ΧΑΡΟΚΟΠΕΙΟ ΠΑΝΕΠΙΣΤΗΜΙΟ
HAROKOPIO UNIVERSITY

Supply Chain Management

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The Value Chain Processes Strategy

Product development strategy specifies the portfolio of new products that a company aims to develop.

Marketing and sales strategy specifies how the market will be segmented and how the product will be positioned, priced, and promoted.

Operations + Distribution + Service strategy = Supply Chain strategy

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Demand Forecasting in SCM

WHAT IS FORECASTING?

Procedure to predict future events.

- ✓ Historical data + mathematical model
- ✓ Intuition (e.g. this new version of the game will sell 30% more than the old one.)
- ✓ Managers' judgement
- ✓ Combination of the above.

DEMAND FORECASTING IN SC: WHY?

Effective supply chain planning depends on demand forecasting of the firm's products and services.

Essential for all strategic and planning business decisions (production, supplies, inventory, human resources, facilities etc.

Key for push and pull processes:

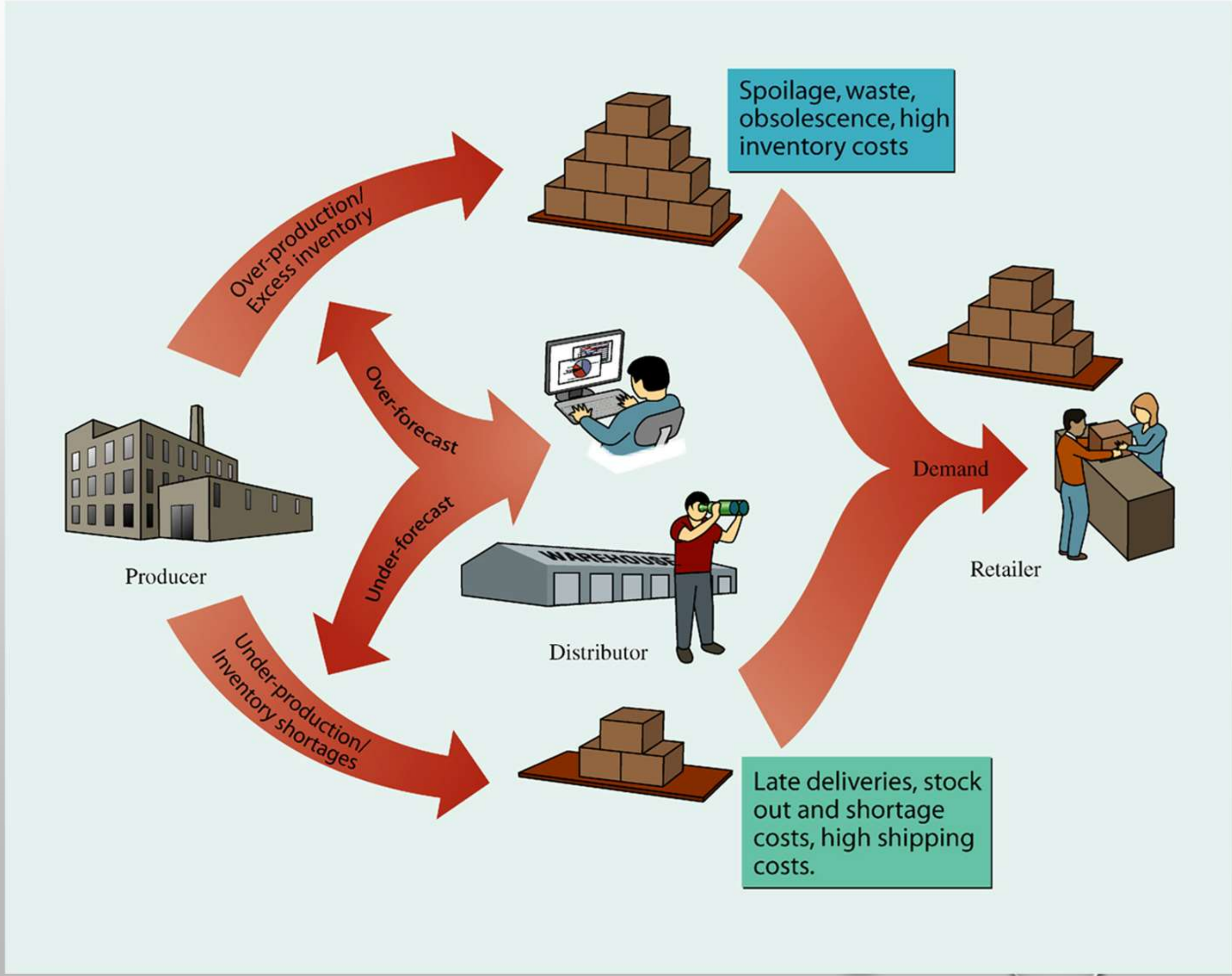
- ✓ Pull processes: act in response to customer demand -> demand forecast to determine the available inventory level of material/ parts to produce the ordered products.
- ✓ Push processes: act in anticipation of customer demand -> demand forecast to plan distribution, production etc.

DEMAND FORECASTING IN SC: WHY?

Demand Driven leaders have:
15% less inventory
17% stronger order fulfillment

Which translates to: 60% better profit margins

EFFECT OF INACCURATE DEMAND FORECASTING IN SCM



Source: Russell and Taylor, 2011. Operations Management, 7th edition, John Wiley & Sons - Chapter 12.

EFFECT OF INACCURATE DEMAND FORECASTING IN SCM

- United Airlines
  - ✓ April, 2017
  - ✓ Overbooked flight
  - ✓ Airlines usually oversell, betting on the number of passengers who will miss their flights.
  - ✓ Result: a passenger being blooded was dragged from his seat.
  - ✓ Social media -> customers call for a boycott of United Airlines
  - ✓ Market capitalization dropped by more than $250 million.
- Nike, 2001
  - ✓ new demand planning system
  - ✓ Inadequate system testing
  - ✓ excess stock of low selling shoes & not enough shoes of fast moving shoes
  - ✓ Sales loss: $100 million.

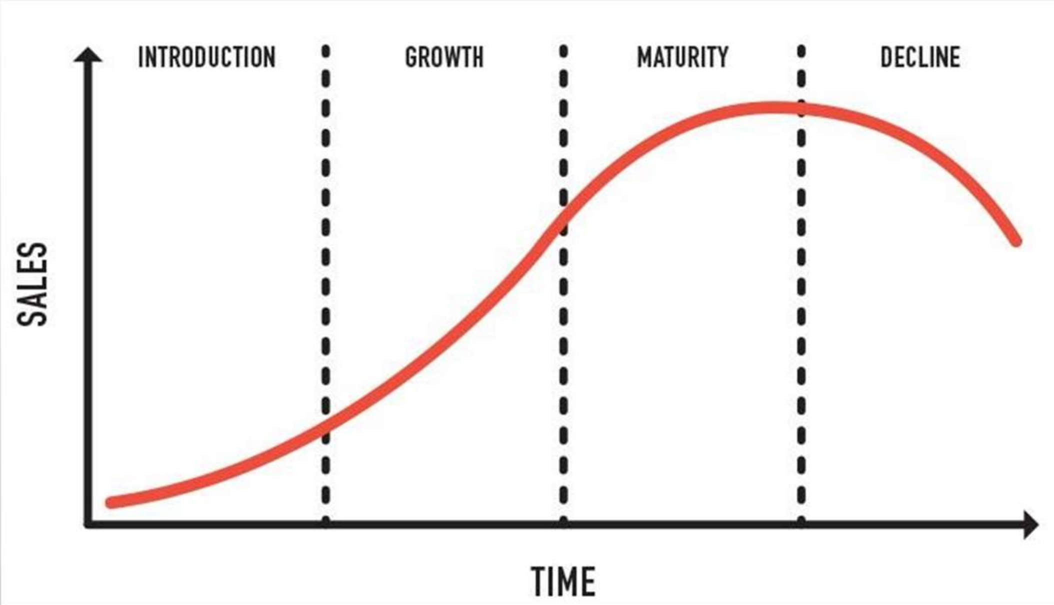
Forecasting: Facts

- Forecasts are always inaccurate.
- Forecasts should always include measures of forecast errors.
- Long-term forecasts are usually less accurate than short-term forecasts.
- There is seldom one superior forecasting method.
- Forecasts may be influenced by:
    - ✓ unpredictable outside factors (e.g. weather changes, unpredicted political events)
    - ✓ product life cycle
    - ✓ demand of related products (e.g. sales of navigation systems and cars)

Forecasting: Facts

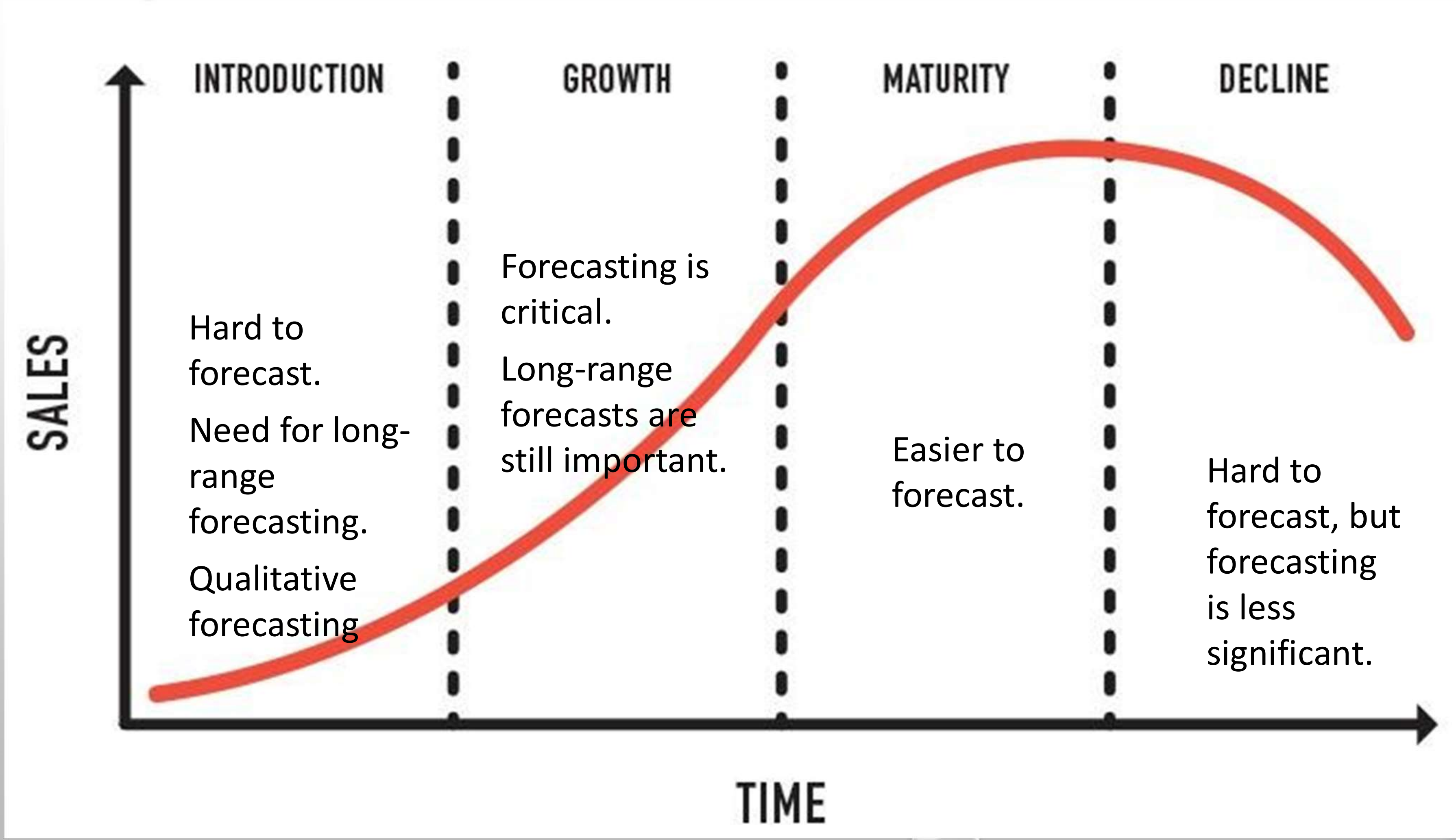
- Aggregated and product family forecasts are more accurate.
- The farther a supply chain partner is from the consumers, the less accurate the demand forecasts.
- Balanced mix of quantitative forecasts + human intuition (managers take the final decision).
- Competitors’ actions, state of the economy, pricing strategy, marketing activities should be considered when generating demand forecasts.
- Forecasts must be updated regularly to maintain their accuracy and integrity.

PRODUCT LIFE CYCLE EFFECT ON FORECASTING



Product life cycle: the stages a product goes through from when it was first thought of until it finally is removed from the market.

- Product introduction and growth require longer forecasts than maturity and decline.
- Forecasting is critical for introduction and maturity stages.
- As products go through their life cycle and reach maturity and decline, forecasts are useful for production capacity and inventory planning.



INTRODUCTION
GROWTH
MATURITY
DECLINE
SALES
TIME
Hard to forecast.
Need for long-range forecasting.
Qualitative forecasting
Forecasting is critical.
Long-range forecasts are still important.
Easier to forecast.
Hard to forecast, but forecasting is less significant.

FORECASTING TIME HORIZON

	Short-range	Medium (Intermediate)-range	Long-range
Time horizon	Usually <3 months and, < 1 year	> 3 months and < 3 years	≥ 3 years
Suitable for	Planning purchasing, job scheduling, workforce levels, job assignments and production levels.	Sales and Production planning, budgeting, operations planning.	Planning new products and facilities locations, research and development.

