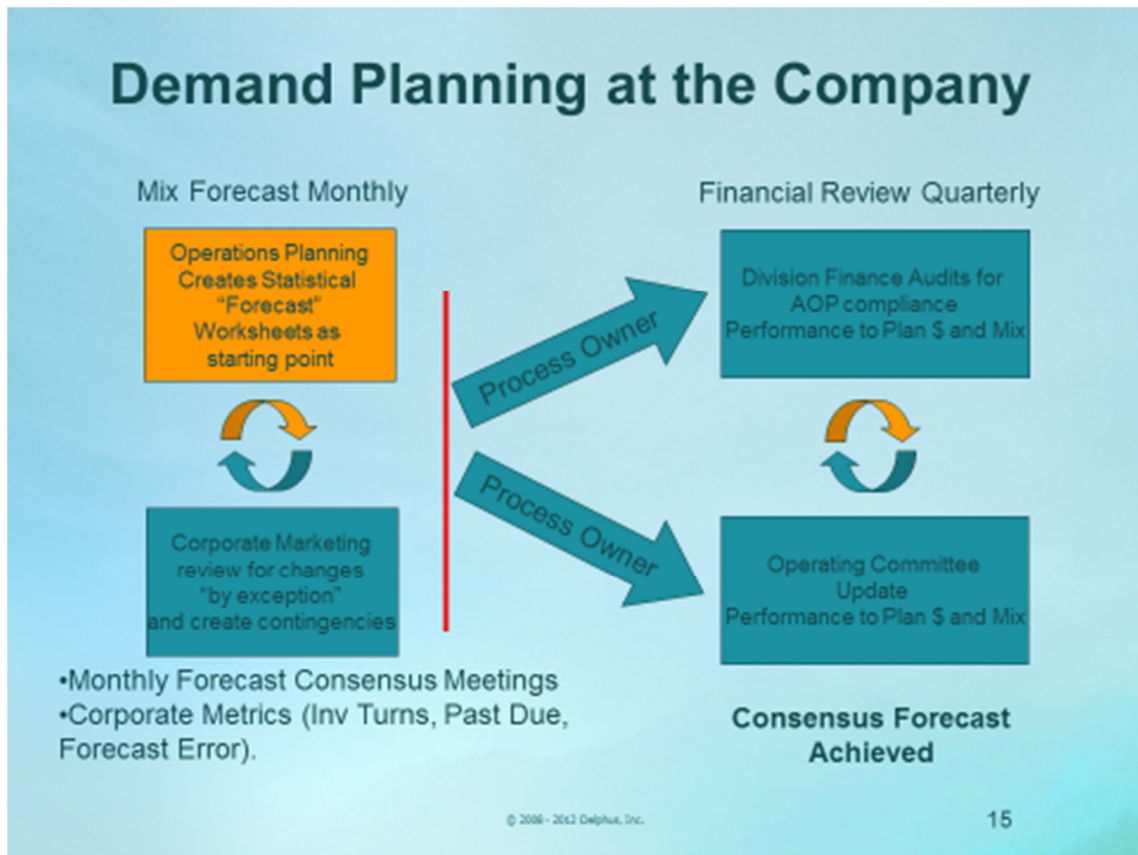


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Complex supply and demand structure

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- Customer Base includes direct sales and distributor sales, generating \$450M net revenue
- Equipment is placed and sold in low and high volumes
- Disposable product types range from simple ancillary sets to complex bowl sets. Volumes vary significantly.
- Seasonal and non-seasonal demand patterns



How is demand planning performed at the company?

- **Process:** Note that there are process owners defined, or PICs, in charge (Person-In-Charge)
- **People:** There are responsibilities and reviews and there is collaboration
- **Technology:** Lastly, there are data warehouses and statistical forecasting tools provided



Forecast Decision Support and Data Warehousing Tools

Corporate Data Warehouse (CDW): actual sales data, management organization structure, world wide statistical and consensus forecast visibility

Forecast Decision Support: generates the statistical forecast, calculates and store consensus over rides

ERP Up Load: Loads forecast data to the Corporate Data Warehouse

Forecast Consensus Tool: View and compare forecast data in the CDW

Business Planning and Control System: Operations Planning Tool (DRP, MPS, MRP)

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What are their forecasting decision support and data warehouse tools?

- Corporate Data Warehouse: actual sales data, management organization structure, world wide statistical and consensus forecast visibility
- Forecast Decision Support: generates the statistical forecast, calculates and store consensus over rides.
- ERP Up Load: Loads forecast data to the Corporate Data Warehouse
- Forecast Consensus Tool: View and compare forecast data in a forecast decision support tool (FSS) or dashboard
- Business Planning and Control System, Operations Planning Tool (DRP, MPS, MRP)

Demand Planning Process Steps

- ◆ Sales data from the prior month is collected on the first day of the new fiscal month
- ◆ A statistical Forecast is generated in the Forecast Decision Support System for sales and marketing to review
- ◆ A monthly meeting is held with representatives from operations and global marketing to discuss market trends, new business opportunities and shifts in product mix
- ◆ Participants agree to forecast over rides, creating a consensus forecast
- ◆ The consensus forecast is loaded into the Operations Planning System to drive DRP and MPS.
- ◆ Major sales and operations planning issues are presented to the Operating Committee for approval

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What are the steps in the demand planning process?

- Sales data from the prior month is collected on the first day of the new fiscal month
- A statistical Forecast is generated in the Forecast Decision Support System for sales and marketing to review
- A monthly meeting is held with representatives from operations and global marketing to discuss market trends, new business opportunities and shifts in product mix
- Participants agree to forecast over rides, creating a consensus forecast
- The consensus forecast is loaded into the Operations Planning System to drive DRP and MPS.
- Major sales and operations planning issues are presented to the Operating Committee for approval



What is the data collection process?

- Disposables sales data is verified
- Equipment sales data is modified to include equipment placed and sold. Sales data pulled from the corporate data warehouse reflects sales only.
- Data is prepared for export to Forecast Decision Support System

Monthly Consensus Meeting

- ◆Participants: Operations Planning and Global Marketing (with input from Sales)
- ◆Agenda: Market trends, obsolescence, new product launches, one-time orders (forecast outliers)
- ◆Specific product data is reviewed and consensus is reached with respect to forecast over rides.

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How is the monthly consensus meeting conducted?

- Participants: Operations Planning and Global Marketing (with input from Sales)
- Agenda: Market trends, obsolescence, new product launches, one-time orders (forecast outliers)
-

Specific product data is reviewed and consensus is reached with respect to forecast over rides.

Post-Consensus Meeting Activities

Significant changes to the Plan are presented to the Operating Committee for approval

- ◆ Increased or decreased capacity requirements
- ◆ Inventory requirements that fall out of standard inventory management policies

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How are changes to the Plan presented to the Operating Committee for approval?

- Increased or decreased capacity requirements
- Inventory requirements that fall out of standard inventory management policies



How is S&OP a plan to success in the supply chain?

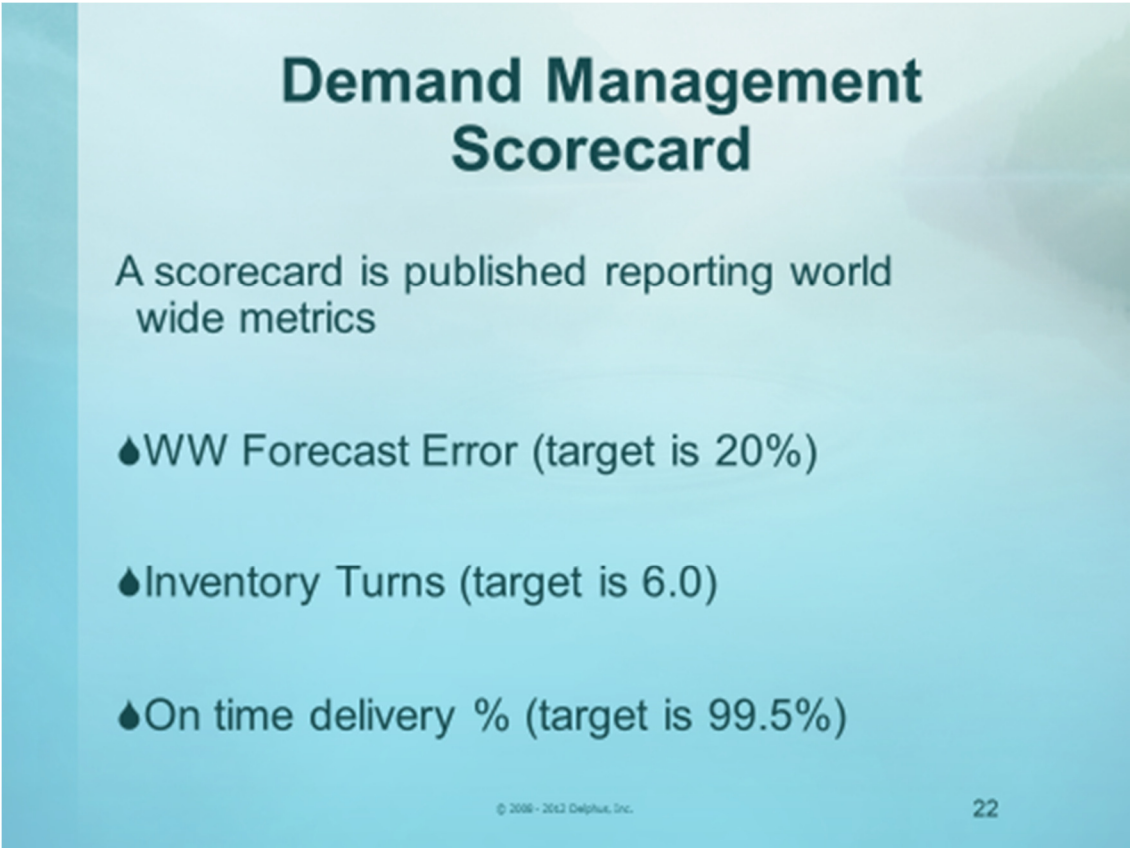
Good advice from Prof. Tom Mentzer, Univ. of Tennessee, and followed in 'best-in-class organizations:

"What gets measured gets rewarded, and what is rewarded gets done"

Just to reiterate, and stress its significance - Measure, measure, measure

- Reduction in total inventory dollars
- Increase in inventory turns
- Percent on-time shipments
- Reduced back-order status
- Reduced cycle time

While many people may not wish to measure or be measured, it is a 'natural' for forecasters - so embrace the opportunity and run with it. You will be rewarded!!

A presentation slide titled "Demand Management Scorecard" with a light blue background and a darker blue vertical bar on the left. The title is in a large, bold, dark blue font. Below the title, a paragraph states "A scorecard is published reporting world wide metrics". This is followed by three bullet points, each preceded by a dark blue diamond icon. The bullet points are: "WW Forecast Error (target is 20%)", "Inventory Turns (target is 6.0)", and "On time delivery % (target is 99.5%)". At the bottom right of the slide, the number "22" is displayed. At the bottom center, in small text, is the copyright notice "© 2008 - 2012 Delphus, Inc.".

Demand Management Scorecard

A scorecard is published reporting world wide metrics

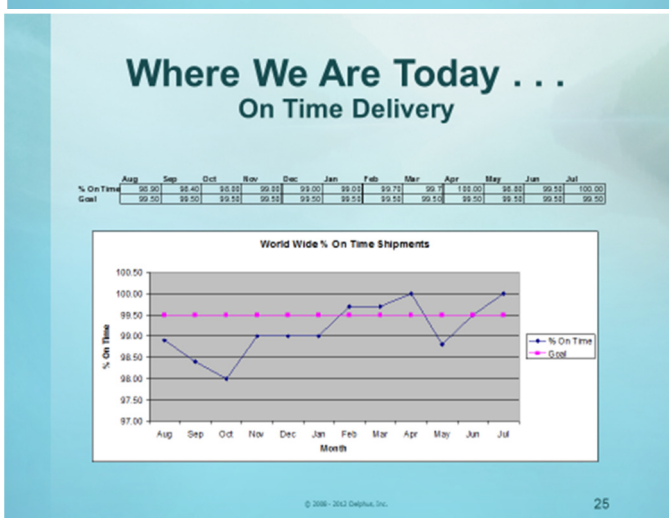
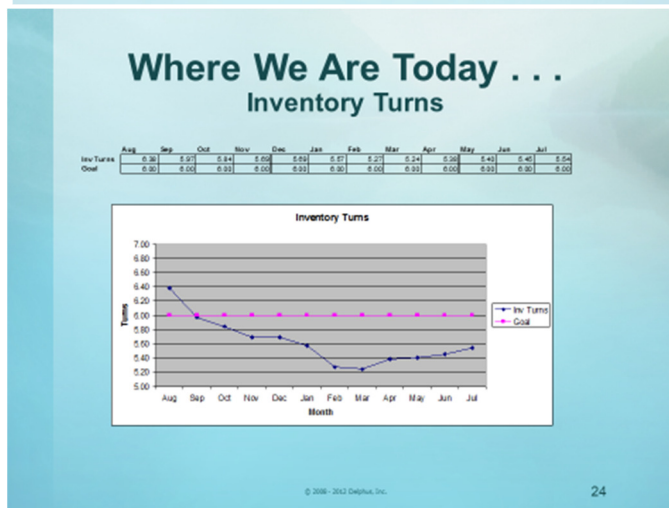
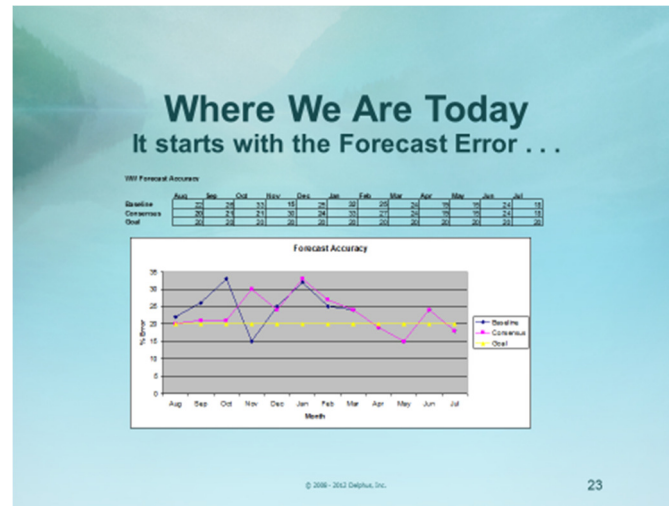
- ◆ WW Forecast Error (target is 20%)
- ◆ Inventory Turns (target is 6.0)
- ◆ On time delivery % (target is 99.5%)

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What is a demand management scorecard?

A scorecard is published reporting worldwide metrics

- WW Forecast Error (target is 20%)
- Inventory Turns (target is 6.0)
- On time delivery % (target is 99.5%)



What the Metrics Say

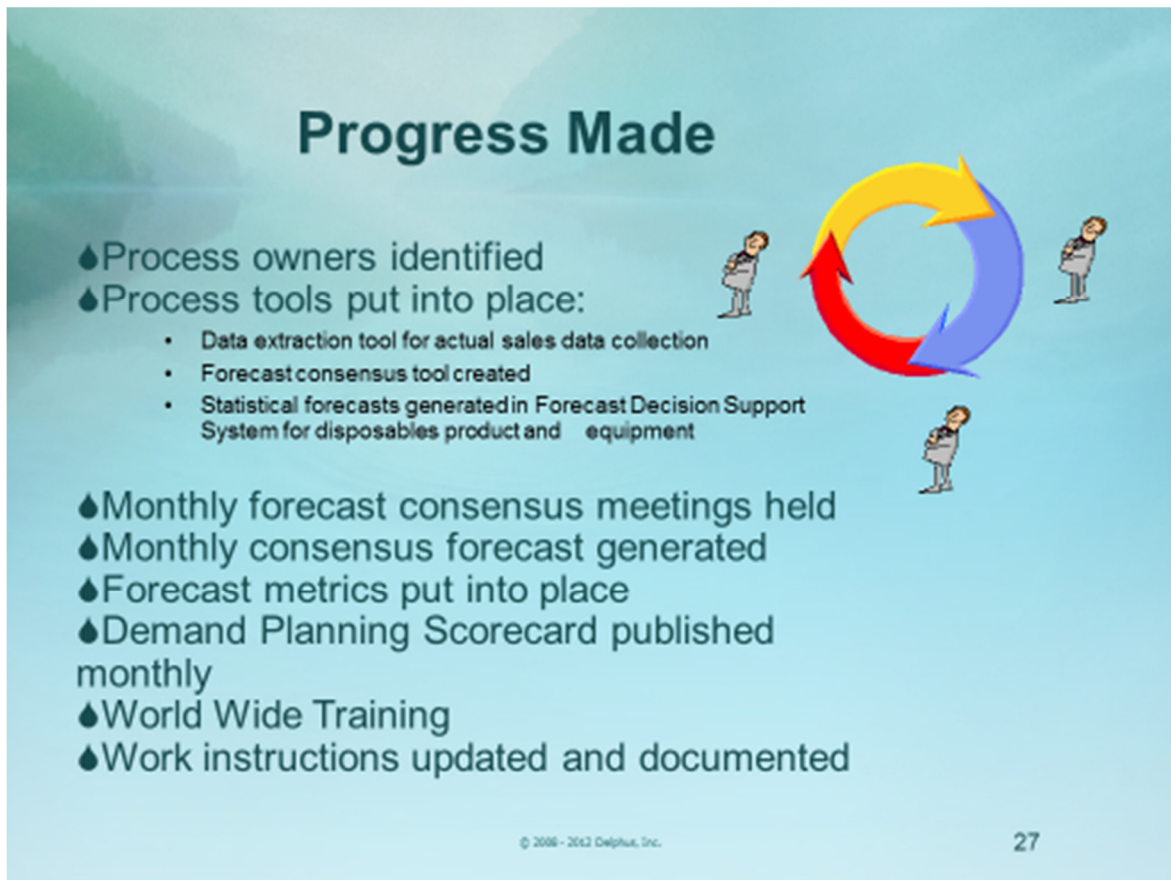
- ◆ Over the past 12 months Forecast Accuracy (MAPE) has averaged 23%, 3% from goal.
- ◆ MPE has been negative most months, indicating that we have been over forecasting.
- ◆ The impact of over forecasting on inventory turns has been a fall in turns from 6.38 in August of last year to 5.54 in July of this year.
- ◆ % On Time Shipments has averaged 99.2%, .3% from goal, largely driven by unforecasted distributor orders.

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What do the metrics tell us?

- Over the past 12 months Forecast Accuracy (MAPE) has averaged 23%, 3% from goal.
- MPE has been negative most months, indicating that we have been over forecasting.
- The impact of over forecasting on inventory turns has been a fall in turns from 6.38 in August of last year to 5.54 in July of this year.
- % On Time Shipments has averaged 99.2%, .3% from goal, largely driven by unforecasted distributor orders.



What is the progress to date?

- Process owners identified
- Process tools put into place:
 - Data extraction tool for actual sales data collection
 - Forecast consensus tool created
 - Statistical forecasts generated in Forecast Decision Support System for disposables product and equipment
- Monthly forecast consensus meetings held
- Monthly consensus forecast generated
- Forecast metrics put into place
- Demand Planning Scorecard published monthly
- **World Wide Training**
- Work instructions updated and documented.

The Demand Planning Process Then and Now		
	BEFORE Demand Planning	AFTER Demand Planning
Data Collection	3 days of manually manipulating sales data and creating files to load sales data into FDS	2 hours to extract and verify disposables sales data and 2 hours to manipulate equipment placements (still manual). Much of the human error factor has been removed.
Reviewing Statistical Forecast	Multiple excel spreadsheets circulated around the world to various business units via email	Forecast data (past and present) is available for operations, sales and marketing to review and critique
Consensus Forecast	Non existent. There was a financial forecast driven by financial goals and a statistical forecast driving operations. The 2 were rarely synchronized.	The consensus forecast is the starting point for the building of the corporate financial forecast. Gaps in the forecast can be identified and addressed.
Consensus Meeting	Many small meetings held to address unforecasted events	Regular monthly forum to discuss trends and special events.
Metrics	Inventory turns and % on time shipments were published separately. No forecast accuracy metric was published.	Metrics are published together, telling a more complete story of how forecast accuracy impacts the business in terms of customer service and inventory value.

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How do you summarize the process then and now by various components in the forecasting cycle?

A “First” For the Company

For the first time, the statistical units forecast and a consensus units forecast exist in one database for review and discussion and can be used as the starting point in the generation of the corporate revenue plan



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What Is Sales & Operations Planning?



APICS Dictionary, 11th Edition
Definition:

Process to develop tactical plans that provide management the ability to strategically direct its business to achieve competitive advantage on a continuous basis by integrating customer-focused marketing plans for new and existing products with the management supply chain.



