Current Issues in Supply Chain Forecasting

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Centre for Marketing Analytics and Forecasting

Webinar, 2 October 2020

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- Supply chain forecasting
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- Machine learning

Applied in a wide variety of sectors (eg FMCG, gov, pharma)


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Dr Sven Crone


Prof Robert Fildes


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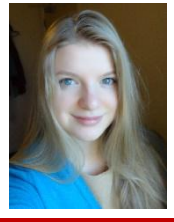
Dr Alisa Yusupova


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Dr Anna Sachs


Dr Rebecca Killick


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Associated Experts:

- Prof. Paul Goodwin (Bath U.)
- Dr Stephan Kolassa (SAP)
- Prof. Kostas Nikolopoulos (Durham U.)
- Dr. Devon Barrow (Birmingham U.)
- Dr. Steve Finlay (Head of Analytics, Computershare)
- Dr. Fotios Petropoulos (Bath U.)
- Dr. Juan Trapero (U. Castilla La Mancha, Spain)
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Agenda

- Framework for Supply Chain Forecasting
  - Stage in supply chain
  - Product/location dimension
  - Time dimension
- Statistical Forecasting
  - Faster moving series
  - Slower moving/intermittent series
- Performance Measurement
  - Accuracy measures
  - Accuracy-implication metrics
- Responding to Structural Breaks

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Supply Chain Data

Life is nasty, brutish and short

(Thomas Hobbes, Leviathan, 1651)

So is data !

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Data Requirements

Sales data and forecasts generated at the appropriate level of resolution

- (eg daily data and forecasts if operating in situation with lead-times less than a week).

Accurate inventory record data

- Appropriate technology
- Responsive correction of inaccuracies

Accurate out-of-stock data

- Sound monitoring of performance
- Appreciation of divergences between sales and demand

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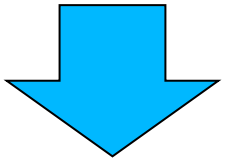
Some Basic Questions

Why Forecast?

- Warehouse Space Planning
- Inventory Planning and Replenishment
- Transport Planning



What to Forecast?

- Level of Aggregation (Product, Location)
- Forecasting Horizon
- Stage of the Supply Chain

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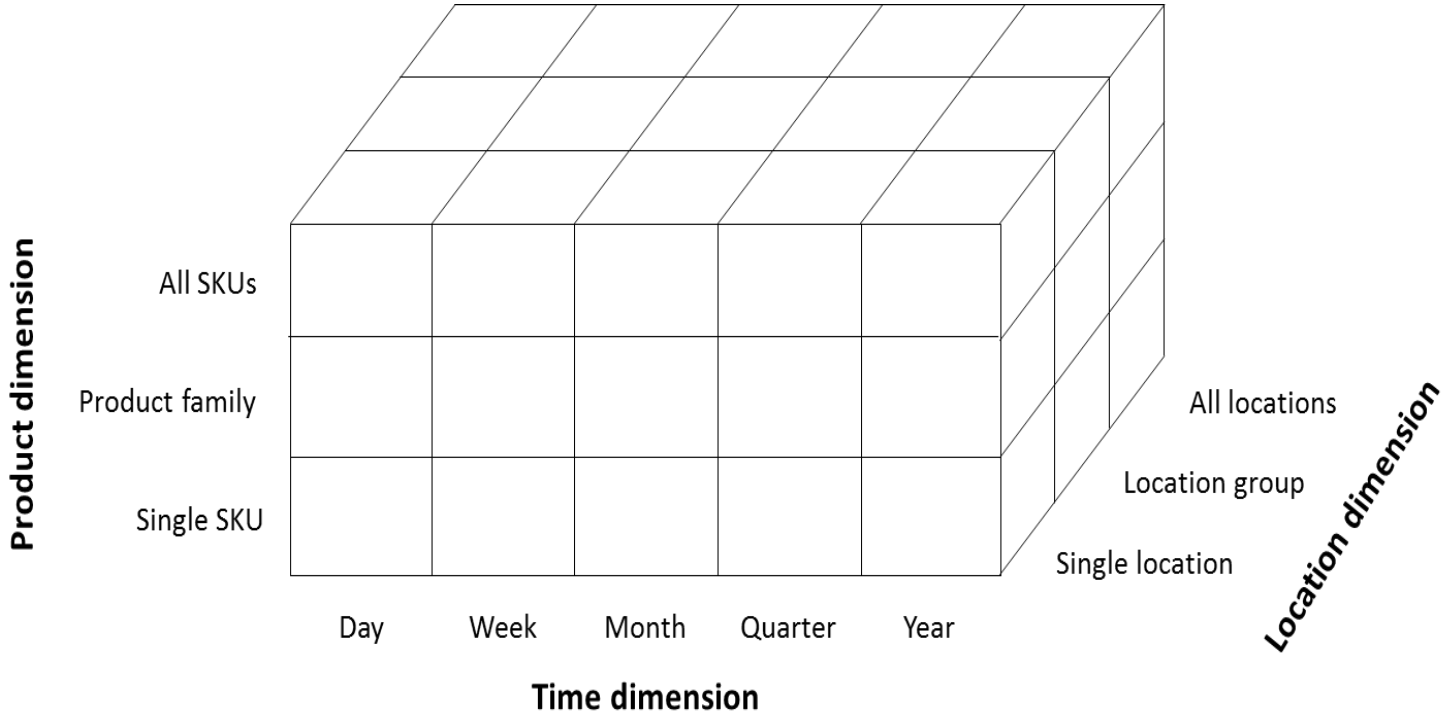
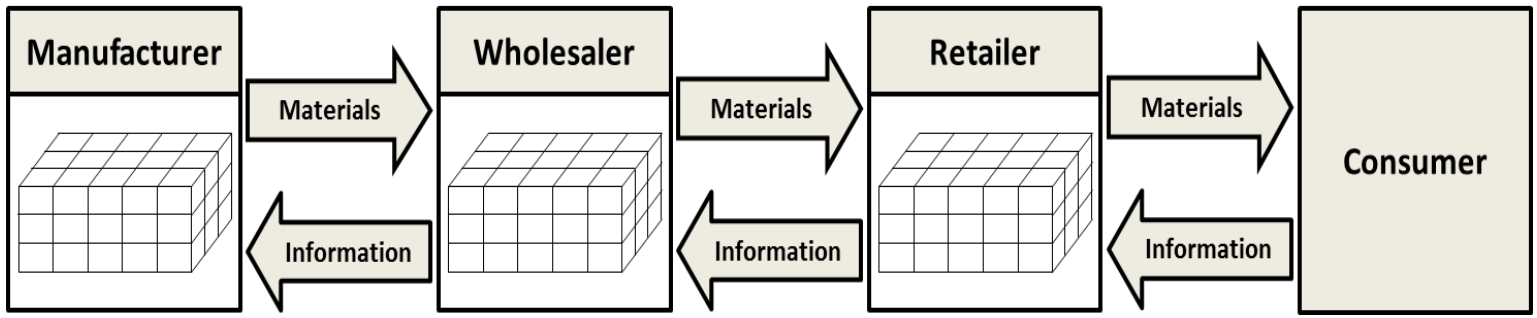
Framework for Supply Chain Forecasting





