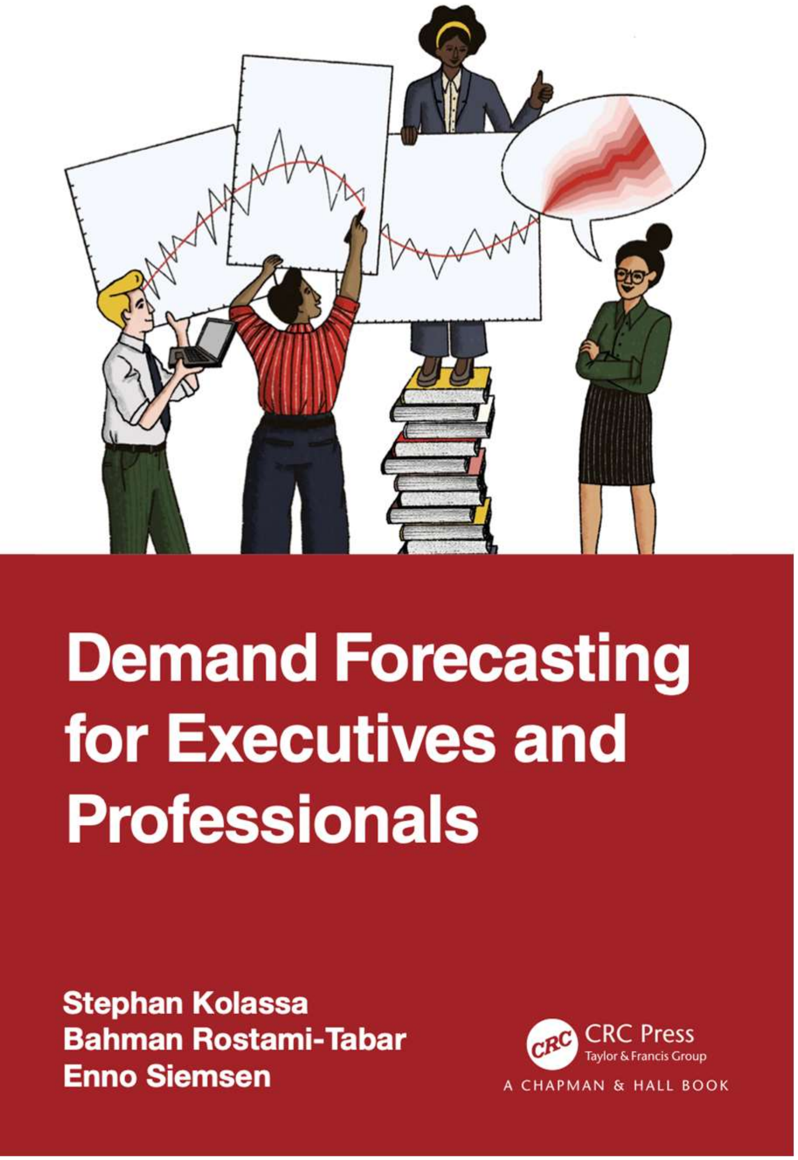


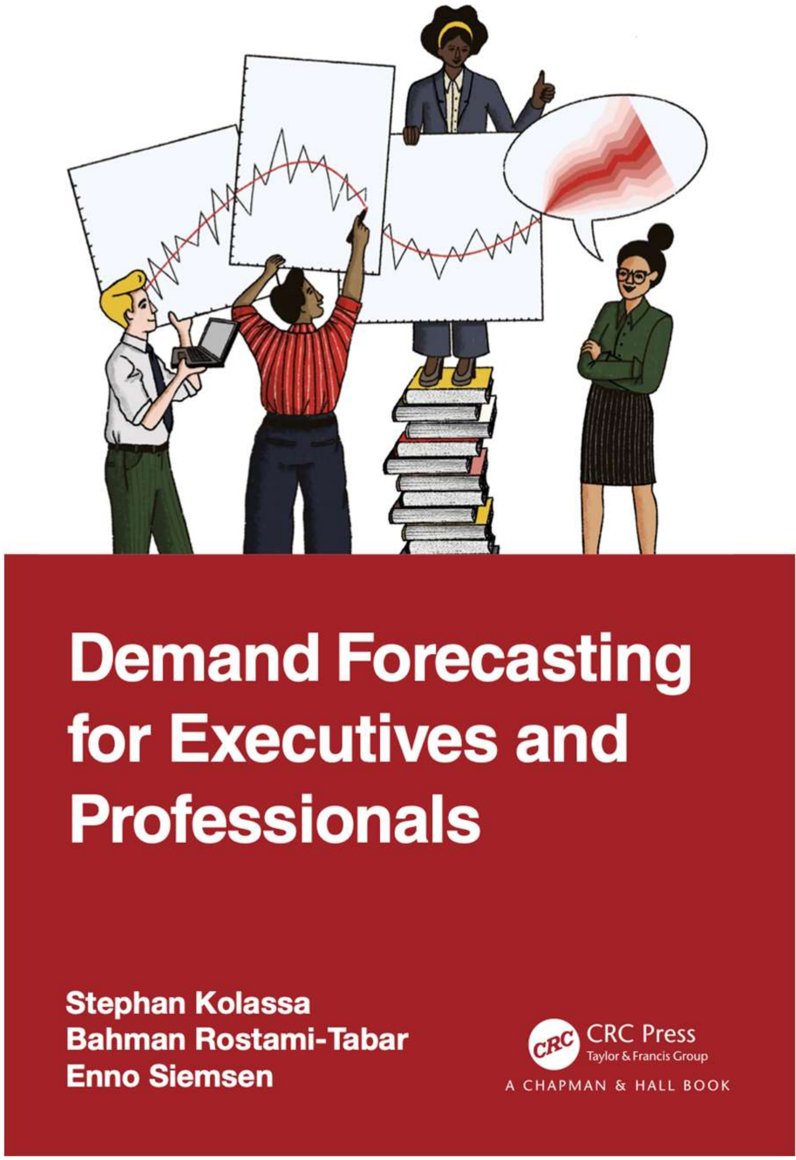
Common forecasting methods and the mindset behind forecasting