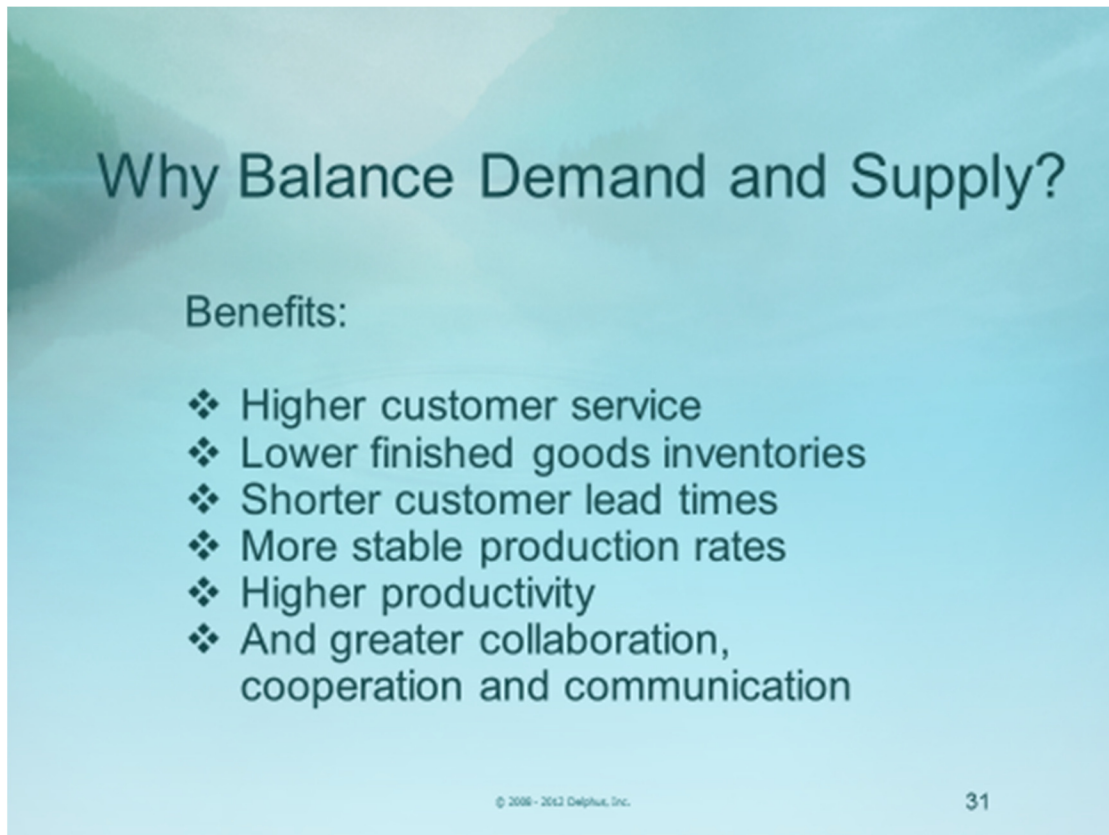
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What is Sales and Operations Planning?

- There is today a lot of effort being spent on S&OP planning. Not a new initiative, it nevertheless is being treated as 'never done before' in the industry.
- The APICS dictionary defines S&OP as a

Process to develop tactical plans that provide management the ability to strategically direct its business to achieve competitive advantage on a continuous basis by integrating customer-focused marketing plans for new and existing products with the management supply chain.

- In short, it is a process that balances supply and demand with considerations of the financial implications. This is 'new' because of a renewed focus and emphasis on the consumer demand.



Why balance demand and supply?

When conducted as a continuous improvement process, S&OP can lead to numerous, MEASURABLE benefits for all departments, such as:

- Higher customer service
- Lower finished goods inventories
- Shorter customer lead times
- More stable production rates
- Higher productivity
- And greater collaboration, cooperation and communication

The S&OP Plan

What does it contain? It links

- Volume and product mix
 - How much and which ones
 - Rates and timing
 - Families and individual products
- Units and dollars
 - Top down and bottom up
 - Consistently related
- Aggregates and detailed reports
- Data from disparate sources
- Simulation for decision making



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What is the Sales and Operations plan comprised of?

- The S&OP function has a central role in the modern company. It tends to be 'run' by the forecasting organization, because of its central role in producing the key forecasts (the one number).
- What does it contain? It links
 - Volume and product mix
 - How much and which ones
 - Rates and timing
 - Families and individual products
 - Units and dollars
 - Top down and bottom up
 - Consistently related
 - Aggregates and detailed reports
 - Data from disparate sources
 - Simulation for decision making

Why Is S&OP So Important?

- ❖ Balancing demand and supply
- ❖ Linking operations with strategic business planning
- ❖ Integrates operational with financial planning
- ❖ Measure, Measure, Measure

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Why is the Sales and Operations planning process so important to the business?

S&OP has definite benefits for a company:

- Balancing demand and supply - the push versus pull phenomenon requires careful coordination among the stakeholders
- Linking operations with strategic business planning - manufacturing becomes a more integral part of the overall process and is no longer its own supply chain.
- Integrates operational with financial planning - profitability of the company must always be an important consideration
- Measure, measure, measure - **"nothing gets done unless measured"** is the old adage. Forecasters play a key role here in coordinating the S&OP function and maintain key performance indicators and scorecards.

Next steps

◆ Focus on forecast metrics

Help forecasting entities world wide use forecast metrics to focus on geographies and product lines where forecast accuracy needs improvement

◆ Improve statistical forecast accuracy

- Analysis of equipment placements and correlation between equipment placements and the timing of related disposables sales
- Explore various forecasting models
- Run forecasts by various geographies/product line/product type combinations

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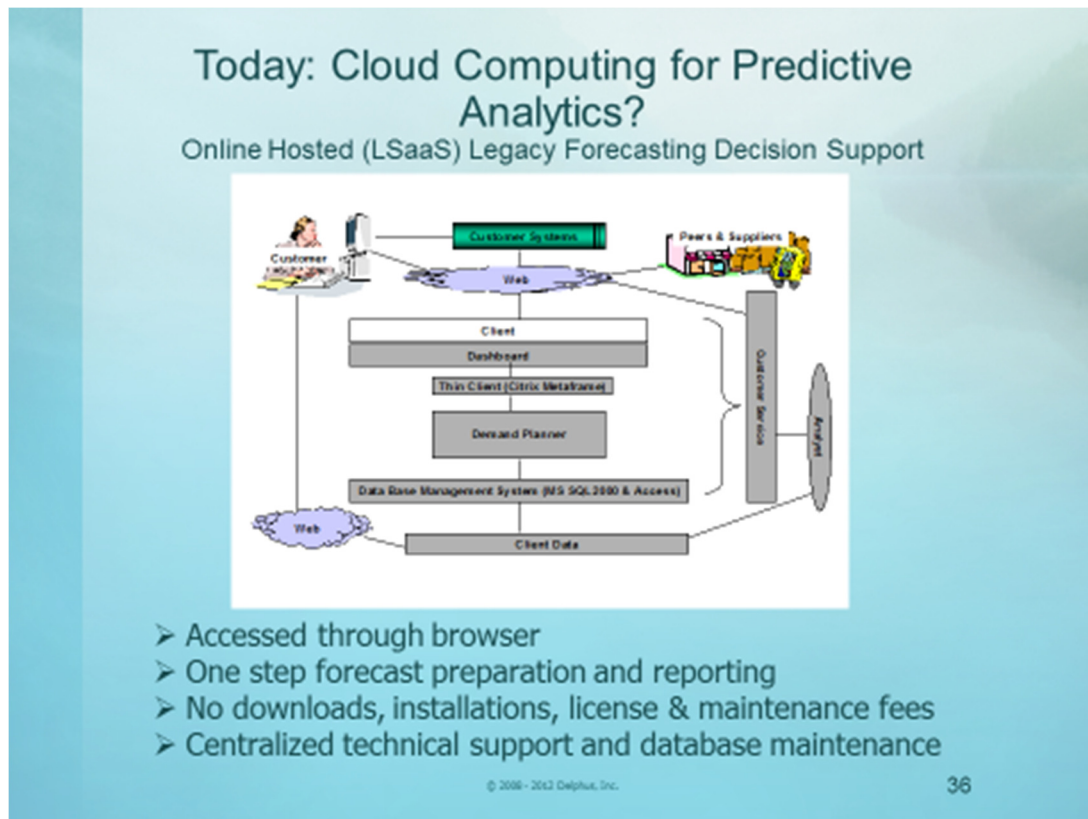
Next Steps (Continued)

◆ Run separate forecast models for distributor markets where sales patterns are traditionally erratic and without visible patterns or trends

◆ It is estimated that for every 1% of forecast accuracy improvement, \$1,096,000 is saved in inventory and/or expediting costs. By improving forecast accuracy from 23% to our goal of 20%, we will realize \$3,288,000 in cost avoidance.

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What will demand forecasting look like in the future? *Virtual Forecasting* is a hosted forecasting application in the cloud

Similar to 'timeshare' forecasting of the olden days when mainframes were the computing environment, there are now opportunities with desktop computing, internet access and 'cloud computing', to consider the Software as a Service solution for forecasting.

- The benefits of such an approach are:
- Accessed through browser
- One step forecast preparation and reporting
- Online, interaction with forecasting
- Centralized technical support and database maintenance

Final Thoughts . . . What We Have Learned?




- **People** – Communicate, Cooperate and Collaborate
- **Process** – PEER model = Structured Forecasting Cycle
- **Technology** – State-Space Forecasting Models for large-volume forecasting with Exponential Smoothing and ARIMA models

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As an active member of the forecasting team . . .

1. **COMMUNICATE** in understanding of
 - a. Changing business environment
 - b. Factors influencing demand
 - c. Forecast model results and forecasting implications
2. **COLLABORATE** with developing
 - a. Model and factor assumptions
 - b. Periodic reconciliations of model projections
 - c. Accuracy and forecasting performance metrics
 - d. Ongoing training in quantitative techniques
 - e. New forecasting approaches as required
3. **COORDINATE** in evaluating
 - a. Structured forecasting approaches
 - b. Raw data sources
 - c. Forecasting software tools

Towards an Agile Forecasting Cycle The PEER Model



- Grasp of economics, statistics and mathematics will not ensure success
- Apply knowledge within a sound framework – A forecasting process
- Reduce chances of inadvertently overlooking a key step
- Omission of key steps can jeopardize a forecaster's credibility, and
- **CREDIBILITY IS A FORECASTER'S LIVELIHOOD!**

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How do you achieve agility while streamlining the forecasting cycle? With the PEER model, of course!!

- Experience has shown that time and money is saved when you follow a structured process, week after week, month after month, quarter after quarter and year after year.
 - The bottom line to an effective forecasting function is that:
 - Grasp of economics, statistics and mathematics will not ensure success
 - Apply knowledge within a sound framework – A forecasting process
 - Reduce chances of inadvertently overlooking a key step
 - Omission of key steps can jeopardize a forecaster's credibility
 - Lack of forecast accuracy is not the worst outcome, lack of credibility is, and

CREDIBILITY IS A FORECASTER'S LIVELIHOOD!

**The PEER process is a four step process to help you achieve credibility in
your forecasting job**

At the conclusion of this course, you will be able to:

- **Define** the benefits of an accurate forecast.
- **Explain** how demand relates to the customer driven value chain.
- **Match** the appropriate forecast model to your business.
- **Assess** where your products fall on the forecast spectrum.
- **Name** the key elements of the demand forecast.
- **Determine** how the demand planning cycle integrates into your organization.

Lesson Take-Away:

The Forecast Managers Checklist

Unintended Consequences from Bad
Forecasting Process



Lucy and the Chocolate Factory
by BagOfMagicFood
52,798 views

www.youtube.com/watch?v=0YGF5R9i53A

The Forecast Manager's Checklist

Source: *Levenbach and Cleary (2005). Forecasting – Practice and Process for Demand Management, Section 16.4*

These checklists can be used as a scorecard to help identify gaps in the forecasting process that will need your attention. It can be scored or color coded on three levels: (Green = YES, Yellow = SOMEWHAT, and Red = NO)

A. Implementation – see C&C, Chapter 14

STEP 1. IDENTIFY A TASK OR PRODUCT. (What are your needs?)

- ☐ Are models to be used for short-term or long-term forecasts?
- ☐ Are models to be used to solve "What if" questions?
- ☐ Are models to be used to determine elasticities?
- ☐ Are models needed at all?

STEP 2. PRIORITIES (Identify these on the basis of your needs.)

- ☐ Which quantitative techniques are useful?
- ☐ Should they be implemented?
- ☐ In what order?
- ☐ What is the implementation schedule?
- ☐ How does qualitative analysis fit into total job responsibility?

STEP 3. IDENTIFICATION OF RESOURCES.

- ☐ Is management interest and support available?
- ☐ Is money available for computer expenses?
- ☐ Do job responsibilities allow time to meet implementation schedules?
- ☐ Is adequate support available to maintain files?
- ☐ Is economic data available for modeling?
- ☐ Is modeling expertise available for consultation?

STEP 4. DATABASE MANAGEMENT.

- ☐ Who will enter and update data files?
- ☐ Who will identify and correct outliers in data?
- ☐ Will an ongoing program of documentation of outliers be implemented?
- ☐ Will appropriate time series be base-adjusted, if necessary, on an ongoing basis?
- ☐ Will seasonally adjusted data be created and updated periodically?
- ☐ Will data be maintained at the local, area, or company level?

STEP 5. INTRACOMPANY COORDINATION OF MODELING TECHNIQUES.

- ___ How many individuals in the company will be using quantitative techniques?
- ___ Can intracompany communications through seminars (and so on) reduce the redundancy and increase the effectiveness of quantitative modeling?

STEP 6. DOCUMENTATION OF MODELING WORK FOR FUTURE REFERENCE.

- ___ Will modeling work be documented for future reference by others engaged in quantitative analysis?
- ___ Will folders be organized for different aspects of modeling work?

Implementing the Forecasting Process

1. **Literature:** for publications about work in the modeling field; including trade journals and textbooks on mathematics, statistics, and economics, literature from vendors, modeling studies done by others, and so on.
2. **Models:** about types of models developed, any changes and reasons for change, including information on statistical tests, estimation of parameters, forecast tests, and simulations.
3. **Data:** about types and sources of data, as well as explanations of adjustments and transformations.
4. **Forecasting:** containing records on forecasts, forecast errors and monitoring information, and any analyses of forecast errors.
5. **Software:** about available computer programs.
6. **Billing and Related Expenses:** about costs related to modeling work.

STEP 7. PRESENTATION OF MODELING WORK FOR EVALUATION.

- ___ What kind of feedback on modeling results should be sent to higher levels of management?
- ___ How should this be done, and how often?

B.. Software selection

STEP 1. IDENTIFY NEEDS

- ___ What level and detail is being forecasted (Product, Customer, Geography, Capacity?)
- ___ Are your end-user needs well understood?
- ___ Are models to be used to solve forecasting problems?
- ___ What are the available sources of data?
- ___ Are staffing and their qualifications adequate?

STEP 2. ESTABLISH GOALS AND OBJECTIVES

- ___ Have you established your goals and objectives for the forecasting process?
- ___ What are the strengths and weakness of your information systems?
- ___ Are there requirements for both hard copy and on-line forecasting output?

___ Have you set up a planned approach to implementation?

STEP 3. DETERMINE FUNCTIONAL REQUIREMENTS

___ Have you determined the scope of the system in terms of number of forecasts, size of historical file, system interfaces, hardware/software performance criteria?

___ What is the environment under which the system is expected to work?

___ What are the time and cost factors related to installing the forecasting system?

___ How are support issues for the system going to be handled?

STEP 4. ESTABLISH SELECTION CRITERIA

___ What are the program features and capabilities required to support the forecasting process?

___ Have the reporting and export functions been identified?

___ Have performance and maintenance standards been established?

STEP 5. REVIEW PRODUCTS

___ What type of systems will be reviewed (mainframe, PC, client-server, Intranet, other)?

___ Have you established and prioritized a list of requirements and options?

___ What features, modeling and reporting capabilities are available?

___ Can you identify pros and cons of each system under review?

___ Are purchase price, implementation/support time and costs provided by vendor?

STEP 6. EVALUATE SYSTEMS

___ Have systems been reviewed based on established criteria?

___ Have you established a short list of potential vendors that fit your needs?

___ Is there a clear set of evaluation standards prepared for the vendor presentations?

___ Can the system be customized and by whom and at what cost?

___ Are there options to develop a system in-house?

STEP 7 CHECK REFERENCES

___ Have you checked functionality against your requirements?

___ Can vendor provide user references in your industry/area?

___ Do vendors provide adequate system documentation?

___ Have you established implementation, training and support schedules?

___ Can you test the system with live data from your own company?

___ Can you review a vendor's operational system in another company

STEP 8 ACQUIRE THE SYSTEM

___ Have you developed a purchasing recommendation?

___ Can you provide a time, cost and implementation schedule?

___ Have you established performance criteria with vendor?

___ Are contracts and payment schedules in place?

Implementing The Forecasting Process

SUMMARY

Improving the overall forecasting process can result from a number of well-planned activities including:

?? **Preparing information systems**, which support the forecasters as well as multiple users, and allow for integrated databases so that manual data transfer is eliminated. The systems should be able to provide on-line as well as reports of forecast accuracy and allow for higher-level management adjustments and results reporting at each level where a forecast was entered. The system should allow for direct input of forecasts by customers and of material availability by suppliers.

?? **Measuring forecast accuracy**, which is important to identify areas for improvement, to understand accuracy capabilities and to develop credibility with users. Two generic approaches can be pursued:

1. Measure only the forecast and make no allowance for difficulty. This approach identifies trouble spots
2. Measure the forecaster by taking into account the relative difficulty of the forecasting environment.

?? **Monitoring forecast performance**, which consists of activities designed to prevent surprise for a company by highlighting the need for a change in the forecast. These activities include monitoring composites or groups of items, the sum of the parts to the whole, ratios of related items, monthly and cumulative results, company and external factors, results in other locations, and user needs.

?? **Reconciling forecasting approaches** that include *top-down* and *bottom-up forecasting* with sales force and/or customer input. Develop the forecast at the same time the business plan is developed with periodic reconciliation, training in forecasting methods and the business environment as well as the forecasting systems, and recognition and reward.

?? **Forecast integration**, which refers to the need to encourage communication, collaboration and coordination among all the organizations involved with forecasting including the forecasting organization, marketing, sales, production, distribution, finance and product management. It involves understanding the needs of all the organizations and developing a process to facilitate information sharing and consensus on the final forecasts that are used in business planning and operations. We recommend a disciplined approach for implementing new forecasting methods or process improvements:

?? **A specific methodology** should be selected for on-the-job implementation; deadlines should be established and the resources that will be made available to complete the project should be specified.

☐☐ **An implementation plan** should indicate the methods to be implemented and indicators of progress to ensure that the plan does not die from lack of follow up. Considerations that should be incorporated into the plan are highlighted in a sample manager's checklist .

☐☐ **Training courses** improve the likelihood that new techniques are implemented; however, the value of training is often dissipated because of lack of specific on-the-job reinforcement. Making the implementation of new methods as routine as you would any other job requirement is the surest way to achieve success

☐☐ **Managing an organization** that utilizes quantitative methods requires above average technical competence: a background in management is also recommended. ☐ Forecasters and managers alike may find that a jointly compiled checklist will help in the technical evaluation of forecasting models. The purpose of such checklists should be to establish standards for the forecasting organization. The forecaster should use the checklists in the preparation of the forecasts and have them available for subsequent review by the forecast manager if an exceptional circumstance makes this advisable. The philosophy of forecast evaluation is one in which primary emphasis is placed on the process rather than the numbers. If the forecaster has meticulously followed a proper forecasting process, the end result will be as good a forecast as can be developed. If not, a manager may need to find a better-qualified forecaster.






Part X

Practical Uses of Predictive Analytic Modeling for Business Planning

Learning Objectives



- Identifying practical uses of predictive analytic modeling for business planning
 - Marketing - Promotion planning
 - Sales – Pricing: Estimating elasticities
 - Operations – Safety stock and inventory
 - Finance – Rolling forecasts and budgeting
- Recognizing the importance of causal (regression models)
- Using a checklist to identify gaps in the modeling process requiring ongoing improvement

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What You Should Be Able To Do

After completing this topic, you should be able to:

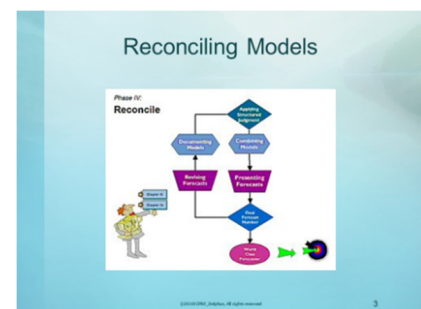
- Identify the practical uses of a forecasting model
- Recognize the value of linear regression models in forecasting applications
- Use checklists to identify gaps in the analyses that would need improvement

How You Will Check Your Progress

- Checkpoint questions
- Relate the material to your current forecasting efforts
- Work problems in L&C, Chapters 8 - 12


Resources

1. Levenbach, H. (2017). **C&C** Chapters 10 and 11.
2. Ord, K., Fildes, R. and Kourntzes, N. (2017). **Principles of Business Forecasting**, Wessex Pub
3. Demand Forecaster Checklist



Practical Uses Of Predictive Analytic Modeling

- ❖ **Marketing**
 - New Products
 - Sales versus Advertising
 - Price Elasticities
- ❖ **Sales Planning**
 - Causal Models
 - Promotions and Brand Management
- ❖ **Operations, Tactical and Strategic Planning**
 - Bull-whip effect
 - Econometric Models for Forecasting and Scenario Analysis
- ❖ **Financial Planning**
 - Rolling forecasts, budget planning and scenario analysis
- Much relies on quantitative modeling (e.g. regression analysis, econometrics and optimization models)



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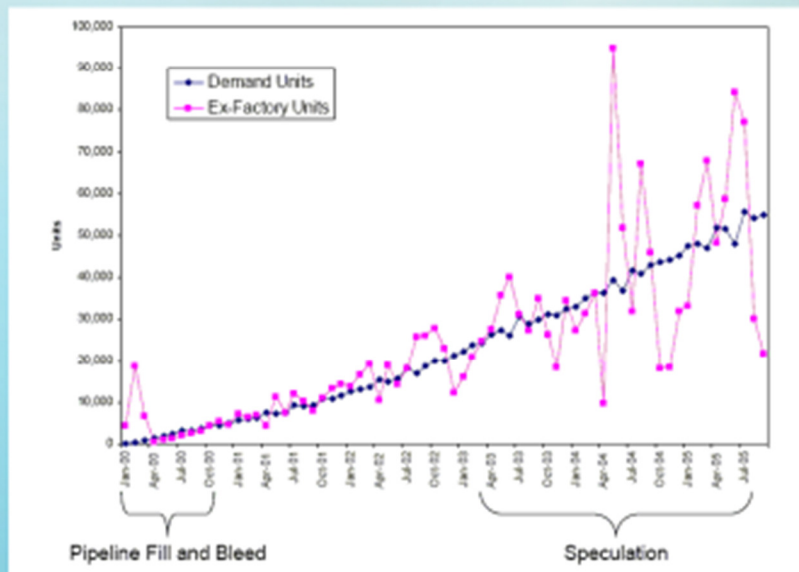
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What are examples of some practical uses of forecast modeling?