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Bullwhip Effect and its Causes

Potential Causes

- Price Fluctuations
- Batch Ordering
- Shortage Gaming
- ‘Demand Signal Processing’

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Countering the Bullwhip

At Source

- Every Day Low Pricing
- Smaller batch sizes
- Rationing policies
- Modified inventory policies

Information Sharing

- Advance price changes and discounts
- Future order information (eg large batches)
- Inventory data
- Demand data

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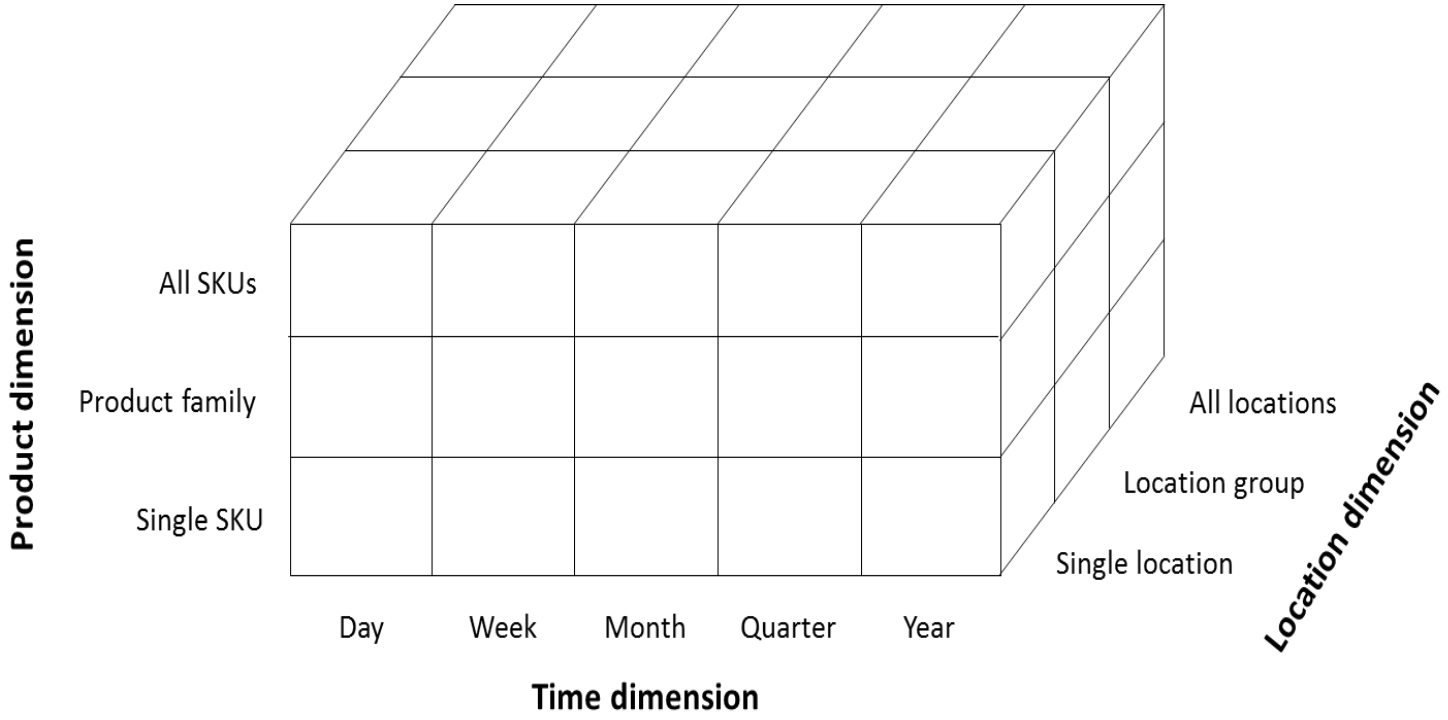
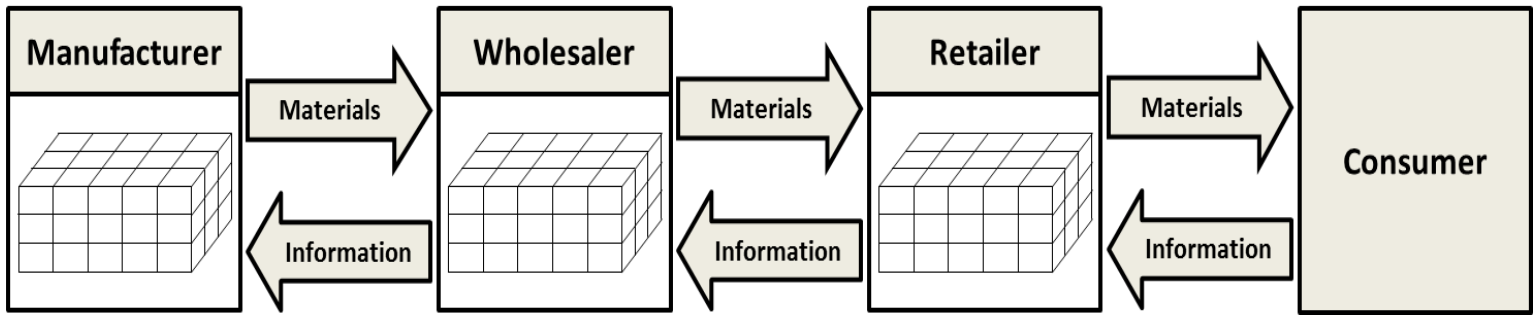
Framework for Supply Chain Forecasting





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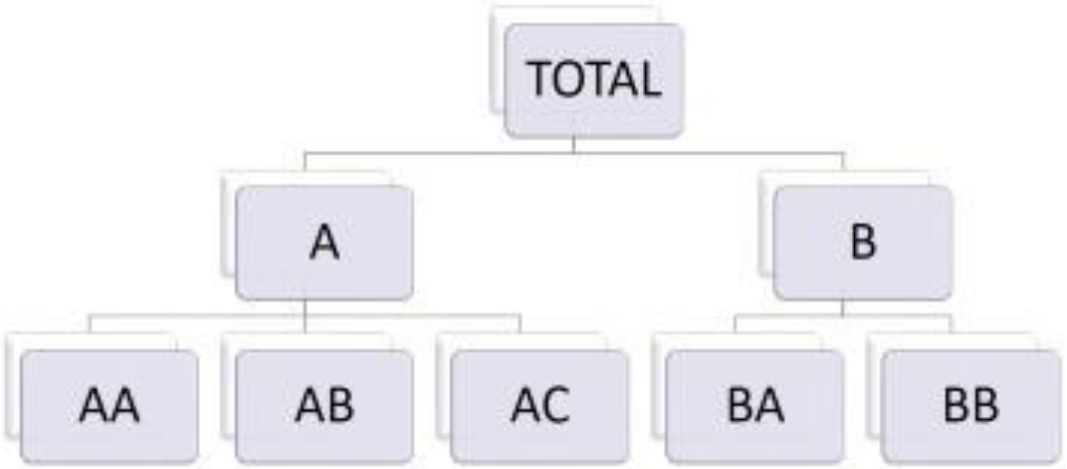
Cross-Sectional Hierarchy