Stephan Kolassa, Data Science Expert, SAP Switzerland
Bahman Rostami-Tabar, Professor, Cardiff University
Enno Siemsen, Professor, University of Wisconsin-Madison

Free online version: https://dfep.netlify.app/

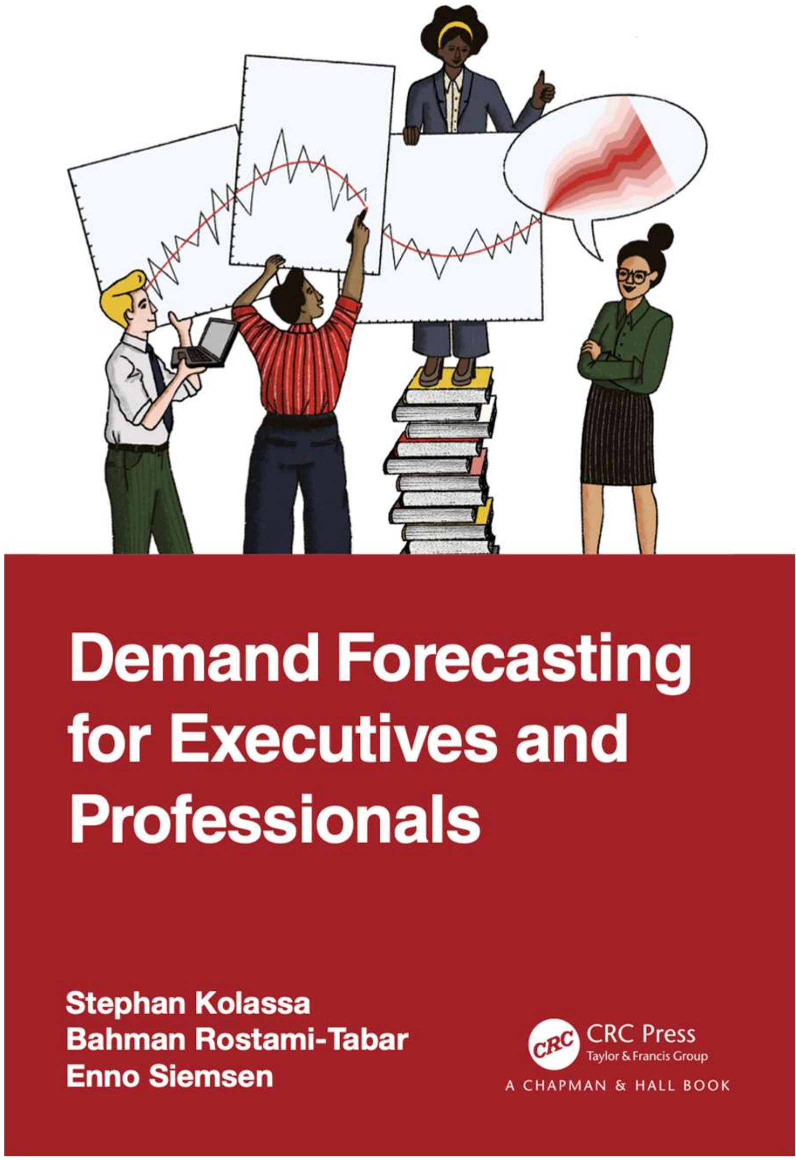
Agenda

- The importance of forecasting in planning and decision-making → Enno
- The forecasting workflow → Bahman
- A simple example → Enno
- Know your data → Bahman
- Data quality → Stephan
- Forecasting methods → Stephan
- Building forecasting models → Stephan
- Forecast quality evaluation → Stephan
- The perfect forecaster → Stephan
- Forecasting organization & organizational barriers → Enno
- When forecasting fails → Bahman



Agenda

- The importance of forecasting in planning and decision-making
- The forecasting workflow
- A simple example
- Know your data
- Data quality
- Forecasting methods
- Building forecasting models
- Forecast quality evaluation
- The perfect forecaster
- Forecasting organization & organizational barriers
- When forecasting fails



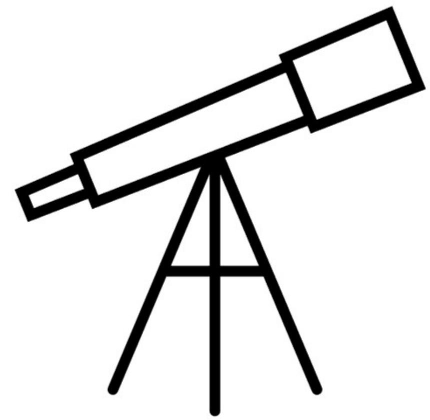
The importance of forecasting in planning and decision-making

- Any plan, any decision relies on forecasts
    - "The future will be like the past" is a forecast
    - "Replenish what is used" relies on a forecast