Uses of forecast models can be found in most organizations in a company:

- Forecasting in Marketing
 - New Products
 - Sales vs. Advertising
 - Price Elasticities
- Forecasting in Sales
 - Promotions
 - Brand Management
- Forecasting in Operations
 - Bull-whip effect
 - Econometric forecasting
- Forecasting in Finance
 - Budget projections
- Much relies on quantitative modeling (e.g. regression analysis, econometrics and optimization)

Consumer versus Customer Demand — The Bullwhip Effect



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What is the difference between consumer and customer demand modeling?

- When referring to consumer demand, we think of quantity demanded by consumers which is what people purchase at retailers' checkout counters. Nowadays these purchases have barcodes that get scanned. The resulting data source for retailers becomes POS (Point of Sale) data. This is represented by the smooth curve in the chart.
- Many companies only have shipment data (also known as customer demand). This is a proxy and can be valuable for forecasting demand. However, it tends to be more volatile because it represents data assembled from various distribution points in the supply chain
- As more distribution points lie between consumers and manufacturers, this volatility results in a bull-whip effect as result of the increasing volatility. This makes forecasting less reliable for manufacturers, hence forecasters need to be particularly careful in using shipment data
- As much as possible, forecasters need to acquire POS data for their companies.

What is a new product

- **Product improvement:** resulting from technological developments
 - iPhone, iPad

Phone Pad



GPS
- **Line extension:** same product lines while number of products versions increases
 - Airbus and the concept of « family »:

A-300 A-310 A-320 A-380
- Netbook



netbook

- **Market extension:** new package design, new advertising campaign, diversification to other markets


5 1st ICFF 2010 11-12 June 2010

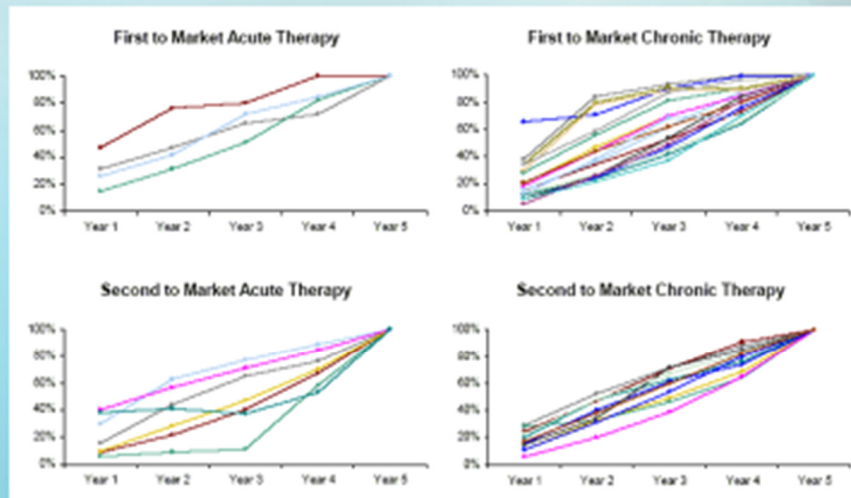
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What is an innovation product?

- By innovations forecasting, we mean the process of demand forecasting for new offerings introduced as a result of the changing environment and changes in new consumer needs. Such offerings can include services as well as products; hence, we will refer to them simply as innovations. Generally, a product is regarded as 'new', if it has been on the market less than three months. Thereafter, it is called a base product or base service.
- "In this regard the only source of profit, the only reason to invest in companies in the future is their ability to innovate and their ability to differentiate. Today, organic growth is the key. It's going to determine who gets rewarded and it is absolutely the biggest task of every company.", Jeffrey Immelt
- "You only get a position in the future by investing, creating something new, and staying ahead of the competition. So it's simple: invest or die.", Craig Barret
- These two quotes best describe the importance of new products to the survival of business: Jeffrey Immelt, Chairman, and CEO of General Electric said in a presentation in 2003 that "In this regard the only source of profit, the only reason to invest in companies in the future is their ability to innovate and their ability to differentiate. Today, organic growth is the key. It's going to determine who gets rewarded and it is absolutely the biggest task of every company." The CEO of Intel Craig Barrett added in 2004 "You only get a position in the future by investing, creating something new, and staying ahead of the competition. So it's simple: invest or die."

New Product Introductions Use analogues to model these



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Are there models for new product introductions?

- From an example in the pharmaceutical industry, these charts show how data can be organized.
 - Group products in similar product groupings with high volatility
 - Group products in similar product groupings with consistent patterns
- New products with similar early growth patterns can be forecasted using analogous early growth with similar past products
- Dissimilar products should have early growth forecasts stated with significant probability limits
- Some modeling examples can be downloaded from

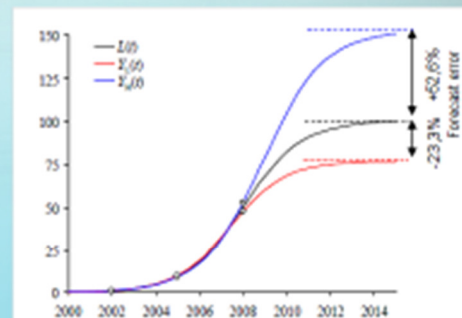
http://www.cpdftraining.org/downloads/IFFC2010_Hamoudia_PredictingNewProductDemand.pdf

Using Limited Data

- Errors in measured data could lead to important uncertainty of new product or service forecasts

Case example: When known data points have measurement error of $\pm 5\%$:

- For this new service, only 3 observations about the number of customers are known (2005, 2008 and 2011) but with measurement error of $\pm 5\%$
- Resulting market capacity without error should be $M = 100$
- Incorporating possible error of measurement, market capacity lies in the interval from $ML = 76.6$ (-23.3%) to $MH = 152.6$ ($+52.6\%$).



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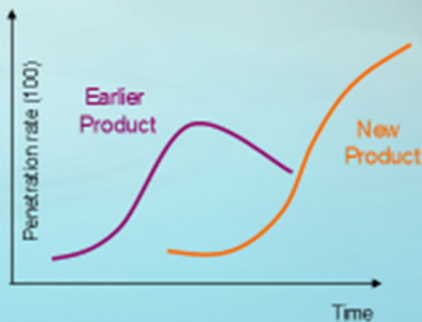
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How do you forecast with limited data?

- New product forecasting cannot take place in isolation. Key to success is that we first develop a deep understanding of the market and its potential consumer base. With this understanding, there is also a need to develop a sound rationale for assessing risks. In essence, we need to develop a structured approach for dealing with change and uncertainty.
- To illustrate this, a market potential is estimated by the maximum attainable market size under a given set of conditions. The potential for the innovation is what volume can be achieved within that market under a given set of assumptions. Thus the market potential is the largest forecast possible, followed by the forecast of the market itself. Within the market, the sales potential is the next largest forecast followed by the sales forecast. Because each may be governed by a different set of assumptions and risks, it is critical in forecasting innovations that each situation is monitored or tracked on an ongoing manner.
- The number of new products introduced into the market has increased dramatically over the past two decades. The numbers are likely to have increased even more in the most recent decade. It should be an interesting exercise to speculate whether the numbers for the next few decades will increase with similar growth rates as the past couple of decades.

Modeling The Analogy Approach

- Find analog products that are similar to the one to be launched
- *Similar analog product*: same characteristics as the new product (customer profile, order of entry in the market, ...)
- Modelling the life-cycle growth curve of the new product:
 - Test the most suitable « S » shaped growth curve
 - Start with the main classes of models: the Bass Model, the Gompertz curve and the Logistic curve
 - Refine the modelling process with more sophisticated specification within each class of models



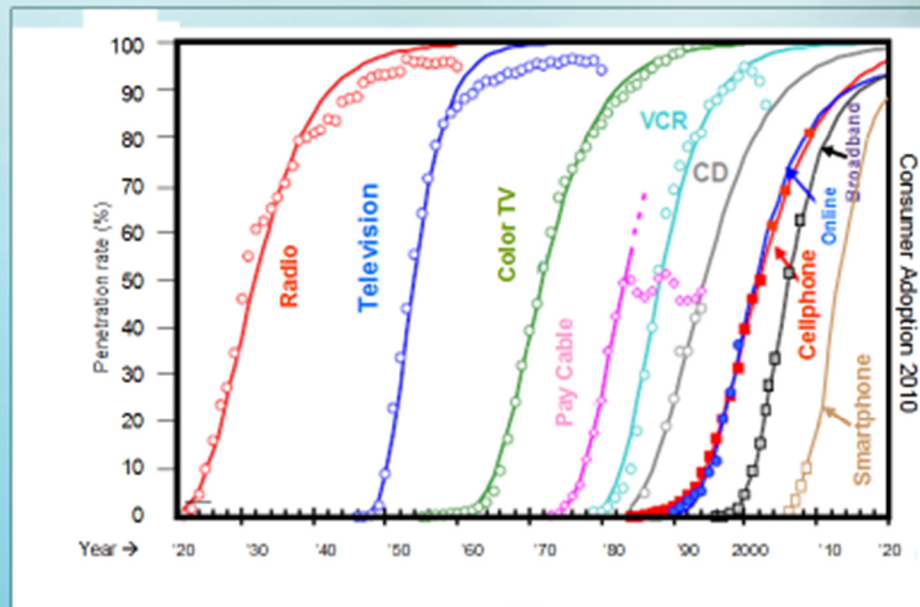
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How do you develop models with the analogy approach?

- Find analog products that are similar to the one to be launched
- Similar analog product: same characteristics as the new product (customer profile, order of entry in the market, ...)
- Model the life-cycle growth curve of the new product
- Test the most suitable « S » shaped growth curve
- Start with the main classes of models: the Bass Model, the Gompertz curve and the Logistic curve
- Refine the modelling process with more sophisticated specification within each class of models

Examples of Consumer Adoptions Using Gompertz Models



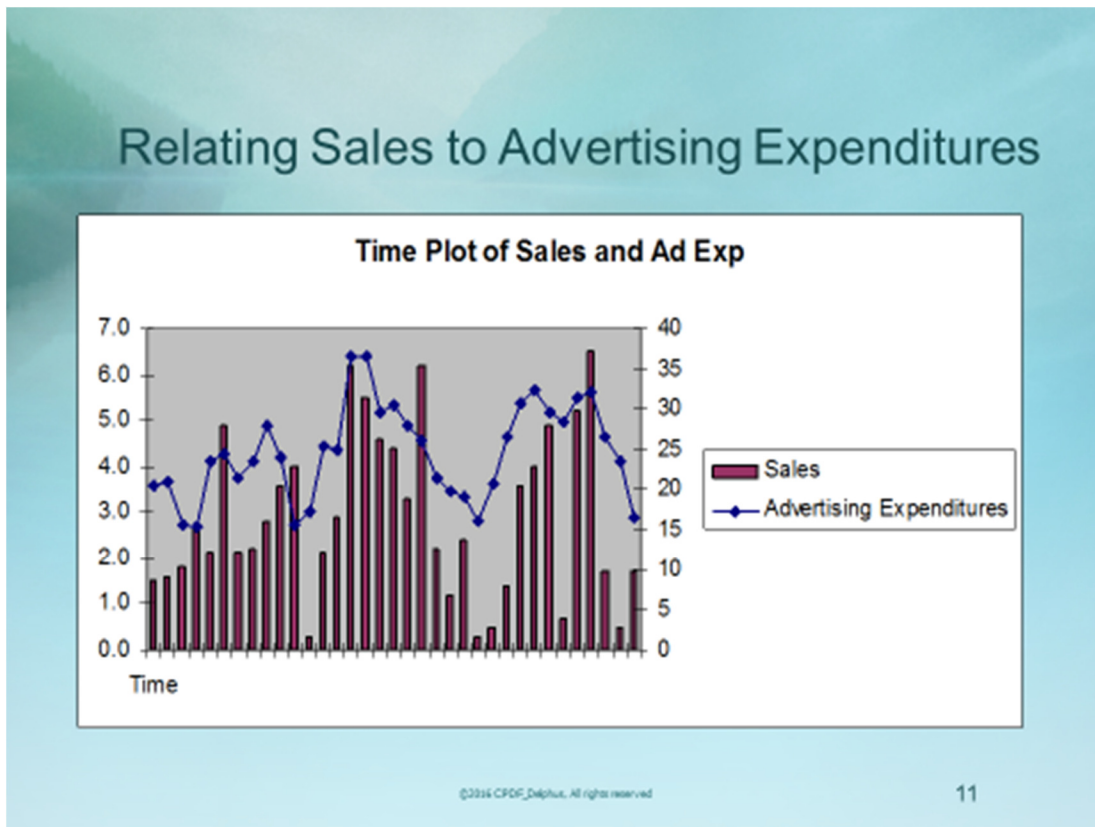
Source: (16) updated from 2004 to 2009 by the author Mohsen Hamoudia

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Courtesy Mohsen Hamoudia 2018

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What are some examples of using Gompertz models for consumer adoptions data?

- Generally, in the short term, most variables can be regarded as fixed. The main issue in this context may be faced when a very important change happens in this period.
- In the medium term, it is reasonable to consider slowly changing variables in the social, regulatory, technological and environmental spheres that can reasonably be ignored in operational decision-making.
- It is important to pay more attention to variables to be included in the forecasting system and their likely impact on the decisions being currently contemplated.

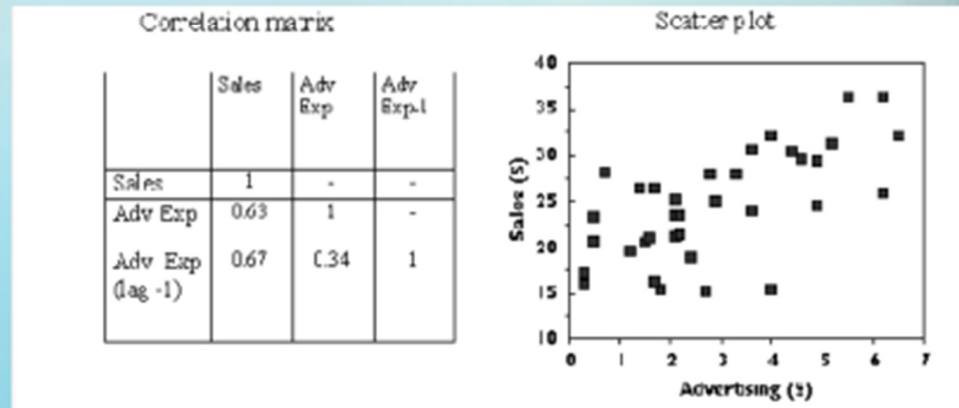


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How do you relate sales to advertising expenditures in a forecasting model?

- By placing the two variables on the same plot, we begin to visually identify a close relationship between the sales and advertising series. Peaks and troughs roughly correspond.
- This scatter plot shows that sales and advertising are correlated. But, how well?
- A simple linear regression model relating Sales (dependent variable) with Advertising expenditures (independent variable) will reveal the strength of this relationship.
- Because there may be a time lag between spending for advertising and seeing the results in sales, it is also useful to consider the relationship between sales and lagged Advertising expenditures. A lag of one period may be sufficient.

Relating Sales to Advertising Expenditures (Lagged)



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Why do you relate sales to (lagged) advertising expenditures?

In line with our multi-method approach, we calculate two measures of correlation:

- The ordinary product moment correlation that can be found in any business statistics text
- A robust correlation coefficient (see L&C, p. 429). This measure offers protection against the outlying values that can distort the validity of the familiar correlation coefficient r .

The scatter diagram on the right frame shows a linear pattern validating the use of linear regression.

It is evident that the relationship with the lagged independent variable is stronger.

It also turns out the degree of association is understated. Using the robust measure r^* , we find that

	Sales	Advertising Exp	Lagged 1 Adv. Exp
Sales	1	-	-
Advertising Exp	0.76	1	-
Lagged 1 Adv. Exp	0.80	0.71	1

A Consumption Model

- Consumption = $\beta_0 + \beta_1 \text{ Income} + \beta_2 \text{ Wealth} + \epsilon$
- Fitted consumption = $-176 + 0.935 \text{ Income} + 0.047 \text{ Wealth}$
- Interpretation:
 - If wealth does not change,
then every \$1 increase in income
will raise consumption on the average by \$ 0.935



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What is a consumption model?

- Consumption models are widely used in economic forecasting, planning and policy analysis
- This is a multiple linear regression model in which the (independent) variables are Income and Wealth, and Consumption is the (dependent) variable.
- It is said to be linear because the equation is a sum of 'coefficient times variable' combinations. The 'epsilon' at the end of the model equation is a random error term. The latter gives rise to estimates of the 'chance' or 'give or take' that describes the uncertainty.
- The equation is used for forecasting, because when we substitute forecasts for the independent variables in the equation, we get estimates or forecasts of the dependent variable.
- These equations also have a useful interpretation. In this case, for example, if wealth does not change or remains relatively constant, then we infer the every \$1 increase in income will raise consumption on the average by \$ 0.935 (the value of the 'Income' coefficient).

Concept of Elasticity

Describes the responsiveness of changes in demand to changes in another variable, like a factor or driver:

In the retail industry, the sale of a product Y related to three variables:

- Price X_1
- Advertising Budget X_2
- Sales Support X_3

Fitted Equation
 $\text{LogDemand} = -2.0 * \text{LogPrice} + 0.125 * \text{LogAdvertising} + 0.250 * \text{LogSalesForce}$

Interpretation
Estimate of price elasticity is -2.0 (the coefficient for LnPrice), which indicates that each 1% price increase, *holding advertising and sales force budgets constant*, results to reduce demand by 2%.

Can you interpret the other two elasticities? Do they make sense?

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What is an elasticity?

- Forecasters can play an important role in helping to make pricing decisions by estimating price elasticities. Because demand varies with tastes, total market size, average income, the distribution of income, the price of the good or service, and the price of competing and complementary goods, multiple elasticities are estimated through linear regression models. (See L&C, section 7.3).
- *Price Elasticity* describes the responsiveness of changes in demand to changes in prices:

Percentage change in Quantity demanded/Percentage change in Price

$$= (\Delta Q/Q) / (\Delta P/P)$$

- In a log-log linear regression model, the coefficients can be interpreted as elasticities
- An important condition in the definition of elasticity is that all factors influencing demand other than own-price (price of item under consideration) are held constant (*ceteris paribus* condition)
- In general, price elasticity is determined by at least four factors:
 - Whether or not the good is a necessity
 - The number and price of close substitutes
 - The proportion of the budget devoted to the item
 - The length of time the price change remains in effect

Short and Long-Term Elasticities

EXHIBIT 7.21 Determining Short- and Long-Term Elasticities for the Consumption of Gasoline in the United States, 1960-1995	Constant	-23.314
	log Price index for gasoline (X_1)	-0.402
	log Per-capita income (X_2)	0.597
	Year (time trend)	0.011
	log Price index for new cars	-0.205
	log Price index for used cars	-0.017
	log Price index for public transportation	0.101
	log General price index for consumer durables	0.588
	log General price index for consumer nondurables	1.146
	log General price index for consumer services	-0.950
	log Consumption of gasoline lagged one period (X_3)	0.383

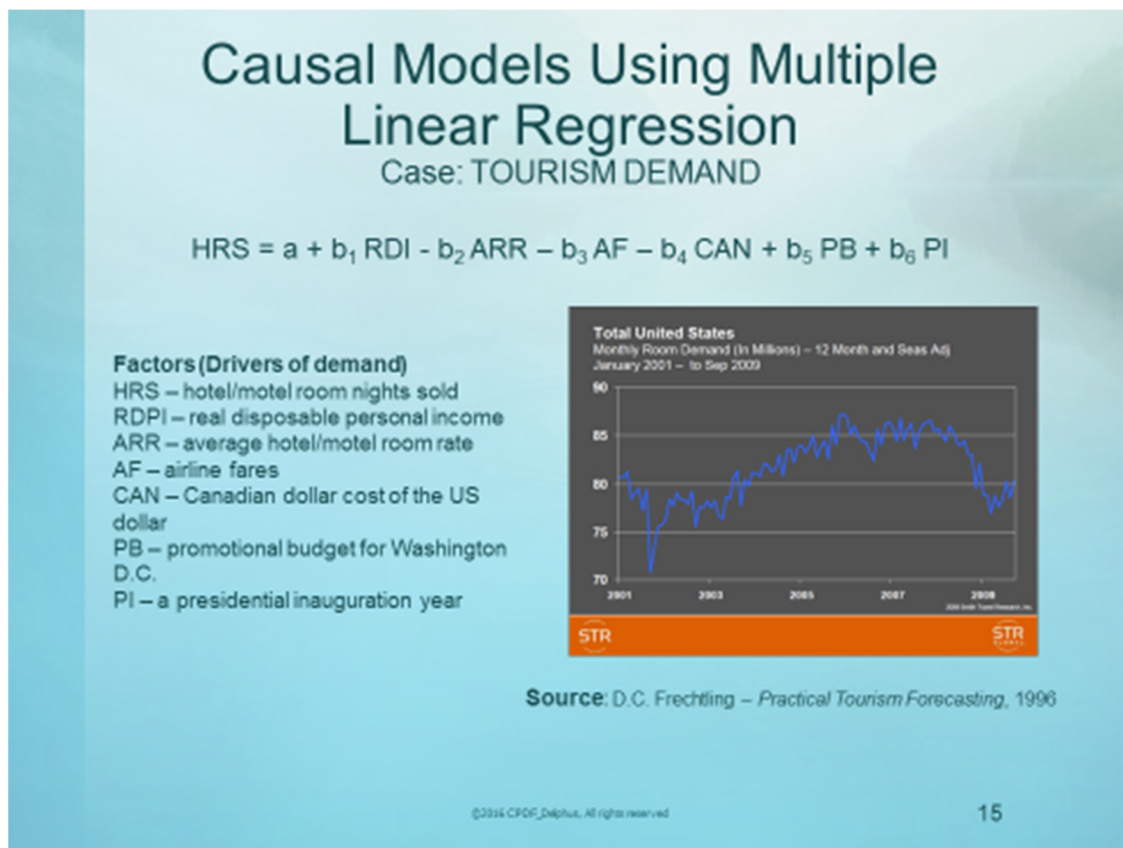
	Price	Income
Short run	Coeff of $X_1 = -0.402$	Coeff of $X_2 = 0.597$
Long run	Coeff of $X_1/(1-\text{Coeff of } X_3) = -0.651$	Coeff of $X_2/(1-\text{Coeff of } X_3) = 0.967$

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What are short and long-term Elasticities?