Examples

- Product Groupings and Categories
- Geographical Locations
- Offline & Online

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Forecasting Approaches

- **Top-Down, Bottom-Up**

  Aggregate or disaggregate to a single level for forecasts

- **Reconciliation**

  Use forecasts at all levels of the hierarchy.

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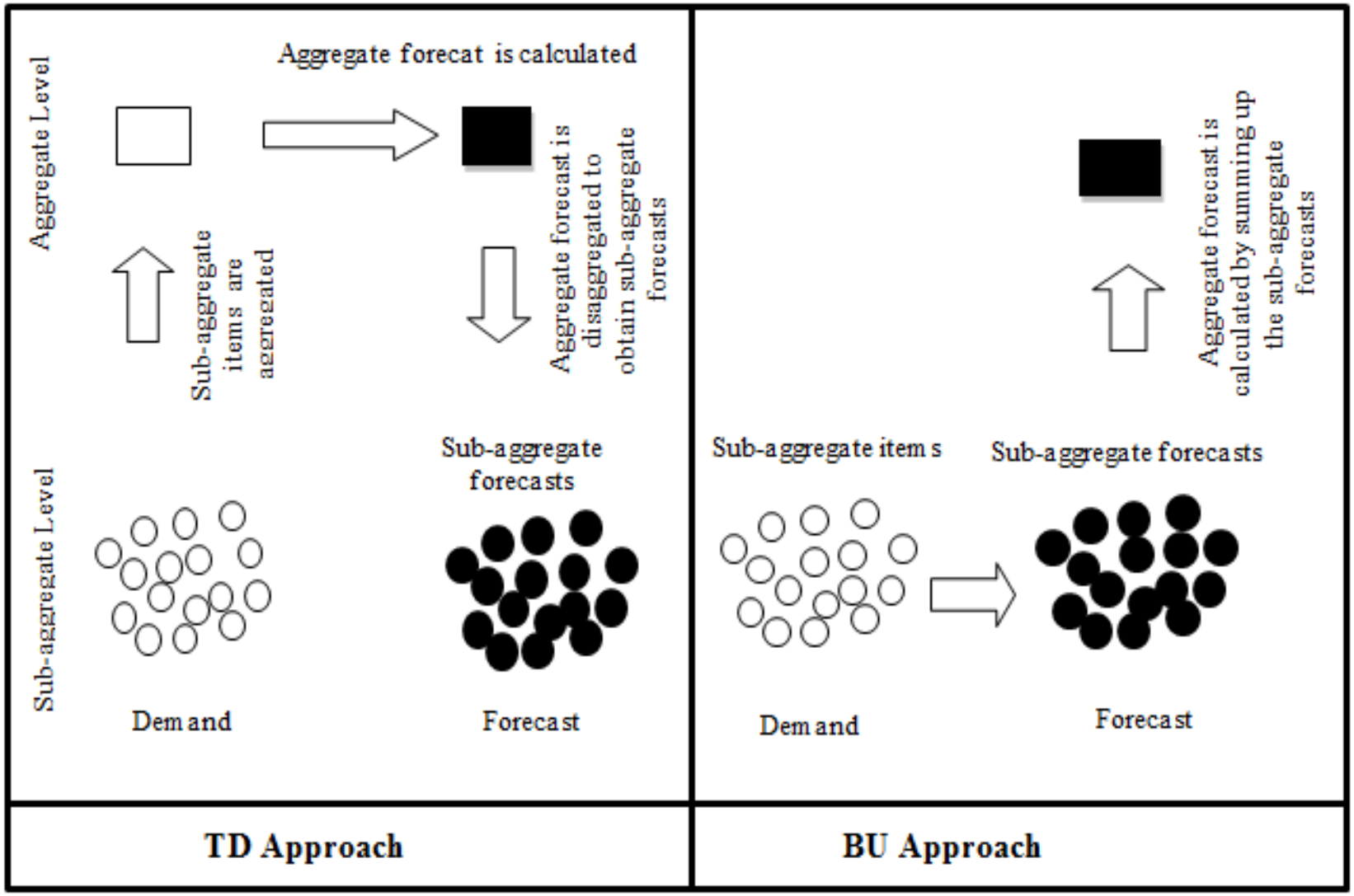
Top-Down and Bottom-Up Approaches



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Reconciliation

- Independently forecasts all series at all levels in the hierarchy
- Combine and reconcile the forecasts.

Caveats:

