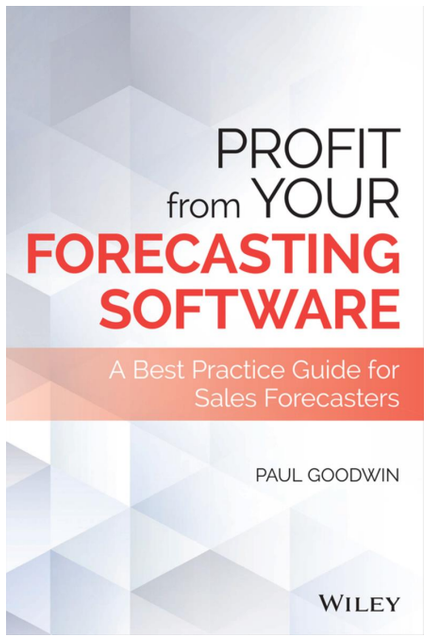
Profit From Your Forecasting Software

A Best Practice Guide for Sales Forecasters

by Paul Goodwin

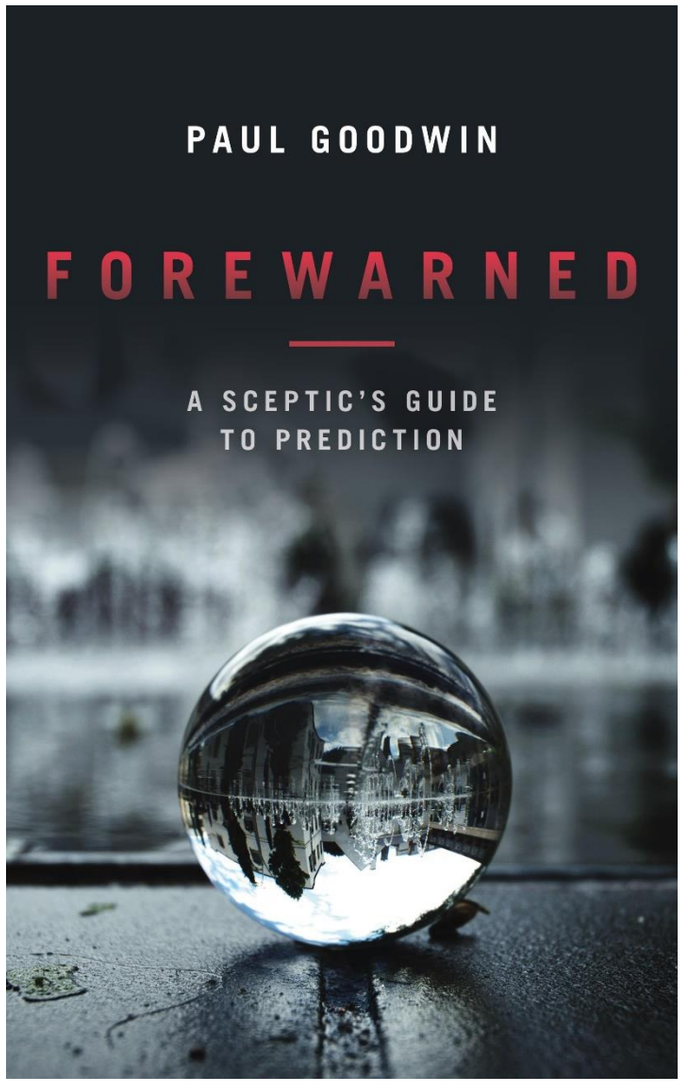
Chapter 8: Automation and Choice
Chapter 9: Judgmental Interventions: When Are They Appropriate?