- To derive long-term elasticities, one needs to construct linear regression models which contain a lagged term of the dependent variable.
- As time goes by, the theory of demand states that demand should become more elastic. The various elasticities are determined in the lower table, where you can see how they are calculated.
- In the above constant elasticity model (log-log), the estimated coefficients are estimates of elasticities. For example, the price elasticity of demand is estimated to be -0.518 and income elasticity is 1.222. All else being, equal, we expect consumption to increase 0.89% per year.
- Because the coefficients for the price indexes for new automobiles are less than zero, these products are complementary with gasoline.
- The elasticity of consumer durables as a group is closer to unity than the elasticities for a more narrowly defined category of new automobiles, which is consistent with economic theory.



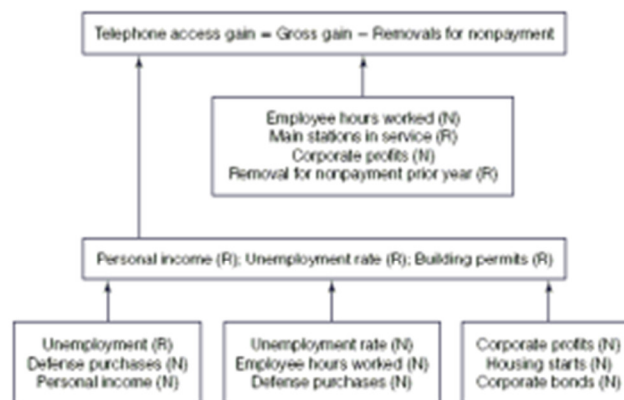
What are causal models? – The case for tourism demand

- This is a multiple linear regression model with six (6) independent variables or factors affecting the demand HRS.
- The dependent variable HRS represents hotel/motel room nights sold in Washington, DC, the capital of the US and site for Presidential inaugurations in a January.
- The factors are:
 - HRS – hotel/motel room nights sold
 - RDPI – real disposable personal income
 - ARR – average hotel/motel room rate
 - AF – airline fares
 - CAN – Canadian dollar cost of the US dollar
 - PB – promotional budget for Washington D.C.
 - PI – a presidential inauguration year

Econometric Modeling

Characterized by many equations describing relationships based on an economic theory

EXHIBIT 7.22
A Recursive Econo-
metric Model for
Telephone Access-
Line Gain in a Region
(R, regional; N,
national)



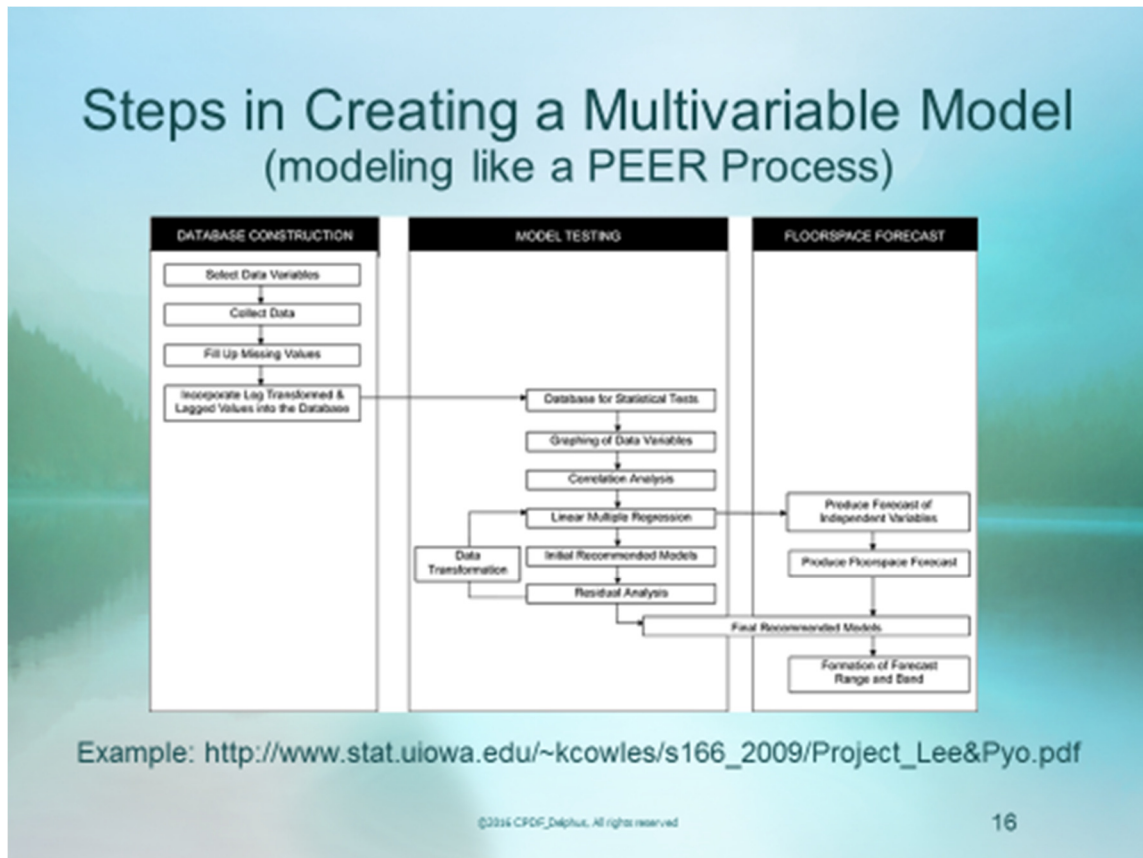
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What is econometric modeling?

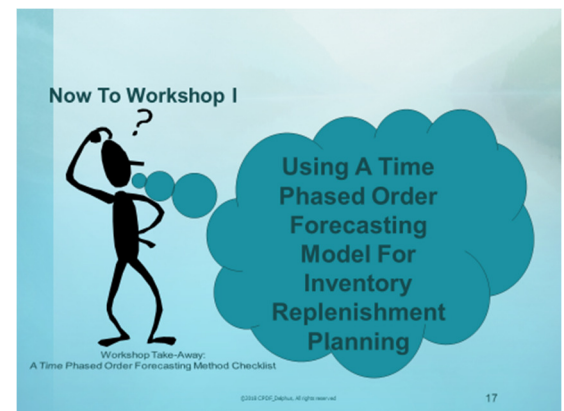
- Flowchart depicts a recursive model for telephone access-line gain in a geographic area. Each individual regression model is built sequentially, starting at the bottom of the chart. The predictions from the previous equations are used as forecasts in later equations. In this example there are forecasts produced for regional, national, economic, and telecommunications data.
- The underlying theory is that the national economy drives the country and its regions; therefore, the economic forecasts for the region are related to the economic forecasts for the whole country. The demand for telephone access lines (land lines) is then related to these forecasts of economic activity. The regression models establish the linkages between the national economy and the region, in turn, the regional economy, and the demand for access lines.

Econometric models are characterized by equations describing relationships based on economic theory.



What is econometric modeling? (Continued)

- Although there is a widespread use of forecasts from econometric systems, there does not appear to be a universal acceptance those econometric forecasting systems- can produce consistently reliable and defensibly accurate forecasts. Hence, it is sometimes called the 'dismal science', perhaps unfairly because econometric systems are widely accepted for policy analyses and developing scenarios.
- Policy models establish 'what-if' questions about the future state of a system in a mathematical model
- Generally, simpler approaches often yield projections that are more accurate than econometric-based forecasts.
- Nevertheless, a vital role of econometric modeling is to provide an economic rationale for the forecasting process along with a mechanism for producing forecasts.



A Hands-on Example – Retail Industry



A grocery chain is investigating the use of scanners to evaluate its promotional activities. A linearized multiplicative model is postulated to relate SALES (in units) to weekly PRICE (in dollars) in a regression model of the form $\log \text{SALES} = \beta_0 + \beta_1 \log \text{PRICE} + \varepsilon$. To incorporate promotional effects, the model is augmented by adding two variables, FLYER (flyer promotion) and DISPLAY (display promotion):

$$\log \text{SALES} = \beta_0 + \beta_1 \log \text{PRICE} + \beta_2 \text{FLYER} + \beta_3 \text{DISPLAY} + \varepsilon$$

Turn to Retail_Workshop.xls

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A hands-on example (Workshop J following Part XI) from the retail industry

$$\log \text{SALES} = \beta_0 + \beta_1 \log \text{PRICE} + \beta_2 \text{FLYER} + \beta_3 \text{DISPLAY} + \varepsilon$$

- For a live demonstration, turn to Retail Workshop in the Workshop_Template.xls
- And if you want to see how this kind of analysis will be done in the future, visit Hans Riesner's 'You Tube' clip:


<http://www.youtube.com/watch?v=jbkSRLYSojo>



Part XI

Designing Regression Models for Demand Forecasting


Learning Objectives



- Defining a linear association between two variables
- Checking ordinary correlation with a nonconventional complement when one or more outliers or unusual values are present
- Understanding regression model assumptions
- Interpreting what is meant by a “best fit”
- Applying diagnostic checks on residual patterns
- Interpreting summary statistics in a regression output
- Creating functional (causal) relationships for forecasting

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2



What You Should Be Able To Do

After completing this topic, you should be able

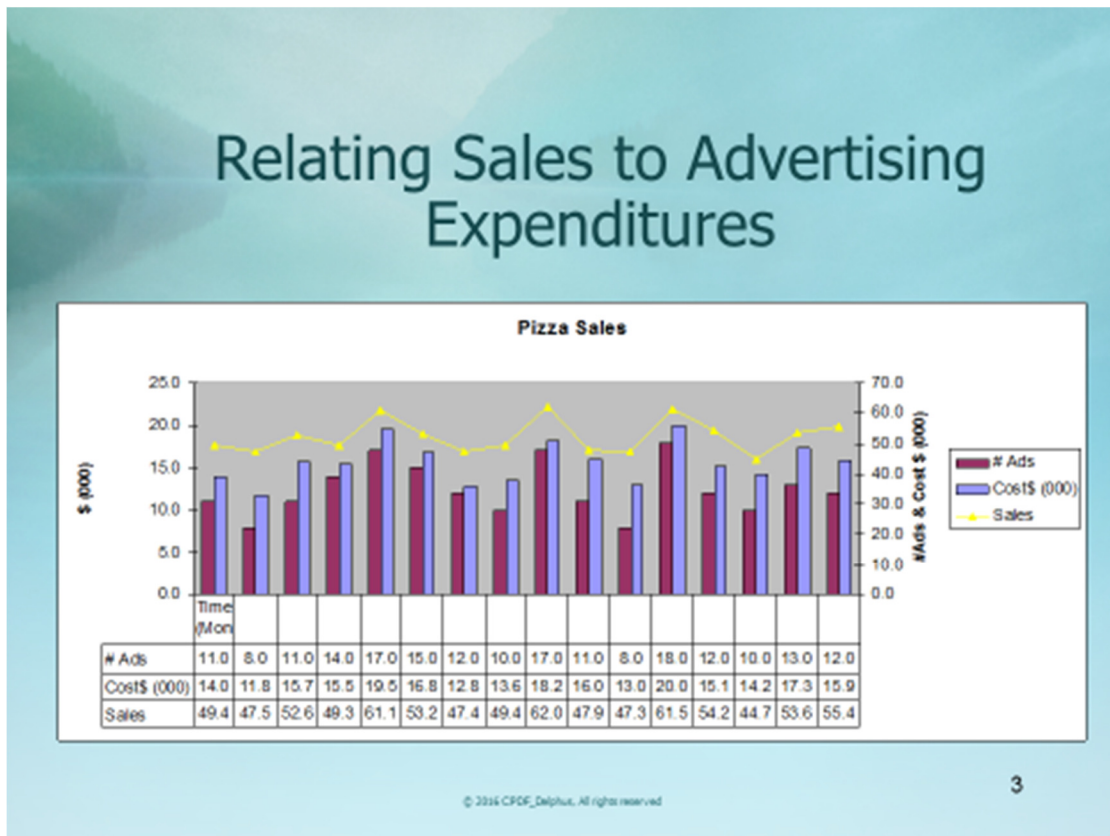
- Describe a linear association between two variables
- Create an estimate of linear correlation between two variables
- Define a regression relationship and its underlying assumptions
- Diagnose residual patterns for patterns not fitting assumptions
- Identify important summary statistics in a regression analysis
- Using functional relationships for causal forecasting

How You Will Check Your Progress

Create a Regression Modeling Checklist

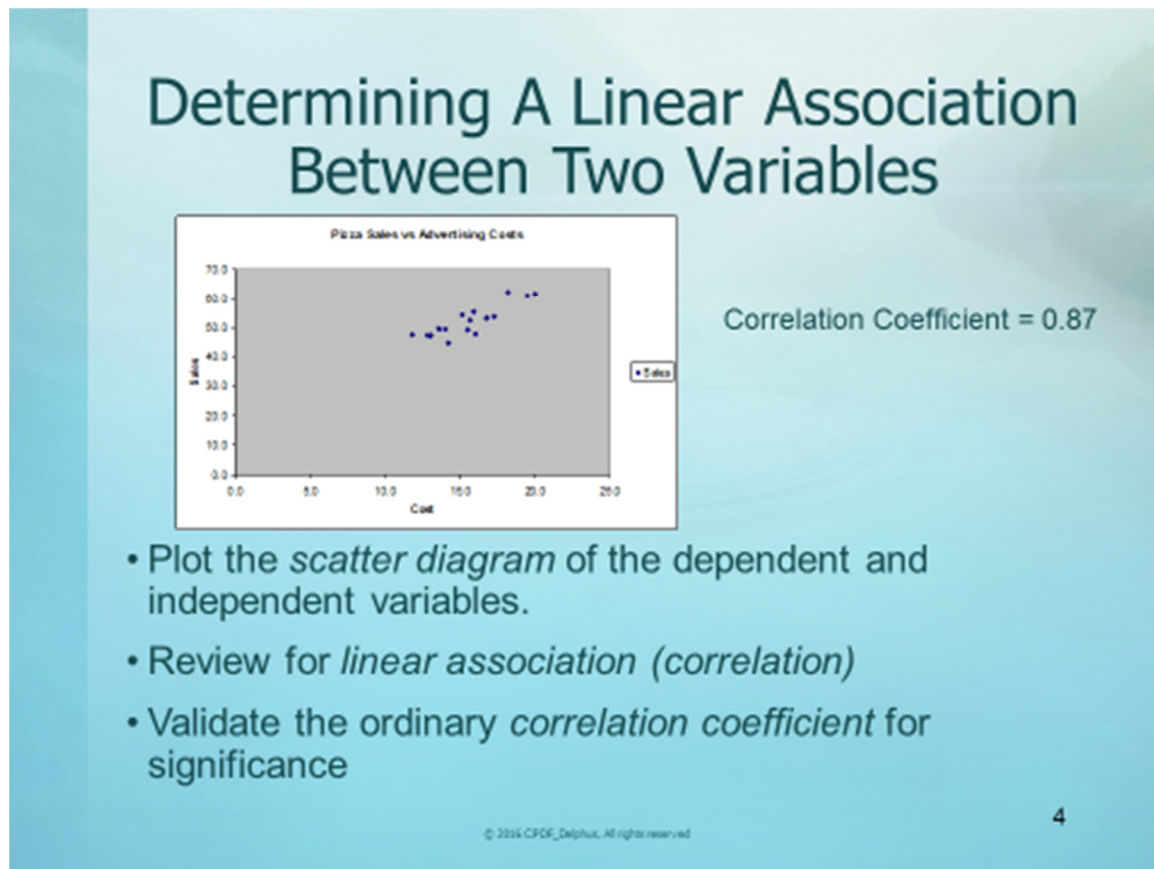
Resources

1. Levenbach, H. (2017). **C&C**. Chapter 10.
2. You Tube – Hans Rosner: World Wealth and Health
3. Ord, K., Fildes, R. and Kourentzes, N. (2017). **Principles of Business Forecasting**, Wessex Pub, Chapters 7 and 8
4. Bass, F.M. and D.G. Clarke (1972). *Testing distributed lag models of advertising effects*, J. Marketing Research, v9.3, 298 – 308.



How do you relate sales to advertising expenditures?

- By placing the two variables on the same plot, we begin to visually identify a close relationship between the sales and advertising series. Peaks and troughs roughly correspond.
- This scatter plot shows that sales and advertising are correlated. But, how well?
- A simple linear regression model relating Sales (dependent variable) with Advertising expenditures (independent variable) will reveal the strength of this relationship. Peaks and troughs correspond to each other.
- Because there may be a time lag between spending for advertising and seeing the results in sales, it is also useful to consider the relationship between sales and lagged Advertising expenditures. A lag of one period may be sufficient.
 - Seasonality is similar in both series
 - So, they are associated, but is there a *linear correlation*?



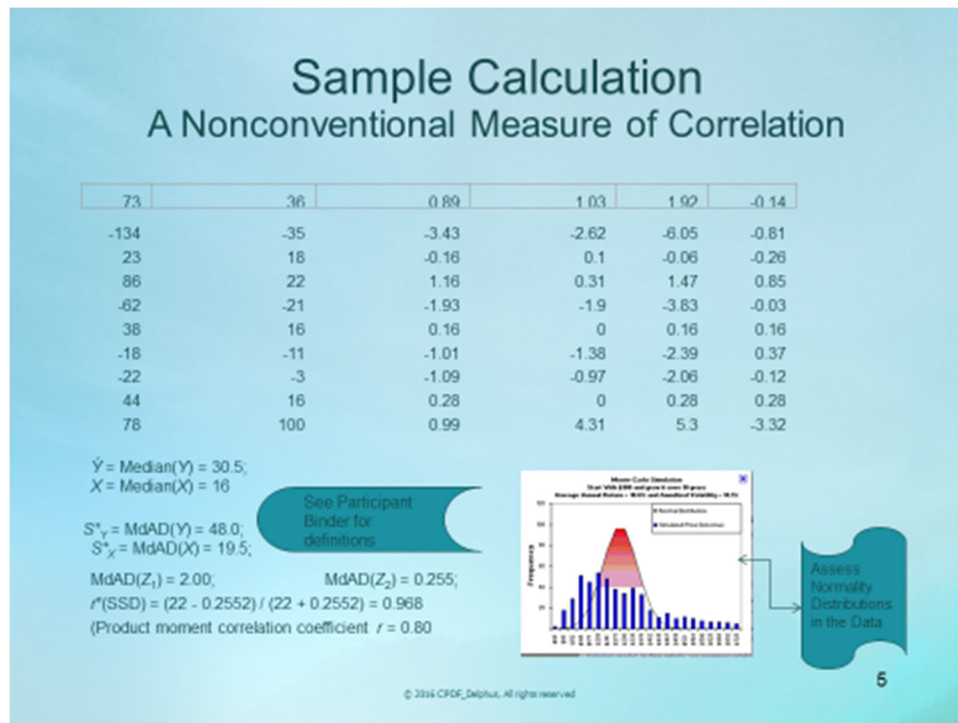
How do you depict a linear association between two variables?

Here are the steps:

- Plot the scatter diagram of the dependent and independent variables.
- Review for linear association
- Determine the correlation coefficient for significance

What to do when the non-normal is the norm

- Consider calculating a nonconventional correlation alternative if outliers appear in the data or the data are clearly not normally distributed.



