

# Forecasting support systems: ways forward

---

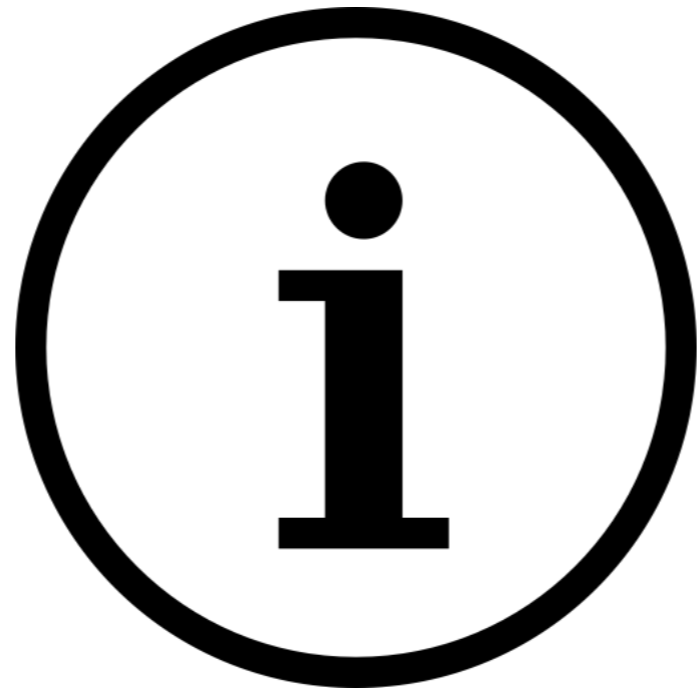
Fotios Petropoulos

Cardiff Business School, Cardiff University, UK



# Disclaimer

---



# Some of my collaborators

---

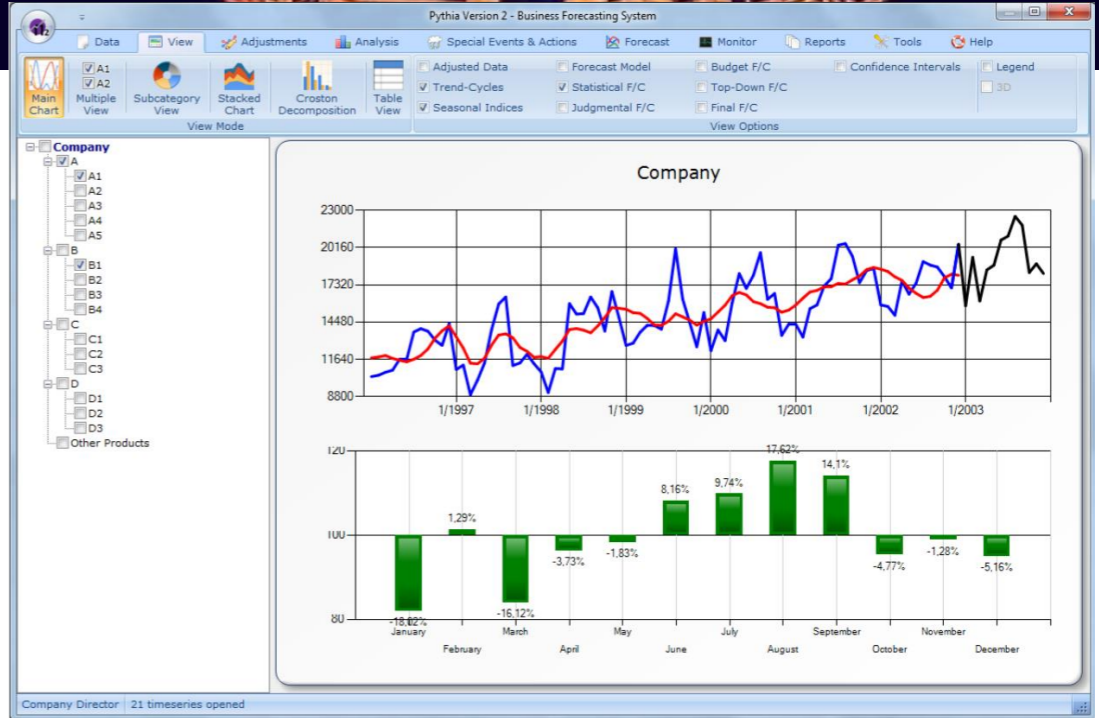
- Prof. Spyros Makridakis (INSEAD Business School, France)
- Prof. Paul Goodwin (University of Bath, UK)
- Prof. Robert Fildes (Lancaster University, UK)
- Prof. Aris Syntetos (Cardiff University, UK)
- Prof. Konstantinos Nikolopoulos (Bangor University, UK)
- Prof. Vassilios Assimakopoulos (NTUA, Greece)
- Dr. Nikolaos Kourentzes (Lancaster University, UK)
- Prof. Rob Hyndman (Monash University, Australia)
- Dr. George Athanasopoulos (Monash University, Australia)



# Forecasting and ancient Greece



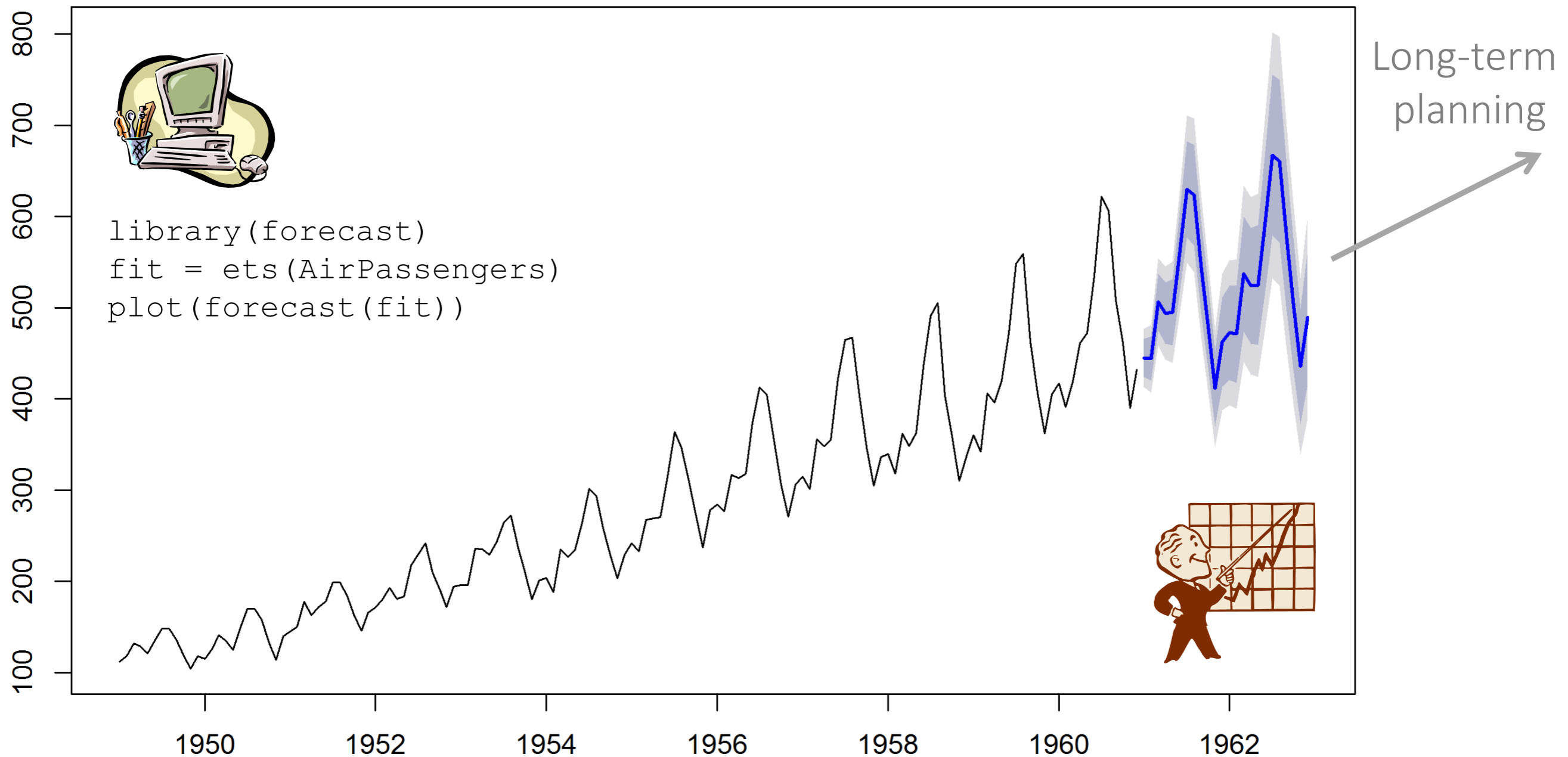
Pythia: the Oracle of Delphi  
(established in the 8th century BC)