FORECASTING TIME HORIZON

<table>
<tr><th>Short-range</th><th>Medium-range</th><th>Long-range</th></tr>
<tr><td>• Utilizing quantitative approaches.
• More accurate than long-range forecasts.</td><td colspan="2">• Utilizing combinations of qualitative and quantitative approaches e.g. launching a new product may require a market survey, a focus group etc.
• Necessary to decide on more comprehensive issues e.g. a firm’s decision to buy a small, national production facility to expand to a new market. Such decisions may take years of study and they are multi-criteria problems.</td></tr>
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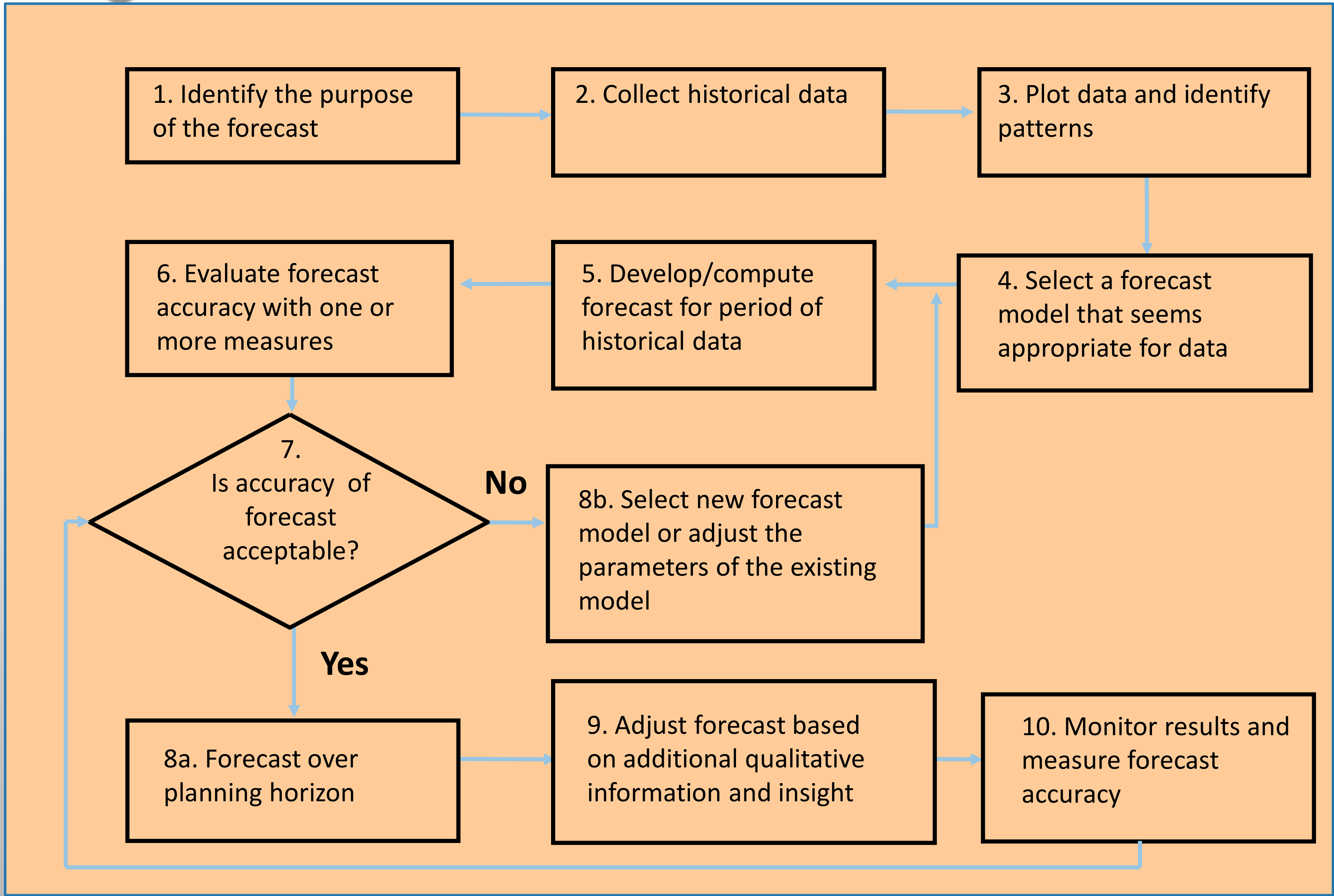
Forecasting: FACTORS INFLUENCING THE CUSTOMER DEMAND LIFE CYCLE

- Seasonality
- Competition
- Type of product / service
- Geography



Source: Russell and Taylor, 2011. Operations Management, 7th edition, John Wiley & Sons - Chapter 12.

DEMAND FORECASTING PROCEDURE

2 Collect historical data + 3 Plot data and identify patterns

Recognize the customer segments and their needs and differences-> different segments may need different forecasting approaches.

Recognize factors that have major influence on demand (seasonality, different sales channels e.g. e-shops, competitive products, substitute products etc.)

TYPES OF FORECASTING METHODS

	Qualitative Methods	Quantitative Methods
1. Characteristics	Based on human judgment, opinions; subjective and nonmathematical.	Based on mathematics; quantitative in nature.
2. Strengths	Can incorporate latest changes in the environment and "inside information."	Consistent and objective; able to consider much information and data at one time.
3. Weaknesses	Can bias the forecast and reduce forecast accuracy.	Often quantifiable data are not available. Only as good as the data on which they are based.

Source: R. Dan Reid & Nada R. Sanders, 2010. Operations Management, 4th Edition, Wiley - Chapter 8.

QUALITATIVE FORECASTING

- Suitable when little prior information/ knowledge is available e.g. launching new products or new technologies, entering new markets etc.
- Involves intuition, experience of experts.

QUALITATIVE FORECASTING APPROACHES

- *Jury of executive opinion*

Group of high-level experts gives its opinion, sometimes complemented by statistical forecasting models.

- *Delphi method*

Group of experts queried iteratively.

- *Sales force composite*

Sales staff provide their intuitive forecasts -> review and aggregation.

- *Market Survey*

Consumers are queried.

JURY OF EXECUTIVE OPINION

- High-level experts and managers form a small group.
- They estimate demand by working together.
- Managerial experience and knowledge + statistical models.
- Advantage: Relatively quick, Good for launching new products and technologies.
- Disadvantage: one members' opinion may dominate the discussion and the results.

DELPHI METHOD

Iterative process until consensus is reached.

Collective intelligence

3 types of participants:

- ✓Decision makers (5-10 experts) make the forecast.
- ✓Survey respondents (people in different places whose opinion matters)
- ✓Administrative staff (supporting the whole procedure – managing the survey and producing the results).

Advantage: Excellent for launching new products and technologies.

Disadvantage: time consuming

DELPHI METHOD

Start - send a questionnaire to a group of demand forecasting experts

Create a summary of the responses from the first round

Share the summary with your panel.

Repeat - successive rounds

The answers from each round, shared anonymously, influence the next set of responses.

The Delphi method is complete when the group comes to a consensus.

Draw on the knowledge of people with different areas of expertise.

Anonymity ->frank answers.

SALES FORCE COMPOSITE

- Each sales employee is asked to forecast sales in his region and for the products he handles.
- Review each sales person's projection.
- Combination and Aggregation at district & national levels and per product/ service line.
- Advantage: sales staff know consumers first hand.
- Disadvantage: over optimistic projections

MARKET SURVEY

- Representative sample of consumers participate to a survey (and on-line).
- Consumers' interviews
- Useful and for product/ service design.
- Advantage: simple and direct
- Disadvantage:
  - ✓collects optimistic perceptions, not actions.
  - ✓difficult to build a good questionnaire

COLLABORATIVE PLANNING FORECASTING & REPLENISHMENT (CPFR)

COLLABORATIVE PLANNING FORECASTING & REPLENISHMENT (CPFR)

- Establish collaborative relationships between buyers and sellers (they share data)
- Create a joint business plan
- Create a collaborative sales forecast
- Identify exceptions for sales forecast
- Resolve/collaborate on exception items
- Create collaborative order forecast
- Identify exceptions for order forecast
- Resolve/collaborate on exception items
- Generate orders

CPFR WHEN:

- Demand is hard to Predict
- New product introductions are frequent
- Lead-times for production and/or replenishment are long
- Product life cycles are short
- Forecast accuracy is low
- High levels of inventory exist in the supply chains
- Consumer expectations are frequently not met
- Seasonal demand variances are significant.

CPFR WHEN:

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3 But:

1. Internal Change
2. Cost
3. Trust

CPFR IN WALMART:

CPFR plays an important role in SCM of WALMART:

- By Avoiding Stock outs
- By Avoiding Lost Sales
- Lost Customers
- By Better controlling inventory
- By Eliminating bullwhip effect
- By Reducing manual orders
- By Reducing excess inventory
- By Improving service levels.

WHAT Role does CPFR Plays:

- By Improving Responsiveness to Consumer Demand
- By Greater Forecast accuracy with single shared forecast
- By Increasing Sales
- By Reducing Inventory
- By Reducing Costs
- By Improving production capacity Utilization and
- By Improving relationship b/w all the trading partners.

CPFR IN WALMART:

- **693 Million Items**
- **20 Million Customers / Day**
- **5000 Stores**
- **3500 Vendors**
- **7.5 TB Data of Inventory**

Wal-Mart
Save Money. Live Better.

Measuring Metrics (Performance)	% age Improvements
Cycle Time	From 25 Days to 3 Days
Increased Sales	11%
On-Time Deliveries	74% to 94%
Inventory Turnover	7 Times / Day
Sales Forecast Accuracy	20% to 60%
Sales Lost due to Stock outs	23% to 15%
Out of Stock Orders	Cut Down by 30%
Cancelled Orders	Reduced 60%
On-time Deliveries	Increased by 95%

CPFR
Collaborative Planning, Forecasting and Replenishment
Enriching Collaboration

Facts & Figures

source
https://www.slideshare.net/DanishAliSyed1/collaborative-planning-forecasting-replenishment-at-walmart

TOP DEMAND PLANNING SOFTWARE

- SAP Integrated Business Planning (Cloud deployment - Real-time scenarios and simulation)
- Oracle Demantra (incremental forecasting, excel-like worksheets, web-based personalized UI)
- Demand Planning (ingests demand-driving variables, uses machine learning)
- Logility Solutions (Logility Digital Supply Chain Platform - blend of artificial intelligence (AI) and advanced analytics)
- NETSTOCK (cloud-based inventory management solution, easy to use dashboard)
- Forecast Pro (off-the-shelf forecasting software trusted by 12,000+ organizations globally to create statistically-based forecasts, integrates into broader planning systems)

Predictive analysis, Machine learning

QUANTITATIVE FORECASTING

- Utilized when there are available historical data and the context is relatively ‘stable’.
- Past is a good indicator of the future.
- Involves mathematical, objective approaches.

QUANTITATIVE FORECASTING

Forecast = Systematic component (S) + Random component (R)

- ✓ S : expected value of demand
- ✓ Forecasting techniques focus on identifying the systematic component.
- ✓ R part of demand (noise) is not explicitly determined.
- ✓ The size and variability of R reflect the forecast error.

Forecasting aspires to filter out the random component and calculate the systematic component.

QUANTITATIVE FORECASTING APPROACHES

Time Series models

- ✓Historical data are formed as a time series of data
- ✓Assume that future resembles the past.
- ✓Demand is only related to time.
- ✓The simplest demand forecasting approach.

Causal/ Associative models

- ✓ Explores cause-and-effect relationships between demand and context factors.
- ✓ Uses leading context indicators to predict the future e.g. how price is related with demand.

TIME SERIES DEMAND FORECASTING

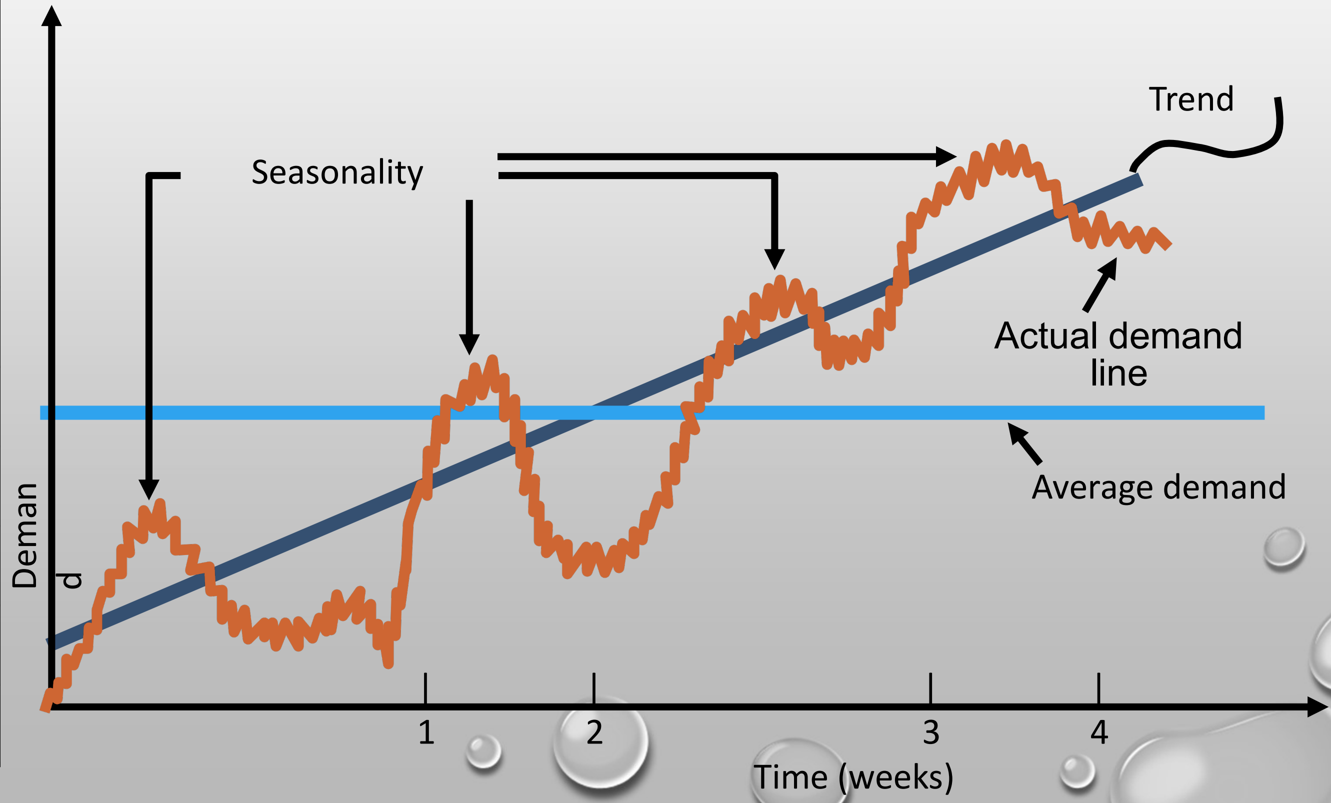
Forecast = Systematic component (S) + Random component (R)

- Systematic component (S) = (level + trend) × seasonal factor
  - ✓ Level : deseasonalized demand
  - ✓ Trend: rate of growth or decline in demand (increasing or decreasing pattern)
  - ✓ Seasonal factor – predictable seasonal fluctuations in demand (demand pattern of constant length that regularly repeats itself)

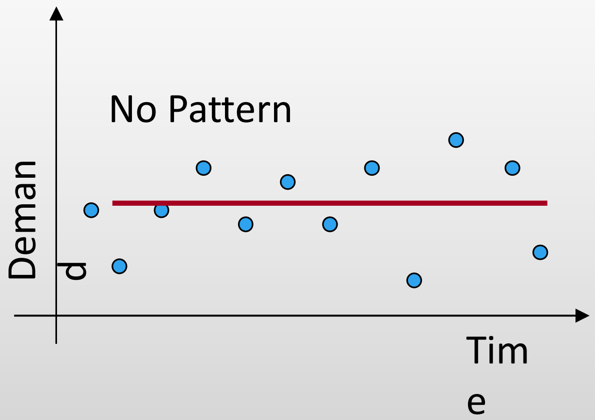
TIME SERIES

Time series: a sequence of evenly spaced (weekly, monthly, quarterly, and so on) data points.