- Only question: explicit or implicit forecasting

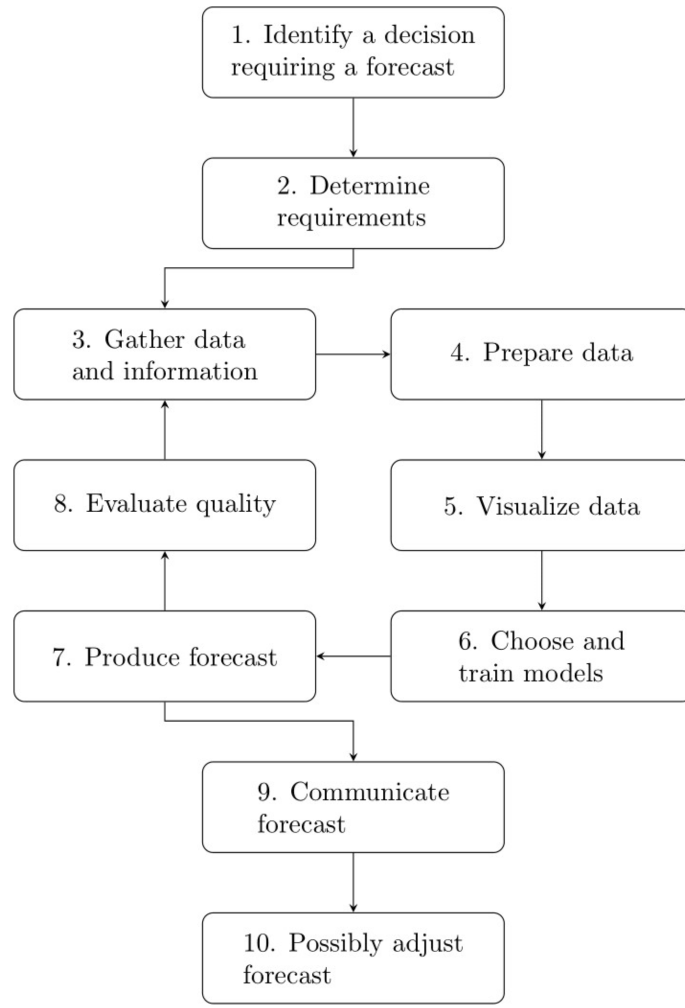
- This does not mean all forecasts must be complex!

- Good demand forecasts can lead to
    - Higher service levels
    - Lower safety stock requirements
    - Less friction in operations

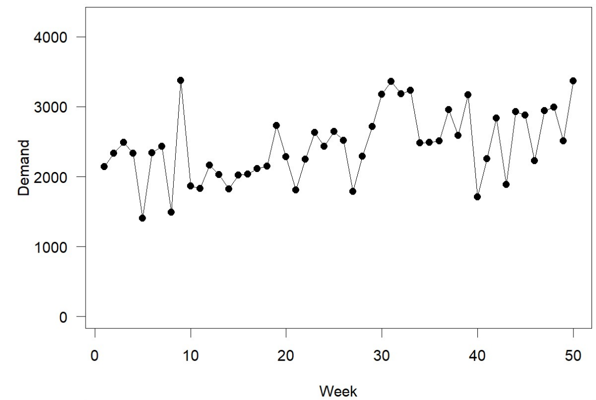


The forecasting workflow

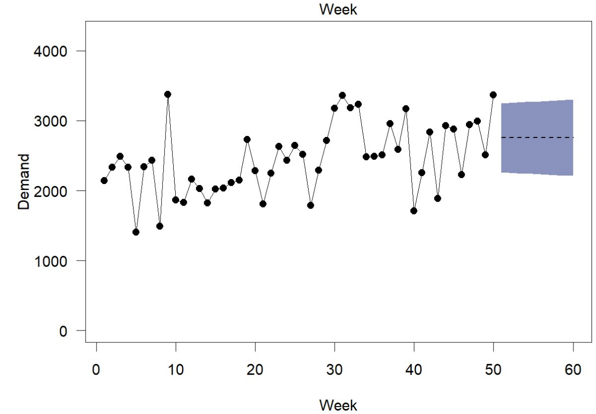
- Be clear about what decision the forecast will support
- This will drive requirements (granularity of forecasts in multiple dimensions, point vs. quantile forecasts, …)
- Forecasting itself is an iterative process
  - “Bad” forecasts are opportunities for learning and improvement
  - Involve domain experts to understand your data
- The communication of forecasts is very important
- Judgmental adjustment should be done with care



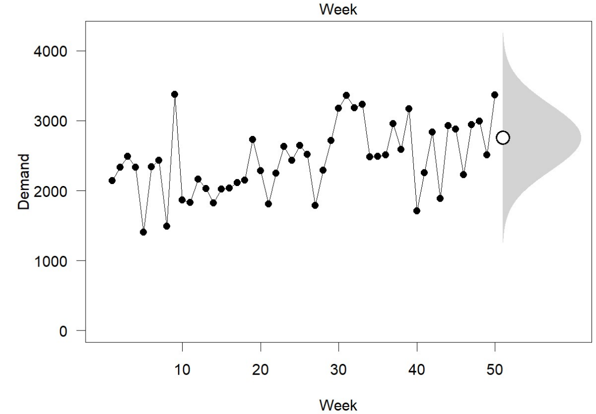
A simple example



- Consider a simple (simulated) time series
- Forecast using Exponential Smoothing (a classical time series forecasting method)



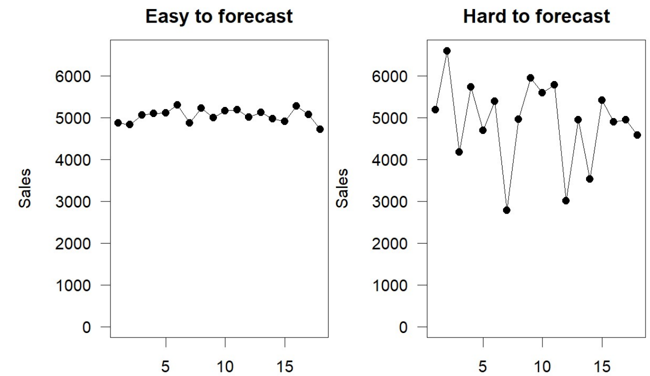
- This gives us a *point forecast*…
- … and *prediction intervals*…
- … or even a *predictive density*