Pythia: Business Forecasting System  
Forecasting & Strategy Unit

# Forecasting

**Airline Passengers Data + FCs**



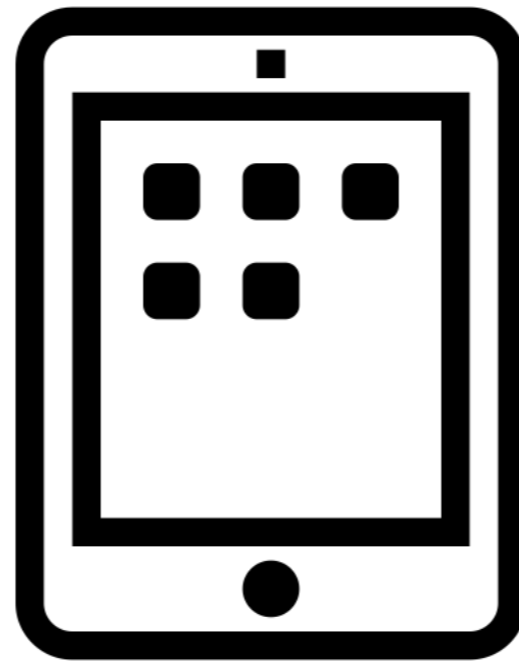
# Forecasting Support Systems

---

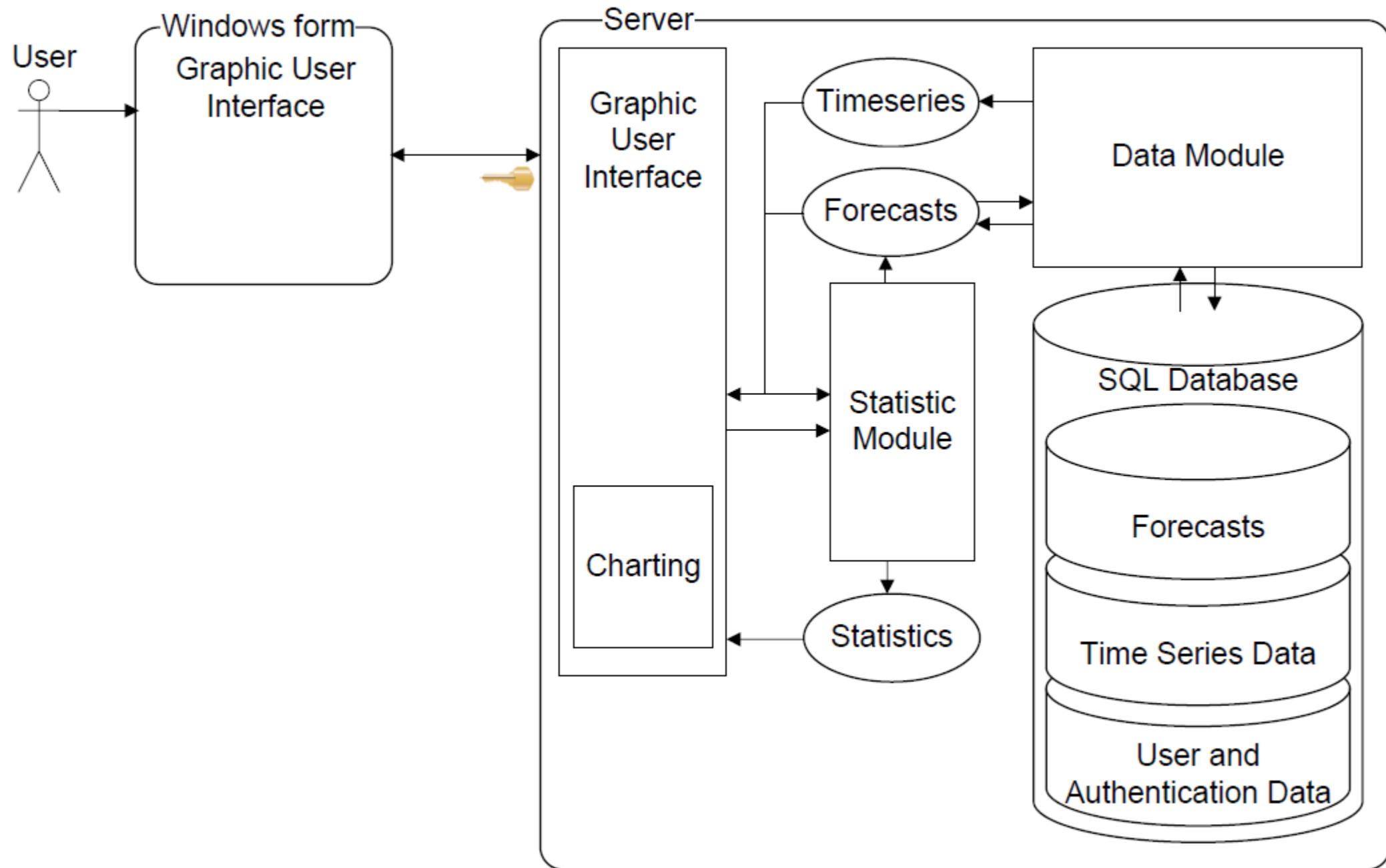
- Sets of “procedures that facilitate **interactive** forecasting of key variables in a given organizational context” [Ord & Fildes, 2013]
- Include aspects of operational forecasting, such as data **pre-processing**, **statistical modelling** and **monitoring** processes.
- Offer to the users the ability to perform **judgmental interventions** to the statistical estimates.
- Forecasting Support Systems can be viewed as integral parts of **decision support systems** [Fildes & Goodwin, 2013]

# Technological dimension

---



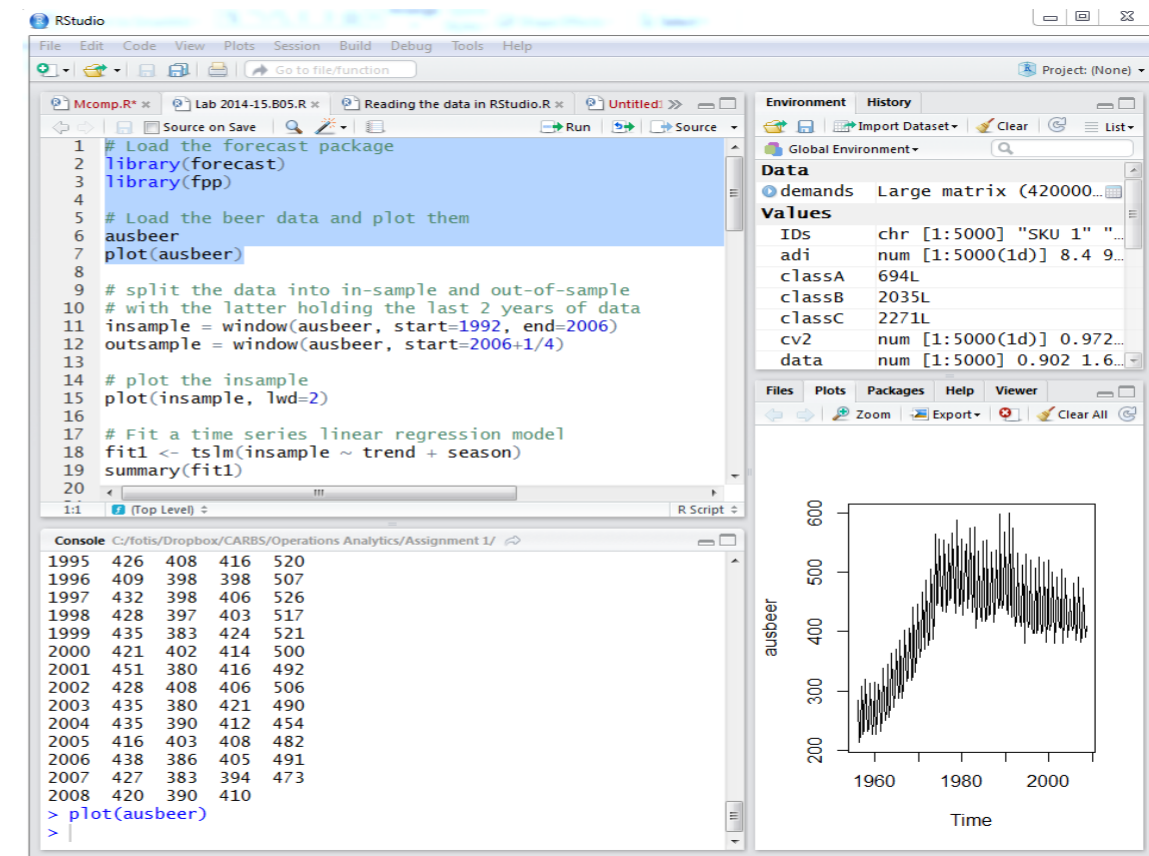
# Forecasting Support System: architecture