Period (Week)	Orders (in cases)
1	275
2	315
3	200
4	285
5	245
6	215
7	240
8	210



TIME SERIES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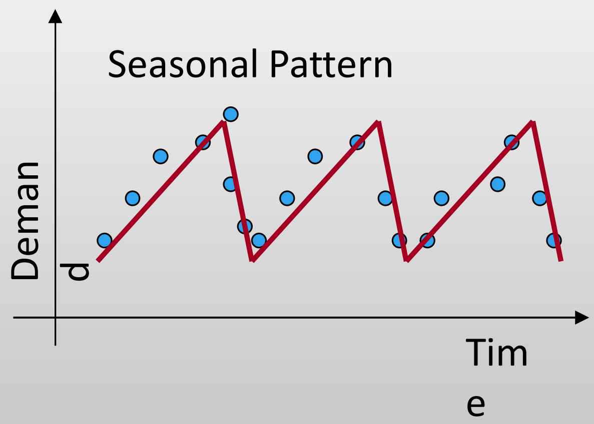
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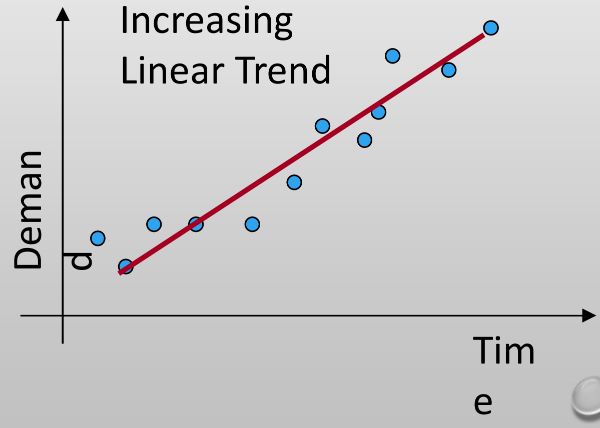
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TIME SERIES FORECASTING

Time Series models

- ✓Naive approach
- ✓Mean
- ✓Moving Average
- ✓Weighted Average

NAIVE APPROACH

Demand in next period = actual demand in the last period

- ✓ $F_{t+1} = L_t$, $L_t = A_t$
- ✓ $F_{t+1} = A_t$
- ✓ F_{t+1}: Forecast of demand for period t+1
- ✓ L_t : Level of demand in period t
- ✓ A_t : Actual demand in period t

- Sometimes cost effective and efficient
- Can be good starting point

Period (Week)	Orders (in cases)
1	275
2	315
3	200
4	285
5	245
6	$F_{5+1} = A_5 = 245$

SIMPLE MEAN

Demand in next period = average of all available demand data in n periods

- ✓ $F_{t+1} = L_t$, $L_t = \sum A_t / n$
- ✓ $F_{t+1} = \sum A_t / n$

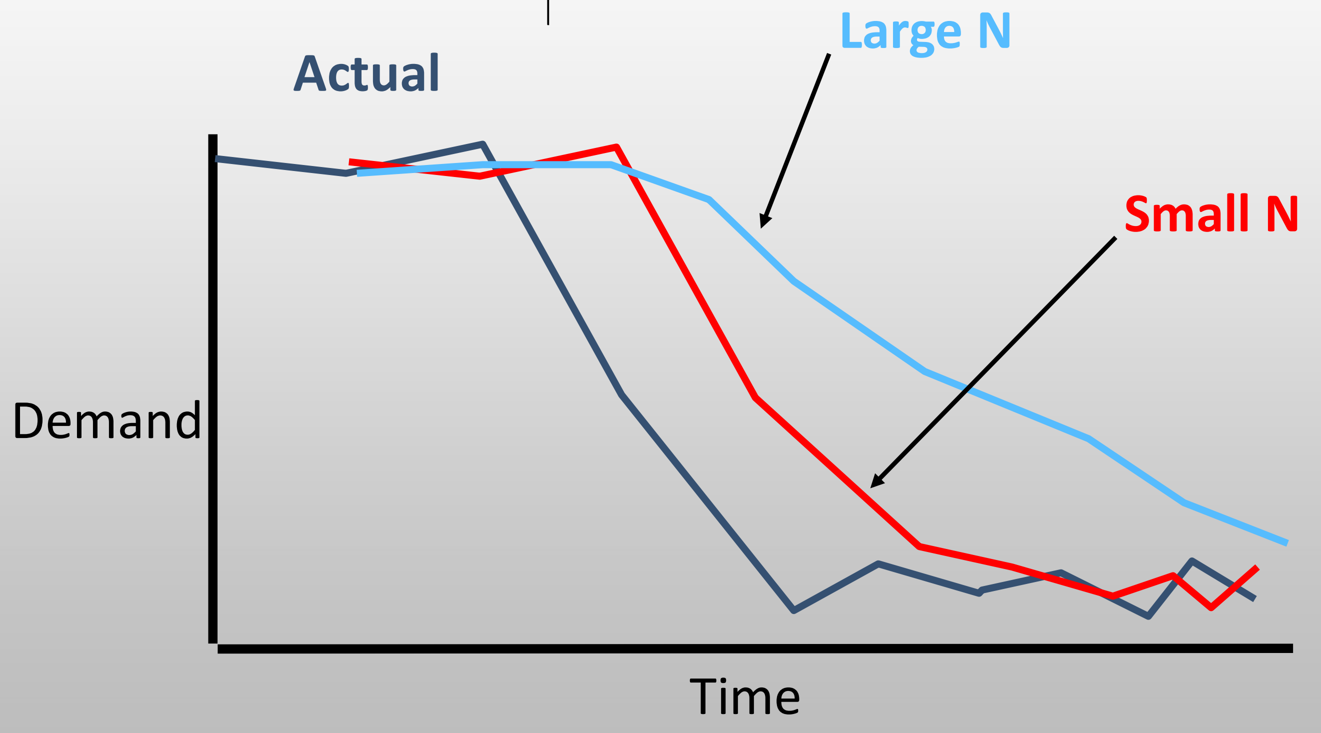
Period (Week)	Orders (in cases)
1	275
2	315
3	200
4	285
5	245
6	$F_{5+1} = (A_5+A_4+A_3+A_2+A_1)/5 \Leftrightarrow F_6 = 1320/5=264$

MOVING AVERAGE

Demand in next period = average of demand in the most recent N periods

- N-period moving average
  - ✓ $F_{t+1} = L_t$, $L_t = D_t + D_{t-1} + D_{t-2} + \ldots + D_{t-N+1} / N$
  - ✓ $F_{t+1} = D_t + D_{t-1} + D_{t-2} + \ldots + D_{t-N+1} / N$
- For each new forecast, you add the most recent demand observation and you drop the earliest.
- Useful if there is little or no trend.
- Useful for smoothing out short-term irregularities in the data series.

Moving Average



Higher N -> bigger smoothing effect

Moving Average Example

t	Month	Actual Demand (A)	3-month Moving Average
1	May	10	
2	June	12	
3	July	13	
4	August	16	$F_4 = (10 + 12 + 13)/3 = 11\ ^{2}/_{3}$
5	September	19	$F_5 = (12 + 13 + 16)/3 = 13\ ^{2}/_{3}$
6	October	23	$F_6 = (13 + 16 + 19)/3 = 16$

Drop A_1, Get A_4

Drop A_2, Get A_5

WEIGHTED MOVING AVERAGE

- Useful when a demand trend or pattern is present -> focus on recent values with weights.
- Weights are selected based on intuition and experience.
- All weights add to 100% or 1.
- N-period weighted moving average
  - ✓ $F_{t+1} = L_t$, $L_t = w_t D_t + w_{t-1} D_{t-1} + w_{t-2} D_{t-2} + \ldots + w_{t-N+1} D_{t-N+1}$
  - ✓ $F_{t+1} = w_t D_t + w_{t-1} D_{t-1} + w_{t-2} D_{t-2} + \ldots + w_{t-N+1} D_{t-N+1}$
  - ✓ $\sum w_t = 1$
- Simple moving average weights equally all demand periods.
- The higher the weight, the more emphasis on the specific demand period over the others.

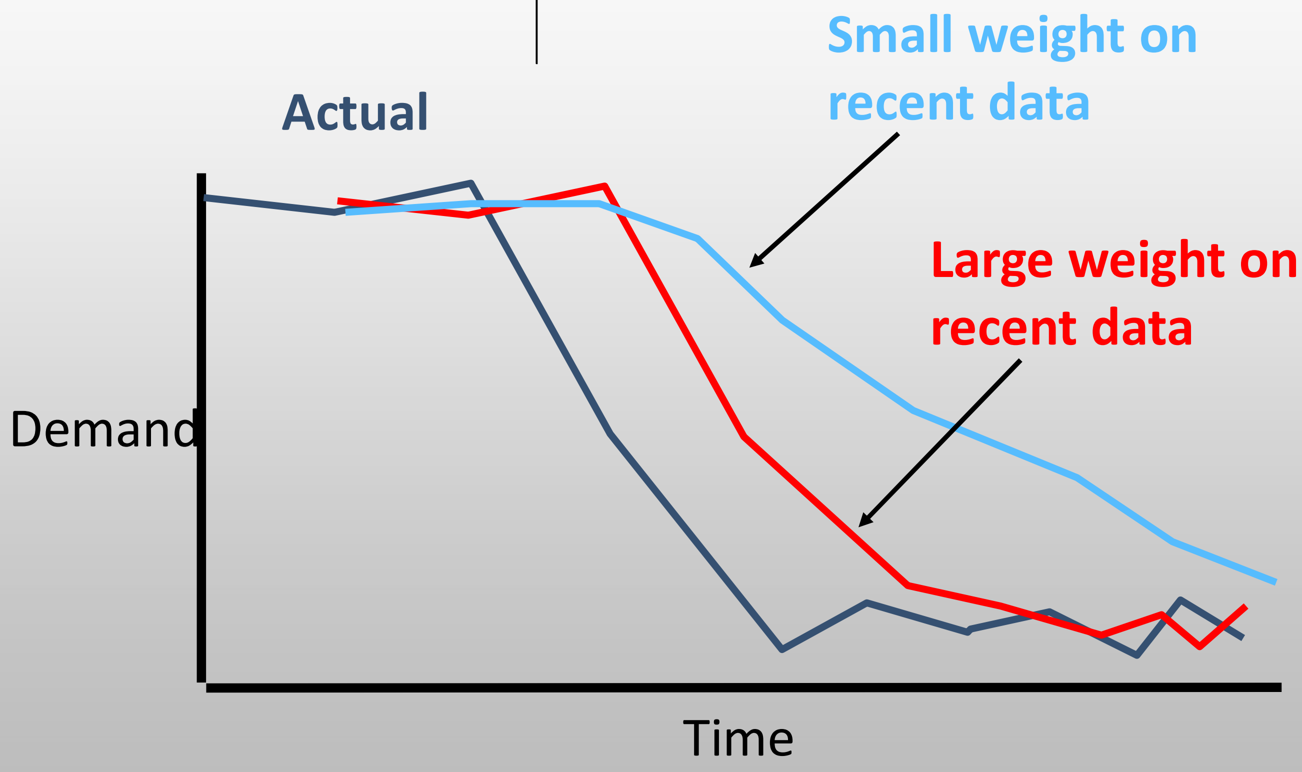
Weighted Moving Average Example

t	Weight (w)	Month	Actual Demand (A)
1	20%	May	10
2	30%	June	12
3	50%	July	13
4		August	16
5		September	19
6		October	23

Weighted Moving Average Example

t	Weight (w)	Month	Actual Demand (A)	3-month Moving Average
1	20%	May	10	
2	30%	June	12	
3	50%	July	13	
4		August	16	$F_4 = 0.2\times10 + 0.3\times12 + 0.5\times13 = 2+3.6+6.5 = 12.1$
2	20%	June	12	
3	30%	July	13	← Drop A_1, Get A_4
4	50%	August	16	
5		September	19	$F_5 = 0.2\times12 + 0.3\times13 + 0.5\times16 = 2+3.9+8 = 13.9$