1. Issue of scalability
2. Not yet implemented in commercial packages, but available as open-source software in R.

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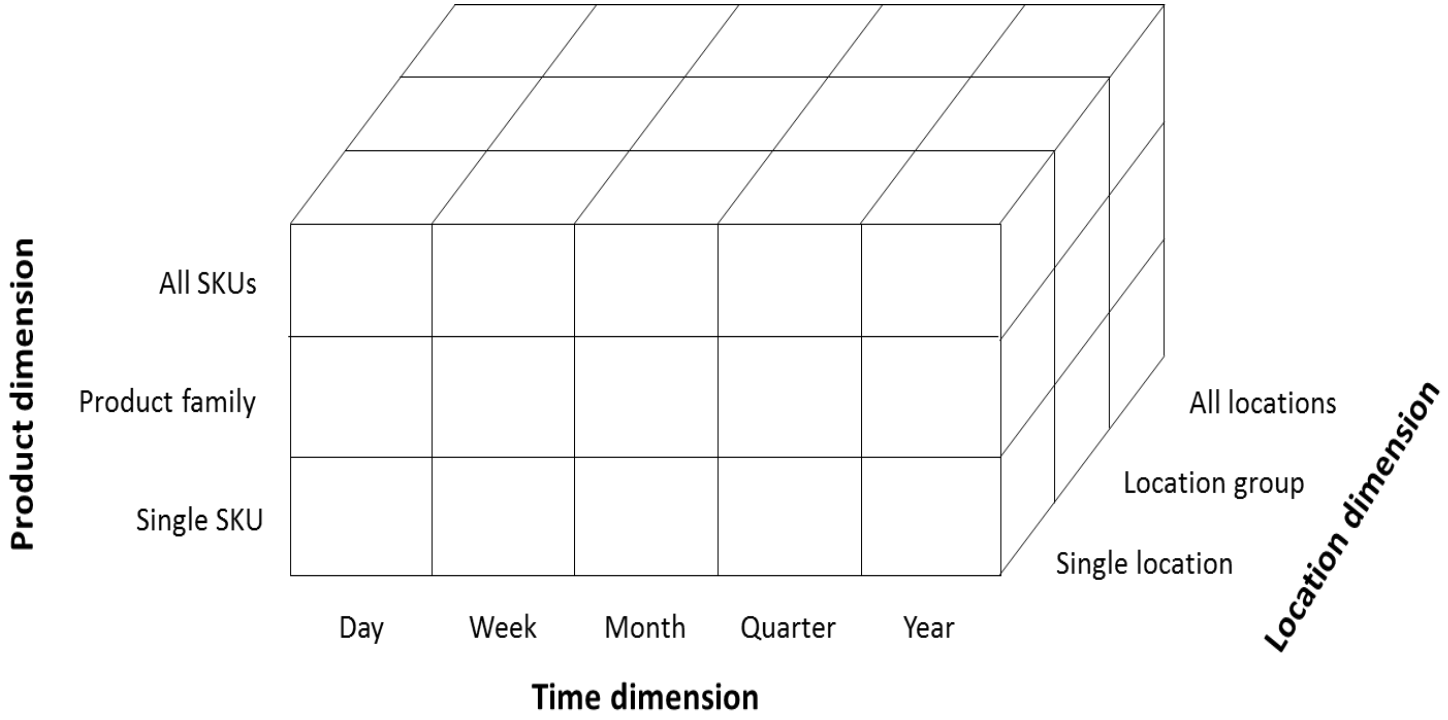

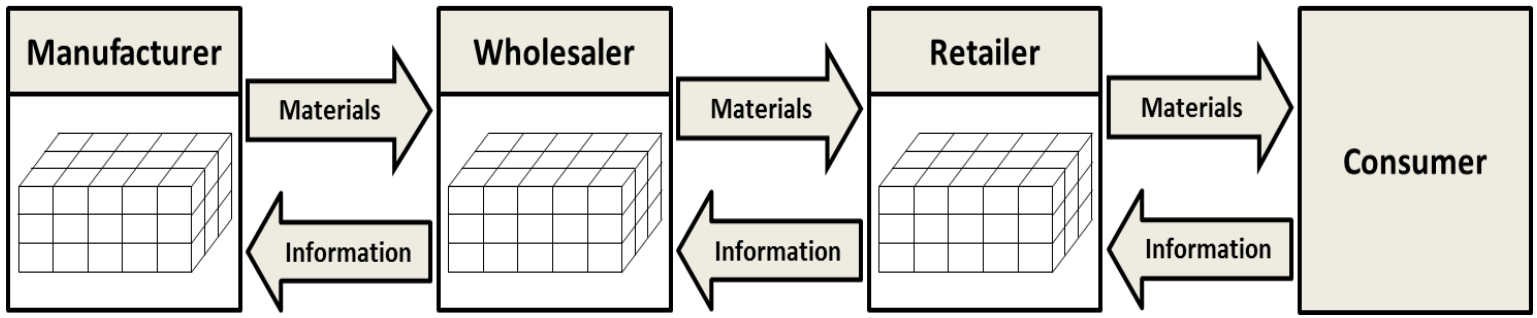

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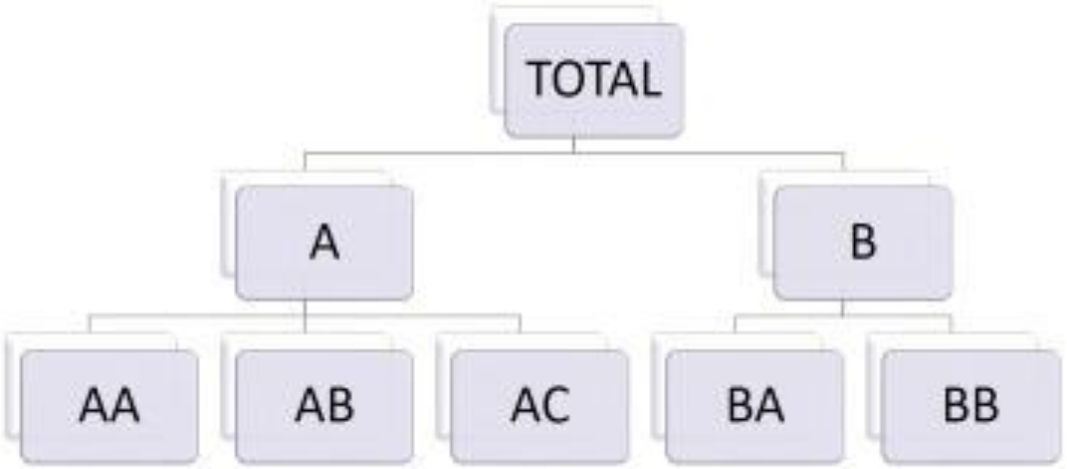
Temporal Hierarchy



Example

- Total = Year
- A, B = Half-Year
  - AA = Jan, Feb; AB = Mar, Apr; AC = May, Jun
  - BA = Jul. Aug, Sep; BB = Oct, Nov, Dec