# Free, open-source software

- Many companies still rely on Excel-like solutions as their main means for producing forecasts.
- **R: free, open-source, publicly available statistical software**
- Well-documented → **acceptability**
- Enthusiastic and big user base, offer advice for free
- Multiple resources (packages)
- State-of-the-art methods
- Great visualisations
- A good educational tool
- **RStudio** is a free GUI for using R
- R requires some programming knowledge



# Time series packages for R

---

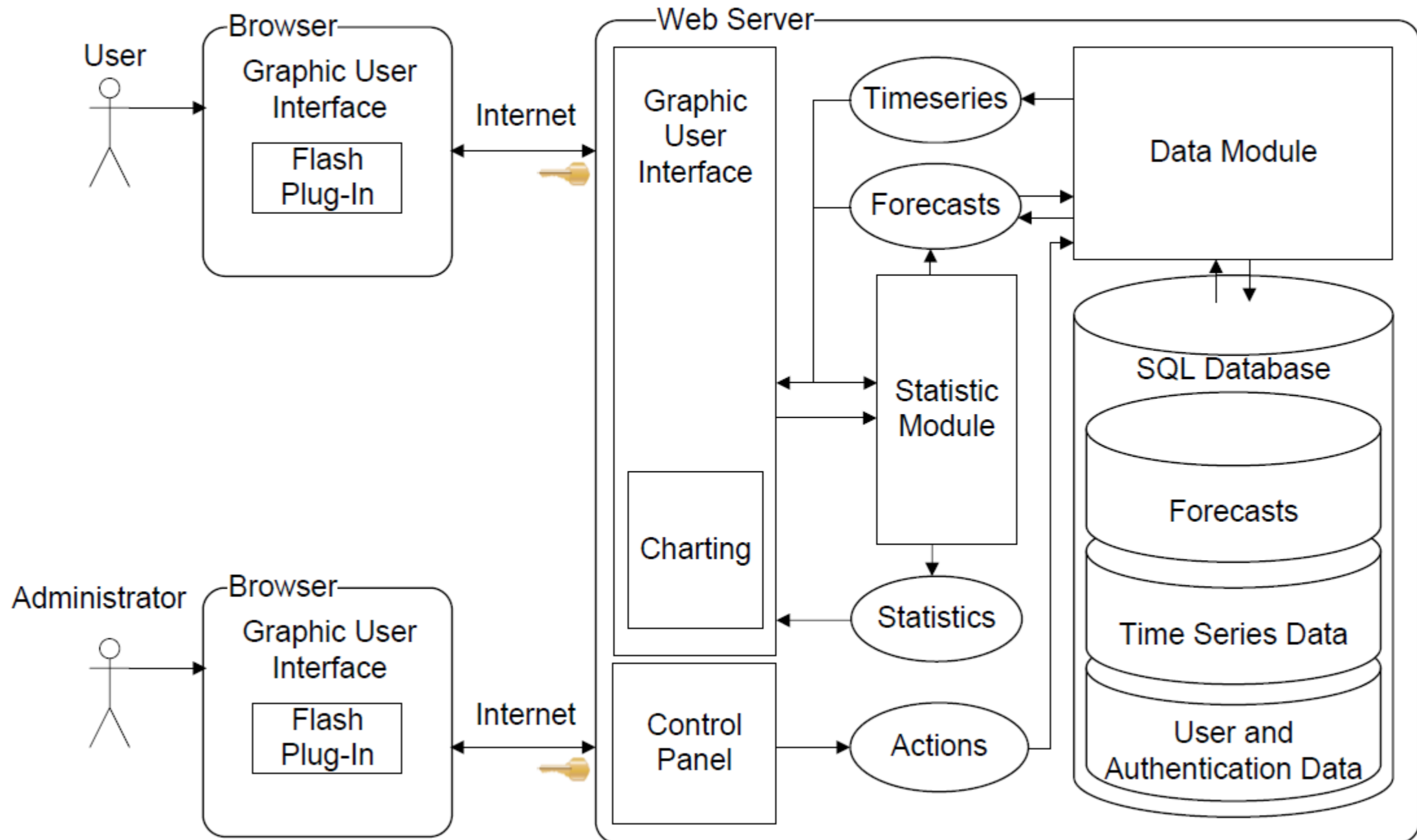
- CRAN Task View: Time Series Analysis, maintained by Rob Hyndman
- **179** time series analysis and forecasting related packages
- Forecasting and univariate modeling (forecast, exponential smoothing, theta, structural models, ARIMA models, GARCH models, count time series, change detection points)
- Frequency analysis (spectral density estimation, wavelet methods, harmonic regression)
- Decomposition, seasonality and filtering (AR and MA linear filters, singular spectrum analysis, analysis of seasonality)
- Stationarity, unit roots, cointegration
- Nonlinear time series analysis
- Dynamic Regression Models
- Multivariate time series models
- Large groups of time series, hierarchical data

# Web-based solutions

---

- **Accessible** anytime (24/7 availability)
- **Compatible** for any OS (cross-platform compatibility) and for a range of devices (work from anywhere)
- **No installation** (all devices have a web-browser), easier to set-up and maintain (always up-to-date)
- Easily **customisable**, increased interoperability
- **Centralised data**, direct access to latest information (increased collaboration), easy backup and recovery
- **Efficiency**: scalable/adaptable to increased workload (cloud storage and computing)
- **Cost efficient**: reduced spending on technology infrastructure
- Online training
- But... technical issues, dependent on an internet connection, security in the cloud, prone to hacking