Weighted Moving Average

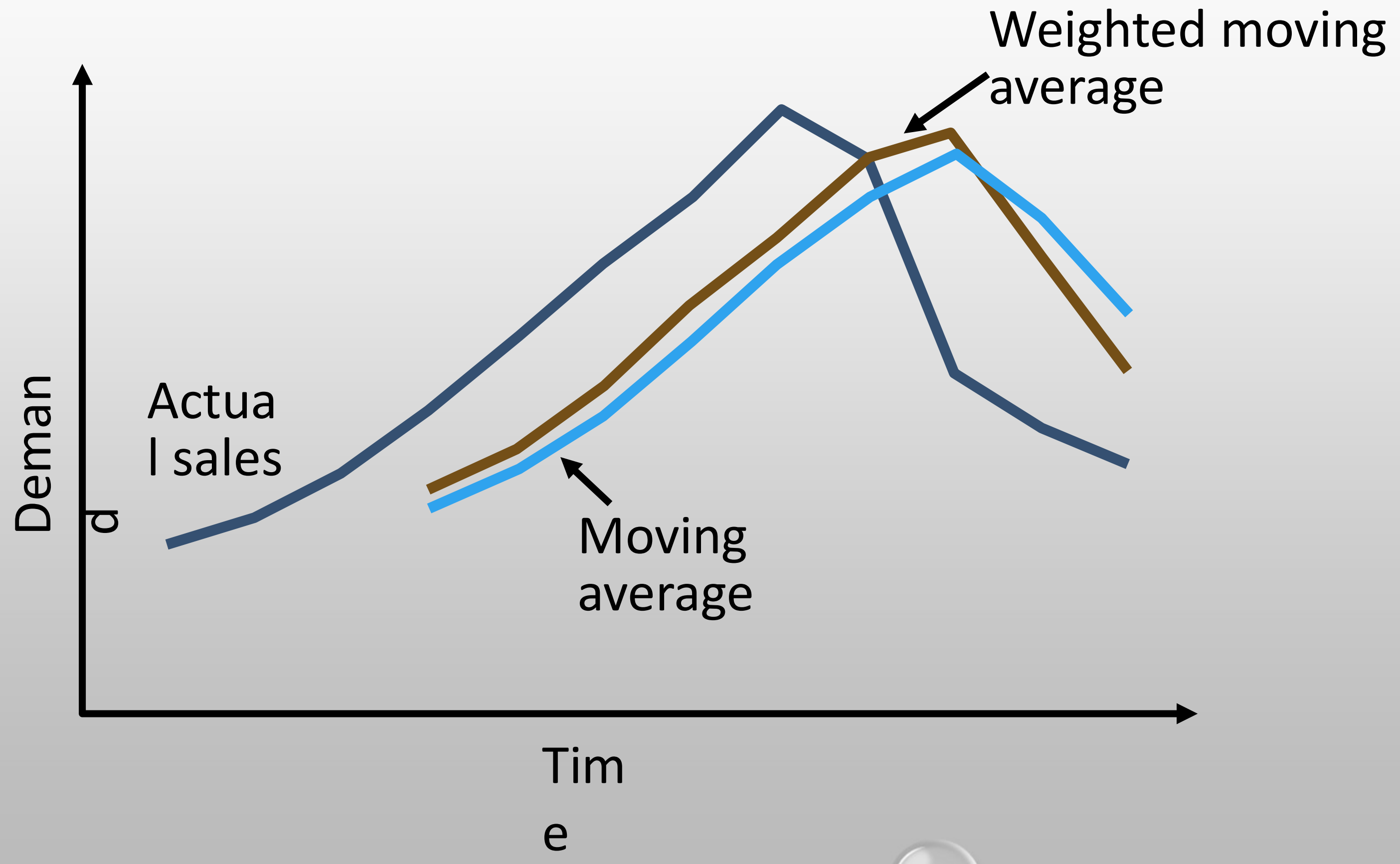


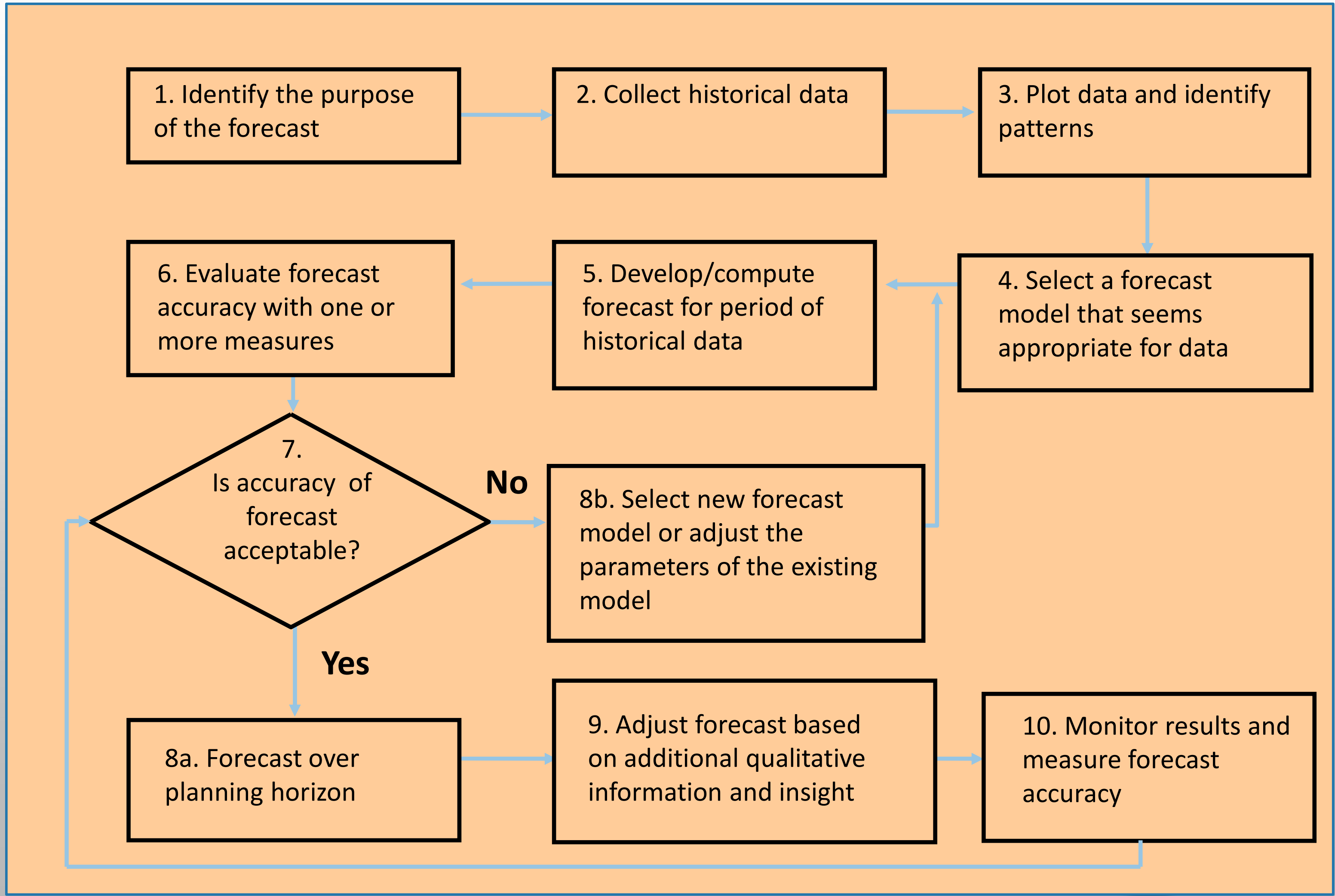
Higher weight on recent demand data -> more accurate forecast

MOVING AVERAGE APPROACHES - PROBLEMS

1. Increasing N smooths the forecast, but it is less sensitive to changes in demand.
2. Trends are not recognized very well; they cannot predict higher or lower levels of demand.
3. We need extensive historical demand data.

Moving Average Approaches - Problems





Source: Russell and Taylor, 2011. Operations Management, 7th edition, John Wiley & Sons - Chapter 12.

TIME SERIES FORECASTING MODELS

F_{t+1}: Forecast of demand for period t+1 A_t : Actual demand in period t		
Time Series Model	**Formula**	**More**
Naive	$F_{t+1} = A_t$	
Mean	$F_{t+1} = \sum A_t / n$	Avg. of all available demand data in n periods
N-period Moving Average	$F_{t+1} = D_t + D_{t-1} + D_{t-2} + \ldots + D_{t-N+1} / N$	For each new forecast, add the most recent demand observation and drop the earliest.
N-period Weighted Average	$F_{t+1} = w_t D_t + w_{t-1} D_{t-1} + w_{t-2} D_{t-2} + \ldots + w_{t-N+1} D_{t-N+1}$	All weights add to 100% or 1. $\sum w_t = 1$

TIME SERIES DEMAND FORECASTING

Forecast = Systematic component (S) + Random component (R)

- Systematic component (S) = (level + trend) × seasonal factor
  - ✓ Level : deseasonalized demand
  - ✓ Trend: rate of growth or decline in demand (increasing or decreasing pattern)
  - ✓ Seasonal factor – predictable seasonal fluctuations in demand (demand pattern of constant length that regularly repeats itself)

TIME SERIES FORECASTING MODELS (MORE)

- Exponential smoothing (Εκθετική Εξομάλυνση)
- Exponential smoothing with Trend adjustment (Holt's model)
- Exponential smoothing with Trend and Seasonality adjustment (Winter's model)

EXPONENTIAL SMOOTHING

- Demand Forecast = Last Forecast + α (Last Actual Demand – Last Forecast Demand)
- Last Actual Demand – Last Forecast Demand: random component
- $F_{t+1} = L_t$, $L_t = F_t + \alpha (A_t - F_t)$
- $F_{t+1} = F_t + \alpha (A_t - F_t)$
  - ✓ F_{t+1}: Forecast of demand for period t+1, F_t: Forecast of demand for period t
  - ✓ L_t : Level of demand in period t
  - ✓ A_t: Actual demand in period t
  - ✓ Smoothing (weighting) coefficient $0 \leq \alpha \leq 1$ (subjective value)
- Easy to implement, minimal amount of data -> most frequently used time series forecasting approach

EXPONENTIAL SMOOTHING

$F_{t+1} = L_t$, $L_t = F_t + \alpha (A_t - F_t)$

$F_{t+1} = F_t + \alpha (A_t - F_t)$

- L_o : Average of all historical demand data
- $L_o = \sum A_t / n$
- New demand observation A_{t+1} -> revision of L
  - ✓ $L_{t+1} = F_{t+1} + \alpha (A_{t+1} - F_{t+1}) = \alpha A_{t+1} + (1-\alpha) F_{t+1} \Leftrightarrow$
  - ✓ $L_{t+1} = \alpha A_{t+1} + (1-\alpha) L_t$
  - ✓ Weighted average of current demand and old level L

Exponential Smoothing Example

t	Month	Actual Demand (A)	Forecast (F) $F_{t+1} = L_t$ $\alpha = 0.3$	Level (L) $L_t = \alpha A_t + (1 - a)F_t$ $L_o = \sum A_t / n$
1	May	37	$F_1 = L_0 = 41.67$	$L_o = (37+40+41+37+45+50)/6 = 41.67$
2	June	40	$F_2 = L_1 = 40.27$	$L_1 = \alpha A_1 + (1 - a)F_1 =$ $= 0.30*37 + 0.70*41.67$ $= 40.27$
3	July	41	$F_3 = L_2 = 40.19$	$L_2 = \alpha A_2 + (1 - a)F_2 =$ $= 0.30*40 + 0.70*40.27$ $= 40.19$
4	August	37	$F_4 = L_3 = 40.43$	$L_3 = \alpha A_3 + (1 - a)F_3 =$ $= 0.30*41 + 0.70*40.19$ $= 40.43$
5	September	45		
6	October	50		

Exponential Smoothing Example

t	Month	Actual Demand (A)	Forecast (F) $F_{t+1} = L_t$ $\alpha = 0.5$	Level (L) $L_t = \alpha A_t + (1 - a)F_t$ $L_o = \sum A_t / n$
1	May	37	$F_1 = L_0 = 41.67$	$L_o = (37+40+41+37+45+50)/6 = 41.67$
2	June	40	$F_2 = L_1 = 39.33$	$L_1 = \alpha A_1 + (1 - a)F_1 =$ $= 0.50*37 + 0.50*41.67$ $= 39.33$
3	July	41	$F_3 = L_2 =$	$L_2 = \alpha A_2 + (1 - a)F_2 =$
4	August	37	$F_4 = L_3 =$	$L_3 = \alpha A_3 + (1 - a)F_3 =$
5	September	45		
6	October	50		

Please, practice

SMOOTHING COEFFICIENT A

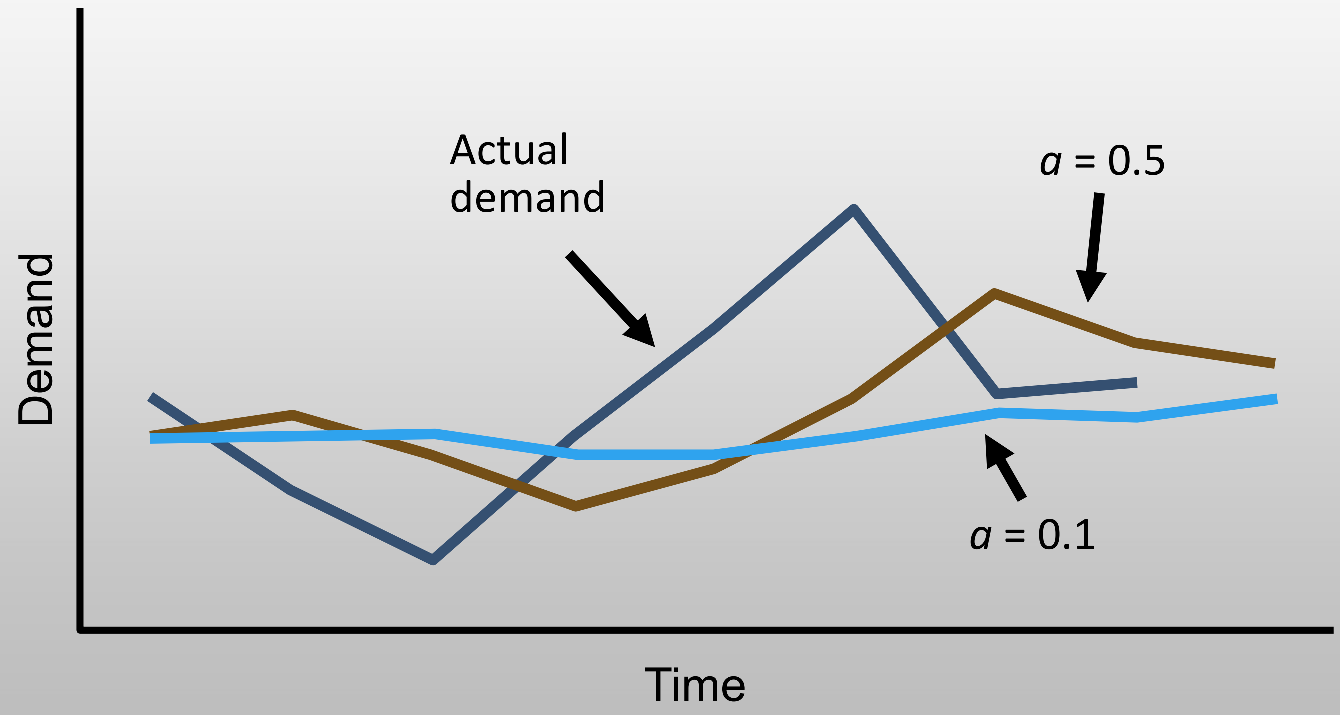
$F_{t+1} = F_t + \alpha (A_t - F_t)$

- α is selected by the forecaster
- $\alpha = 0$, $F_{t+1} = F_t$ (the forecast does not focus on the recent data)
- $\alpha = 1$, $F_{t+1} = A_t$ (the forecast focuses on the most recent data – naïve approach)

The higher the α becomes, the less we consider the older demand values.