How to calculate a nonconventional measure of correlation (see L&C, p. 425 for details)

Y	X	$Y = (Y - \hat{Y}) / S^*_Y$	$X = (X - X) / S^*_X$	$Z_1 = \hat{Y} + X$	$Z_2 = \hat{Y} - X$
73	36	0.89	1.03	1.92	-0.14
-134	-35	-3.43	-2.62	-6.05	-0.81
23	18	-0.16	0.1	-0.06	-0.26
86	22	1.16	0.31	1.47	0.85
-62	-21	-1.93	-1.9	-3.83	-0.03
38	16	0.16	0	0.16	0.16
-18	-11	-1.01	-1.38	-2.39	0.37
-22	-3	-1.09	-0.97	-2.06	-0.12
44	16	0.28	0	0.28	0.28
78	100	0.99	4.31	5.3	-3.32

$$\hat{Y} = \text{Median}(Y) = 30.5;$$

$$X = \text{Median}(X) = 16$$

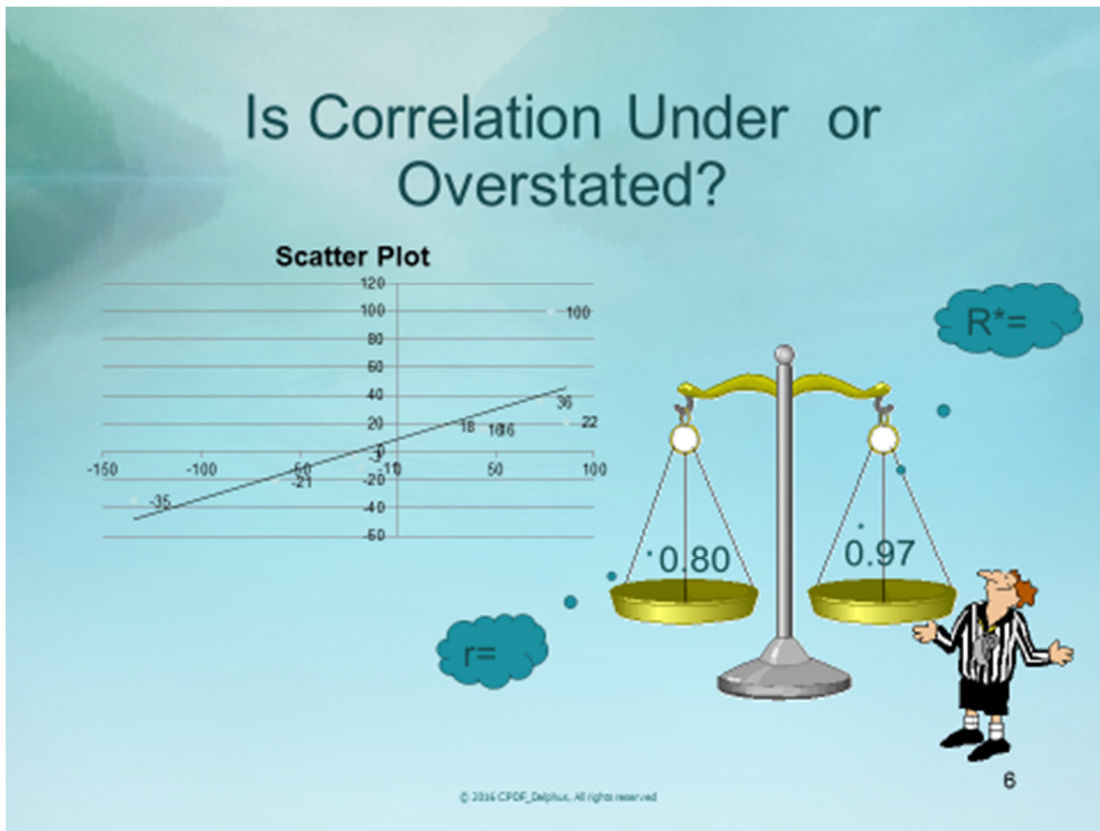
$$S^*_Y = \text{MdAD}(Y) = 48.0; \quad X = \text{Median}(X) = 16.0;$$

$$S^*_X = \text{MdAD}(X) = 19.5;$$

$$\text{MdAD}(Z_1) = 2.00; \quad \text{MdAD}(Z_2) = 0.255;$$

$$r^*(\text{SSD}) = (22 - 0.2552) / (22 + 0.2552) = 0.968$$

$$(\text{Product moment correlation coefficient } r = 0.80)$$




Is correlation under- or overstated?

- Measure correlation two ways: ordinary product moment correlation coefficient and nonconventional, outlier resistant r^*
- Performing a nonconventional (outlier resistant) correlation minimizes the influence of outliers and unusual values
- If the measures are close (for practical purposes), use ordinary product moment correlation coefficient
- If measures seem far apart (like above), investigate data more closely for outliers or nonlinear patterns.



What Are Regression Models?

- Regression models are used for forecasting and for managerial decision making with policy variables (e.g., prices, promotions)
- **Simple** Linear Regression (SLR) model - one explanatory variable
- **Multiple** Linear Regression (MLR) - two or more explanatory variables



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What are regression models?

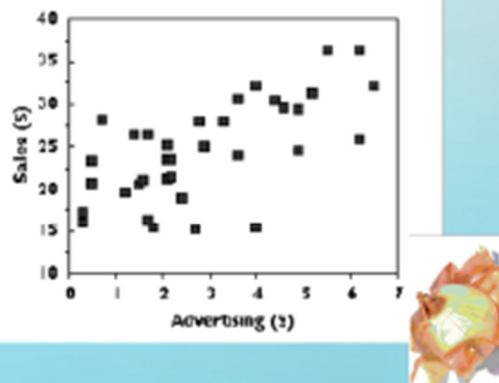
- Regression models are used for forecasting and for managerial decision making with policy variables (e.g., prices, promotions)
- Simple Linear Regression (SLR) model - single explanatory variable
- Multiple Linear Regression (MLR) - two or more explanatory variables

How Are Sales Related to (Lagged) Advertising Expenditures?

Correlation matrix

	Sales	Adv Exp	Adv Exp-1
Sales	1	-	-
Adv Exp	0.63	1	-
Adv Exp (lag -1)	0.67	0.34	1

Scatter plot



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Why is sales often related to (lagged) advertising expenditures?

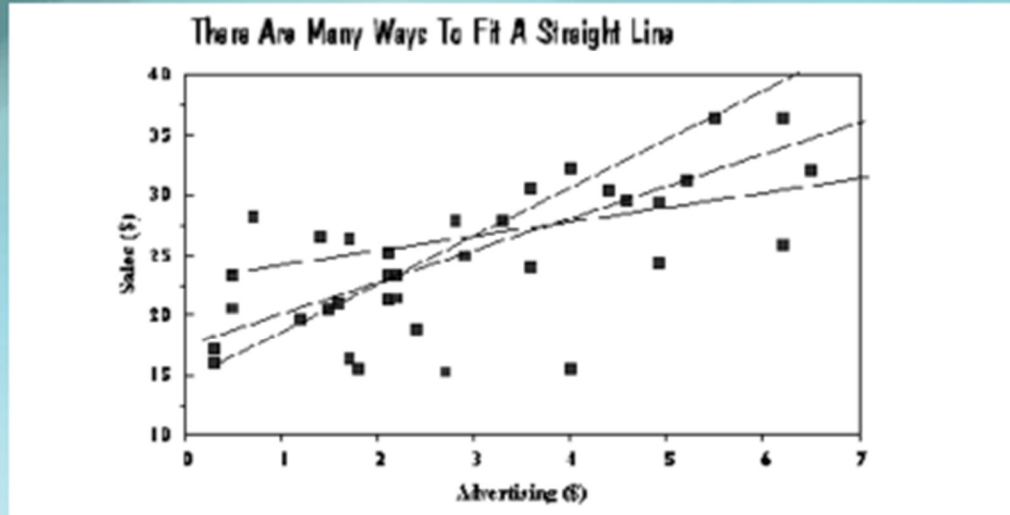
In line with our multi-method approach to modeling, we calculate two measures of *linear correlation*:

- The ordinary product moment correlation coefficient that can be found in any business statistics text. It represents the conventional approach
- A robust correlation coefficient (see C&C, Chapter 11). This non-conventional measure offers protection against the outlying values that can distort the validity of the familiar correlation coefficient r .

The scatter diagram on the right frame shows a linear pattern validating the use of linear regression. It is evident that the relationship with the lagged independent variable is stronger. It also turns out the degree of association is understated. Using the robust measure r^* , we find that

	Sales	Advertising Exp	Lagged 1 Adv. Exp
Sales	1	-	-
Advertising Exp	0.76	1	-
Lagged 1 Adv. Exp	0.80	0.71	1

What Is a Best Fit?



9

What does best fit mean?

- There are many ways that a straight line can be laid on the scatter
- Best known criterion is called least squares, or Ordinary Least Squares (OLS)
- There are other, no so 'ordinary', kinds of least squares
- There are other, no so well-known, criteria for fitting a relationship
- First, what are the properties of a (straight line) regression curve?
- The fit is 'best' because it is based on a widely accepted criterion yielding a unique solution. It is "best" because it is unique.

There are no 'best' models for forecasts, either. It depends on the criterion that has the greatest acceptance, but does not assure more accurate projections.

The Regression Curve in Theory

- ❑ *Key assumption* - for any value of X , the value of Y is scattered around a mean value
- ❑ For SLR, a straight line relationship is given by:

$Y = \beta_0 + \beta_1 X + \text{random error}$
 $Y = \beta_0 + \beta_1 X +$

It's OK
You don't
have to
memorize this

This is
Pete, who
does not
like
equations!

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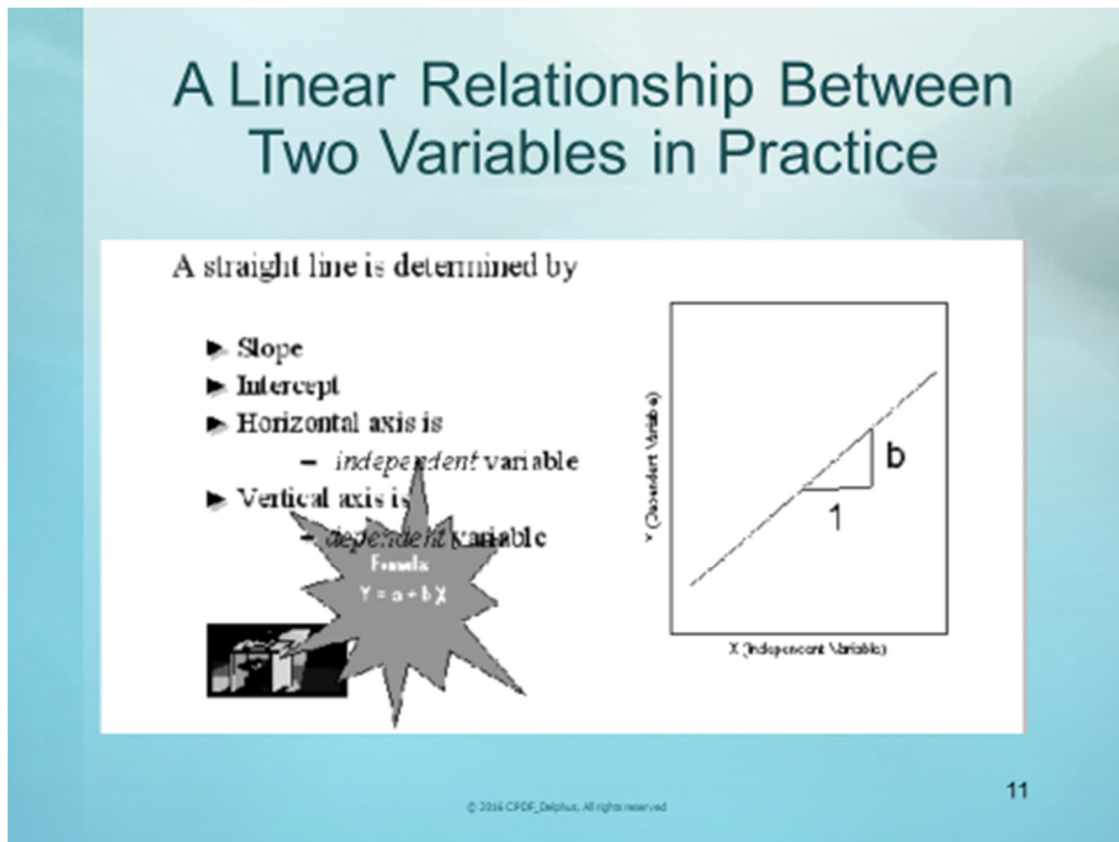
10

What is the regression curve in theory?

- Key assumption - for any value of X , the value of Y is scattered around a mean value
- For SLR, a straight line relationship is given by:
-

$$I. Y = \beta_0 + \beta_1 X + \varepsilon$$

- Terminology
 - Y – dependent variable
 - X – independent variable
 - β_0, β_1 – regression coefficients
 - ε – random error term (source of randomness in the scatter)




What is a linear relationship between two variables in practice?

- In theory, use Greek symbols to describe the functional relationship
- In practice, use Latin letters for the estimated regression coefficients:
 - Estimated intercept = a
 - Estimated slope = b
 - Estimated equation $Y = a + bX$
 - Independent variable Y (horizontal axis)
 - Dependent variable X (vertical axis)

How to Determine Slope and Intercept Without Computer Program

For SLR, need only five summary statistics to determine intercept a and slope b:

- Mean and SD of X
- Mean and SD of Y
- Correlation (X, Y)



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How do you determine the slope and intercept in a simple linear regression (without a computer program)?

For SLR, we only need five summary statistics: (Δ Hous vs. mortgage Rates)

- Mean of Y = -21.02
- Standard deviation (SD_Y) of Y = 302.9
- Mean of X = 0.115
- Standard deviation (SD_X) of X = 0.885
- Correlation r between X and Y = -0.597

Then


$$\text{Slope } b = r SD_Y / SD_X = (-0.597) (302.9) / (0.885) = -206.5$$

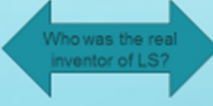
$$\text{Intercept } a = (\text{mean } Y) - b (\text{Mean } X) = -21.02 - [(-206.5) (0.115)] = 14.47$$

The Least Squares Assumption


The most widely used criterion - the sum of the squared residuals is less than the sum of the squared vertical deviations for any other line through the data:

- Minimum of Sum of $(\text{Data-fit})^2 = \text{Sum} [(\text{Residuals})^2]$





Who was the real inventor of LS?



Gauss
1777-1855

Legendre
1752-1833

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What is the least squares assumption?

The most widely used criterion - the sum of the squared residuals is less than the sum of the squared vertical deviations for any other line through the data:

$$\text{Minimum of Sum of } (\text{Data-fit})^2 = \text{Sum} [(\text{Residuals})^2]$$

Why is the least squares line the best fit?

- BEST FIT is only as good as the rule adopted
- Idea is to minimize the total spread of the Y-values from the line
- For each point in the scatter diagram, visualize a square obtained by connecting the point to the line vertically and drawing a box of equal lengths
- Calculate the sum of the areas of the squares
- Try with another line and repeat above procedure
- The line with the SMALLEST sum of squared deviations is the Least Squares Line
- The least squares line is called BEST FIT.

Historical note: Around the turn of the century, geneticist Francis Galton discovered a phenomenon called 'regression toward the mean.' Seeking laws of inheritance, he found that a son's height tended to regress toward the mean height of the fathers. Thus, tall fathers tended to have somewhat shorter sons, and vice versa. Galton developed regression analysis to study this effect, which he optimistically referred to as "regression toward mediocrity."

Preparing the Output

- Total variation is the variation of Y about the overall mean of Y
- It is composed of two components:
 - Explained by the regression
 - Unexplained variation due to error



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How do you get the output you need?

Like peeling that first layer off the data-analytic modeling onion, it reveals two components (a) explained variation due to regression and (b) unexplained variation due to error.



Showing Results: ANOVA Table

(a) ANOVA				
	df	SS	MS	F
Regression	1	874316.16	874316.16	13.9
Residual	25	1577595.06	63103.80	
Total	26	2451911.21		
	Coefficients		Standard Error	t Statistic
Intercept	14.47		49.00	0.30
X variable 1	-206.50		55.48	-3.72

(b) ANOVA				
	df	SS	MS	F
Regression	1	82189241.34	82189241.34	1603
Residual	118	605011236.7	5127213.87	
Total	119	8823935371		
	Coefficients		Standard error	t Statistic
Intercept	-1848.93		1035.34	-1.79
X variable 1	3.42		0.09	40.04

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What is the ANOVA table for regression analysis? What to look for in the ANOVA table of a regression output

R² Statistic (A measure of goodness of FIT)

- $R^2 = (\text{Explained variation}) / (\text{Total variation})$
- $= (\text{Total SS} - \text{Error SS}) / \text{Total SS}$



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Caution! Don't rely too heavily on mistaken interpretations of the appearance of a good, high number for the R-square statistic. This can be very misleading, especially when interpreted in the context of selecting a good FORECASTING model. A high R-square statistic does not imply a good forecasting model. On the other, if you are entertaining a good regression-based forecasting model, it is likely that the R-square will be good too.

Interpreting t Statistics For Coefficients

- Measures statistical significance of regression parameter associated with specific independent variable
- Based on assumption that other variables are included.
- Rule of thumb: $|t| > 2 \rightarrow$ significant (i.e. coefficient not zero)
- Equivalent use with Confidence Intervals (later)



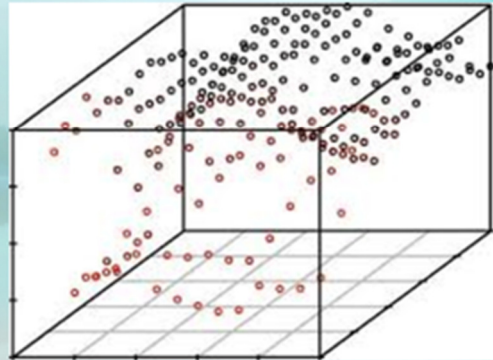
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Interpreting t-statistics for the coefficients in a regression model

- Measures statistical significance of regression parameter associated with specific independent variable
- Based on assumption that other variables are included.
- Rule of thumb: $|t| > 2 \rightarrow$ significant (i.e. coefficient not zero)
- Equivalent use with Confidence Intervals (later)

The Regression Plane



The Regression Equation As a Forecasting Formula

- Pizza Sales = $b_0 + b_1 * (\text{\# Ads}) + b_2 * (\text{Cost of Ads})$
- $b_0 = 24.8$, $b_1 = 0.66$, $b_2 = 1.23$
-
- $R^2 = 348.1428 / 446.9644 = 0.78$
- If #Ads = 16, Cost = 18, what are expected Sales?



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How do you write down a regression equation as a forecasting formula?

Forecasted Pizza Sales = $24.8 + 0.66 * \text{Forecasted \#Ads} + 1.23 * \text{Forecasted Cost of Ads}$


Interpreting A Regression Output For Pizza Sales

• Least squares estimates



	Estimate	Std. Error	t value
Intercept	24.82	5.66	4.4 *
# of Ads X_1	0.66	0.54	1.2
Cost of Ads X_2	1.23	0.70	1.8

• ANOVA table



Source	df	SS	MS	F
Regression	2	348.1428	174.0714	22.9
Residual	13	98.8216	7.6017	
Total	15	446.9644		

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How do you interpret the regression output for pizza sales?

- What are the values for the intercept and slope of the linear equation?
- How do you use the t-values to assess the statistical significance or importance of individual coefficient values?
- How can you tell how many data values were used in the regression?
- How can you establish what the percent contribution in the SS comes from CHANGE (Regression) and CHANCE (Residual)?
- How is the overall significance of the model measured?
- How do you calculate the goodness of fit statistic R-squared from this table?

Multicollinearity in Pizza Sales Model

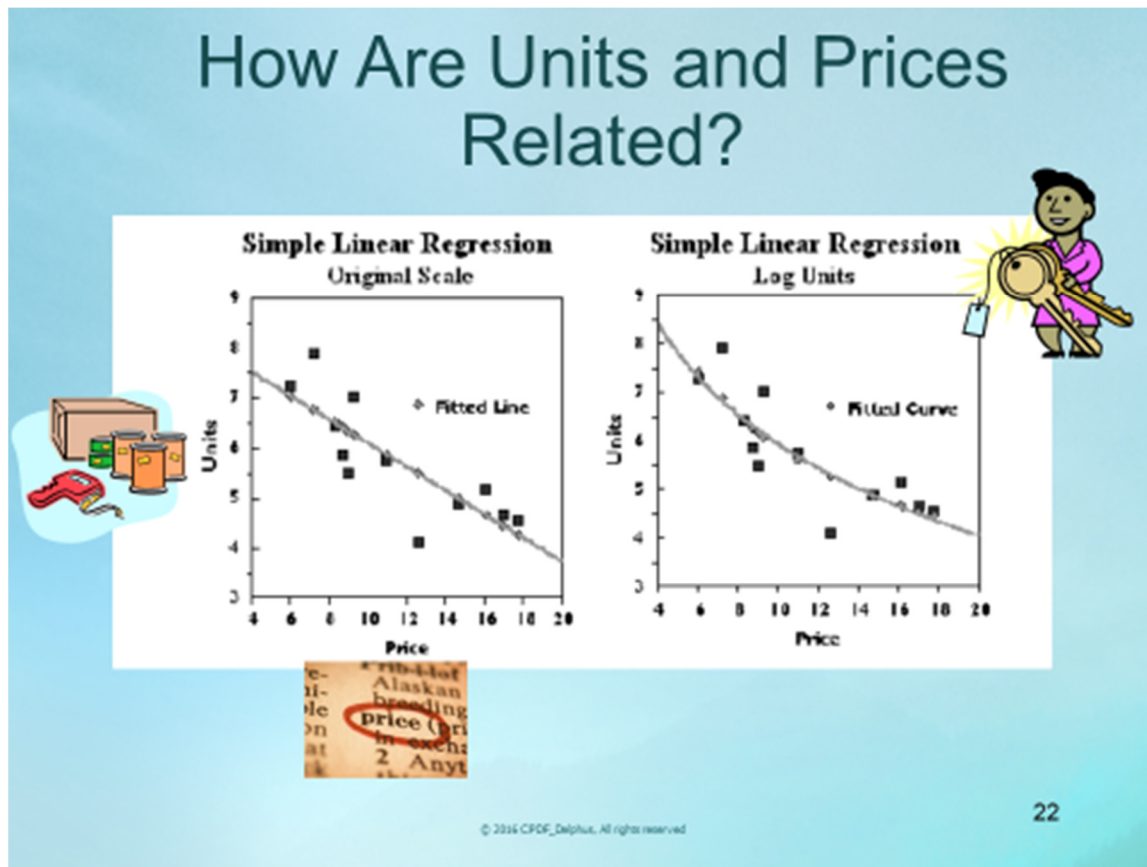
	Coefficients				
Variables in Model	β_0	β_1	β_2	Regression SS	R^2
X_1 only	33.35	1.52		324.3	0.73
	* (significant)				
X_2 only	21.02		2.01	336.6	0.75
	*		*		
X_1, X_2	24.82	0.66	1.23	348.1	0.78
	*				

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Why is multicollinearity a problem in the pizza sales model?