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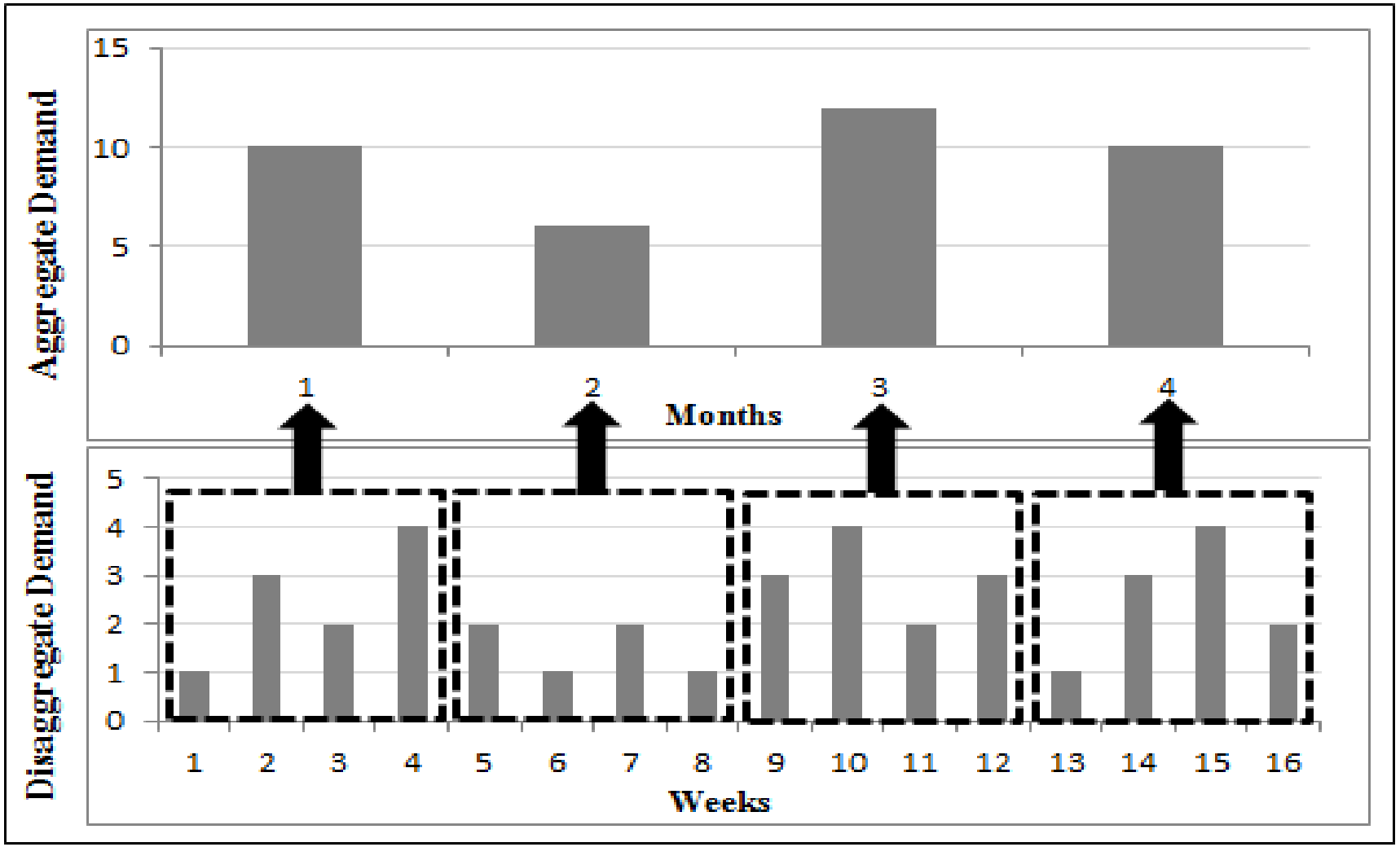
Treatment of Time

Example of non-overlapping temporal aggregation



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Opportunity for Stock Replenishment Systems

Set level of aggregation to the lead-time

Advantages

- Clearer trend and seasonal patterns may emerge at lower frequency (aggregate) level
- Intermittent demand may become non-intermittent, and less 'lumpy'

Disadvantages

- Can be less responsive to recent changes in trend.
- Need different levels of aggregation, depending on lead-times.

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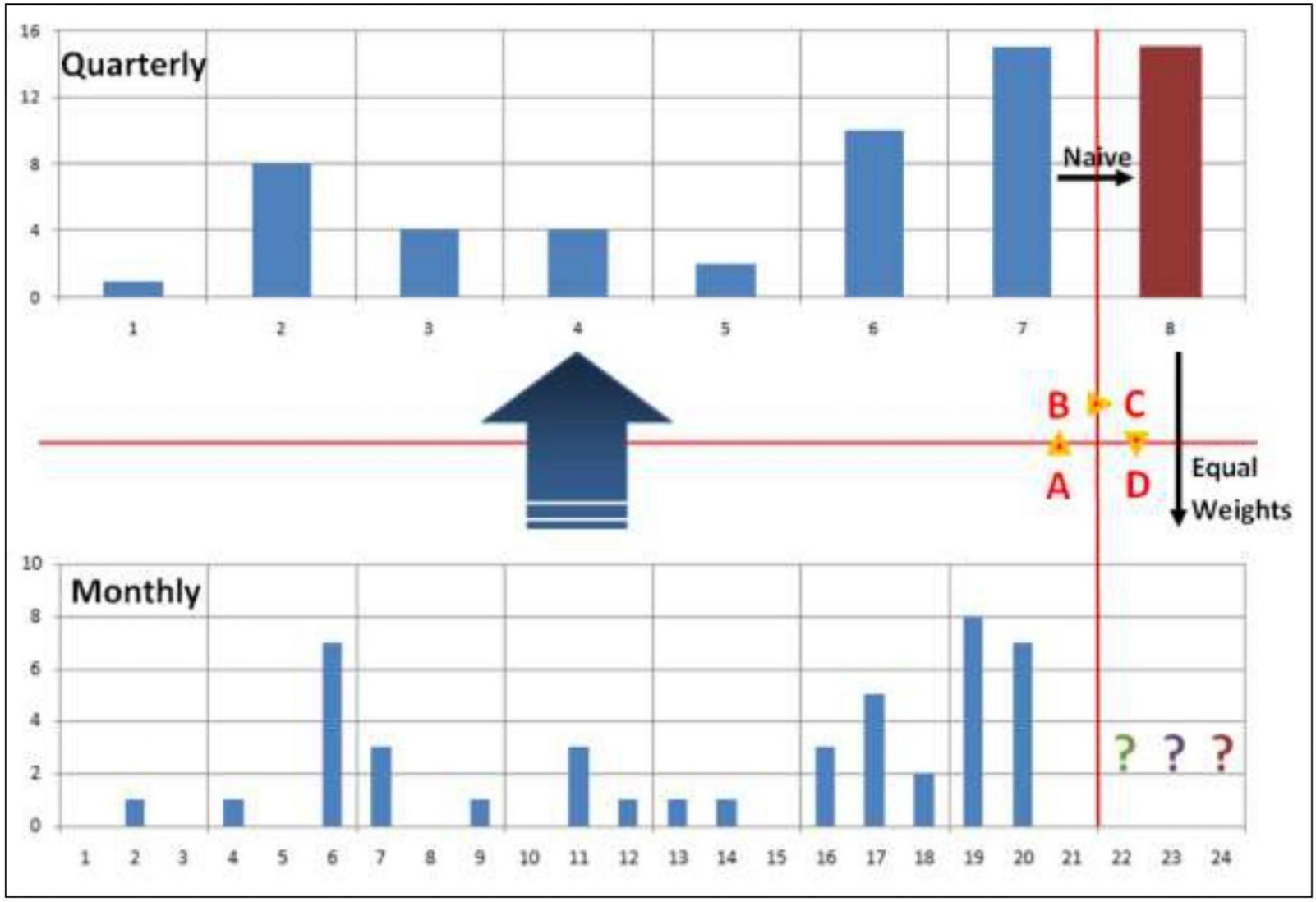
Aggregate – Disaggregate Issue



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Statistical Methods

Medium / Fast Series

Normality assumption more reasonable

Exponential smoothing (non-causal)

Regression-based (causal)