- $\alpha = 0.2$, $F_{t+1} = 0.2A_t + 0.8F_t$
- $\alpha = 0.35$, $F_{t+1} = 0.35A_t + 0.75F_t$
- $\alpha = 0.5$, $F_{t+1} = 0.5A_t + 0.5F_t$

SMOOTHING COEFFICIENT A



- 0.05 ≤ α ≤ 0.5 for business applications
- Higher α -> more responsive to recent observations

TREND-ADJUSTED EXPONENTIAL SMOOTHING

- Suitable for data that exhibit a trend, but no seasonality.
- Exponentially smoothed/ weighted average of demand data + adjustment for positive or negative lag in trend.
- $F_{t+1} = L_t + T_t$
- $L_t = F_t + \alpha (A_t - F_t) \Leftrightarrow L_t = (L_{t-1} + T_{t-1}) + \alpha [A_t - (L_{t-1} - T_{t-1})] \Leftrightarrow$
- $L_t = \alpha A_t + (1-a)(L_{t-1} + T_{t-1})$
- $T_t = (1-\beta)T_{t-1} + \beta (L_t - L_{t-1})$
  - ✓ L_t : exponentially smoothed average of demand in period t
  - ✓ T_t: exponentially smoothed trend in period t
  - ✓ β: smoothing (weighting) coefficient of trend $0 \leq \beta \leq 1$ (subjective value)

TREND-ADJUSTED EXPONENTIAL SMOOTHING

$F_{t+1} = L_t + T_t$

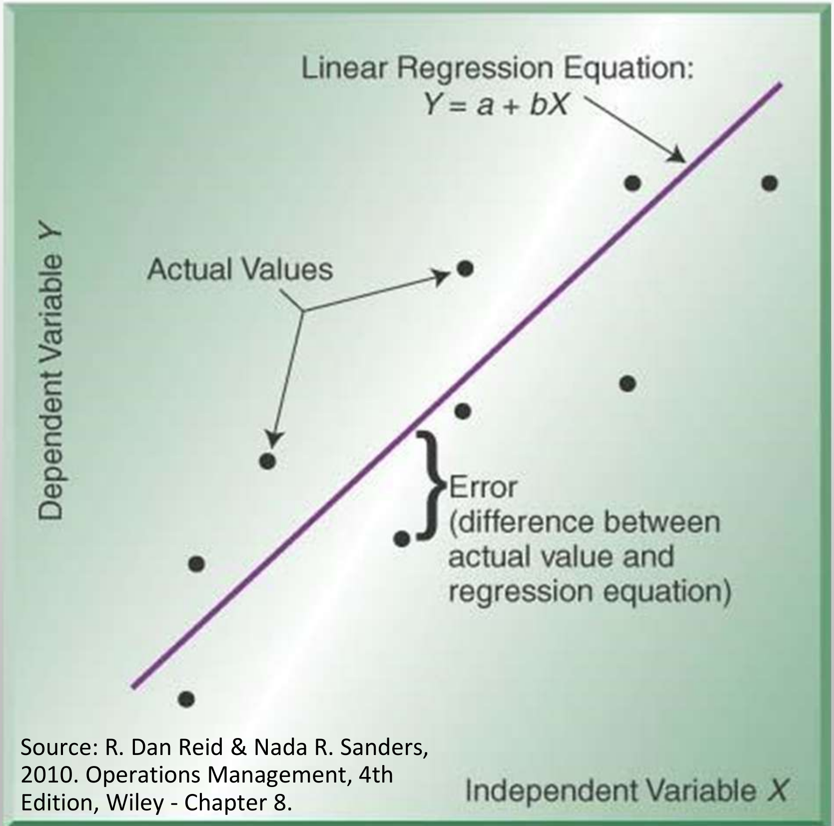
- $L_t = \alpha A_t + (1-a)(L_{t-1} + T_{t-1})$
- $T_t = (1-\beta)T_{t-1} + \beta (L_t - L_{t-1})$
- Linear regression between demand (A) and time (t) -> T_0, L_0

✓ $A_t = at + b$

✓ $T_0 = a$

✓ $L_0 = b$

Linear Regression



Source: R. Dan Reid & Nada R. Sanders, 2010. Operations Management, 4th Edition, Wiley - Chapter 8.

Models the relationship between two variables as a straight line.

Fits a straight line to a time series data.

$y = a + bx$

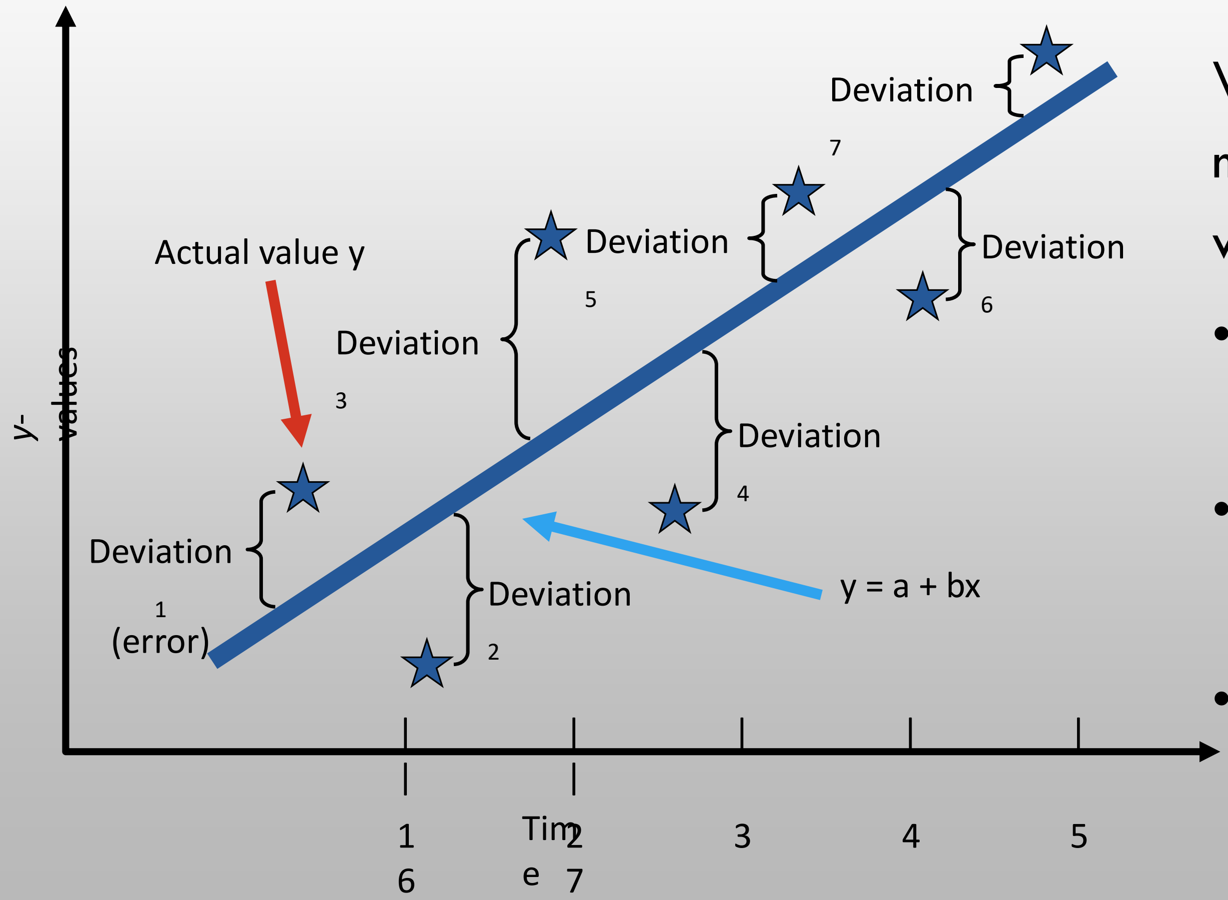
x: time period (independent variable)

y: value for time period x (dependent variable)

a: y-intercepts of the line - height at which the line intercepts the y-axis (y value at x=0)

b: slope of the line (expected change)

Linear Regression



We select to build a straight line that minimizes the deviations of the actual values from the line, namely

- a and b define a straight line that minimizes the sum of the squared errors.
- error = difference between actual value and y
- Least-squares straight line

Linear Regression

- $y = a + bx$
- $b = (\sum xy - n\text{avg}(x)\text{avg}(y)) / (\sum x^2 - n\text{avg}(x)^2)$
- $a = \text{avg}(y) - b\text{avg}(x)$
- n: number of data points
- avg(x): average of the x-values
- avg(y): average of the y-values

PERFORM TREND-ADJUSTED EXPONENTIAL SMOOTHING

1. Smoothing the demand series

   $L_t = \alpha\, A_t + (1\text{-}a)(L_{t\text{-}1} + T_{t\text{-}1})$

2. Smoothing the trend

   $T_t = (1\text{-}\beta)T_{t\,\text{-}1} + \beta\,(L_t\ \text{-}\ L_{t\text{-}1})$

3. Forecasting including Trend

   $F_{t+1} = L_t + T_t$

Trend-adjusted Exponential Smoothing Example

t	Actual Demand (A)
1	8,000
2	13,000
3	23,000
4	34,000
5	10,000
6	18,000
7	23,000
8	38,000
9	12,000
10	13,000
11	32,000
12	41,000

1. Calculate L_o, T_o
2. Smoothing the demand series

   $$L_t = \alpha A_t + (1-a)(L_{t-1} + T_{t-1})$$

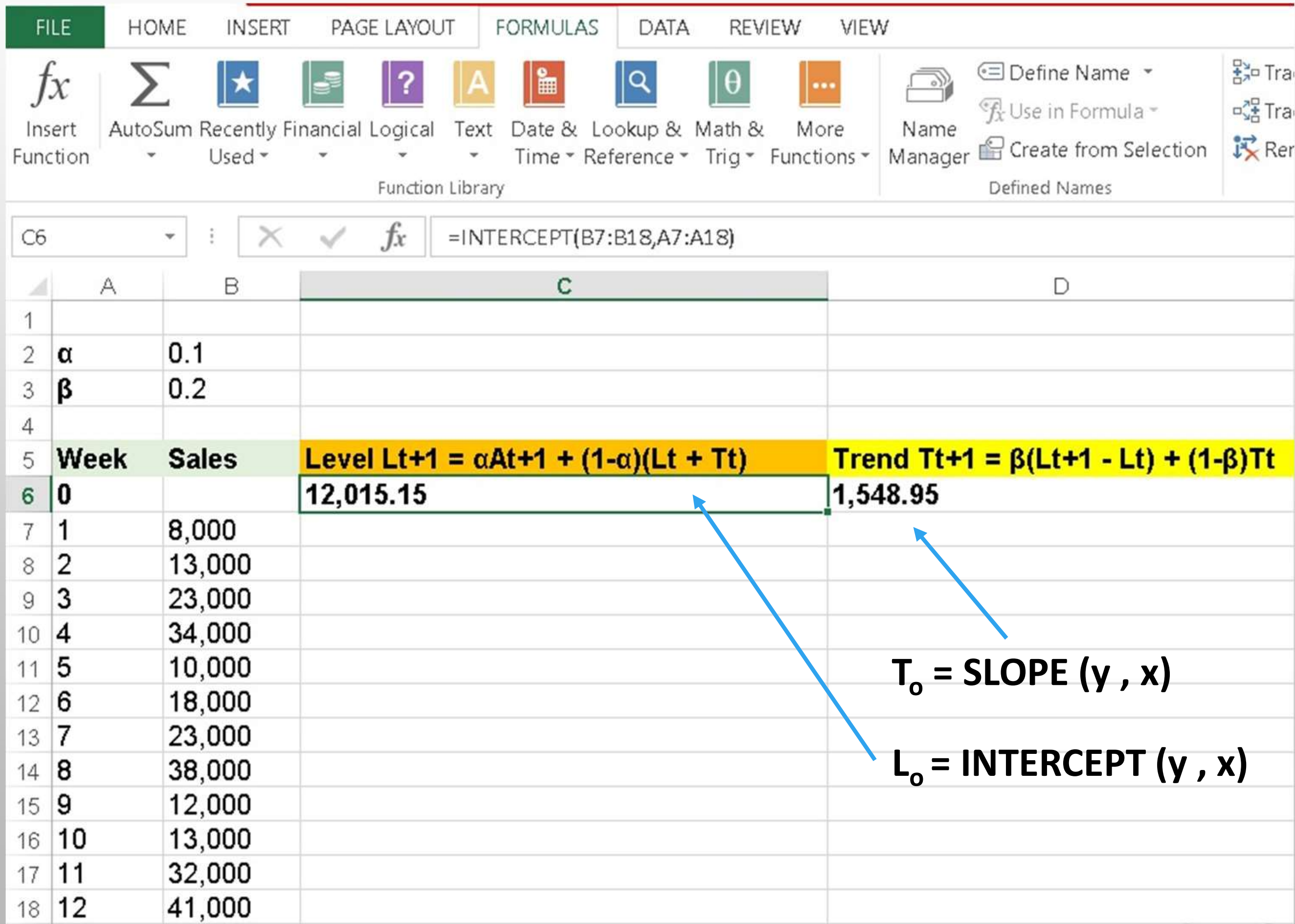
3. Smoothing the trend

   $$T_t = (1-\beta)T_{t-1} + \beta (L_t - L_{t-1})$$

4. Forecasting including Trend

   $$F_{t+1} = L_t + T_t$$

Perform Trend-adjusted Exponential Smoothing – Using Excel



	A	B	C	D
1				
2	α	0.1		
3	β	0.2		
4				
5	**Week**	**Sales**	**Level Lt+1 = αAt+1 + (1-α)(Lt + Tt)**	**Trend Tt+1 = β(Lt+1 - Lt) + (1-β)Tt**
6	**0**		**12,015.15**	**1,548.95**
7	1	8,000		
8	2	13,000		
9	3	23,000		
10	4	34,000		
11	5	10,000		
12	6	18,000		
13	7	23,000		
14	8	38,000		
15	9	12,000		
16	10	13,000		
17	11	32,000		
18	12	41,000		

T_o = SLOPE (y , x)

L_o = INTERCEPT (y , x)

1. Calculate L_o, T_o

Perform Trend-adjusted Exponential Smoothing – Using Excel

C7 =$B$2*B7+(1-$B$2)*(C6+D6)

	A	B	C	D
1				
2	α	0.10		
3	β	0.20		
4				
5	**Week**	**Sales**	**Level Lt+1 = αAt+1 + (1-α)(Lt + Tt)**	**Trend Tt+1 = β(Lt+1 - Lt) + (1-β)Tt**
6	**0**		12,015.15	1,548.95
7	1	8,000	13,007.69	1,437.67
8	2	13,000	14,300.83	1,408.76
9	3	23,000	16,438.63	1,554.57
10	4	34,000	19,593.88	1,874.71
11	5	10,000	20,321.73	1,645.33
12	6	18,000	21,570.35	1,565.99
13	7	23,000	23,122.71	1,563.27
14	8	38,000	26,017.38	1,829.55
15	9	12,000	26,262.23	1,512.61
16	10	13,000	26,297.36	1,217.11
17	11	32,000	27,963.02	1,306.82
18	12	41,000	30,442.86	1,541.42
19				