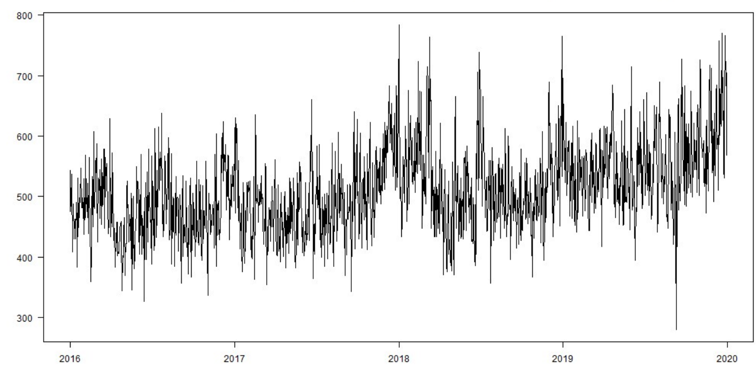


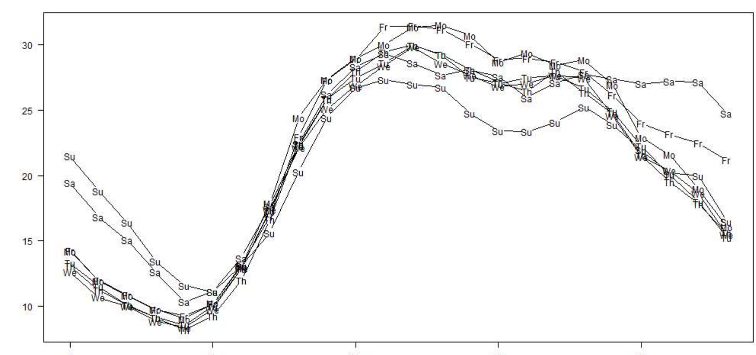
- Prediction intervals or predictive densities can be used to set safety stocks

Know your data

- Plot some time series – use different visualizations
- Is some seasonality obvious? Trend?
- Any peaks/troughs that can be causally explained?
- Does domain knowledge suggest any drivers?
- If there are few obvious patterns, the series is likely hard to forecast