# (Web) Forecasting Support System: architecture



# Customisable

---

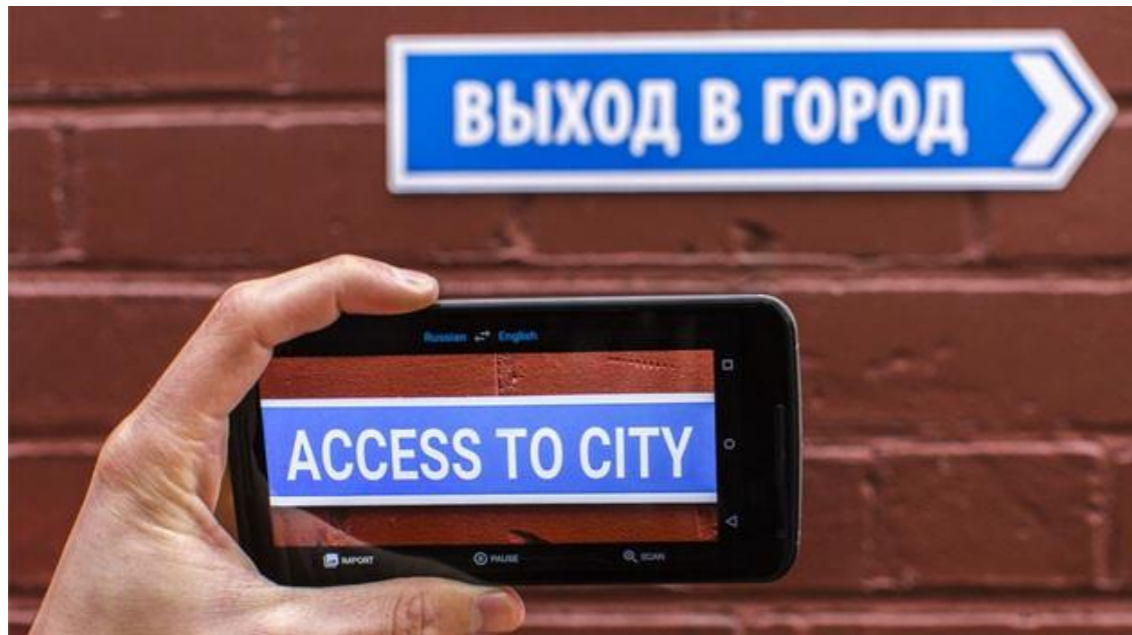
- Each company has its very individual forecasting needs
- **Is there is one FSS to fit them all?**
- Forecasting for retailers' demand, forecasting for call centres, energy consumption forecasting
- Different data (low/high frequencies, fast/slow-moving)
- Different forecasting process (pre-processing, post-processing, monitoring)
- Special events/promotions and integration of managerial judgment
- Different forecasting methods
- Does it make sense to provide a super-complex FSS that is able to do all, or to allow for a **customisable user interface**:
  - for different companies
  - for different levels/groups within a company
- Clean interface = **easier to use**

# Mobile forecasting

---

- Mobile devices (such as smart phones and tablets) are continuously featuring high-end specifications.
- Forecasting “in the pocket” [Asimakopoulos et al., 2014, Foresight]
- Opportunities:
  - routine-use, communication, instant access to forecasts and reports, recording tool, exception list reporting, tracking and sharing of events and promotions
- Challenges:
  - loss and hacking, mobile limitations, data visualisation difficulties
- Design practices:
  - Interactive dashboards
  - Easy to read in a smaller form factor
  - Drill-down, filtering, content search
  - **Take advantage of the technical specs of mobile phones**

# Click & forecast



2015: Google translate



2014: Photomath

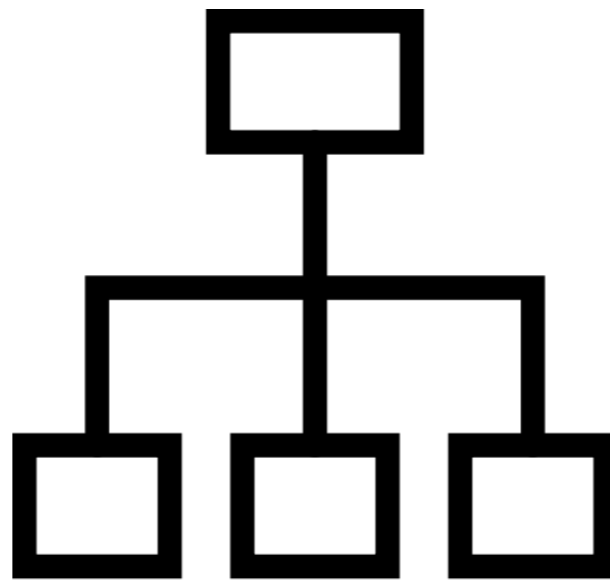


2013: Foredroid

Skiada F., Raptis A., Petropoulos F. & Assimakopoulos V. (2013)  
"A forecasting support system for mobile devices",  
*26<sup>th</sup> European Conference on Operational Research*

# Methodological dimension

---



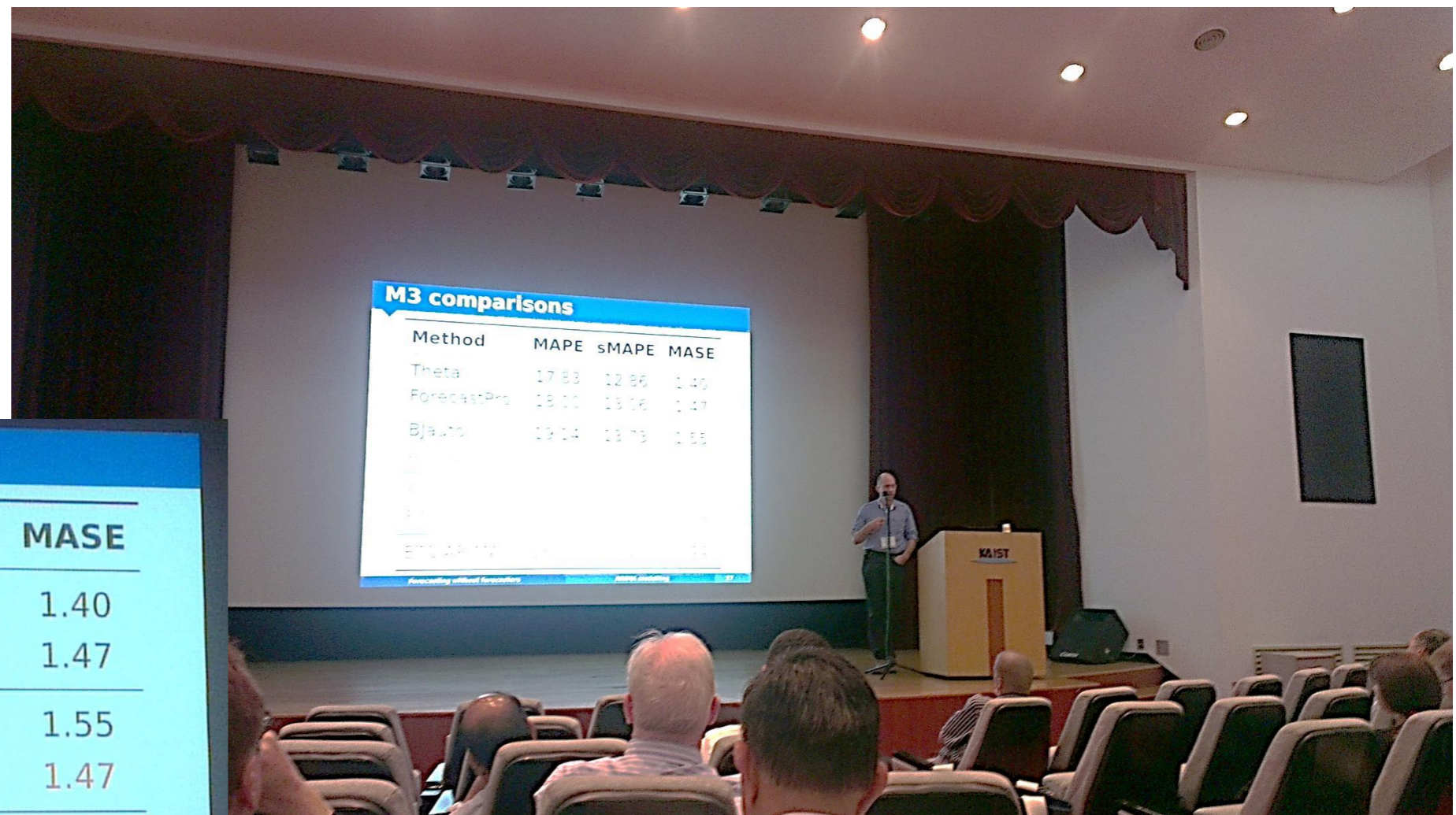


# Forecasting methods

Rob J. Hyndman (2013) "Forecasting without forecasters"  
Keynote Speech at the ISF2013

M3 comparisons			
Method	MAPE	sMAPE	MASE
Theta	17.83	12.86	1.40
ForecastPro	18.00	13.06	1.47
Bjauto	19.14	13.73	1.55
AutoARIMA	18.98	13.75	1.47
ETS-additive	18.58	13.69	1.48
ETS	19.33	13.57	1.59
ETS-ARIMA	18.17	13.11	1.44