2. Smoothing the demand series

Perform Trend-adjusted Exponential Smoothing – Using Excel

D7 =$B$3*(C7-C6)+(1-$B$3)*D6

	A	B	C	D
1				
2	α	0.10		
3	β	0.20		
4				
5	**Week**	**Sales**	**Level Lt+1 = αAt+1 + (1-α)(Lt + Tt)**	**Trend Tt+1 = β(Lt+1 - Lt) + (1-β)Tt**
6	**0**		12,015.15	1,548.95
7	1	8,000	13,007.69	1,437.67
8	2	13,000	14,300.83	1,408.76
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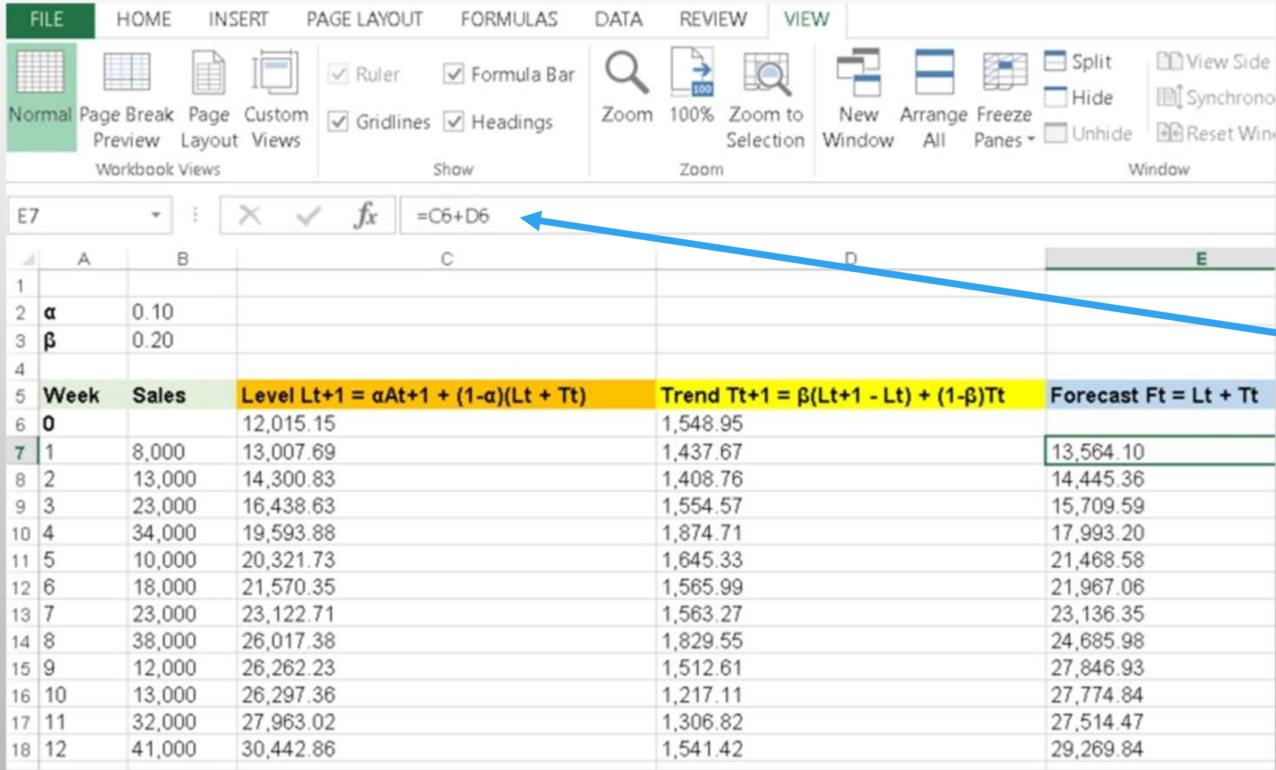
16	10	13,000	26,297.36	1,217.11
17	11	32,000	27,963.02	1,306.82
18	12	41,000	30,442.86	1,541.42

3. Smoothing the trend

Perform Trend-adjusted Exponential Smoothing – Using Excel



E7 =C6+D6

	A	B	C	D	E
1					
2	α	0.10			
3	β	0.20			
4					
5	**Week**	**Sales**	**Level Lt+1 = αAt+1 + (1-α)(Lt + Tt)**	**Trend Tt+1 = β(Lt+1 - Lt) + (1-β)Tt**	**Forecast Ft = Lt + Tt**
6	**0**		12,015.15	1,548.95	
7	1	8,000	13,007.69	1,437.67	13,564.10
8	2	13,000	14,300.83	1,408.76	14,445.36
9	3	23,000	16,438.63	1,554.57	15,709.59
10	4	34,000	19,593.88	1,874.71	17,993.20
11	5	10,000	20,321.73	1,645.33	21,468.58
12	6	18,000	21,570.35	1,565.99	21,967.06
13	7	23,000	23,122.71	1,563.27	23,136.35
14	8	38,000	26,017.38	1,829.55	24,685.98
15	9	12,000	26,262.23	1,512.61	27,846.93
16	10	13,000	26,297.36	1,217.11	27,774.84
17	11	32,000	27,963.02	1,306.82	27,514.47
18	12	41,000	30,442.86	1,541.42	29,269.84

4. Forecasting with trend

SMOOTHING COEFFICIENT Β

- β is selected by the forecaster
- High β -> more responsive to recent changes in trend.
- Low β -> smooths out the present trend.
- Values of α and β can be found by the trial-and-error approach -> test different values and calculate the respective forecast error.

FORECASTING ACCURACY

Forecasting results are never perfect!!

The accuracy of forecasting models should be assessed over time.

$E_t = F_t - A_t$, Forecast error in period t

- over-forecast = negative forecast error
- under-forecast = positive forecast errors

FORECASTING ACCURACY METRICS

Mean Absolute Deviation (MAD) : average of the absolute forecast error over all periods n

$$MAD = \sum \text{Absolute}(E_t) \;/\; n$$

Mean Squared Error (MSE)

$$MSE = \sum (E_t)^2 \;/\; n$$

- Mean Absolute Percentage Error (MAPE)

$$MAPE = [\sum \text{Absolute}(E_t \,/ A_t)*100] / \, n$$

FORECASTING ACCURACY METRICS

Bias : sum of forecast errors over all periods n

- ✓ shows whether the forecast model consistently under- or overestimates demand
- ✓ If bias fluctuate around 0, the error is truly random.

$$\text{Bias} = \sum E_t$$

Tracking signal TS: how well a forecasting model performs

- ✓ should be within the range of ± 6
- ✓ TS<-6 under forecasting, TS>6 over forecasting

$$TS_t = bias_t \,/\, MAD_t = \sum E_t \,/\, MAD_t$$

SELECTING THE RIGHT FORECASTING MODEL

1. Amount & Type of available data
2. Degree of forecast accuracy expected
3. Length of forecast horizon
4. Presence of data patterns

Big data analytics and demand forecasting in supply chains: a conceptual analysis

Στοχος – Πως Big Data Analytics (BDA) βελτιωνει forecasts' accuracy

Το 2012, η αμερικανική αλυσίδα λιανικής Target έστειλε κουπόνια για βρεφικά ρούχα σε μια μαθήτρια λυκείου, προβλέποντας την εγκυμοσύνη της πριν καν το μάθει η οικογένειά της. Οι λιανοπωλητές γνωρίζουν τους καταναλωτές καλύτερα από ό,τι οι ίδιοι τον εαυτό τους.

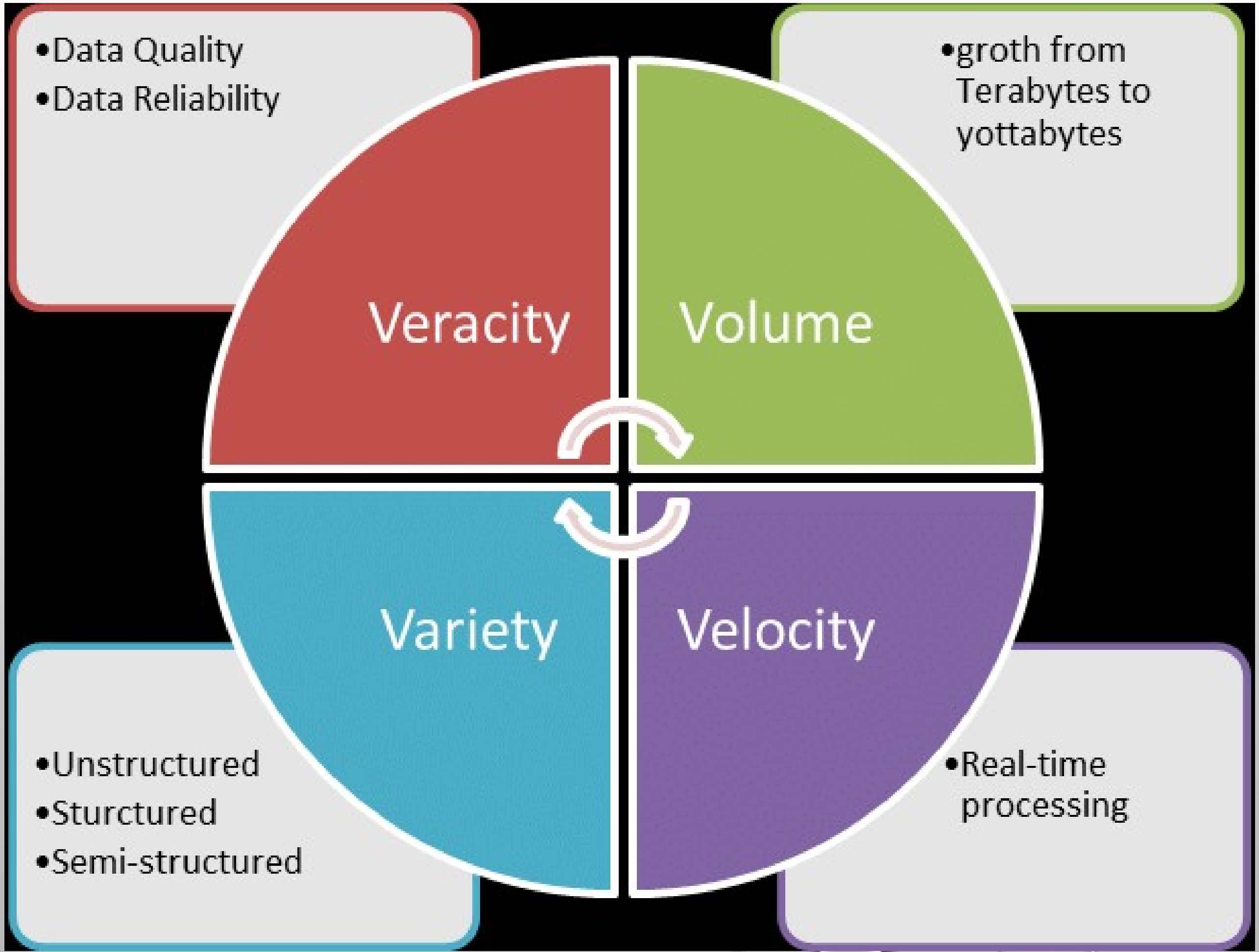
Παρά τον τεράστιο όγκο δεδομένων, οι παραδοσιακές μέθοδοι πρόβλεψης αποτυγχάνουν σε ένα περιβάλλον VUCA (Αστάθεια, Αβεβαιότητα, Πολυπλοκότητα, Ασάφεια). Η Αναλυτική Μεγάλων Δεδομένων (BDA) είναι το εργαλείο μετατροπής αυτού του θορύβου σε ακριβείς προβλέψεις.

Το Οικοσύστημα Λιανικής: Παράγοντες Επιρροής της Ζήτησης

Παραδοσιακες μεθοδοι Forecasting

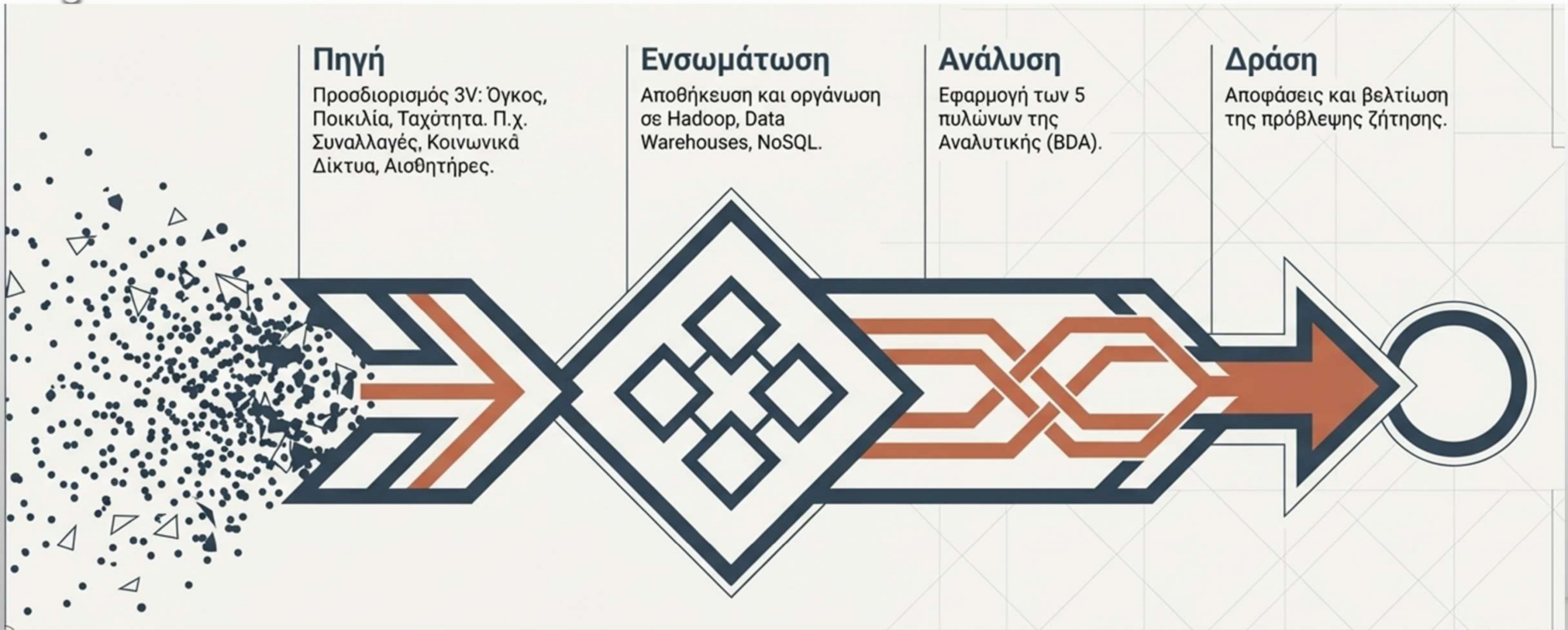
Ποιοτικές Μέθοδοι	Ποσοτικές Μέθοδοι
Βάσης / Πωλητών (Grassroots) ⚠ Εξαρτάται από σχέσεις. Πολύπλοκο και ασαφές στη λιανική.	**Χρονοσειρές (Time-Series)** ⚠ Βασίζεται σε ιστορικά στοιχεία. Αποτυγχάνει όταν προκύπτουν ειδικά, απρόβλεπτα γεγονότα.
Έρευνα Αγοράς (Market Research) ⚠ Απαιτεί ποικίλα δεδομένα για έγκαιρο εντοπισμό τάσεων.	**Αιτιακά Μοντέλα (Causal)** ⚠ Γνωστές μόνο λίγες αιτιακές σχέσεις. Εξαιρετικά ακριβό και δύσκολο να παραχθεί εγκαίρως.
Εκτιμήσεις Ειδικών (Experts) ⚠ Αδυναμία δοκιμής υποθέσεων, απουσία αποφάσεων βάσει σκληρών δεδομένων.	