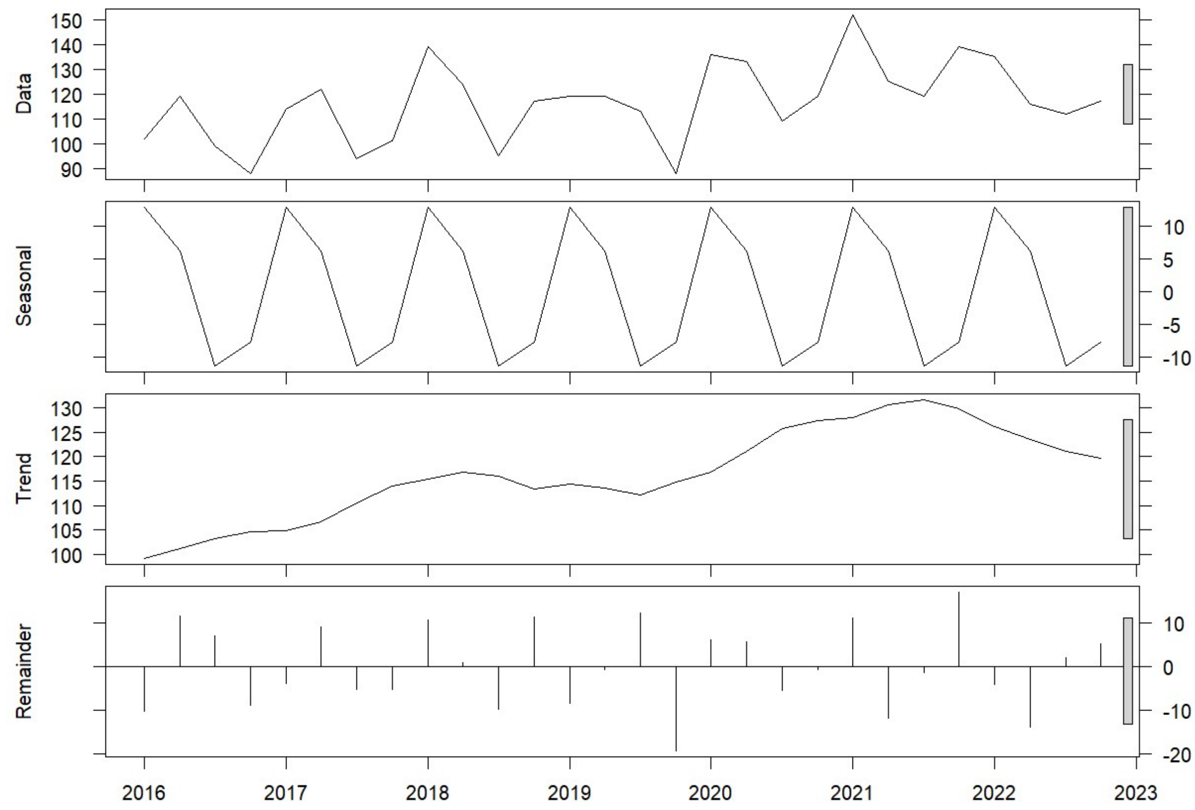




Time series components

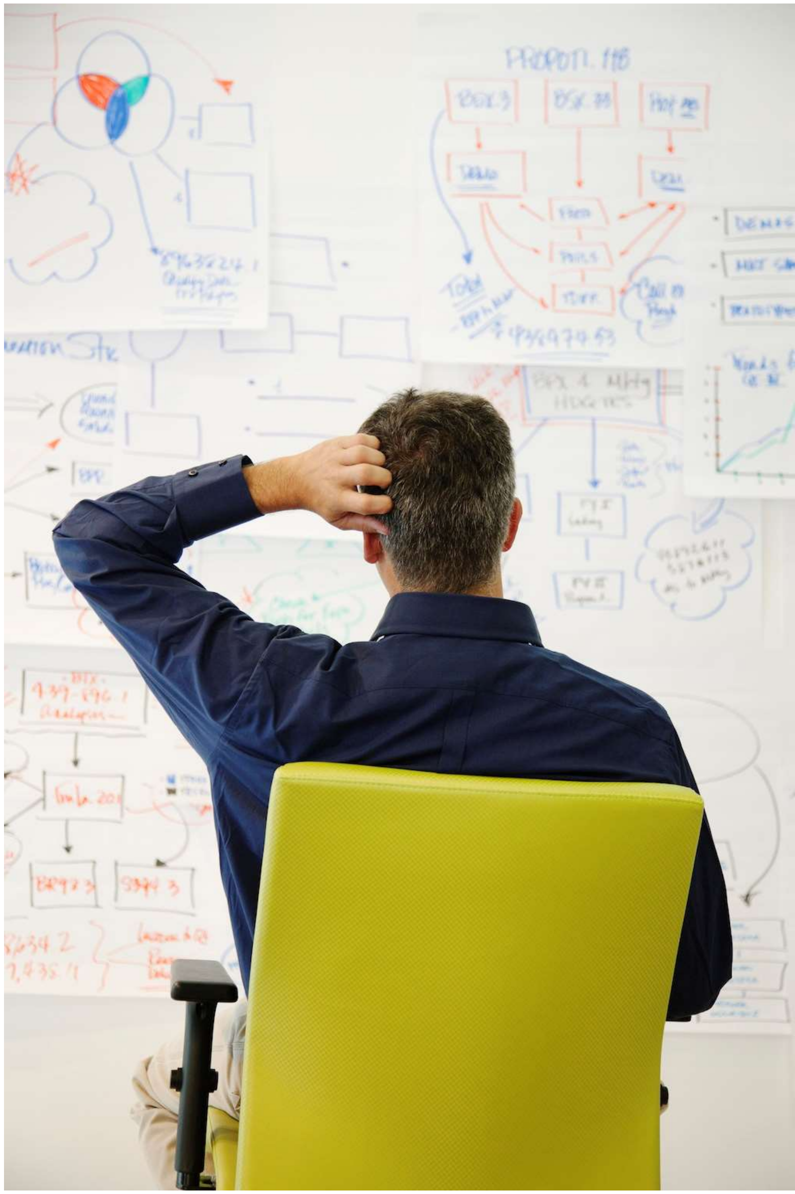
- Classical time series forecasting methods consider components like:
  - Trend
  - Seasonality (-ies)
  - Autoregression
  - Moving Average components
  - Remainder

- More and more important: causal predictors or drivers



Data quality

- Data quality and availability is key
  - The focal time series
  - Any causal drivers
- Better data (and better understood data) is usually more important than fancy modelling
- Use domain knowledge to understand
  - What data is likely important
  - How to look for data issues
  - How to get better data
- What to do with data problems:
  - Impute missing data
  - Correct or impute problematic data
  - Mark problematic data by predictors

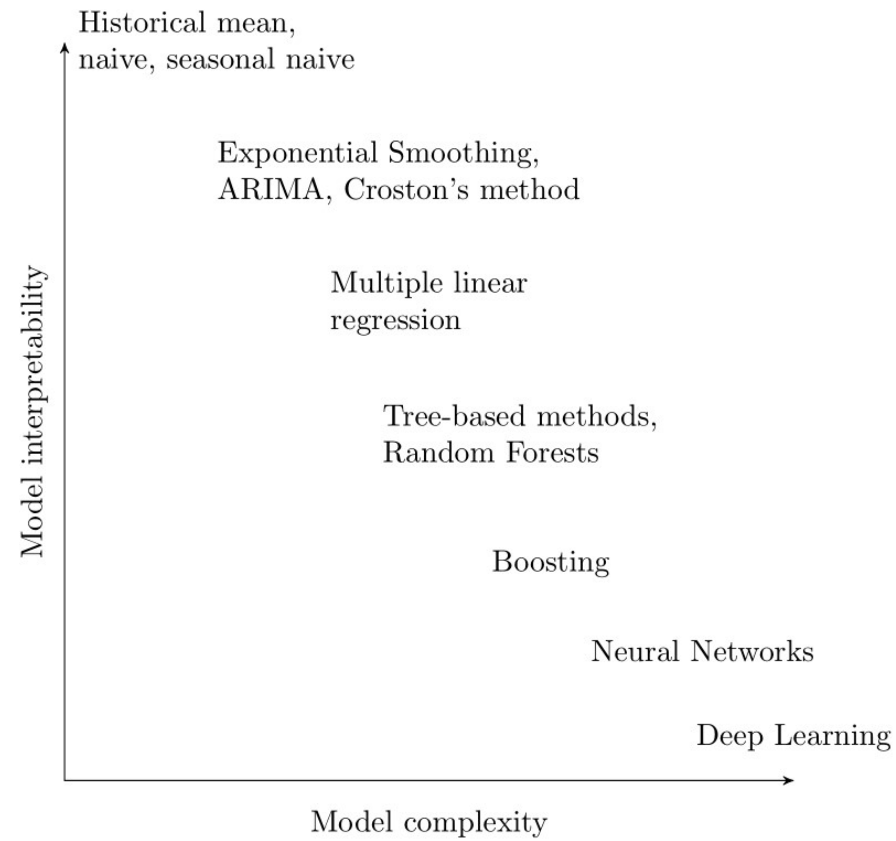


Forecasting methods

- Interpretable, fast, cheap:
  - Simple methods (mean, naïve) often work surprisingly well
  - "Classical" time series methods: Exponential Smoothing and ARIMA – cannot model causal factors
  - Linear regression: still simple, models causals

- Less interpretable, slower, more expensive:
  - Tree-based methods, Random Forests
  - Boosting
  - Neural Networks and Deep Learning

- Plus: human judgment!