Forecasting without forecasters ARIMA modelling 27



M3 comparisons			
Method	MAPE	sMAPE	MASE
Theta	17.83	12.86	1.40
ForecastPro	18.00	13.06	1.47
Bjauto	19.14	13.73	1.55
AutoARIMA	18.98	13.75	1.47
ETS-additive	18.58	13.69	1.48
ETS	19.33	13.57	1.59
ETS-ARIMA	18.17	13.11	1.44

Forecasting without forecasters ARIMA modelling 27

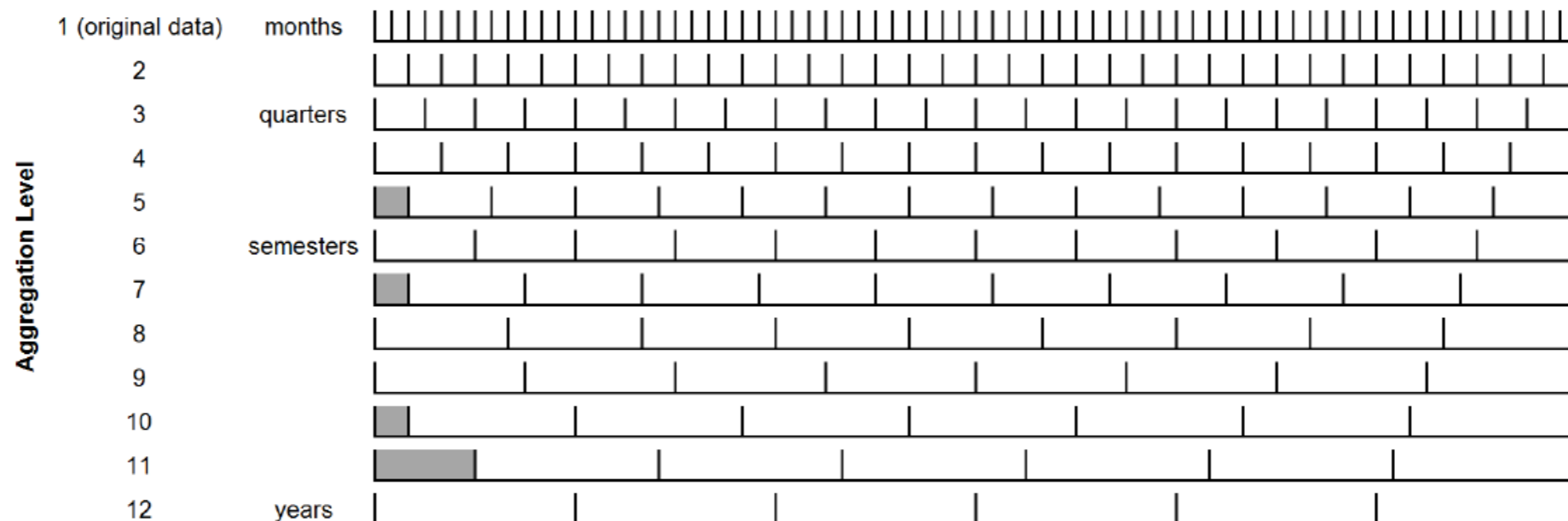
# Forecasting for intermittent demand

---

- Intermittent demand: infrequent demand arrivals coupled with variable demand sizes, whenever demand occurs.
- **60% of the stock keeping units (SKUs)** in a standard industrial setting are characterised as **intermittent** [Johnston et al., 2003]
- **Very limited support** in handling count data and integration of methods specialised for forecasting intermittent demand.
- In the best case, only Croston's method is implemented (using fixed smoothing parameters), without even considering the Syntetos-Boylan approximation for bias correction.
- On the bright side: several **inventory software** include these techniques, as well as classification strategies suggested in the literature.
- Publicly available `tsintermittent` package for R allows for incorporation these methods into FSSs.

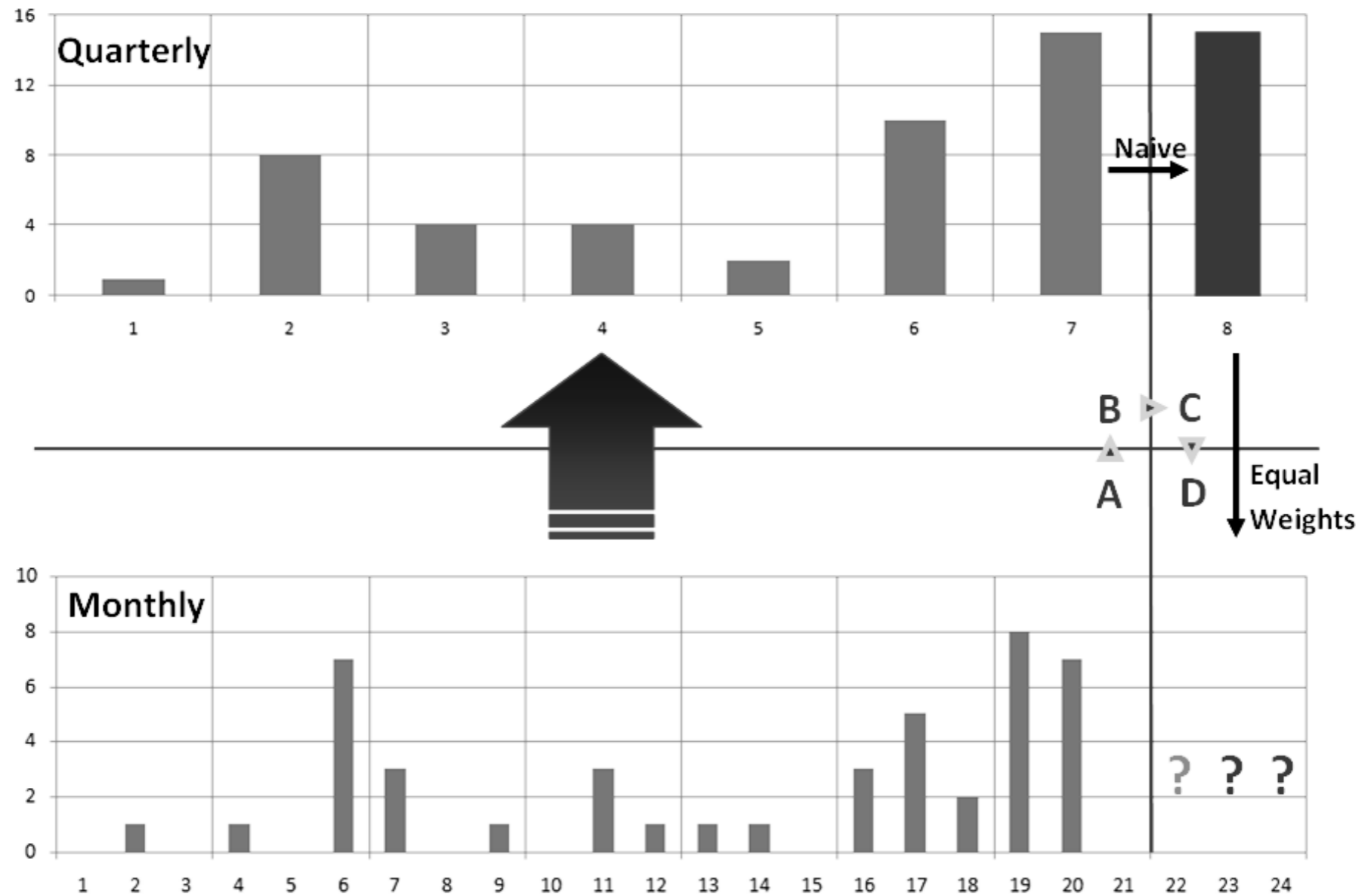
# Temporal aggregation

- Temporal aggregation refers to aggregation in which a low frequency time series (e.g. quarterly) is derived from a high frequency time series (e.g. monthly).
- This strategy **highlights or attenuates different series characteristics** on each level of aggregation:
  - At lower aggregation (high frequency time series) periodic components, such as seasonality will be prominent.
  - At higher aggregation levels high frequency signals are filtered and more importance is given to the lower frequency components, such as the level and trend of a time series. Also, demand is less intermittent.