Big Data – 4 Vs

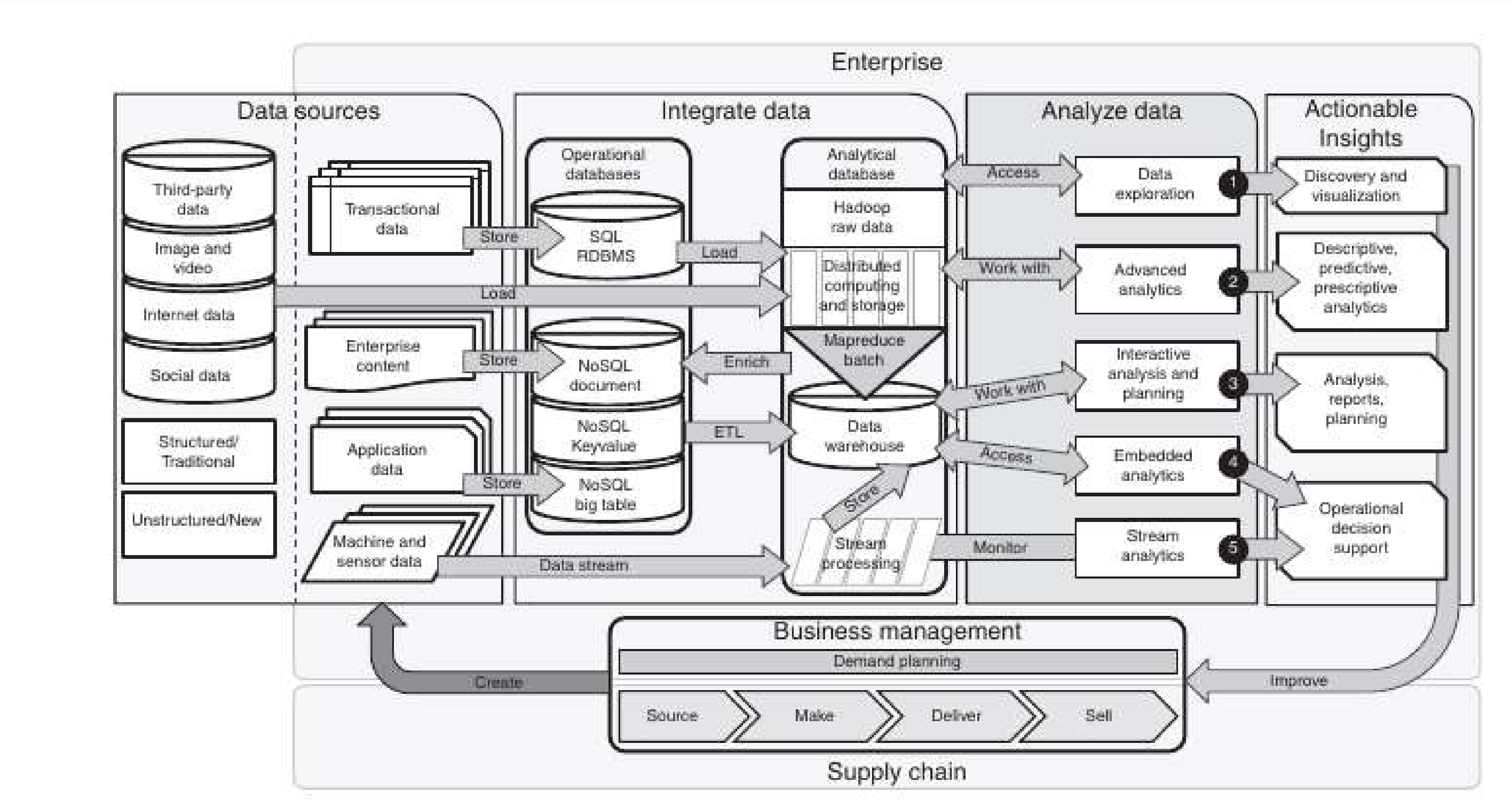


•Data Quality
•Data Reliability
•groth from Terabytes to yottabytes
Veracity
Volume
Variety
Velocity
•Unstructured
•Sturctured
•Semi-structured
•Real-time processing

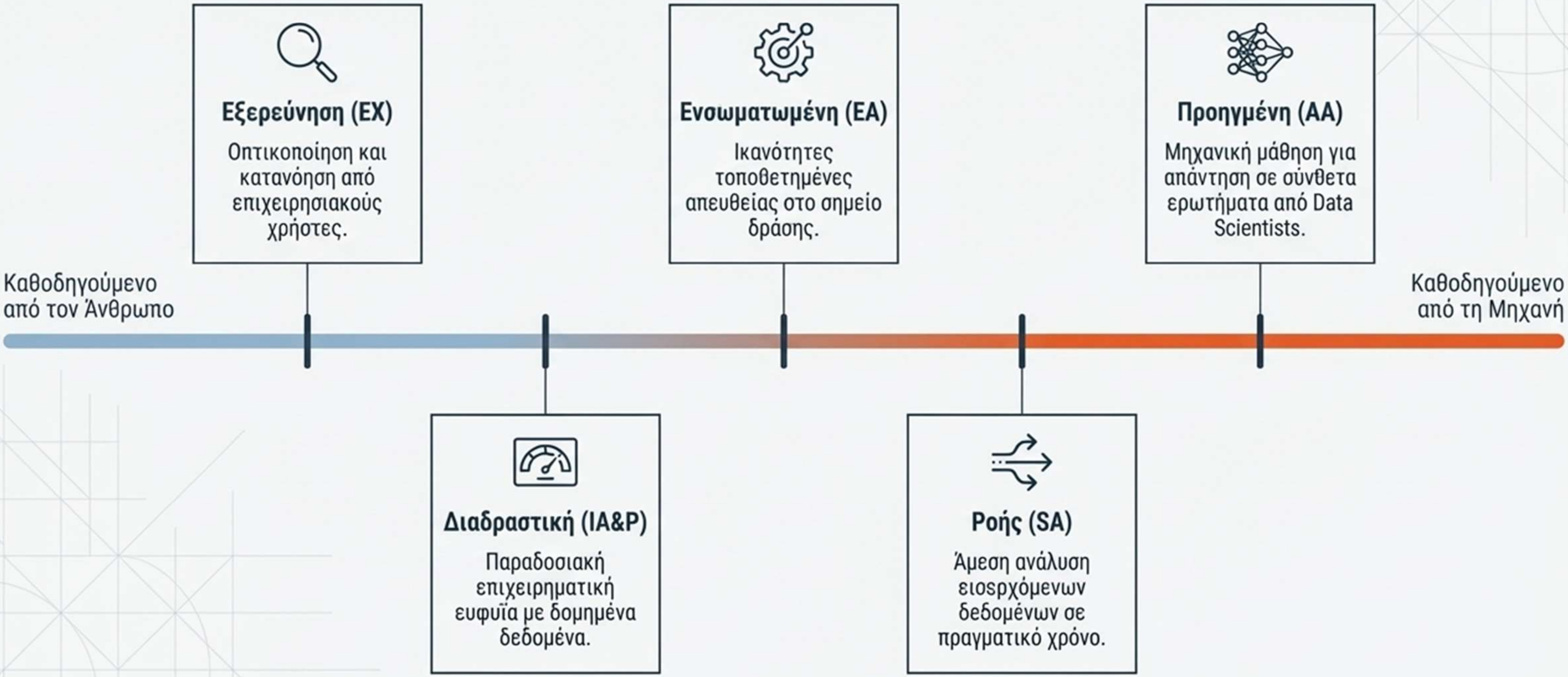
Αλυσιδα αξιας Big Data



Αλυσιδα αξιας Big Data



Το Φάσμα της Αναλυτικής (Οι 5 Πυλώνες του BDA)



		computing				
(2) Advanced analytics (AA)	Every kind of data accessed from Hadoop, NoSQL DBs, or EDW	Data preparation technologies to bring structure to unstructured data, distributed computing and storage, Hadoop, graph analytics, cognitive computers, cloud computing	Advanced analytics modeling software: IBM SPSS Modeler SAS Enterprise Miner, Text Miner, SAS/OR, SAS Visual Data Discovery KNIME RapidMiner Oracle Data Miner	Data scientists	Descriptive, predictive, and prescriptive models; processed data; embedded analytics and stream analytics solutions	Lozano (2013) Kadochnikov (2013) Laumanns and Squillante (2013) Abbott (2014)
(3) Interactive analysis and planning (IA&P)	Dimensional, structured data stored in the EDW (financial, CRM, etc.)	EDW, relational database, OLAP, SQL	Traditional BI software: SAS Office Analytics IBM Cognos QlikView SAP Lumira	Business users, business analysts	Financial analysis, reports, simple forecasts, interactive dashboards, and business understanding	Petitclerc (2013) Sallam *et al.* (2015)

(4) Embedded analytics (EA)	Processed data from machines, social media, CRM, temporal, geospatial, financial, etc.	Special-purpose solutions, cloud computing, technologies to embed analytics in CRM, ERP, etc.	Custom-built applications: Pentaho embedded analytics IBM MobileFirst for iOS	Operational user	Operational decision support, easy-to-grab data presentations, accessible on various devices, interactive computer models	Logi Analytics (2014) Aberdeen Group (2014) Apple (2014) Dorschel (2015) Loshin (2015)
(5) Stream analytics (SA)	Incoming data streams from machines, the internet (weather, market, etc.), and supply chains	Stream processing technology, complex event processing, fast-access database	Complex event processing software: IBM InfoSphere Streams Apache Spark and Storm Informatica Stream Analytics	Operational user	Event-driven notifications, dashboards, processed streaming data, real-time insights	Aslett (2013) Spicer (2013) Dorschel (2015)

Ακτινογραφία των Εργαλείων BDA

Τεχνική	Τύπος Δεδομένων	Κύριος Χρήστης	Παραδοτέο Insight
Εξερεύνηση (EX)	Μη δομημένα / Κείμενο	Business Analyst	Οπτικοποιήσεις & Αναφορές
Προηγμένη (AA)	Όλα τα είδη (Hadoop/NoSQL)	Data Scientist	Περιγραφικά & Προγνωστικά μοντέλα
Διαδραστική (IA&P)	Δομημένα οικονομικά (EDW)	Business Analyst	Dashboards & Οικονομική Ανάλυση
Ενσωματωμένη (EA)	Επεξεργασμένα επιχειρησιακά	Επιχειρησιακός Χρήστης	Υποστήριξη αποφάσεων στην πρώτη γραμμή
Ροής (SA)	Συνεχείς ροές (Αισθητήρες, Web)	Επιχειρησιακός Χρήστης	Ειδοποιήσεις & Ανάλυση πραγματικού χρόνου

Αποκωδικοποιώντας την Προηγμένη Αναλυτική (ΑΑ)

1. Περιγραφική
Τι συνέβη?

Δομεί ακατέργαστα δεδομένα. Ομαδοποίηση, κανόνες συσχέτισης, ανάλυση κειμένου. Αξιολόγηση εκ των υστέρων.

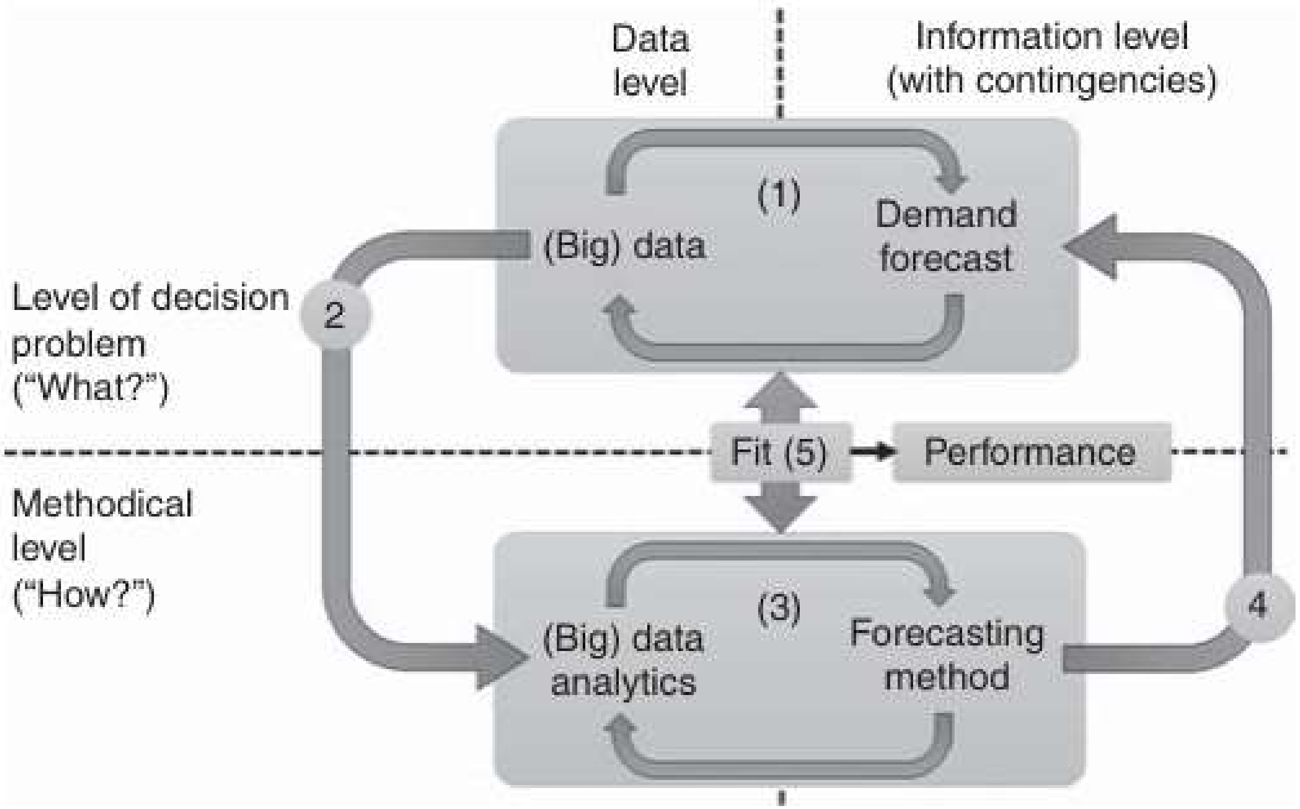
2. Προγνωστική
Τι θα συμβεί?