Building forecasting models

Simple methods
- Historical mean
- Historical quantiles
- Last observation

- Often surprisingly effective and hard to beat
- Simple to build
- Should always serve as a benchmark

Time series methods
- Exponential smoothing
- ARIMA

- Use established tools (e.g., forecast, fable or smooth packages in R)
- Do not try to select models on your own
- Do not use ACF/PACF plots to select ARIMA orders
- Do not follow random internet advice on model selection

Causal methods
- Regression
- Boosting
- Neural Networks/DL

- Include predictors in order of importance, data quality and forecastability
- … as guided by domain knowledge
- Balance effort in data collection against accuracy improvement
- Beware of overfitting

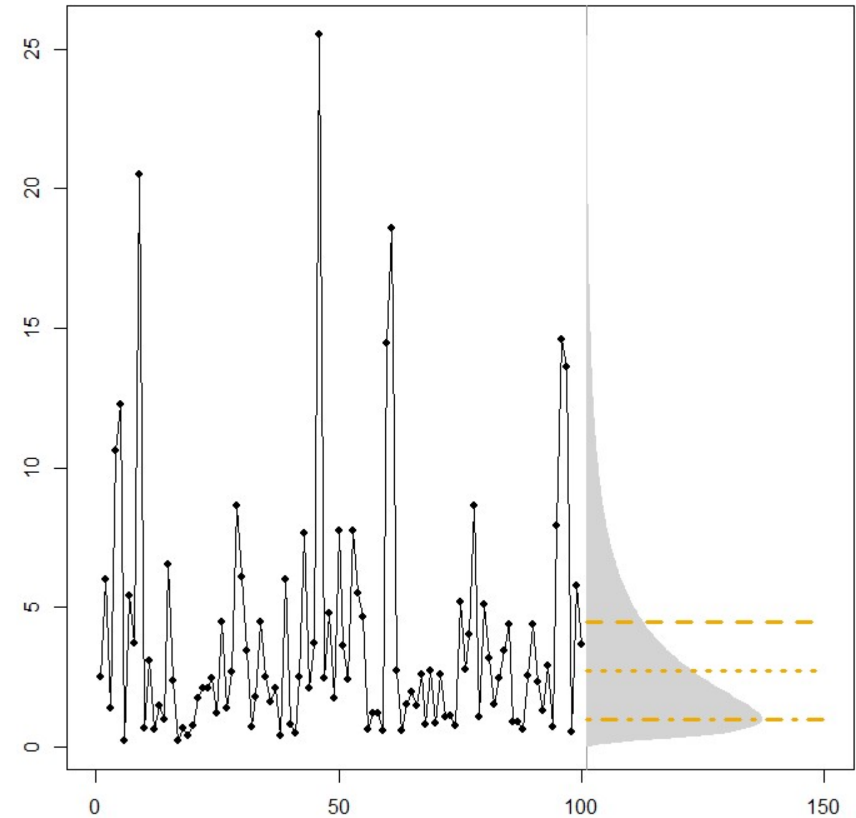
Combinations
- Weighted
- Unweighted

- Combinations of forecasts often outperform single selected forecasts
- Combinations of “very different” methods often work well
- Unweighted combinations are often better than weighted ones (the “Forecast Combination Puzzle”)

Forecast quality evaluation

- There is a bewildering array of accuracy measures
  - Squared, absolute, percentage for point forecasts
  - Pinball losses for quantile forecasts
  - Interval scores for interval forecasts
  - Proper scoring rules for density forecasts

- These may be actively misleading – especially for
  - Intermittent/low volume series
  - Highly variable series
  - → Take care when deciding what you use