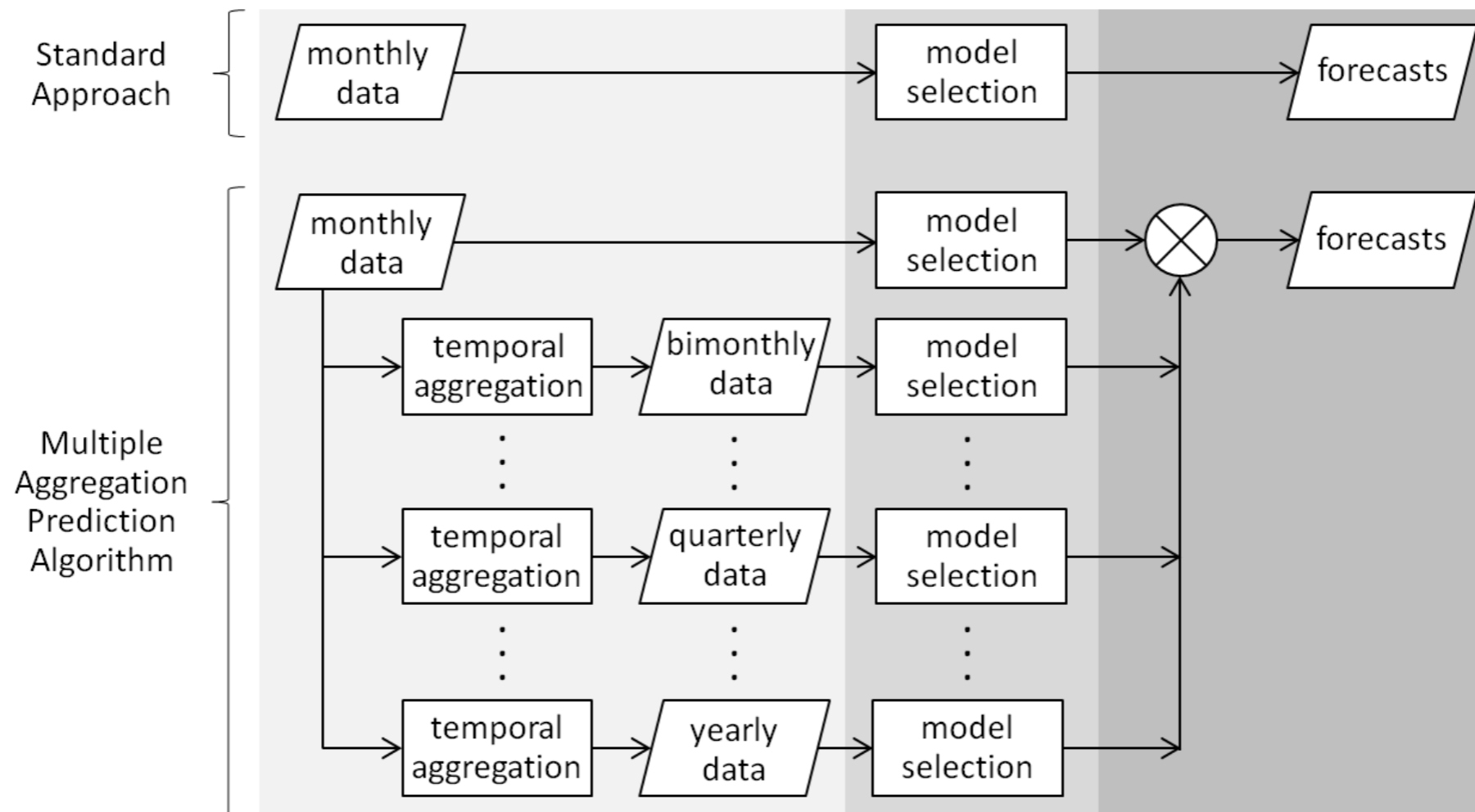


# Aggregate-disaggregate intermittent demand approach (ADIDA)



- A: Original data (months)
- B: Aggregate data (quarters)
- C: A quarterly forecast is produced
- D: The quarterly forecast is broken down to three equal monthly forecasts

# Multiple aggregation prediction algorithm (MAPA)



- Combination across forecasts derived from transformed frequencies is efficient and **improves the forecasting performance**.
- Also removes the problem of appropriately selecting the hyper-parameter for the ADIDA framework.
- Combining across multiple aggregation levels results in reconciled forecasts for all frequencies, suitable for **matching operational, tactical and strategic forecasts**.

# Cross-sectional aggregation

---

- Producing forecasts at different hierarchical levels (company-level, sector-level, SKU-level) using different aggregations of the data can lead to numerical differences.
- Various statistical **reconciliation approaches** have been considered: bottom-up, top-down, middle-out, optimal combination.
- Hierarchical forecasting can help **improve the accuracy** of the relevant decision making series.
- **Duality of hierarchies**: “forecasting-optimal” hierarchies that are dual to the decision making hierarchies, i.e. provide outputs relevant to the operations of an organisation, while maximising the accuracy gains due to the hierarchical structure.
- Grouped seasonal indices → better estimation of the seasonal component.

# “Is it safe to assume that software is accurate?”

---

- No. [McCullough, 2000]
- (In some cases) user-friendliness is appreciated more than accuracy.
- Even for the simplest methods (SES) different software packages might provide different predictions.
- Different assumptions in optimisations and initialisations ...or bugs?
- Full documentation of the implemented algorithms and provision of simple code/examples → increase user's trust
- Software reviews in both academic and practitioners' journals.
- **Replicability** and **reproducibility** → better software.