Συνεχείς εκτιμήσεις κάθε τιμής-στόχου. Γραμμική παλινδρόμηση, δέντρα απόφασης. Παρέχει μηχανική διαίσθηση.

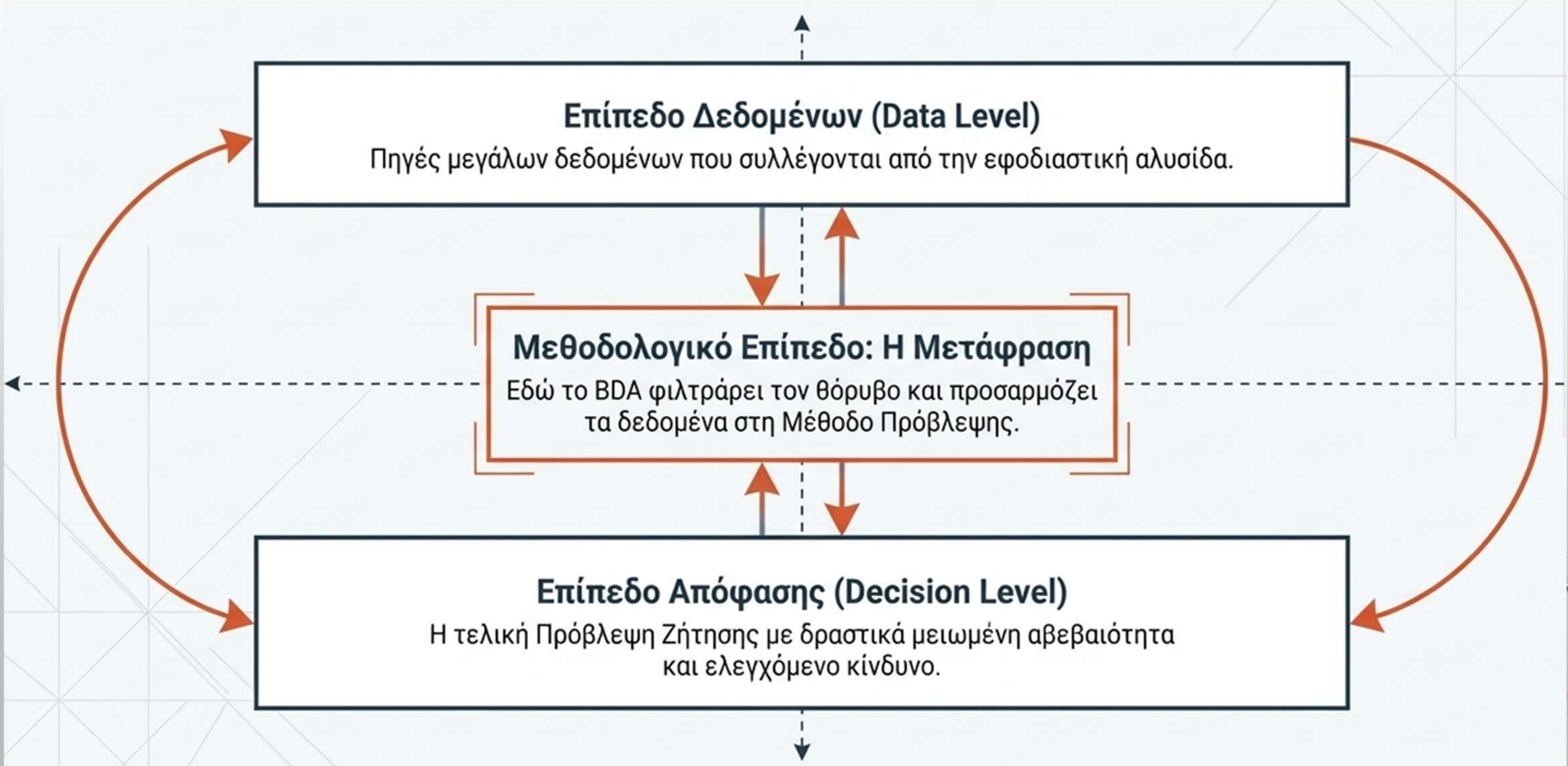
3. Καθοδηγητική
Τι πρέπει να κάνουμε?

Προηγμένη βελτιστοποίηση, θεωρία παιγνίων, προσομοίωση για τον καθορισμό της απόλυτα καλύτερης δυνατής ενέργειας.

Πλαισιο που συνδυαζει Big Data + Demand Forecasting



Πλαισιο που συνδυαζει Big Data + Demand Forecasting



Η Έξυπνη Αναβάθμιση: Εξέλιξη των Μεθόδων

Έρευνα Αγοράς	+	Περιγραφική + Προγνωστική	=	**Έρευνα Αγοράς Εμπλουτισμένη με Δεδομένα** Εντοπισμός τάσεων πολύ πριν εκδηλωθούν μαζικά.
Χρονοσειρές	+	Αναλυτική Ροής (SA)	=	**Χρονοσειρές Βάσει Κανόνων** Αυτόματη διακοπή και διόρθωση της πρόβλεψης όταν ανιχνεύονται ξαφνικά γεγονότα.
Αιτιακά Μοντέλα	+	Προηγμένη + Ροής + Ενσωματωμένη	=	**Αιτιακή Πρόβλεψη Βάσει Δεδομένων και Θεωρίας** Η απόλυτη σύνθεση για τον έλεγχο πολύπλοκων, δυναμικών περιβαλλόντων λιανικής.

Πλαισιο που συνδυαζει Big Data + Demand Forecasting - Εφαρμογη

Ξαφνική Αλλαγή Καιρού	Εκπτωτική Ενέργεια	Κίνδυνος Εξάντλησης (Out-of-Stock)
Αναλυτική Ροής (SA): Παρακολούθηση μετεωρολογικών συνθηκών σε πραγματικό χρόνο και άμεση ειδοποίηση των τοπικών καταστημάτων. **Προγνωστική (AA):** Βελτιστοποίηση των κωδικών αποθέματος ανάλογα με την αλλαγή ζήτησης λόγω καιρού.	**Ενσωματωμένη Αναλυτική (EA):** Ζωντανή ενημέρωση των τοπικών διευθυντών στα tablet τους για την άμεση επιρροή της έκπτωσης στις τοπικές πωλήσεις και την ανάγκη ανεφοδιασμού.	**Αναλυτική Ροής (SA):** Συνεχής παρακολούθηση των αποθεμάτων στο ράφι και έκδοση αυτοματοποιημένων σημάτων αναπλήρωσης προς την κεντρική αποθήκη πριν το προϊόν εξαντληθεί.

Εφαρμογη

Σενάριο: Ένα ηλιόλουστο Σαββατοκύριακο

Παλιά Μέθοδος
Έρευνα Αγοράς / Χρονοσειρές.
Δεν προσαρμόζονται γρήγορα.

→

Νέα Μέθοδος
Αιτιακή Πρόβλεψη
Άμεση ενσωμάτωση μετεωρολογικών δεδομένων στο μοντέλο για αύξηση αποθεμάτων σε καλοκαιρινά είδη.

Σενάριο: Ζήτημα Ποιότητας (π.χ. αναφορά μόλυνσης)

Παλιά Μέθοδος
Έρευνα Αγοράς.
Αργή αντίδραση και συγκέντρωση δεδομένων.

→

Νέα Μέθοδος
Έρευνα Εμπλουτισμένη με Δεδομένα. Ανάλυση συναισθήματος (sentiment analysis) σε πραγματικό χρόνο από κριτικές και social media για άμεση απόσυρση.

Σενάριο: Έκτακτος Φόρος ή Νομοθεσία

Παλιά Μέθοδος
Εκτιμήσεις Ειδικών.
Βασίζονται στο ανθρώπινο ένστικτο.

→

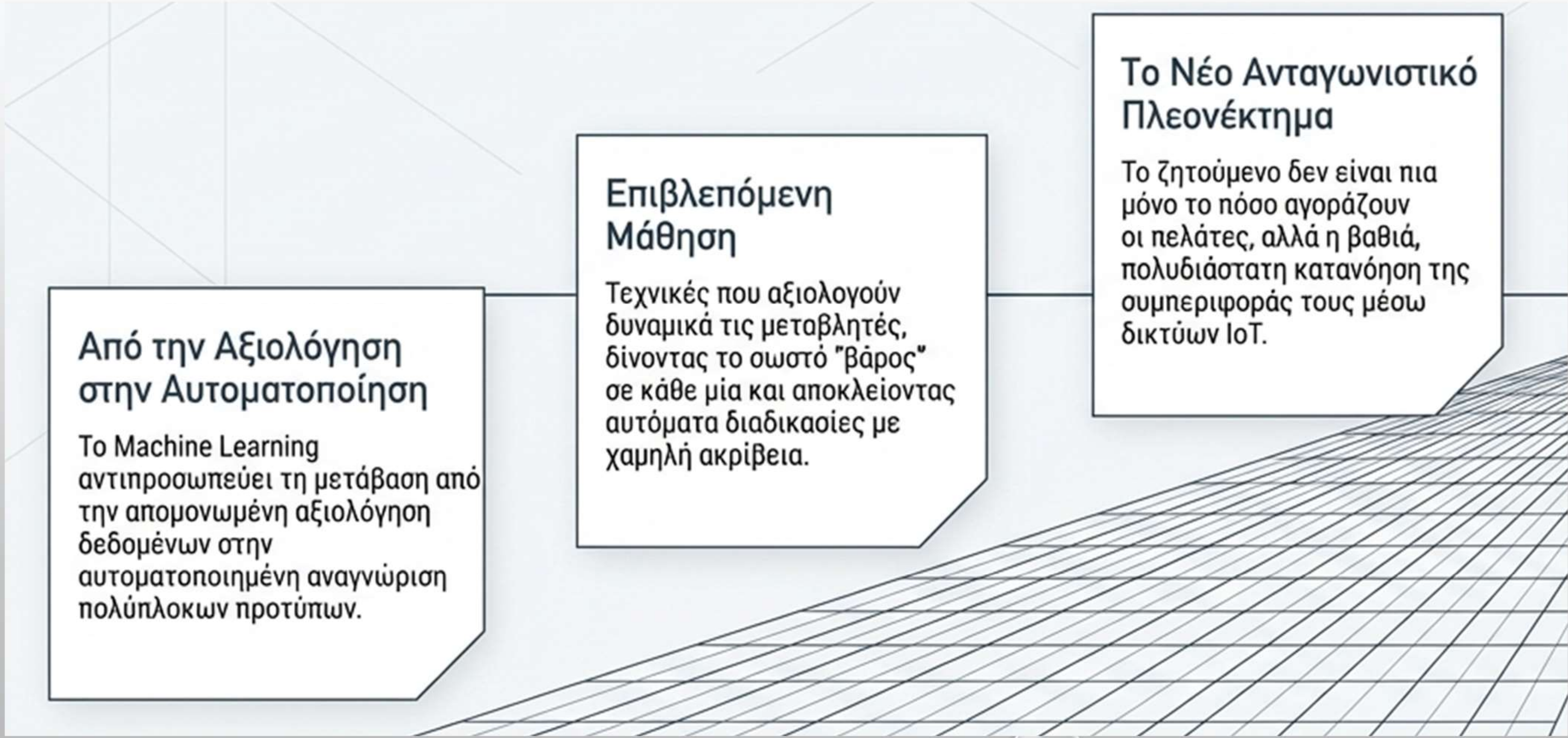
Νέα Μέθοδος
Αιτιακή Πρόβλεψη. Αντικατάσταση των απλών χρονοσειρών με ενσωμάτωση των νέων μεταβλητών κόστους στον προγνωστικό αλγόριθμο.


Χρονικοί Ορίζοντες:
Δεν Υπάρχει Μία Λύση Για Όλα
Στόχος: Ανταπόκριση σε πραγματικό χρόνο, αποφυγή out-of-stock ραφιού.
Κυριαρχεί η Αναλυτική Ροής (SA) & Ενσωματωμένη (EA)
Στόχος: Βελτιστοποίηση τιμολόγησης, σχεδιασμός ποικιλίας, αναλύσεις τάσεων αγοράς.
Κυριαρχεί η Προγνωστική (PDAA) & Περιγραφική (DAA)
Στόχος: Επιλογή τοποθεσιών νέων καταστημάτων, κατανόηση τεράστιων μακρο-τάσεων (π.χ. κλιματική αλλαγή).
Κυριαρχεί η Εξερεύνηση (EX) & Προηγμένη (AA)
Βραχυπρόθεσμα (Ημέρες/Εβδομάδες)
Μεσοπρόθεσμα (Μήνες/Εποχές)
Μακροπρόθεσμα (Έτη)

Μην επενδύετε τυφλά στην τεχνολογία. Προσδιορίστε τον τύπο της πρόβλεψης (στρατηγική, τακτική, επιχειρησιακή) και επιλέξτε το κατάλληλο BDA που γεφυρώνει το κενό.

Οι παραδοσιακές μέθοδοι δεν θα εξαφανιστούν, αλλά πρέπει να αναβαθμιστούν. Το BDA είναι το φίλτρο που μετατρέπει την αβεβαιότητα σε διαχειρίσιμο ρίσκο.

Μελλον


Από την Αξιολόγηση στην Αυτοματοποίηση
Το Machine Learning αντιπροσωπεύει τη μετάβαση από την απομονωμένη αξιολόγηση δεδομένων στην αυτοματοποιημένη αναγνώριση πολύπλοκων προτύπων.
Επιβλεπόμενη Μάθηση
Τεχνικές που αξιολογούν δυναμικά τις μεταβλητές, δίνοντας το σωστό "βάρος" σε κάθε μία και αποκλείοντας αυτόματα διαδικασίες με χαμηλή ακρίβεια.
Το Νέο Ανταγωνιστικό Πλεονέκτημα
Το ζητούμενο δεν είναι πια μόνο το πόσο αγοράζουν οι πελάτες, αλλά η βαθιά, πολυδιάστατη κατανόηση της συμπεριφοράς τους μέσω δικτύων IoT.