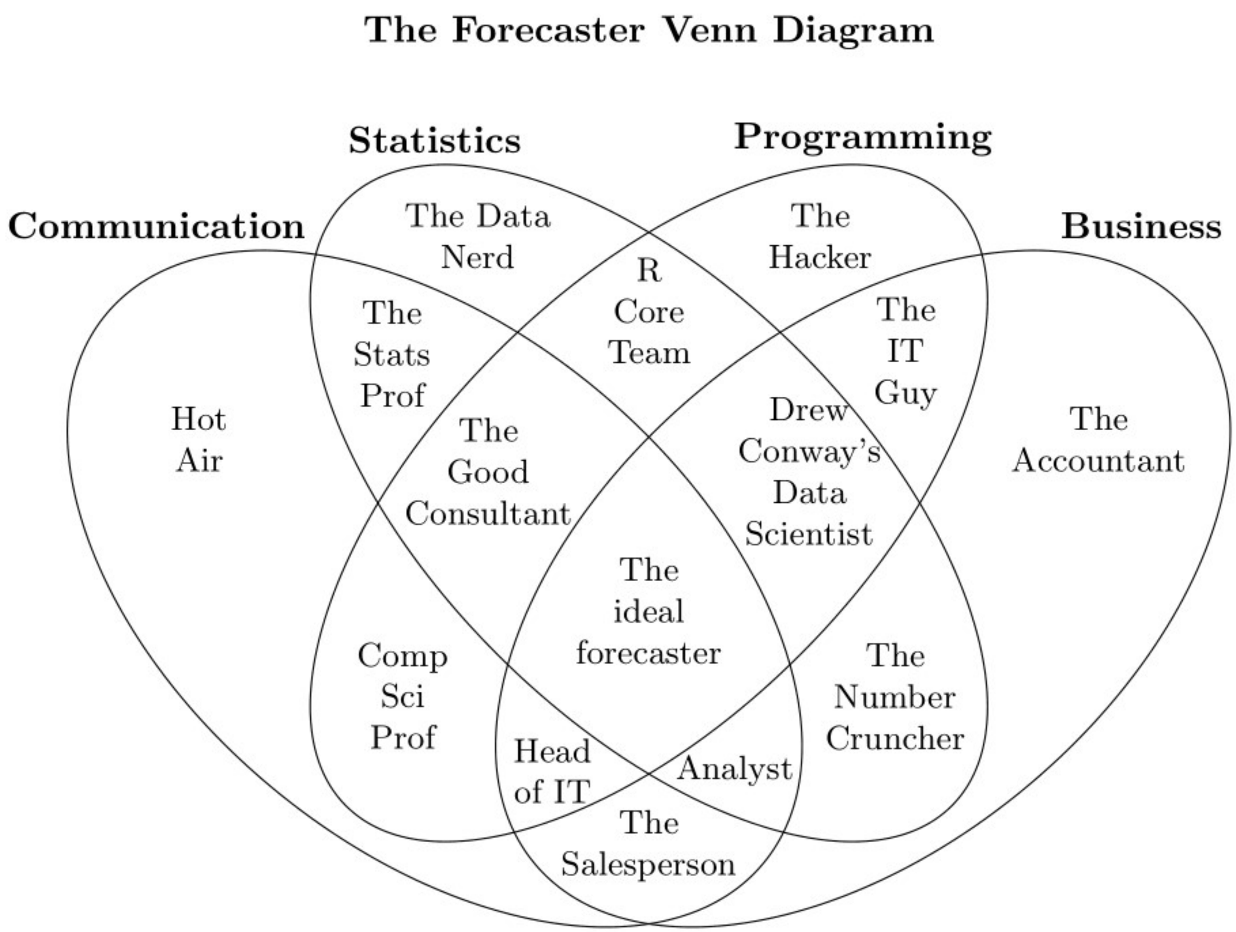


https://stats.stackexchange.com/q/299712/1352

- External benchmarks worse than meaningless – benchmark *processes*, not *accuracy*

- Better forecast accuracy does not necessarily yield better outcomes!

The perfect forecaster

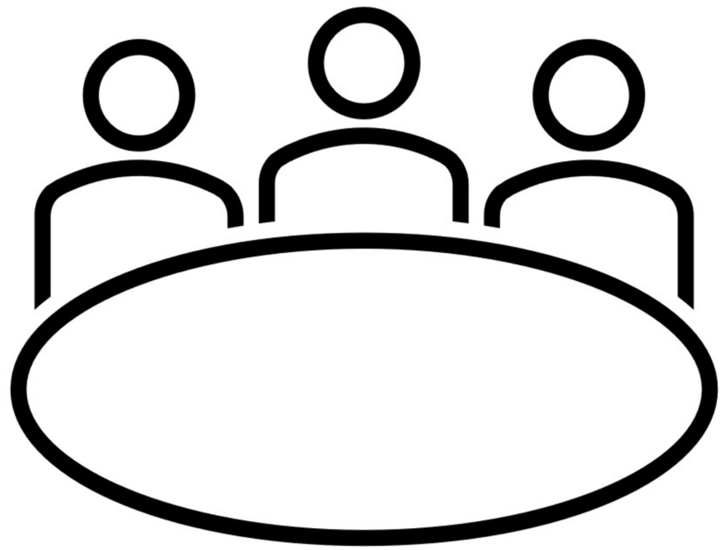


Forecasting organization and organizational barriers

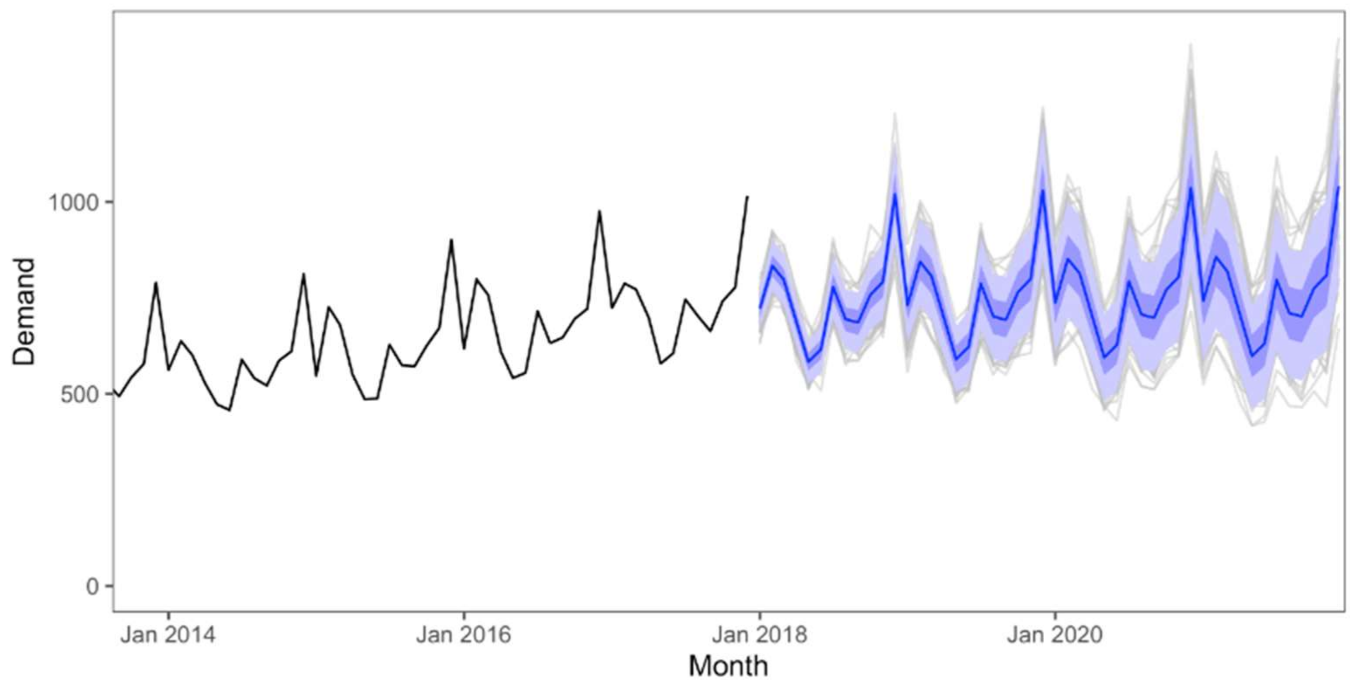
- Forecasting is always embedded in an organizational and process context (e.g., S&OP)

- Beware of individual *biases*…
  - Anchoring and recency
  - Representativeness
  - Seeing patterns in randomness
  - Over-precision and hindsight bias