- Regression on X_1 only → X_1 not significant ($1.52 < 2.0$)
- Regression on X_2 only → X_2 is significant
- Regression on X_1 and X_2 → Now neither X_1 and X_2 are significant



How are units and prices related?

- Contrast two models, one with the *original* scale of the data and a second one with the *logarithms* of the data
- Left frame – scatter of unit volumes and price, including line of ‘best fit’
- Next, create a scatter of logarithm of unit volumes versus logarithms of price, including a line of ‘best fit’. How did we get this line? It appears to be curved
- Right frame - When we ‘untransform’ (i.e take anti-logs) the best fit line to the original units and price scale, the model will appear curved. This is the ‘**Fitted Curve**’
- **Note:** both models are best fit models: one in terms of original units and the other in terms of log-transformed units.
- These models clearly give different looking fits. In particular, you will find that the prediction limits around the forecast (projections) is symmetrical for the original model and not (i.e. asymmetrical) for the log-transformed model

Units versus Price: Different Interpretations

Original Data				Log Transformed Data			
The regression equation is $y = 849 - 0.24x$				The regression equation is $y_{\log} = 1.25 - 0.46x_{\log}$			
Predictor	Coef	StDev	T	Predictor	Coef	StDev	T
Constant	849	0.66	12.9	Constant	1.25	0.10	12.3
x	-0.24	0.05	-4.4	xlog	-0.46	0.01	-4.9
S = 3.73 R-Sq = 65.6%				S = 0.05 R-Sq = 70.7%			
For every 100 unit decrease in price you would expect a corresponding increase of 24,000 units in volume				For every percent decrease in price you would expect a corresponding 0.5% increase in volume			



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How are units and prices related: linear or nonlinear?

- Original data - interpretation of the regression coefficient is -0.24 , which means that for every 100 unit increase in price you would expect a corresponding increase of 24,000 units in volume.
- Log-transformed data – Interpretation of the regression coefficient is -0.46 , which means that for every percent decrease in price you would expect a corresponding 0.5% increase in volume.
- Note that the R-square statistics in the two models are not comparable, because the units of the two dependent variables are different. These models could be equally good (or bad!). The important consequence of this is that the ranges of uncertainty are different for the two models.

Example: A Consumption Model

$$\text{Consumption} = \beta_0 + \beta_1 \text{ Income} + \beta_2 \text{ Wealth} + \varepsilon$$
$$\text{Fitted consumption} = -176 + 0.935 \text{ Income} + 0.047 \text{ Wealth}$$

Interpretation:
If wealth does not change,
then every \$1 increase in income
will raise consumption on the average by \$ 0.93



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What is a consumption model?

$$\text{Consumption} = \beta_0 + \beta_1 \text{ Income} + \beta_2 \text{ Wealth} + \varepsilon$$

$$\text{Fitted consumption} = -176 + 0.935 \text{ Income} + 0.047 \text{ Wealth}$$

Interpretation: If wealth does not change, then every \$1 increase in income will raise consumption on the average by \$ 0.93

Example: An Elasticity Model

- Model:

$$\ln Y = \ln \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \dots + \varepsilon$$

- Fitted log-linear model:

$$\ln \text{Demand} = \beta_0^* + \beta_1 \ln \text{Price} + \beta_2 \ln \text{Advertising\$} \\ + \beta_3 \ln \text{Sales_Force\$} + \varepsilon^*$$

- Interpretation:

- For each 1% price increase,
holding the advertising and
sales force budgets constant,
is estimated to reduce demand by 2%



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How do you measure elasticity with a regression model?

- This is a log-linear model

$\ln Y = \ln \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \dots + \varepsilon$ A relationship is linear because the equation for the dependent variable is linear in the parameters.

- This is a linear model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \varepsilon$$

$$Y = \beta_0 + \beta_1 X_1^{\beta_2} + \dots + \varepsilon$$

- The second equation is not linear because the coefficient β_2 does not enter the relationship in a linear fashion.

What is an Econometric Model?

- Causal relationships
- Multi-equation model
- Sophisticated software
- Uses seasonally adjusted data
- Better for answering policy issues than forecasting accuracy



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What is an econometric model?

- **Causal model** – a quantitative forecasting approach that relates a time series value to other variables that are believed to cause its pattern
- Multi-equation format to describe relationships among variables
- Uses sophisticated estimation methods
- Seasonally adjusted data
- Better for policy orientation than forecasting accuracy

Utility Industry Example – Demand for Electricity: $ED = f(Y, P_i, P_j, Pop, T)$

ED = Electricity Demand

Y = Output or Income

P_i = Own price

P_j = Price of related fuel

POP = Population

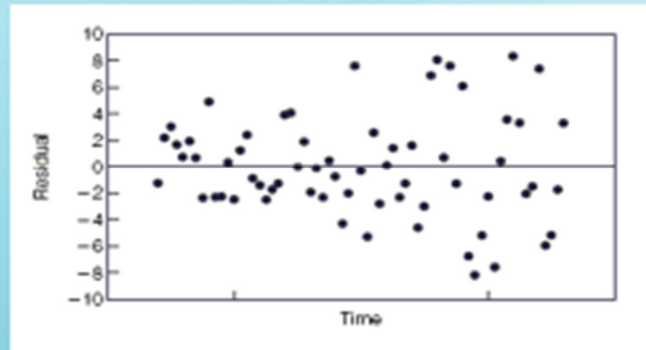
T = Technology

Residential ED – Use Y/ Capita

Industrial ED – Use Y as Gross Capital Formation

What is Heteroscedasticity?

- Variability in data is not constant or not homogeneous (non-constant σ^2 assumed)
- Typical residual pattern is fan-shaped
- Requires weighted regression



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What is Heteroscedasticity?

If you see a pattern of increasing dispersion in residual

- Use logarithmic transformations of variables
- Consider log-linear model

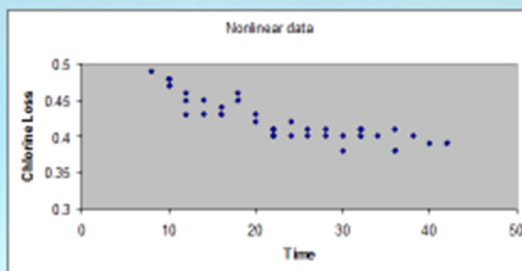
$$\ln Y = \ln \beta_0 + \beta_1 \ln X_1 + \dots + \ln e$$

This is a constant elasticity model (logarithm on both sides of the equation)

Example: A Nonlinear Model

$$Y_t = \beta_0 + (0.49 - \beta_0) \exp[-\beta_1 (X_t - 8)] + \varepsilon$$

- Interpretation of model:
 - At $X = 8$, expected $Y = 0.49$
 - Thereafter, exponential decay
 - Exponential decay flattens out at level $= \beta_0$
- Sample data:



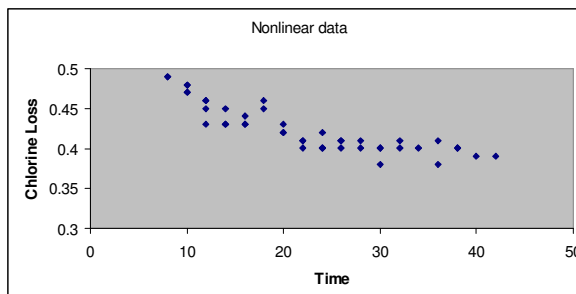
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What is a nonlinear regression model?



$$Y_t = \beta_0 + (0.49 - \beta_0) \exp [-\beta_1 (X_t - 8)] + \varepsilon$$

- Interpretation of model:
 - At $X = 8$, expected $Y = 0.49$
 - Thereafter, exponential decay
 - Exponential decay flattens out at level $= \beta_0$
- Sample data:



A Logit Model

- Analyzing proportions from binary response data
- Used extensively in biological and epidemiological
- Also for risk analysis and consumer choice
- Related: Probit model




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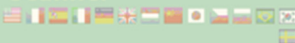
28

Why use Logit models?

- Analyzing proportions from binary response data
- Used extensively in biological and epidemiological
- Also for risk analysis and consumer choice
- Related: Probit model

Workshop J Using Causal Models For Advertising and Promotion Analysis



Barcode Scanner
Available in : 

Lesson Take-Away: Regression Analysis Checklist

<http://www.youtube.com/watch?v=jbkSRLYSojo>

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Part XII

Taming Volatility: Root-Cause Analysis and Exception Handling

Learning Objectives



- Interpreting classical normality assumptions in regression models
- Examining residuals for deviations from expected patterns
- Avoiding 'black swan' events
- Using prediction intervals for forecast monitoring
- Developing a checklist for linear regression models

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What You Should Be Able To Do

After completing this topic, you should be able to:

- Understand the normality assumptions in regression models
- Examine residuals for deviations from expected patterns
- Recognize Black Swan events
- Use models to generate projections and prediction limits.

How You Will Check Your Progress


- Create a Regression Checklist

Resources

Levenbach, H. (2017). **C&C**. Chapters 2, 10, and 11.

What Are Normality Assumptions in Regression Analysis?

- ❑ The mean μ_Y of response variable Y is linear in the β coefficients
- ❑ The ε_i are independent, identically distributed with a standard normal $N(0, \sigma^2)$ distribution
- ❑ In practice, check and validate assumptions with the data



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What are normality assumptions?

- Certain aspects in a regression output can only be properly interpreted if we make additional assumptions about the random errors. Up to this point, we have not made any assumptions about the distribution of the random error term in the regression model. If the random errors are normally distributed, then an extensive statistical theory is applicable
- The *standard normal assumption* (as in normal or Gaussian distribution) states that, in a random sample of n outcomes $\{Y_1, Y_2, \dots, Y_n\}$ of a variable Y , the corresponding random error terms $\{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n\}$ arise independently from a common normal (also called Gaussian) distribution with mean 0 and (unknown parameter) variance σ^2
- The n independent values (Y_1, \dots, Y_n) of Y , observed together with the values of the corresponding independent variables, will be used to make inferences about the regression parameters $\beta_0, \beta_1, \dots, \beta_k$ and the error variance σ^2 .

Selecting Variables

What Are the Drivers of Demand?

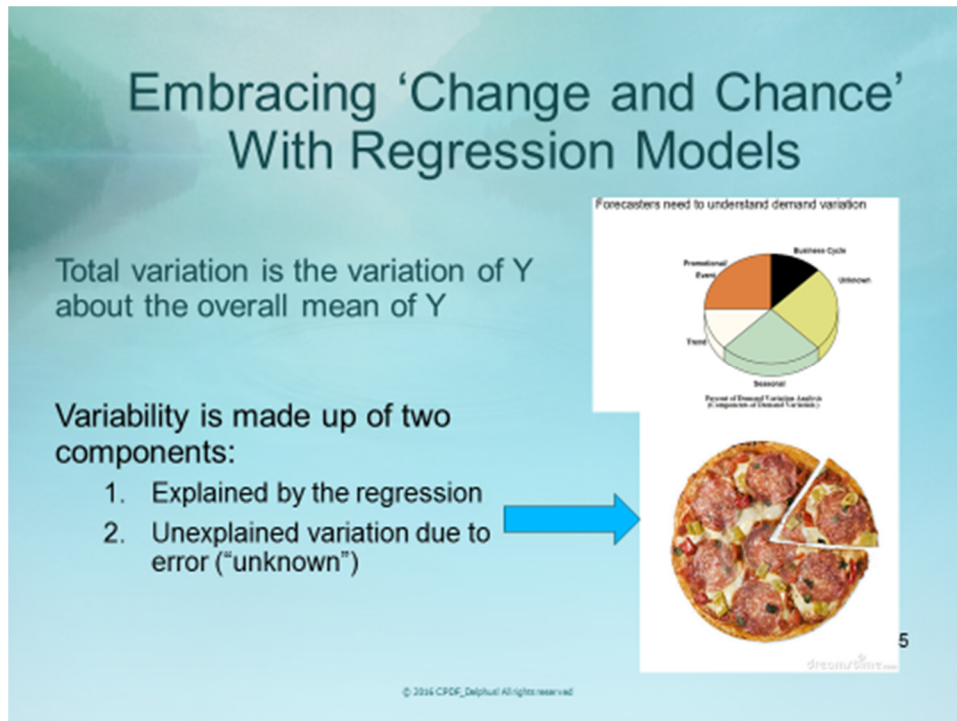
- Find a theoretical basis
- Are they practically beneficial?
- Do they have desirable intuitive or statistical properties?
- Use regression by stages
- Select lack-of-fit criteria
 - Mallows's C_p
 - Allen's Press



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How do you select variables in a regression model?

- Theoretical basis – Let the context of the forecasting situation dictate what factors or drivers of demand should be used
- Practically beneficial – Consider established or published modeling results suggest the initial model structure and variables to be considered
- Desirable intuitive or statistical properties – Let the data patterns suggest what variables to select for seasonality, trends and cycles
- Regression by stages – Use established software algorithms
- Minimize a lack-of-fit criterion – Create a methodology based on alternative criteria of 'best fit', such as
 - – Mallows's C_p
 - – Allen's Press



How do you determine Change and Chance from regression models?

- Total variation (entire pie) is the variation of Y about the overall mean of Y
- The pie is composed of two components:
 - Slices explained by the regression. This is CHANGE
 - Slice that is unexplained variation due to error ("unknown"). This is CHANCE


Review Model Adequacy

How Good Is The Fit?

- Derive inferences from summary statistics
 - R^2 - Goodness of Fit
 - The t Statistic
 - The F Statistic

and

- Review significance of regression coefficients with and without data outliers




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How to review model adequacy – (CHANGE)?

- Derive inferences from summary statistics
 - R^2 - Goodness of Fit
 - The t Statistic
 - The F Statistic, and
- Review significance of regression coefficients with and without data outliers

Comparing Regression Results (with and w/o outliers)



Variable	With Outliers			Without Outliers		
	Coefficient	OLS (SD)	Robust Coefficient	Coefficient	OLS (SD)	Robust Coefficient
Interest	-13.33	-2.26	-13.37	-9.69	-3.47	-13.37
Income	1.93	-0.26	1.94	1.55	-0.39	1.94
White-collar employment	0.032	-0.004	0.031	0.03	-0.006	0.031
Households > 1 auto	0.017	-0.004	0.015	0.017	-0.005	0.016

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How should you compare regression results (with and without outliers)?

- An analysis was performed to help identify the potential for increased sales of additional telecom services within 470 geographic areas. A requirement was that the model should incorporate local economic and demographic data so model can be used by the sales force responsible for stimulating demand. Areas with below-average development, as predicted by the model, would be candidates for future sales campaigns.
- This is a cross-sectional regression model for a telecommunications demand variable with four drivers (interest rate, income, white-collar employment and # households with more than one car)
- A robust regression model could offer some protection against outliers. The left-hand part of the table shows that OLS and robust regression analyses yield almost identical results, with no extreme values and approximately normal residuals. A comparison of the left-hand and right-hand sides shows that the outliers distorted the OLS results but not the robust results. Only three of the 473 observations were extreme, yet these three altered the income coefficient and the constant term significantly. This suggests that a difference between OLS and robust regression coefficients of approximately one standard error is sufficient cause to review the OLS model and the original data in much greater detail.

How to Use Linear Regression With Prediction Intervals

- ✓ Is the fit reasonable?
- ✓ Are accuracy levels acceptable?
- ✓ Do residuals appear random?



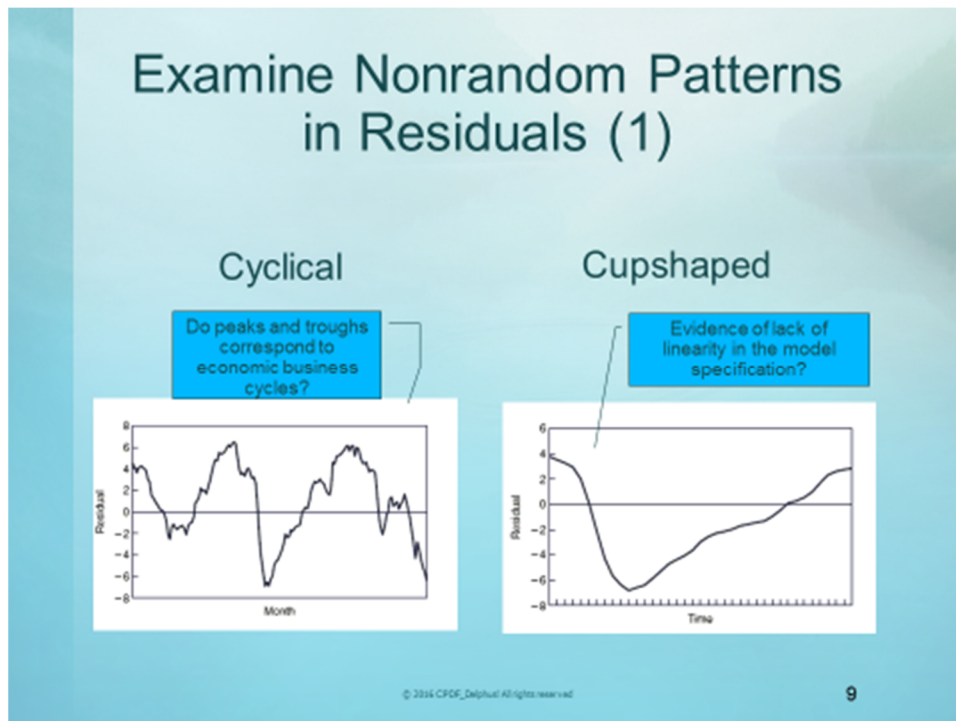
Then use *Probability Intervals* and *Cumulative Sums* for monitoring results

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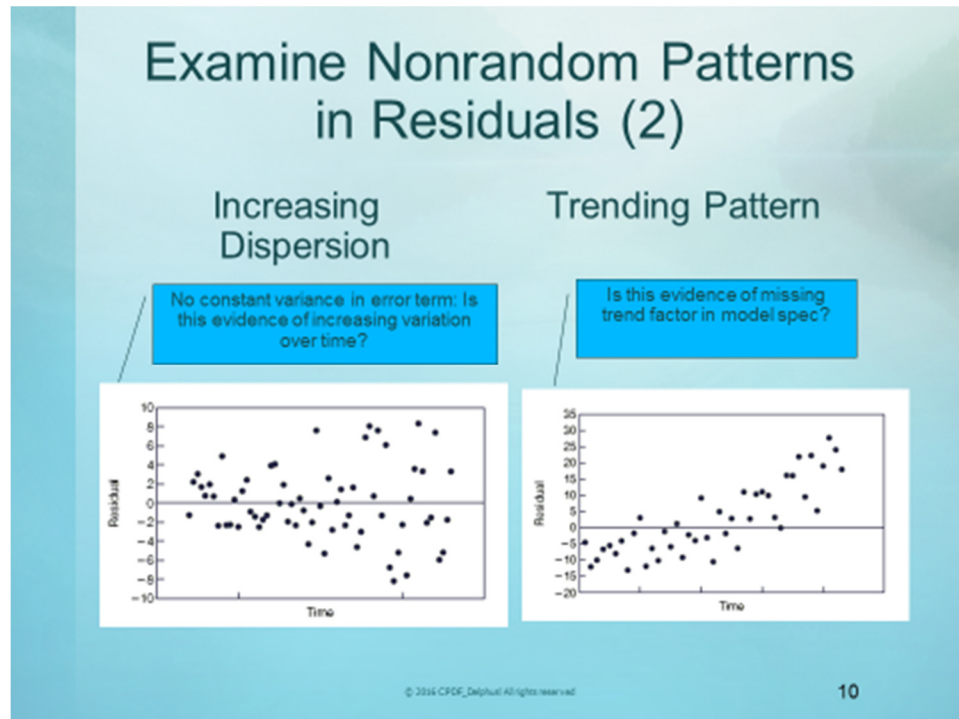
How to use linear regression models with prediction intervals?

- Is the fit reasonable?
- Are accuracy levels acceptable?
- Do residuals appear random?
- Then use Probability Limits and Cumulative Sums for monitoring




How do you look for nonrandom patterns in residuals (1)?

- Much of a residual analysis for time series models can be carried out effectively through a visual inspection of data patterns and correlograms
- These data patterns can typify a violation of one or more assumptions about randomness in a regression model
- A *cyclical pattern* is often evident when we fit linear models to economic data
- Economic expansions and recessions in the business cycle can often be seen in a residual plot
- The appearance of nonrandom patterns occurs because a linear model is being fit to an inherently nonlinear phenomenon. For instance, a plot of sales of a new product may show a rate of growth that is faster than linear growth
- Likewise, the income tax rate on individual earnings has a nonlinear relationship with earnings. When we attempt to fit such nonlinear relationships with a linear model, the residuals often appear to have a *cup-shape* or inverted cup shape.



How do you investigate nonrandom patterns in residuals (2)?

- The residuals for a nonlinear relationship may not look cup shaped over the entire regression period. However, if we make forecasts from the straight-line model, the forecast errors might show increasing dispersion, known as *heteroscedasticity*
- If residuals do not appear nonlinear over the entire regression period, a pattern of over- or under **forecasting** can still exhibit nonlinearity over a long enough period
- Distinguish between nonlinear growth in trend and nonlinear variations as a result of a short-term cycle. In the first case, the nonlinear relationship between two variables will continue in the same direction over a long time. In the latter, the nonlinear relationship will change direction at the peaks and troughs of each cycle
- Trends, up or down, may be apparent in the residuals. This can be the result of a nonlinear relationship between the variables.