Slow / Intermittent Series

Poisson / Negative Binomial assumption more reasonable

Causal methods in some contexts (eg maintenance)

Need variants of exponential smoothing

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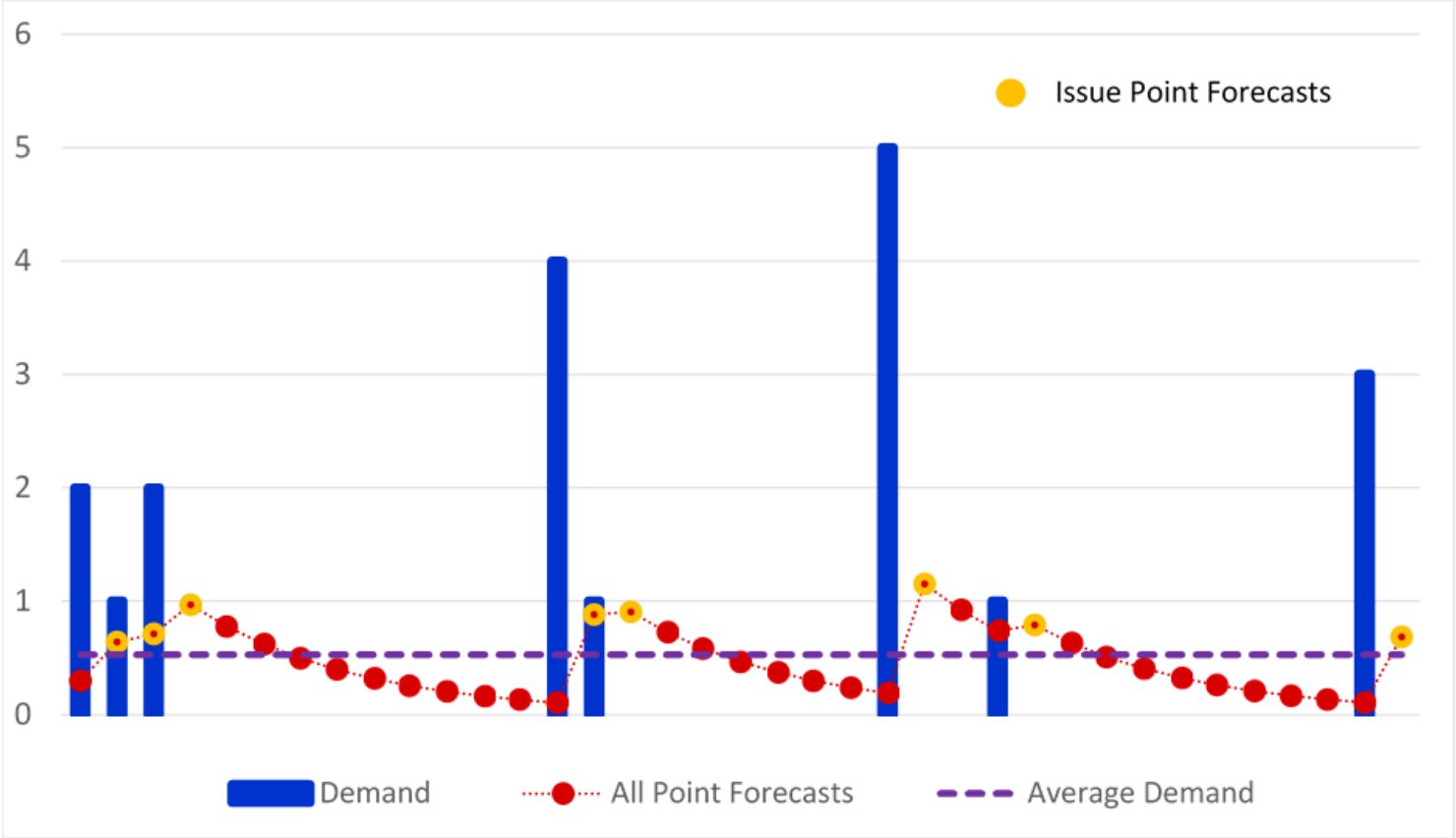
Biases from Single Exponential Smoothing



Alternatives

- Croston's Method (but has inversion bias)
- Syntetos-Boylan Approximation, SBA

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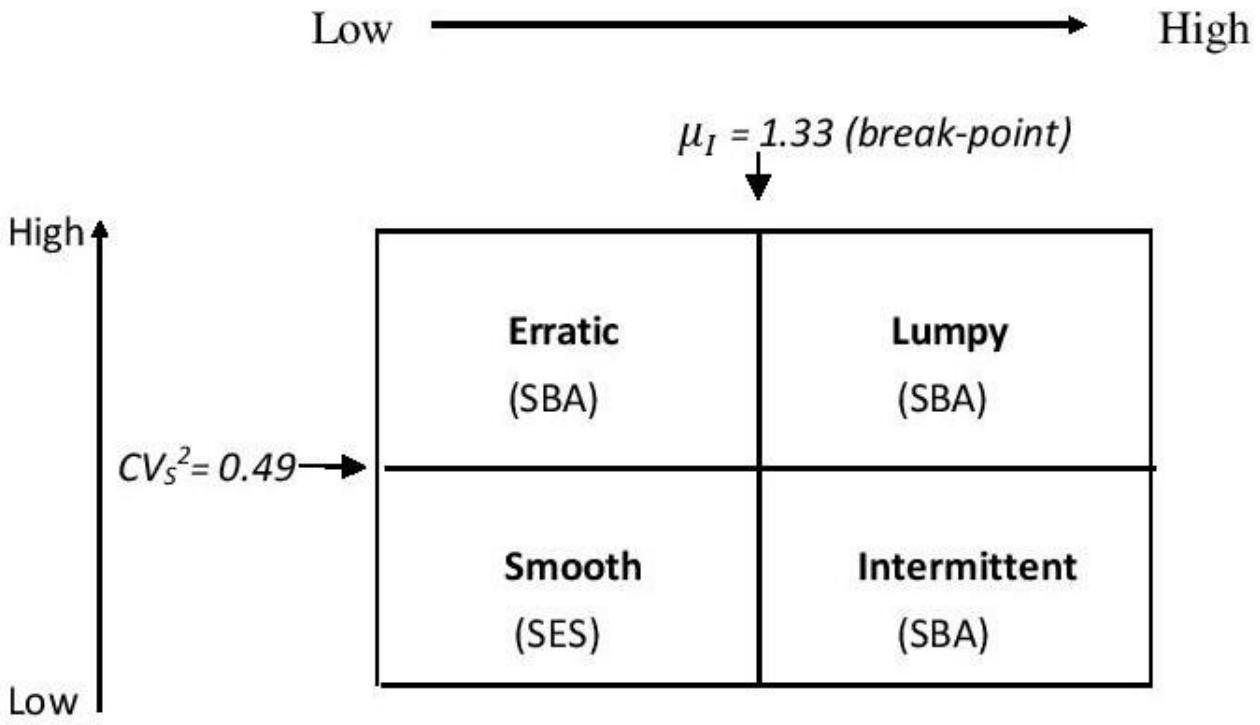
Classification for Forecasting (if data includes zeroes)