# Judgmental component

---





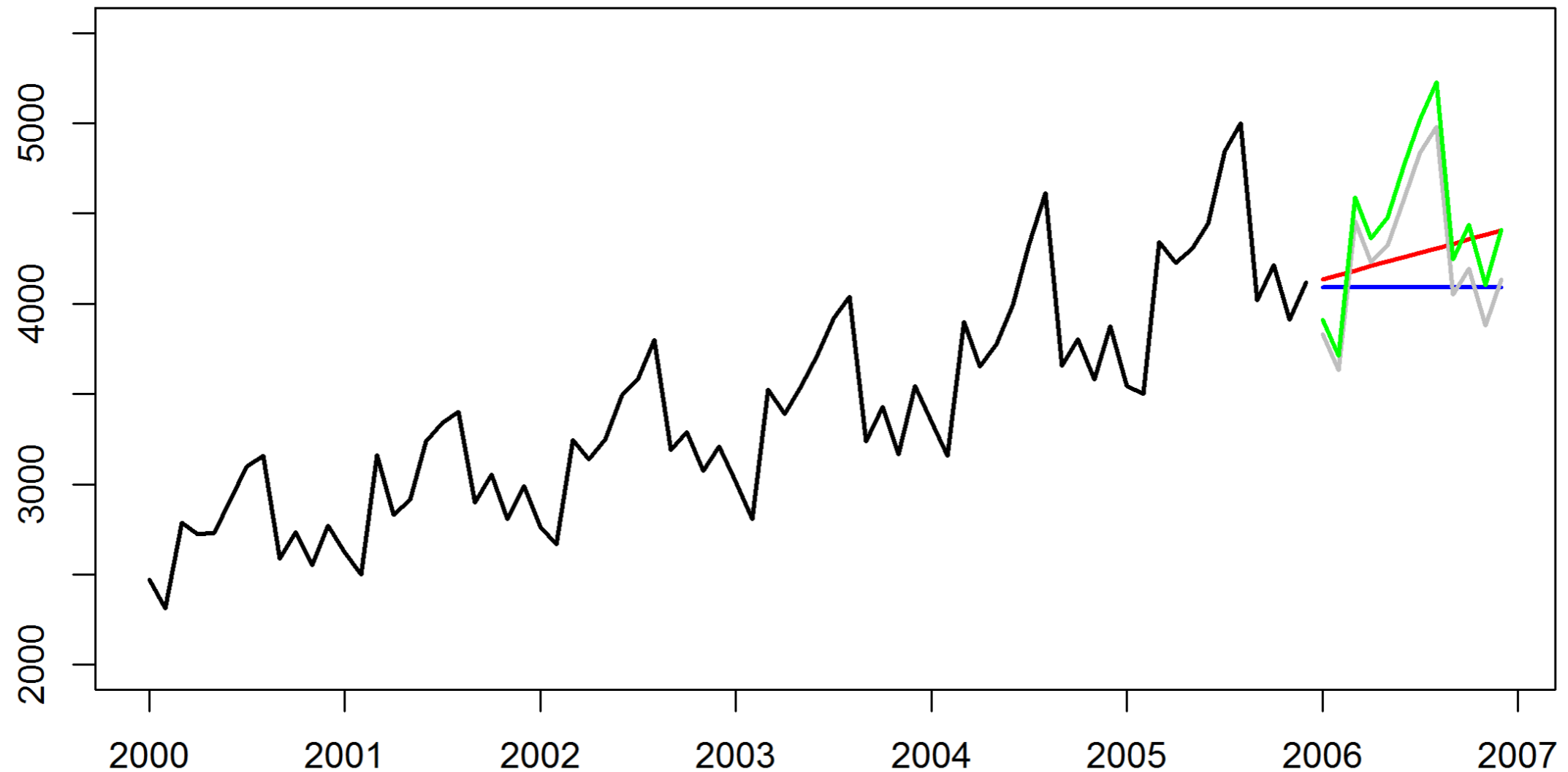
# Judgmental forecasting & adjusting

---

- Improving judgmental forecasts through feedback, decomposition, combinations, and advice [Lawrence et al., 2006, IJF]
- Statistical outputs are often adjusted by managers/experts:
  - Special events/promotions
  - Ownership vs “black box”
  - Politically-related or budget targets
  - Confusion of the signal with the noise
- Better facilitate judgmental adjustments by:
  - Memory support [Lee et al., 2007, IJF] → structured analogies [Kesten & Armstrong, 2007, IJF]
  - Monitor and report performance for both statistical and judgmentally adjusted forecasts
  - Requiring note recording → better understanding market intelligence [Fildes et al., 2009, IJF]
- Support through **restrictiveness** (low flexibility) *versus* support through **guidance** (“expert system”) [Fildes et al., 2006, DSS]

# Judgmental model selection\*

---



- An 'optimal' model may be selected automatically by the software...
- ... or judgmentally!

\* Based on a work in progress with Nikolaos Kourentzes and Kostas Nikolopoulos, under the title "DIY forecasting: judgment, models and judgmental model selection"

# Judgmental model selection: experiment

Model Selection

Model Build

The interface displays a time series plot on the left and a seasonal plot on the right. A central table lists four models with their applicable trend and seasonality patterns. Below the table are instructions and a 'Submit' button.

Model	Trend	Seasonality
Simple exponential smoothing (SES)	✗	✗
SES with seasonality	✗	✓
Damped trend	✓	✗
Damped trend with seasonality	✓	✓

Select the model:

- Model A
- Model B
- Model C
- Model D

Press only once!

Select patterns that are applicable (if any):

- Trend
- Seasonality

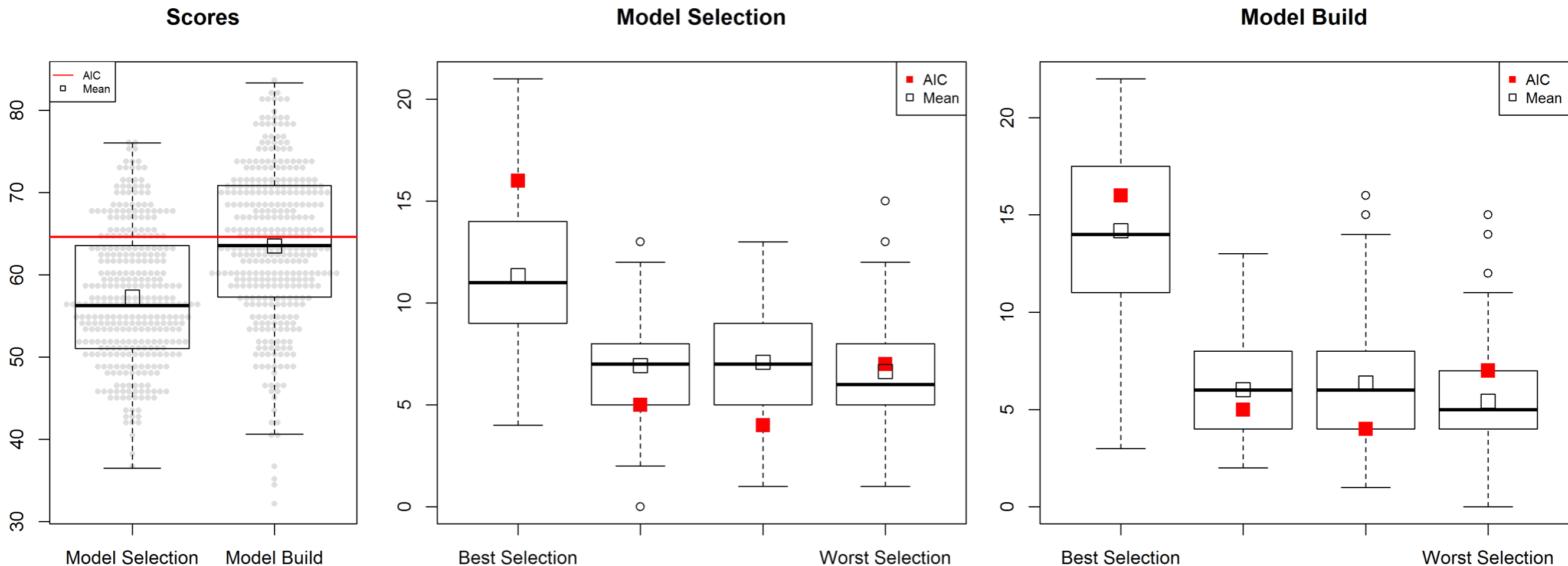
If you are confident with your selection, you can proceed to the next series by clicking once on the 'Submit' button.

Submit

Press only once!

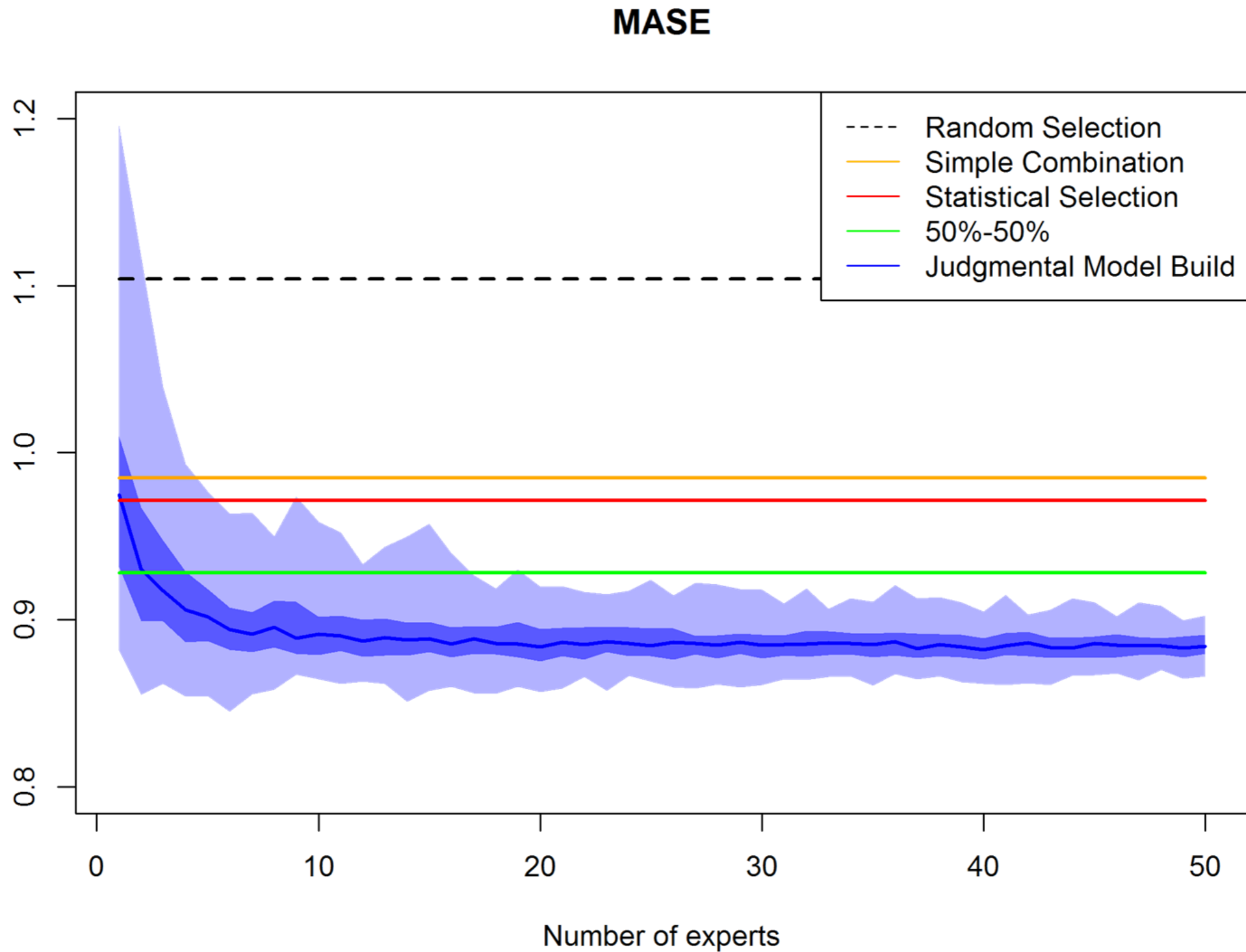
Each of the **693 participants** was randomly assigned in one of the two approaches and was asked to provide selections for **32 time series**.