Remedies For Handling Data Exceptions in Residuals

- ☐ **Replace of outliers if warranted**
 - Use a model to predict unusual value
 - Replace value with prediction
 - Run model over extended period and refine replacement predicted value
- ☐ **Include “dummy” variable in models**
- ☐ **Utilize alternative (robust/resistant) methods and compare results with conventional method**
- ☐ **Be on guard for ‘Black Swans’**



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How do you find remedies for handling exceptions in data?

- Replace of outliers if warranted
 - Use a model to predict unusual value
 - Replace value with prediction
 - Run model over extended period and refine replacement predicted value
 - Include “dummy” variable in models
- Utilize alternative (robust/resistant) methods and compare results with conventional method
- Be on guard for ‘Black Swans’. View short video by Taleb Nassim, inventor of the idea.

URL:<http://www.youtube.com/watch?v=BDbuJtAiABA>

Finding Exceptions In Datasets (a nonconventional method)


The *Interquartile difference (IQD)* is the difference between the 75th and 25th percentile in an ordered data set

Unusual values can be detected by considering *outer fences*

Lower outer fence = 25th percentile – 1.5 IQD
Upper outer fence = 75th percentile + 1.5 IQD

Alternatively, using Median +/- 2.7 UMdAd

UMdAd = [Med {Abs Deviation from Med}]/0.6745



John Tukey (1915-2000)
The Original Data Scientist

Nonconventional Measures - Reason Why? Because it Works!!

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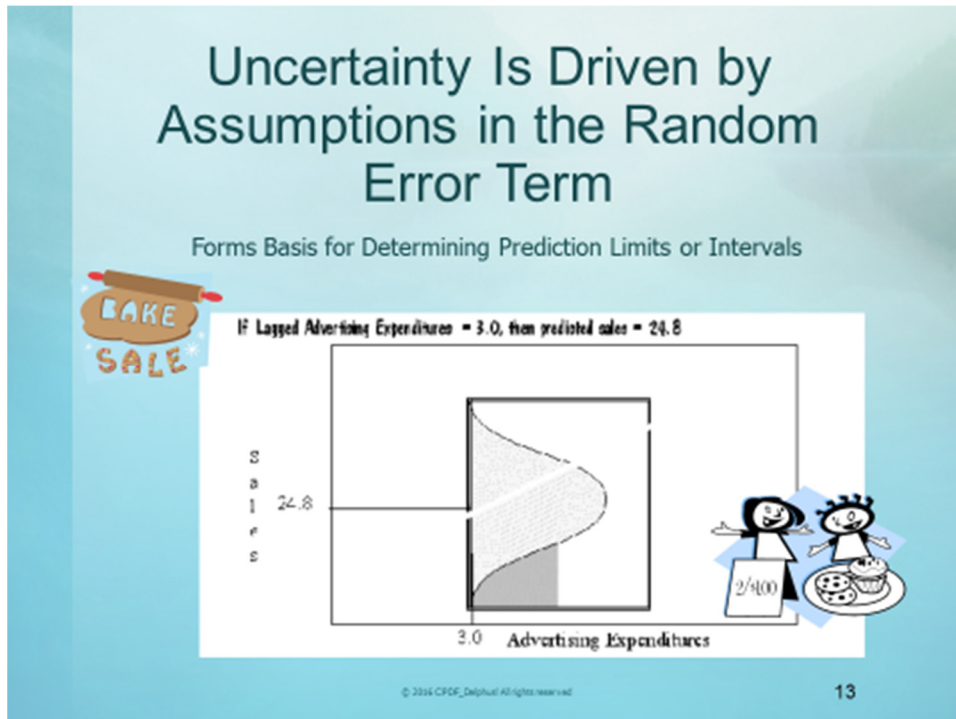
How do you use a nonconventional method to find exceptions in datasets?

- Methodology attributed to the first Data Scientist John W. Tukey, going back to the 1970s
- The Interquartile difference (IQD) is the difference between the 75th and 25th percentile in an ordered data set
- Unusual values can be detected by considering outer fences
 - Lower outer fence = **25th percentile – 1.5 IQD**
 - Upper outer fence = **75th percentile + 1.5 IQD**
 - For outer fences, use 2.7 instead of 1.50
- Alternatively, using **Median +/- 2.7 UMdAd**

$$\text{UMdAd} = [\text{Med} \{\text{Abs Deviation from Med}\}] / 0.6745$$

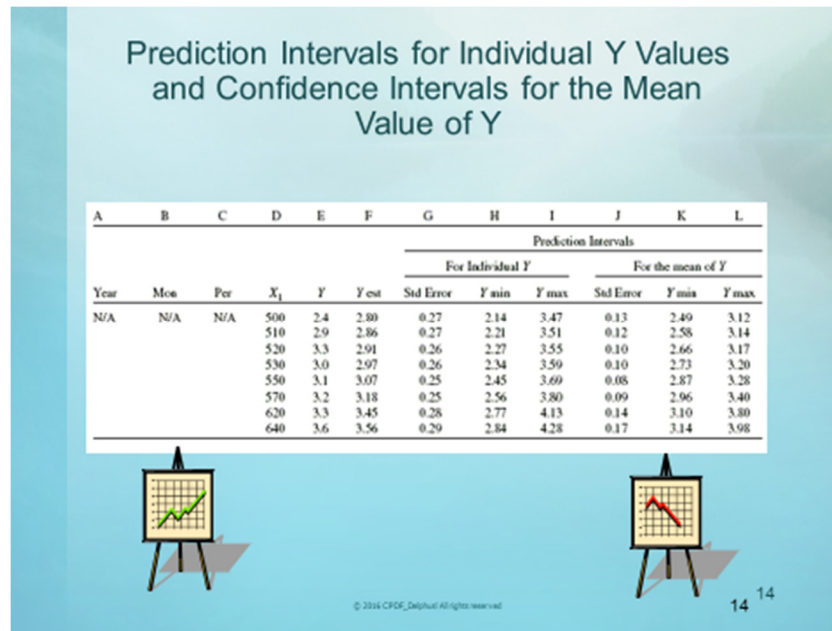
- Contrast this with conventional method of mean +/- 3 St.Dev, based on normality theory

You can find these summary measures in the Data Analysis Add-in in Excel.



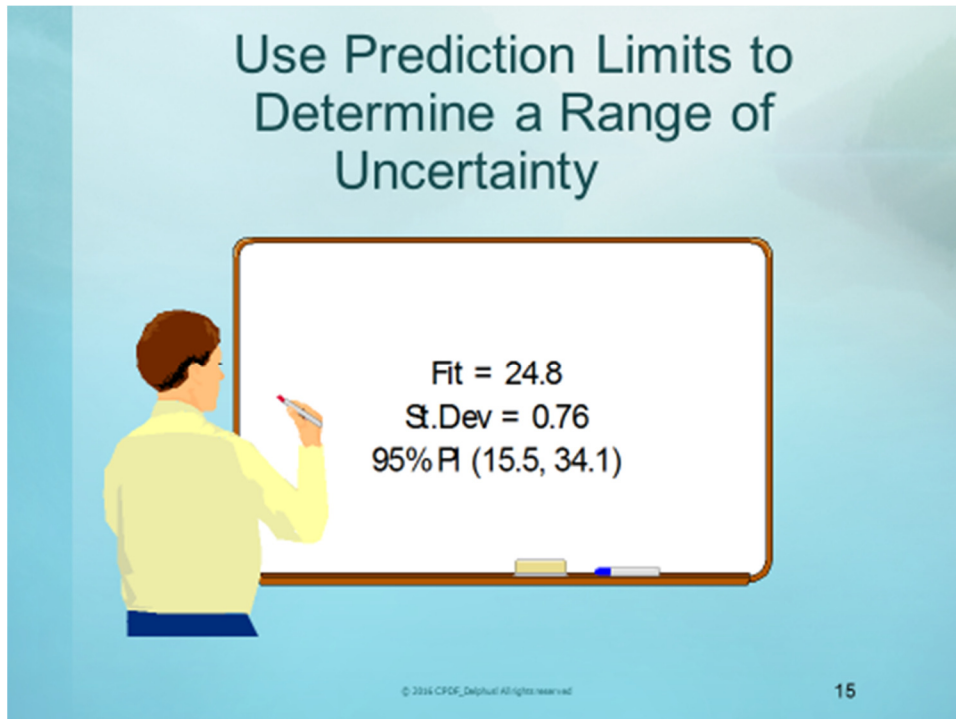
What is the role of the normality assumptions for the random error term in determining prediction limits and forecast ranges?

- Recognize assumptions on which probability limits are based
- Pattern of error distribution is assumed to be normally distributed (usually for theoretical reasons more than practical reasons)
- Normal distribution is mound or bell-shaped and symmetrical distribution may not be realistic.



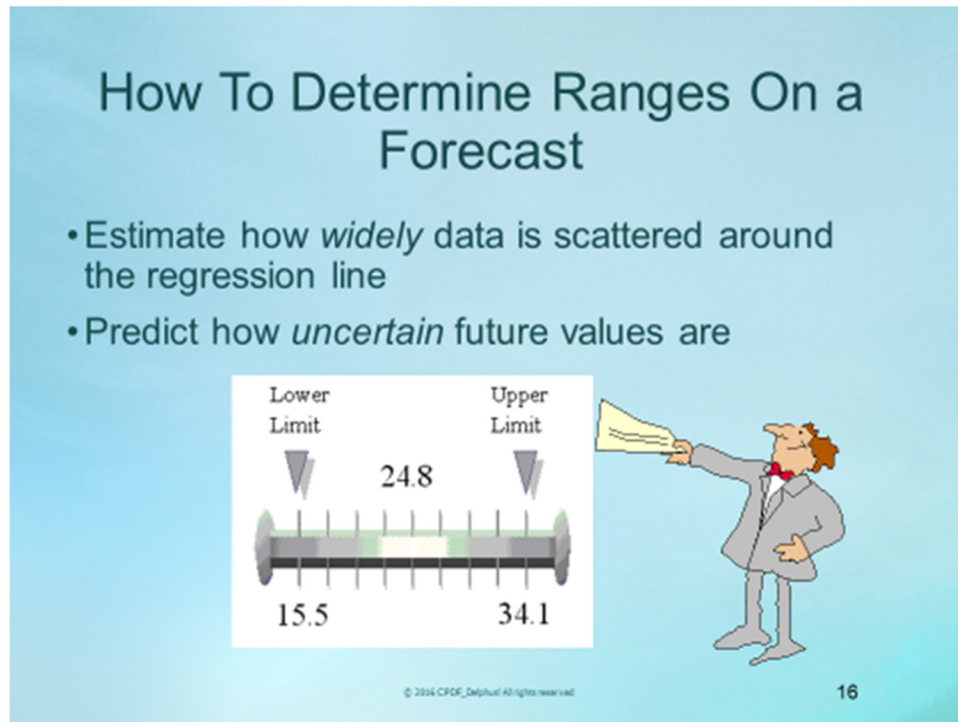
How do you use prediction intervals for individual values of Y and contrast that with confidence intervals for the mean value of Y?

- First, identify an appropriate model for the data
- Next, estimate the parameters of the model. Include summary statistics and significance tests to document results:
- What are the forecasts given by the model? Are they reasonable?
- Make a comparison of forecasts with history. Is the accuracy level acceptable?
- Analyze residual patterns over the fitted and and forecast errors over the forecast periods. Do they appear random?
- Calculate probability limits for the forecast errors and their cumulative sum over the forecast period. These are useful for monitoring the forecasts, as actual results become available. A pattern of over-forecasts, under-forecasting, or too many values falling outside the limits suggests that the model may need to be reevaluated.
- Exhibit shows prediction intervals for a simple linear regression model. Prediction intervals for individual (new) values of Y are shown in columns H and I
- Confidence intervals for the true mean of Y are shown in columns J and K. These intervals are different because it is easier to forecast the mean than individual values
- Confidence interval for the true mean is tighter than the prediction intervals for the individual Y values corresponding to a given X value.



How do you use prediction limits to determine a range of uncertainty?

- Based on regression assumptions, the theory explains how we can construct uncertainty levels (prediction limits) about predicted values as well as the mean (fitted) values
- Uncertainty is expressed as an interval around future values with an upper and lower limit (associated with a particular probability, expressed as a percentage)



How do you determining ranges on a forecast

- If lagged advertising expenditures is assumed to be 3.0, then the regression model determines a predicted value of 24.8
- The prediction limit on this forecast is determined to range from 15.5 to 34.1 with a probability of 0.95, a range of about 38%.
- The model output gives:

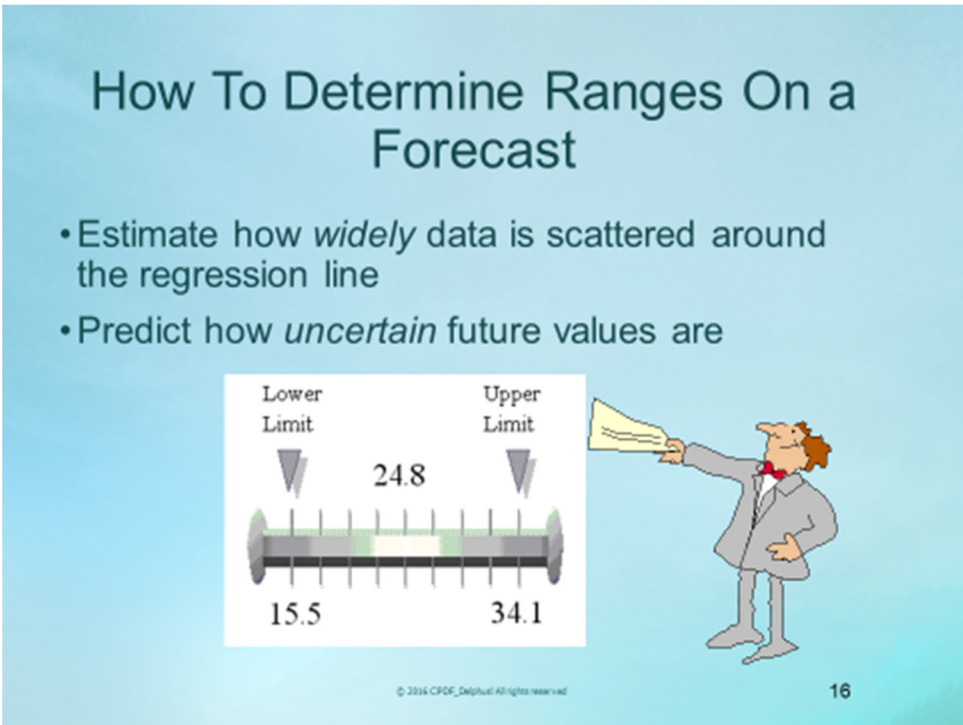
Fit	StDev Fit	95.0% CI	95.0% PI
24.814	0.762	(23.264, 26.364)	(15.528, 34.100)

- The eleventh value between sales and advertising appears unusual. For an advertising expenditure of 4, the sales were only 15.5, which appears to be low by about 11.4 as would be suggested by the model

Unusual Observations:

Obs	C1	C2	Fit	StDev Fit	Residual	St Resid
11	4.00	15.500	26.983	0.895	-11.483	-2.60R

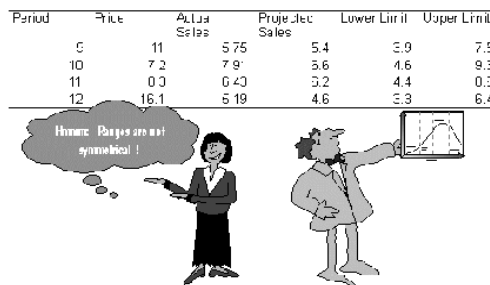
R denotes an observation with a large standardized residual.



Projections and ranges using simple linear regression

Period	Price	Actual Sales	Projected Sales	Lower Limit	Upper Limit
9	11	5.75	5.7	3.7	7.7
10	7.2	7.91	6.5	4.4	8.6
11	8.3	6.43	6.3	4.2	8.3
12	16.15	19	4.6	2.5	6.7

Projections and Ranges (Log Transformed Data)



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Projections and ranges for log-transformed data

Period	Price	Actual Sales	Projected Sales	Lower Limit	Upper Limit
9	11	5.75	5.4	3.9	7.5
10	7.2	7.91	6.6	4.6	9.3
11	8.3	6.43	6.2	4.4	8.6
12	16.1	4.6	3.3	3.3	6.4

Workshop K

Working with Residuals and Forecast Errors to Improve Forecasting Performance

- 1. Run Trend-Seasonal-Irregular Decomposition on Tourism data (Precourse workshop) and note contributions to total variation**
In Excel, press *Tools > Addins > Data Analysis > ANOVA: Two-Factor Without Replication*
- 2. Create a Trend Seasonal Model**
 - Use Damped Trend Seasonal Exponential Smoothing to make a forecast over a 24-month forecast horizon
 - Review the model residuals
 - Graph the residuals (model errors) over the fit period
 - Can you VISUALLY note BIAS and outliers in the fitted values? → Under- or overfit?

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Workshop K

Working With Residuals and Forecast Errors To Improve Forecasting Performance

... after the Black Swan has appeared
(Black Swan with Nassim Taleb)
<http://www.youtube.com/watch?v=BDbuJtAiABA>

Workshop Take-away: Multiple Linear Regression Checklist

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A Checklist for Multiple Linear Regression

The following checklist can be used as basis for developing a scorecard to help identify gaps in the forecasting process that will need attention. It can be scored or color coded on three levels: Green = **YES**, Yellow = **SOMEWHAT**, Red = **NO**


- € Is the relationship between the variables linear?
- € Have linearizing transformations been tried?
- € What is the correlation structure among the independent variables?
- € Have seasonal and/or trend influences been identified and removed?
- € Have outliers been identified and replaced when appropriate?
- € Do the residuals from the model appear to be random?
- € Are any changes in the variance apparent (is there heteroscedasticity)?
- € Are there any other unusual patterns in the residuals, such as cycles or cup shaped or trending patterns?
- € Have *F* tests for overall significance been reviewed?
- € Do the *t* statistics indicate any unusual relationships or problem variables?
- € Can the coefficients be appropriately interpreted?
- € Have forecast tests been made?



Part XIII

Improving Forecasts with Informed Judgment

Learning Objectives



- Using a structured approach to integrate qualitative (mostly judgmental) and quantitative (mostly numerical) techniques
- Recognizing the pros and cons of subjective techniques in forecasting
- Understanding when and how to make judgmental overrides to **unconstrained, unbiased**, baseline demand forecasts
- Creating the final forecast embracing Change and Chance
- Developing a plan for process improvement
- Certification: Developing a process for setting standards and establishing checklists

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What You Should Be Able To Do

After completing this topic, you should be able to:

- Use a structured judgment to apply forecasting techniques in practice
- Recognize the pros and cons of subjective techniques
- Understand when and how to make judgmental overrides
- Use informed judgment to evaluate a model's forecasting applicability
- Use model simulations to quantify uncertainty
- Develop a plan for forecast process improvement

How you will check your progress

Benchmark yourself against a Forecaster Checklist and a Forecast Manager Checklist found at the end of this lesson.

Resources

Levenbach, H. (2017). **C&C**, Chapter 14

Ord, K. and R. Fildes. **Principles of Business Forecasting** (2013). Chapters 11 and 13

What Is Informed Judgment?

- Provides natural framework to future-oriented thinking
- Minimizes use of informal forecast adjustments
- Focuses on predictability rather than desired outcomes
- Clarifies meaning of forecast accuracy and performance measurement
- Avoids adopting spurious relationships
- Requires documentation of forecasting process



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What is informed judgment?

- Provides natural framework to future-oriented thinking
- Minimizes use of informal forecast adjustments
- Focuses on predictability rather than desired outcomes
- Clarifies meaning of forecast accuracy and performance
- Avoids adopting spurious relationships
- Requires documentation of forecasting process



When should you make judgmental forecasts?

- Strong domain knowledge available
 - Absence can lead to reduced accuracy
 - Overcomes human weaknesses in judgmental behavior

Use informed judgment that produces specific output, namely advice about the future

Human Limitations in Making Judgmental Forecasts

Poorer forecasts but also

- Too much weight on personal information/knowledge
- Reading too much into the noise process
- Treating individual events as unique
- Lack of experience with past errors
- Falling into judgmental traps



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What are human limitations in making judgmental forecasts?

Poorer forecasts but also

- Too much weight on personal information/knowledge
- Reading too much into the noise process
- Treating individual events as unique
- Lack of experience with past errors
- Falling into judgmental traps

Judgmental Traps in Forecasting

- Focusing on wrong problem
- Requiring quick forecasts
- Recalling events selectively
- Unable to learn from past experience
- Relying on heuristics and biases



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What are some judgmental traps in forecasting?

- Focusing on wrong problem
- Requiring quick forecasts
- Recalling events selectively
- Unable to learn from past experience
- Relying on heuristics and biases

Avoiding Judgmental Error

- Consider alternative forecasting approaches
- Construct and assess alternative scenarios
- Examine spurious relationships
- Learn from past experiences
- Accept that forecasts will never be perfect – reject that as a myth!
- Accept accountability and avoid blaming others for unexpected results



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How you can avoid judgmental error

- Consider alternative forecasting approaches
- Construct and assess alternative scenarios
- Examine spurious relationships
- Learn from past experiences
- Accept that forecasts will never be perfect – reject that as a myth!
- Accept accountability and avoid blaming others for unexpected results

Classification of Forecasting Methods

○ Subjective and judgmental forecasting

- Useful when a product and service does not have an order history, for example, new products or product upgrades
- Forecasts are subject to biases like **optimism** and **overconfidence**
- Main disadvantage is the possibility of misleading information, which could prove costly to the business

○ Objective forecasting

- Most often used on existing product lines
- Involves research and analysis to determine what is needed based on empirical data
- To gather the most accurate data on future product usage, we need to:
 - ✓ examine historical data
 - ✓ identify and interpret trends
 - ✓ analyze existing usage
 - ✓ guess factors in known changes in future demand



Objective forecasting is less risky than subjective methods, as it relies on past performance and quantitative facts to create more accurate forecasts.