Categorise by :

- Speed of movement (horizontal axis)
- Variability of demand size (vertical axis)

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Performance Measurement

Basic requirements

- Appropriate level of aggregation
- Appropriate horizon (even if short)
- Assess by relevant categories

Two perspectives

- Forecast accuracy measures
- Accuracy-implication metrics

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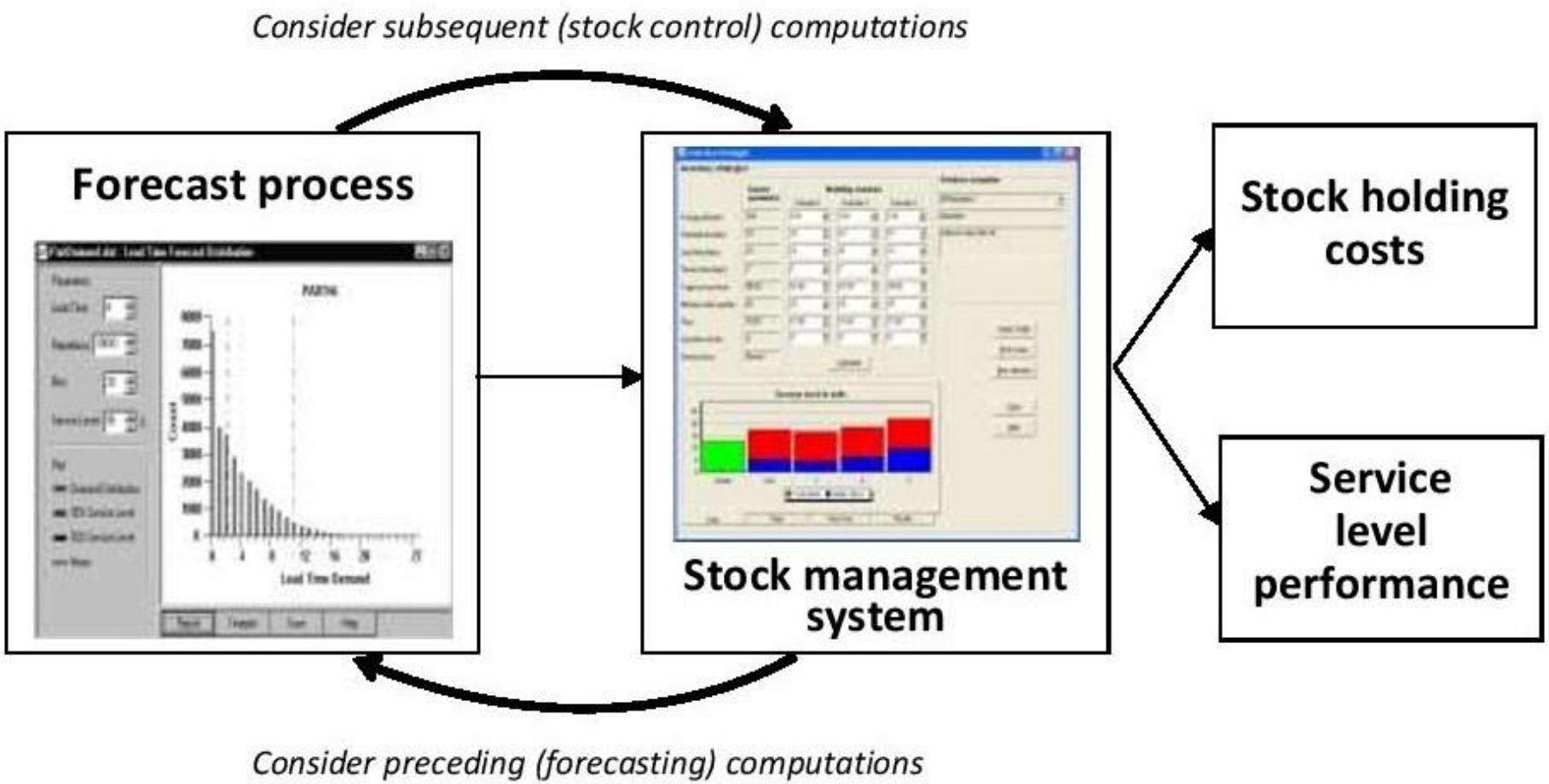
Accuracy-Implication Metrics



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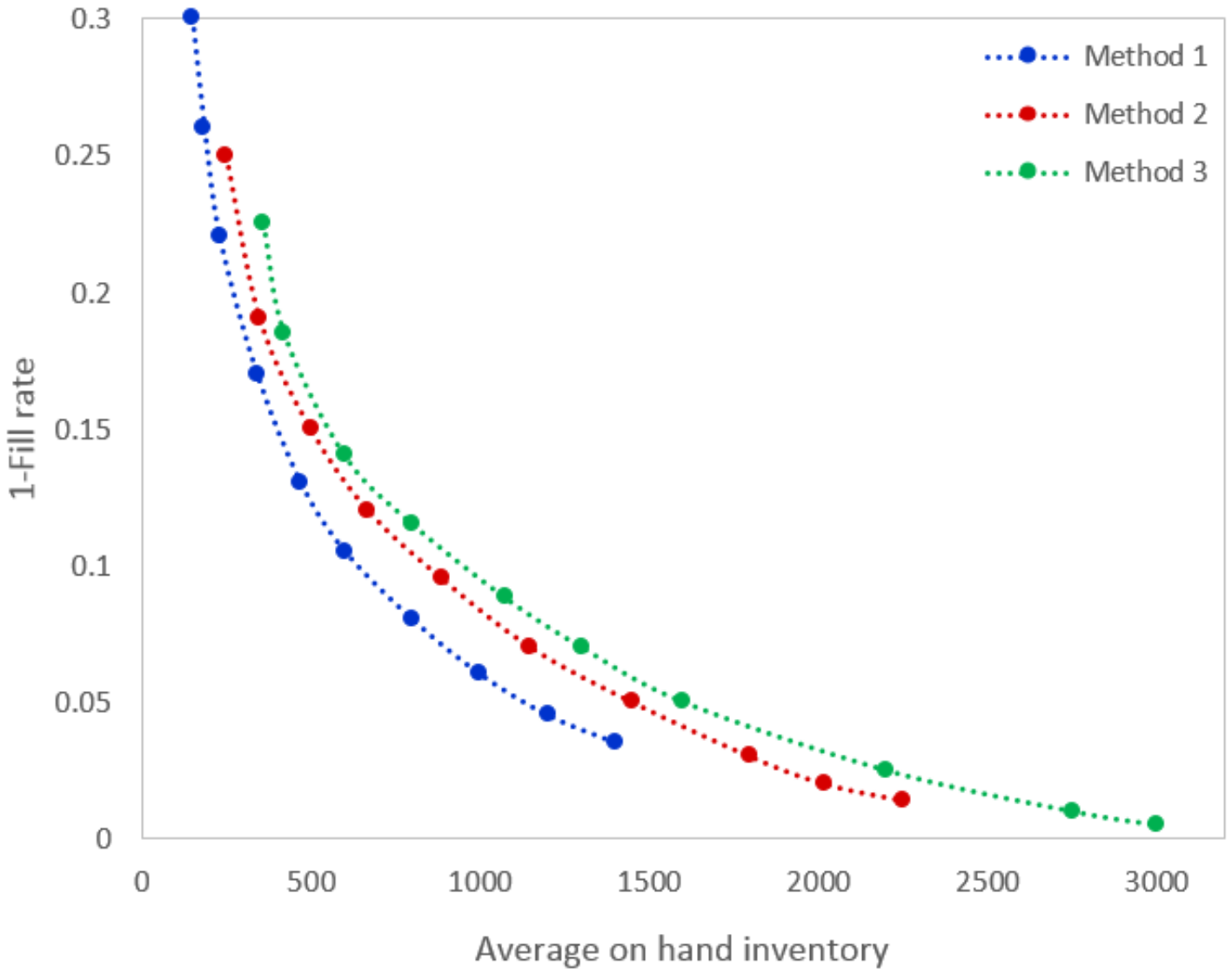
Trade-Off Curves