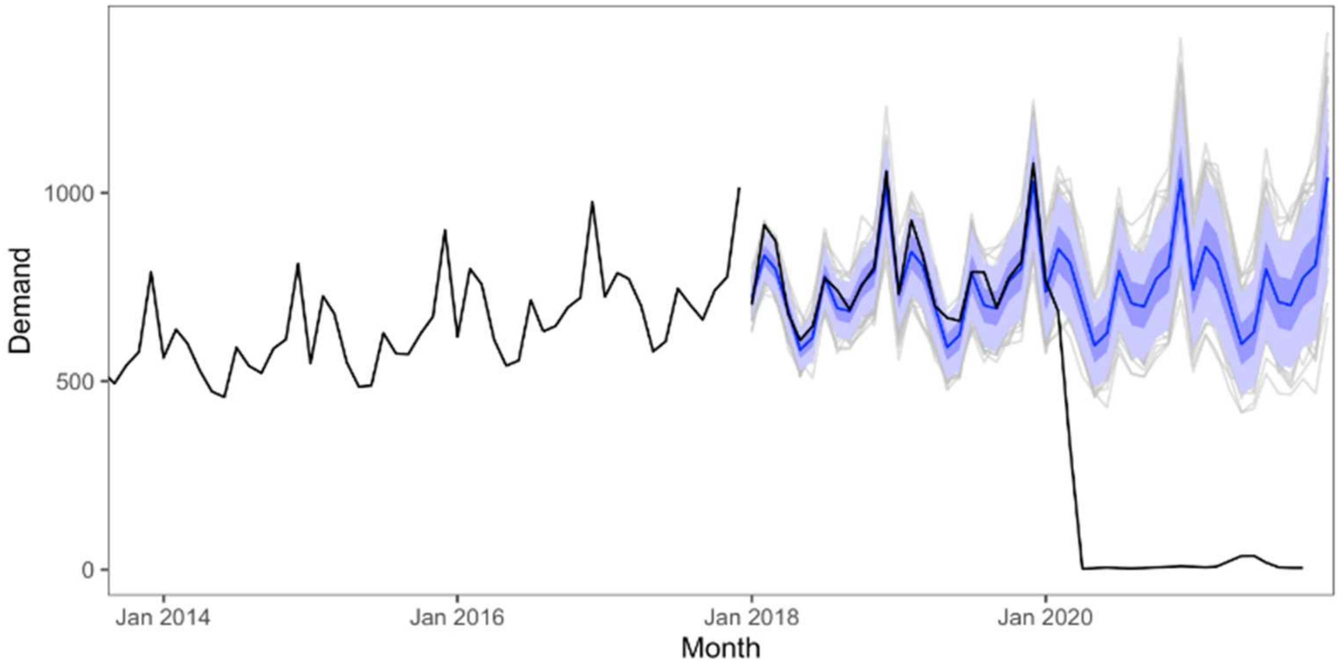
- … and problematic *incentives*
  - "Sandbagging" by sales
  - Overforecasting by operations
  - Minimizing MAPEs biases forecasts downward

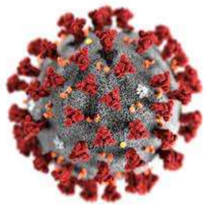


When forecasting fails



When forecasting fails

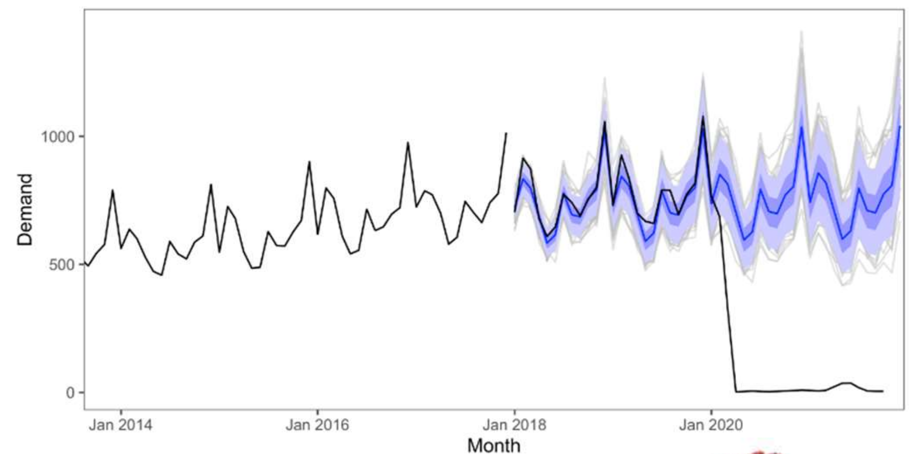


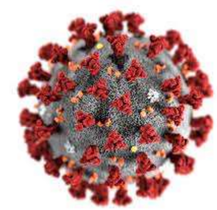


He who sees the past as surprise-free is bound to have a future full of surprises.
(Amos Tversky)

When forecasting fails

- There is no alternative to forecasting…
- What we can forecast
- Relying only on point forecasts
- We can't always achieve the accuracy we want
- Forecasts ≠ targets ≠ decisions ≠ plans
- No tracking of forecast quality (or inappropriate error measures)
- Data availability and quality
- Too much judgmental intervention





Thank you for your attention!

Use discount code SMA39 for 20% off at Routledge until November 30, 2023

- Stephan Kolassa
  Data Science Expert, SAP Switzerland
  Stephan.Kolassa@sap.com

- Bahman Rostami-Tabar
  Reader, Cardiff University
  Rostami-TabarB@cardiff.ac.uk

- Enno Siemsen
  Professor, University of Wisconsin-Madison
  esiemsen@wisc.edu

- Buy the book: https://www.routledge.com/Demand-Forecasting-for-Executives-and-Professionals/Kolassa-Rostami-Tabar-Siemsen/p/book/9781032507729

- Or read for free at https://dfep.netlify.app/