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How you can classify forecasting methods

Forecasting techniques can be classified as either **qualitative** or **quantitative**. This distinction may have no bearing on the accuracy of the forecast achievable by a particular approach. What is the difference between a qualitative and quantitative method? To describe what one of two mutually exclusive things are, we only need to define one. It is easier to define quantitative as something that involves *mostly* numbers and *some* judgment. Then, the concept of qualitative is the opposite—*mostly* judgment and *some* numbers.

Quantitative methods are characterized by a rigorous data acquisition procedure along with a mechanical application of techniques. Qualitative methods may lack rigorous data acquisition and involve techniques that are more intuitive.

Delphi Method

- Use domain experts with different experiences and backgrounds
- Keep participants anonymous
- Provide feedback in several iterations
- Average results



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What is the Delphi method?

- Use domain experts with different experiences and backgrounds
- Keep participants anonymous
- Provide feedback in several iterations
- Average results

The Forecasting Audit

- Understanding the current practice
 - How it is done
- Establishing goals for improvement
 - How it should be done
- Developing a pathway to the future
 - How we get to world-class performance



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What is a forecasting audit?

- Understanding the current practice
 - How it is done
- Establishing goals for improvement
 - How it should be done
- Developing a pathway to the future
 - How we get to world-class performance

A Framework For Setting Forecasting Standards

- Four management dimensions
 - Functional integration
 - Approach
 - Systems
 - Performance measurement
- Development stages
 - Four maturity stages for each dimension



Dr. John T. Mentzner
1933-2010

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What is a framework for setting forecasting standards?

- Four management dimensions
 - Functional integration
 - Approach
 - Systems
 - Performance measurement
- Development stages
 - Four stages for each dimension




What is meant by functional integration?

In the entire supply chain of the company, practice and preach the **three C's**:

- Communication among functional groups
- Coordination of forecasting data
- Collaboration with sales force and trading partners

Best Approach to Forecast Improvement

- ❑ Distinguish between forecasting and planning
- ❑ Gain understanding of forecasting techniques
- ❑ Decide on what to forecast, when and for whom
- ❑ Emphasize ongoing training support



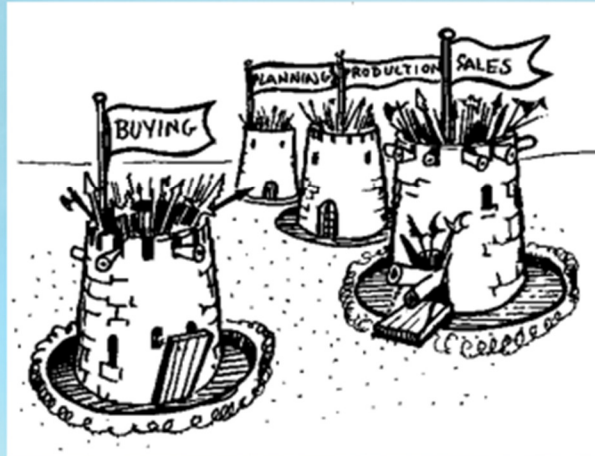
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What is the best approach to forecast improvement?

- Distinguish between forecasting and planning
- Gain understanding of forecasting techniques
- Decide on what to forecast, when and for whom
- Emphasize ongoing training support

Maturing As a Company Means Moving From This...



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... To This

Shared goals
Collaboration

Integrated Planning

Integrated Scorecards and KPIs



www.kamikaze.net

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Navigate Uncertainty through Agile Execution: See. Amell and Larsson - <https://www.amazon.com/Mastering-Agility-Successfully-Navigating-Uncertainty/dp/1522787844>

Technology – Create Useable Systems

- Use Forecast Decision Support Systems (FDSS), now available in the cloud for tablet and smartphone, wisely incorporating a support mechanism for a structured forecasting process
- Ensure usability through easy-to-use interfaces with internal and external data sources
- Maintain up-to-date forecasting engines based on generally accepted, tested and documented procedures
- Provide customized reporting and display screens for gap and performance analyses



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Using technology, how do you create useable forecasting decision support systems?

- Use Forecast Support Systems wisely incorporating a support mechanism for a structured forecasting process
- Ensure usability through easy-to-use interfaces with internal and external data sources
- Maintain up-to-date forecasting engines based on generally accepted procedures
- Provide customized reporting and display screens for gap and performance analyses

How To Measure Forecast Performance

- Recognize impact of *forecast horizons* on the business in establishing these metrics
- Develop *multiple metrics* for measuring performance for both forecasts and forecasters
- Avoid exclusive use of *accuracy* in measuring forecasting effectiveness



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What is performance measurement?

- Develop multiple metrics for measuring performance for both forecasts and forecasters
- Recognize impact of forecasts on the business in establishing these metrics
- Avoid exclusive use of accuracy in measuring forecasting effectiveness
- A case example:

A quote:

“Our accuracy is measured for active items only. That is to say, items that require inventory purchases for replenishment. Unplanned sales of discontinued/excess inventory are not measured. New items are included upon launch, but not before, even though there is early demand for sampling/ranking purposes. Weighting is not considered, but our category breakdown tells the story, one being almost 100% imported at the upper echelon of our cost scale, the other being almost 100% domestic, and less expensive. We pull data on a sku by sku basis, but aggregate the absolute error for our measurements. We also freeze our forecasts that we’re comparing 3 months (inclusive) in advance.”

How Can We Use Quantitative Tools for Forecast Improvement?

Recommendation:

- Benchmark studies to check out 'best' forecasting techniques used in practice
- Based on applicable horizon, apply holdout samples to evaluate a model's forecasting applicability
- Run model simulations to measure uncertainty
- Embrace informed judgment



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How do we use quantitative techniques for process improvement?

Use

- Benchmark studies to check out forecasting techniques used in practice
- Based on applicable horizon, holdouts to evaluate a model's forecasting applicability
- Model simulations to measure uncertainty
- Informed judgment
- Embrace informed judgment

Is There A “Best” Technique?

Benchmark studies rely on

Data attributes

- Characteristic data patterns
- Minimum data requirements

Forecast objectives and resources

- Forecast horizon
- Desired accuracy
- Applicability
- Knowledgeable resources



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Is there a best technique?

Benchmark studies rely on

- Data attributes
 - Characteristic data patterns
 - Minimum data requirements
- Forecast objectives and resources
 - Forecast horizon
 - Desired accuracy
 - Applicability
 - Knowledgeable Resources

Role of the Forecast Horizon

- Driven by lead time
 - Short-term → univariate, qualitative
 - Intermediate term → causal regression
 - Long-term → qualitative, simulation
- Desired accuracy driven by business objectives
 - Patterns → univariate, causal regression
 - Turning points → qualitative




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What is the role of the forecast horizon?

- Driven by lead time
 - Short-term → univariate, qualitative
 - Intermediate term → causal regression
 - Long-term → qualitative, simulation
 -
- Desired accuracy driven by business objectives
 - Patterns → univariate, causal regression
 - Turning points → qualitative

Using Rolling Hold-Out Periods



- Omit data at end of time series
- Based on forecast horizon, use statistical modeling to make rolling forecasts and set prediction limits
- Evaluate forecast performance in hold out sample period using



Waterfall charts
Multiple accuracy measures

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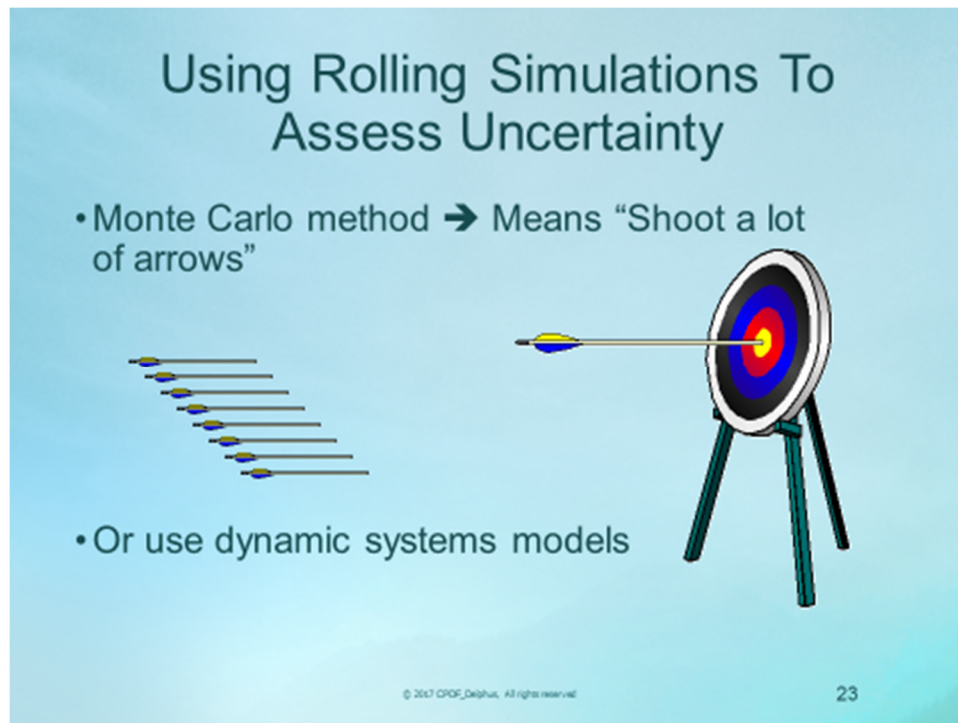
Why do you use rolling hold-out periods for evaluating forecasting performance?

- Omit data at end of time series
- Use model to make projections and prediction limits
- Evaluate model performance in hold out period
 - Multiple accuracy measures
 - Waterfall charts



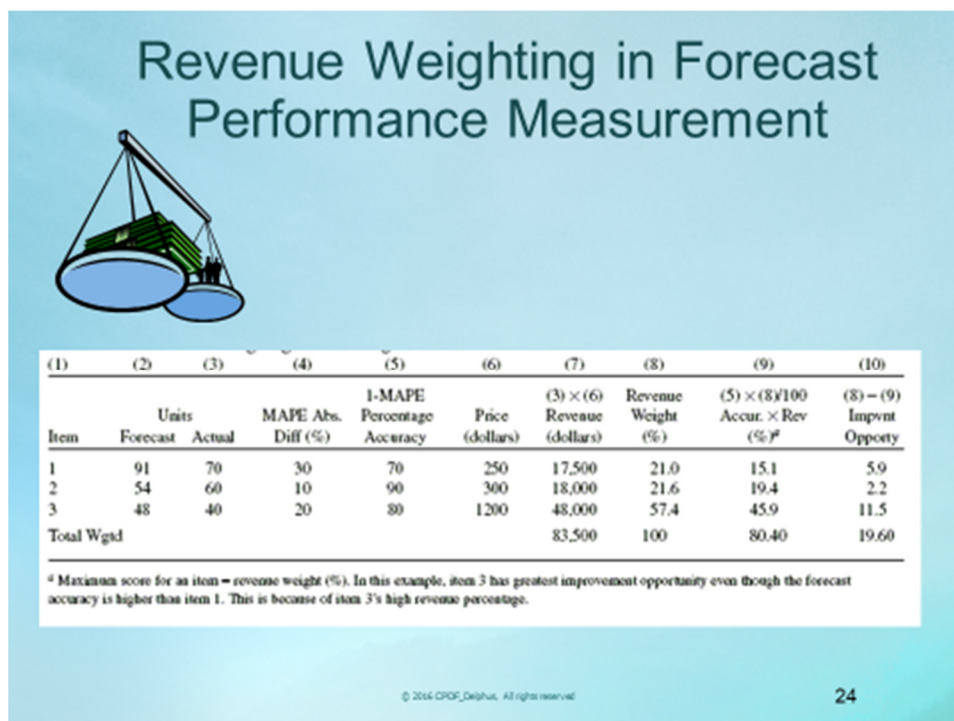
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- First column shows the different rolling forecasts made at different starting months
- Subsequent columns give the one to many-step ahead forecasts over the forecast horizon
 - Tables can be reproduced using different measures based on the forecast errors, such as percentage error or absolute percentage error
- Summarizing each column gives the performance of a given month summarized over the different rolling forecasts
- Summarizing over rows measures performance of a given forecast over the forecast horizon



How do you use rolling simulations to assess uncertainty?

- “Shoot a lot of arrows” → Monte Carlo Method
- Dynamic systems models are complex systems emulating the dynamics of the forecasting process



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How do you use revenue weighting in forecasting performance measurements?

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Item	Units Forecast	Units Actual	MAPE Abs. Diff (%)	1-MAPE Percentage Accuracy	Price (dollars)	(3) × (6) Revenue (dollars)	Revenue Weight (%)	(5) × (8)/100 Accur. × Rev (%) ^a	(8) – (9) Impvmt Opportunity
1	91	70	30	70	250	17,500	21.0	15.1	5.9
2	54	60	10	90	300	18,000	21.6	19.4	2.2
3	48	40	20	80	1200	48,000	57.4	45.9	11.5
Total Wgtd						83,500	100	80.40	19.60

^a Maximum score for an item = revenue weight (%). In this example, item 3 has greatest improvement opportunity even though the forecast accuracy is higher than item 1. This is because of item 3's high revenue percentage.

Planning for Forecast Improvement

- Organizational issues
 - Changes, location, staffing
- Forecast process reviews
 - Periodic and documented
- Performance measurement
 - Adequacy, detail
- System development
 - Upgrades, new technology
- Training development
 - New systems, staffing requirements, reorganizations



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Planning for improvement

- Organizational issues
 - Changes, location, staffing
- Forecast process reviews
 - Periodic and documented
- Performance measurement
 - Adequacy, detail
- System development
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- Training development
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Overcoming Barriers and Closing Gaps

- Role of culture in the business
 - Breaking down silos
 - Gaining credibility
- Controlling system technologies
 - First the process, then the system
- Keeping management involved and educated about forecasting
 - Provide management reviews and training opportunities
 - Establish a Person-in-Charge (PIC) of forecasting
 - Show how forecasts affect the bottom line!!

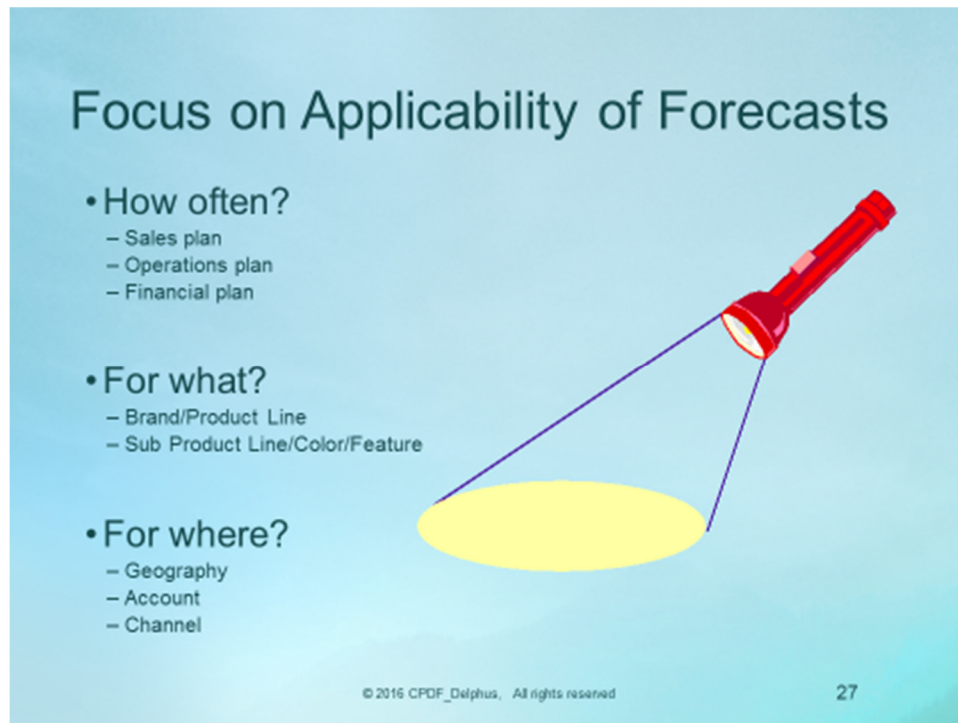


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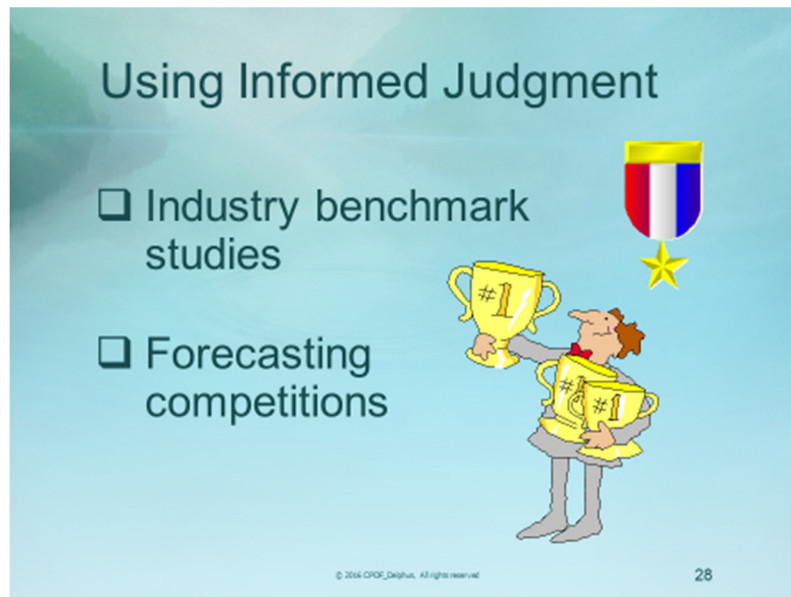
How do you overcome barriers and close gaps?

- Role of culture in the business
 - Breaking down silos
 - Gaining credibility
- Controlling system technologies
 - First the process, then the system
- Keeping management involved and educated about forecasting
 - Provide management reviews and training opportunities
 - Establish a Person-in-Charge (PIC) of forecasting
 - Show how forecasts affect the bottom line!!



How applicable are the forecasts?

- How often?
 - Sales plan
 - Operations plan
 - Financial plan
- For what?
 - Brand/Product Line
 - Sub Product Line/Color/Feature
- For where?
 - Geography
 - Account
 - Channel

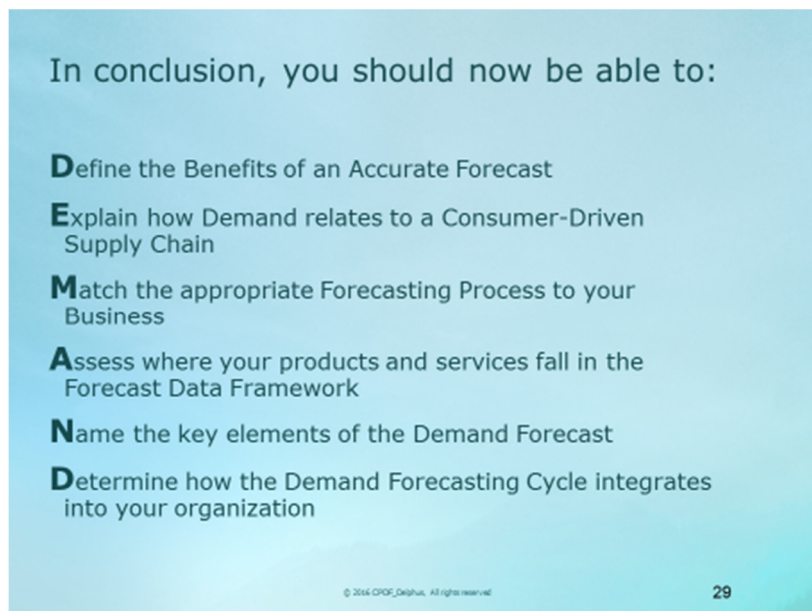


Using informed judgment

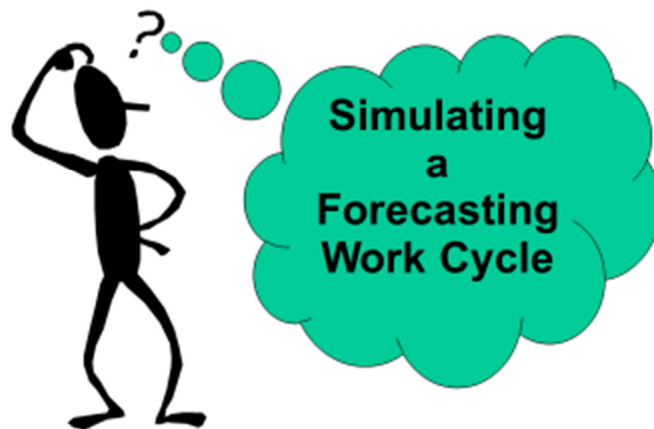
Use your best judgment to study

- Industry benchmark studies
- Forecasting competition

In conclusion, you should be able to:



Final Workshop L (13)



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Follow-on Workshop: Agile Demand Forecasting (**CPDF III**) is a dynamic, hands-on simulation of the demand forecasting work cycle using a real company 'big database' with forecast simulations using hold-out samples. Conducted 'in the cloud,'. Check schedules on <http://www.cpdftraining.org>.