# Selecting models judgmentally



- Overall, humans' score is lower than statistics...  
...while they select the ex-post best model less frequently.
- However, they do succeed in avoiding the worst model.
- How does this translate to forecasting performance?

# Judgmental model selection: results



# Judgmental model selection & FSS

---

- Do not over-rely on the automatic “optimal” forecast selected by the system.
  - Humans can be as good as (if not better) in selecting models as AIC.
  - Improvements in forecasting performance are significant when a weighted combination of the selections of multiple humans are considered.
  - Model build (selecting models based on data decomposition) is better than traditional model selection.
- Advice the managers that manual selection has its merits!
- Provide the means for model build (decomposition) approach
- Allow for grouped judgmental model selection (wisdom of crowds)

# Judgmental hierarchical reconciliation

---

- A disadvantage of all statistical reconciliation approaches is their full reliance on statistical weighting schemes that **do not take into account the special circumstances of each case**, thus lacking the judgmental component.
- Different stakeholders should be able only to **share information**, but also their **views and opinions** with regard to the impact of future special events.
- Systems that would render the demand planners able to **judgmentally reconcile the differences in the forecasts** of the various levels.
- The result of this approach would be **consensus**, and not only in terms of numbers!
- By allowing the forecasters to manually fix any differences in the forecasts, they keep the sense of “**ownership**” but in a **collective manner**.

# A forecasting-foresight support system

---

- A need for audit and expand the **means of communication** and **co-operation** between demand planners of the various hierarchical levels.
- Foresight Support Systems: “collaborative computer-based systems aimed at supporting: communication; decision modelling; rules of order in foresight processes” [Banuls & Salmeron, 2011]
- Combine knowledge base and group models with quantitative data processes [Skulimowski, 2012]
- Integration of more qualitative structured methods, such as the **Delphi method** [Rowe & Wright, 1999; 2001]
- **Forecasting and foresight support systems (F<sup>2</sup>SS)** [Spithourakis et al., 2015, IJF]
- A prototype web-based **F<sup>2</sup>SS** was introduced in a group of students, showing good levels of satisfaction and influence from team co-operation.



# A forecasting-foresight support system

---

- A system that combines features of both forecasting & foresight processes can:
  - enhance the **user experience**
  - allow for a **deeper understanding** of the underlying process
- By enabling collaboration and communication between members of the same team:
  - increased **input** from members of different hierarchical levels
  - increased **levels of satisfaction** in terms of collaboration
- The application of such a system design in real life can lead to **improved operational performance**, making forecasts **highly acceptable** to managers of all different hierarchical levels.

# FSSs: ways forward

---

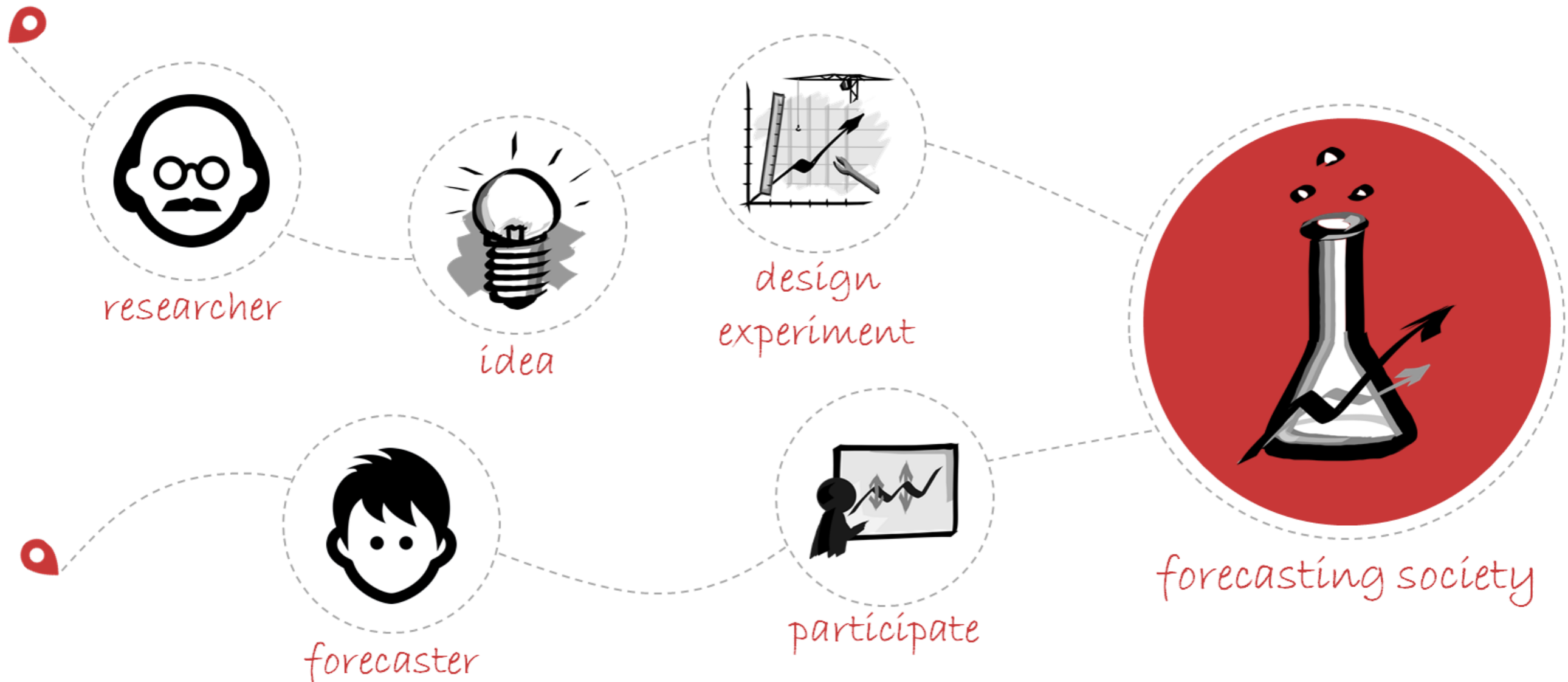
1. Use of **open-source** software
2. Web- and **cloud-based** solutions
3. Customisable
4. Forecasting **on-the-go**
5. Implementation of **state-of-the-art** methods
6. Methods for **intermittent demand**
7. Temporal and cross-sectional **aggregation**
8. Better integration of managerial **judgment**
9. Support for **judgmental model selection**
10. Support for **judgmental forecast reconciliation**
11. Bring in **foresight** features
12. Full **documentation** of approaches and procedures



# Forecasting Society

bringing researchers and forecasters together

[www.forsoc.net](http://www.forsoc.net)



Thank you for your attention

---