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Accuracy Measures: Signed and Unsigned

Unsigned Errors

- Based on absolute (or squared) errors, eg MAPE
- Ignores direction of error

Signed Errors (Bias)

- Based on errors, allowing +ve and –ve errors to cancel
- Detects direction of error

Use Both for Supply Chain Forecasting

- Inventory benefit if reduction in signed errors only
- Bias detection can help to diagnose problems

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Accuracy Measures: Requirements

1. Interpretability
    - Communicable to non-technical staff
    - Improves interaction with the forecasting system
2. Robustness to outliers
    - ‘Outlier’ = atypical observation, very high or low
    - Measure should not be unduly affected
3. Scale independence
    - Not affected by a scale of data
    - Can summarise errors across series of different volumes

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Examples of Scale Independent Measures

Relative to Mean Demand

- Scaled Mean Absolute Error
- Scaled Mean Error

Relative to Benchmark Method

- Ratio of Root Mean Square Errors
- Scaled Mean Error

Percentage Best

- Decide on appropriate measures & benchmark method(s)
- Calculate percentage of series with winning methods

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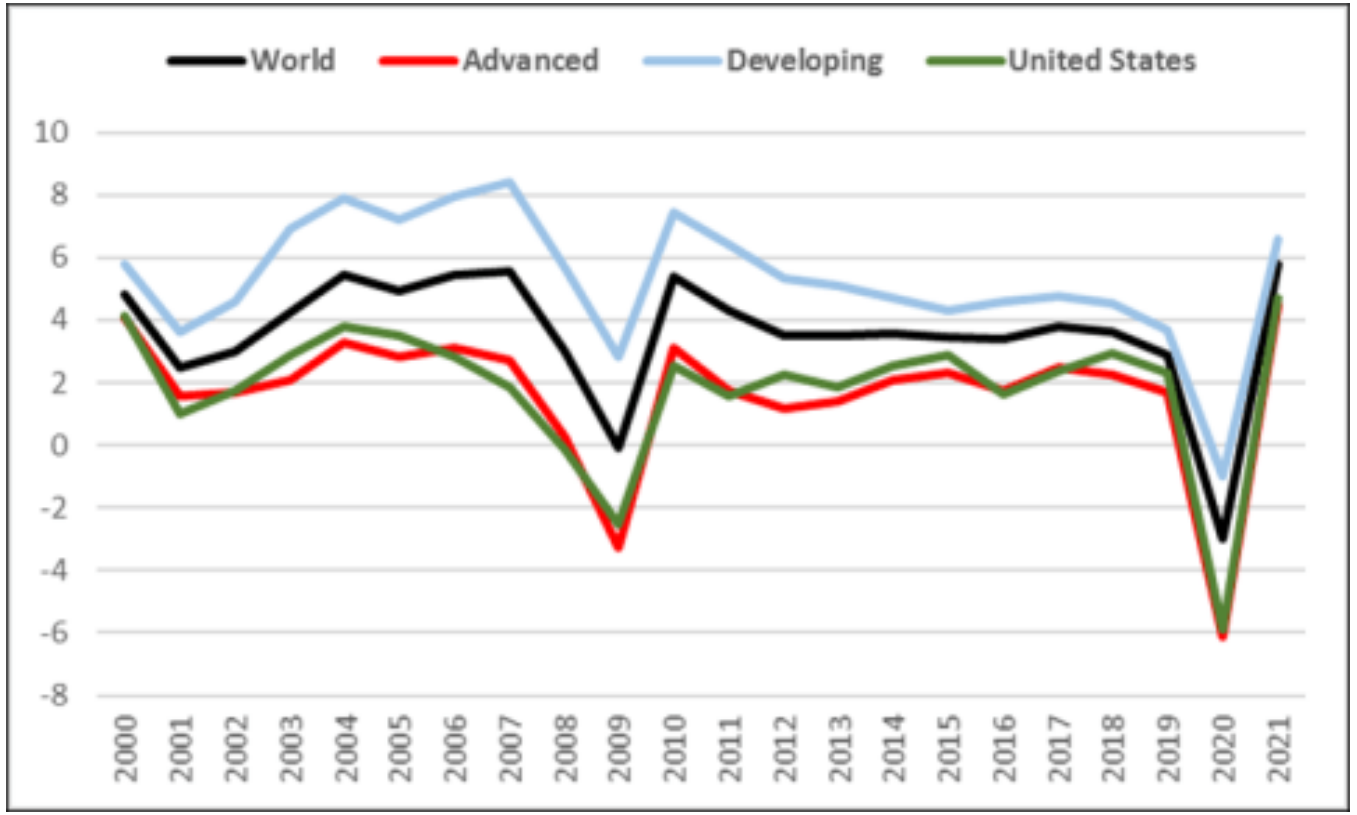
Structural Breaks



- Graph shows year-on-year GDP growth (decline)
- Future breaks likely but timing unpredicatble

Response to Structural Breaks

Judgemental Forecasts

- Statistical forecasts slow to respond
- Statistical error measures slow to respond

Questions

- Can judgemental forecasts be better informed?
- How should forecasts evolve to take more account of statistical forecasts as situation stabilizes?

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Thank you for your attention!

Q&A?

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