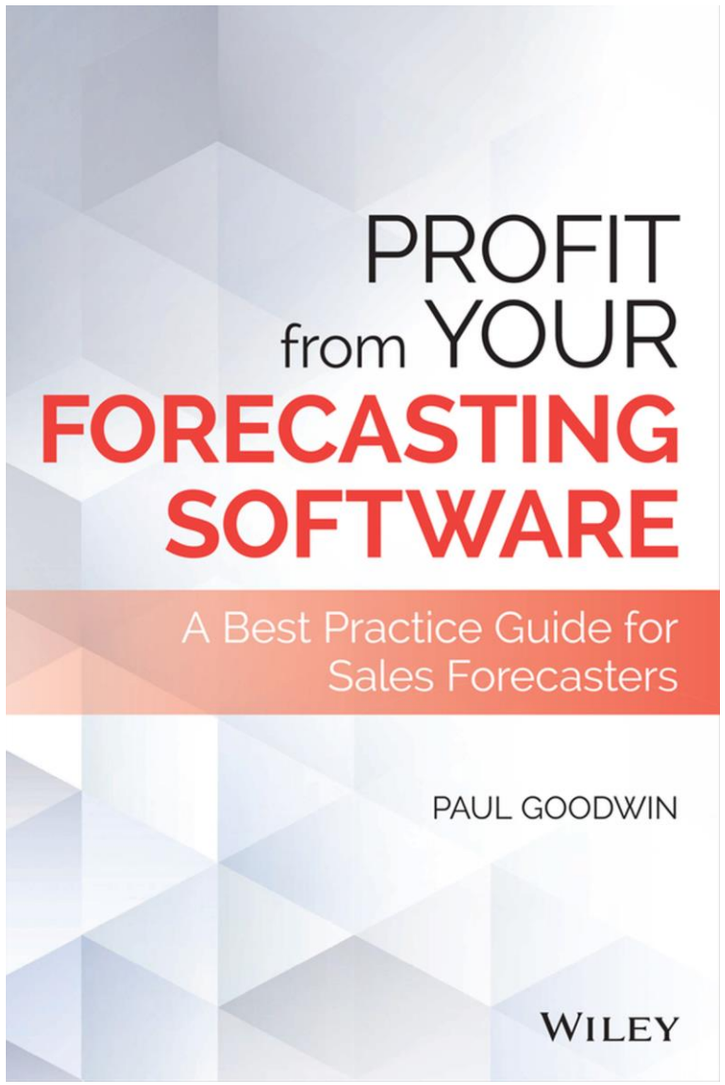
Fotios Petropoulos
School of Management, University of Bath

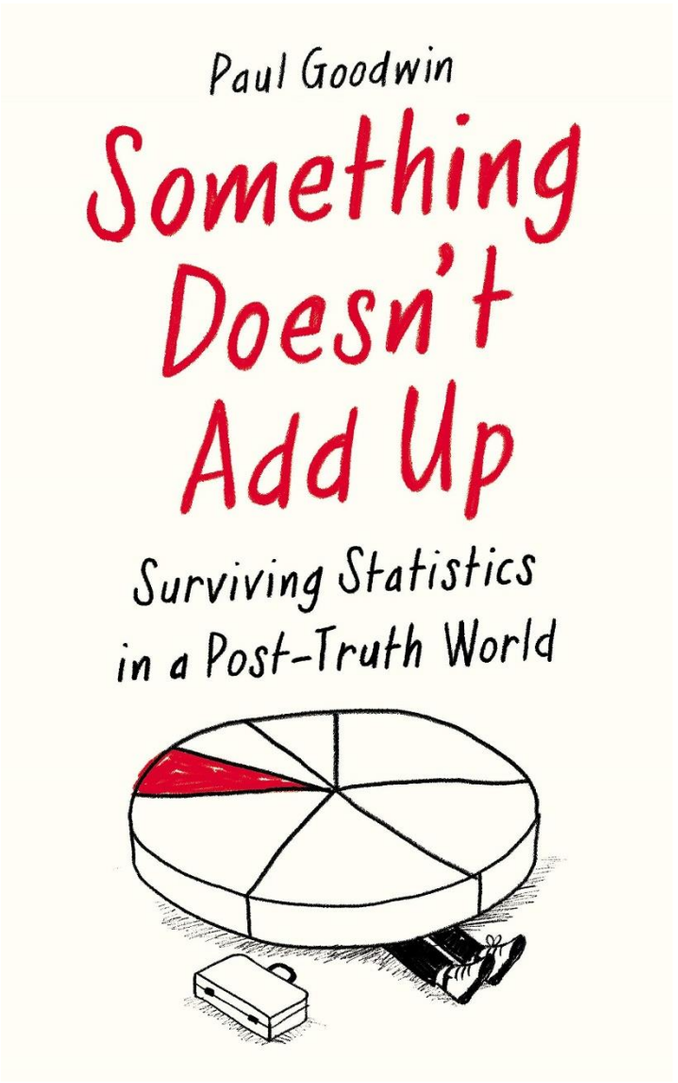


UNIVERSITY OF BATH
SCHOOL OF MANAGEMENT

Which one?


PAUL GOODWIN
FOREWARNED
A SCEPTIC'S GUIDE
TO PREDICTION


PROFIT
from YOUR
FORECASTING
SOFTWARE
A Best Practice Guide for
Sales Forecasters
PAUL GOODWIN
WILEY


Paul Goodwin
Something
Doesn't
Add Up
Surviving Statistics
in a Post-Truth World

Chapter 8: Automation and Choice

Automation requires judgment…

- Quantity of data history.
  - Short histories restrict the available pool of methods.
  - Some software have inherent restrictions on the amount of the history.
- Sophistication of forecasting methods.
  - Credibility amongst managers.
  - Lack of transparency: black boxes.
  - Complex methods: More data? More predictors?

…but automation is welcome

- Automate stages of the forecasting process.
- Expert systems give reasonings for selecting methods…
- …or even predictors.
- Preprocess data.
  - Outliers.
  - Pattern/structural changes.
- Automation may be the only choice if one has to forecast multiple of thousands of products.

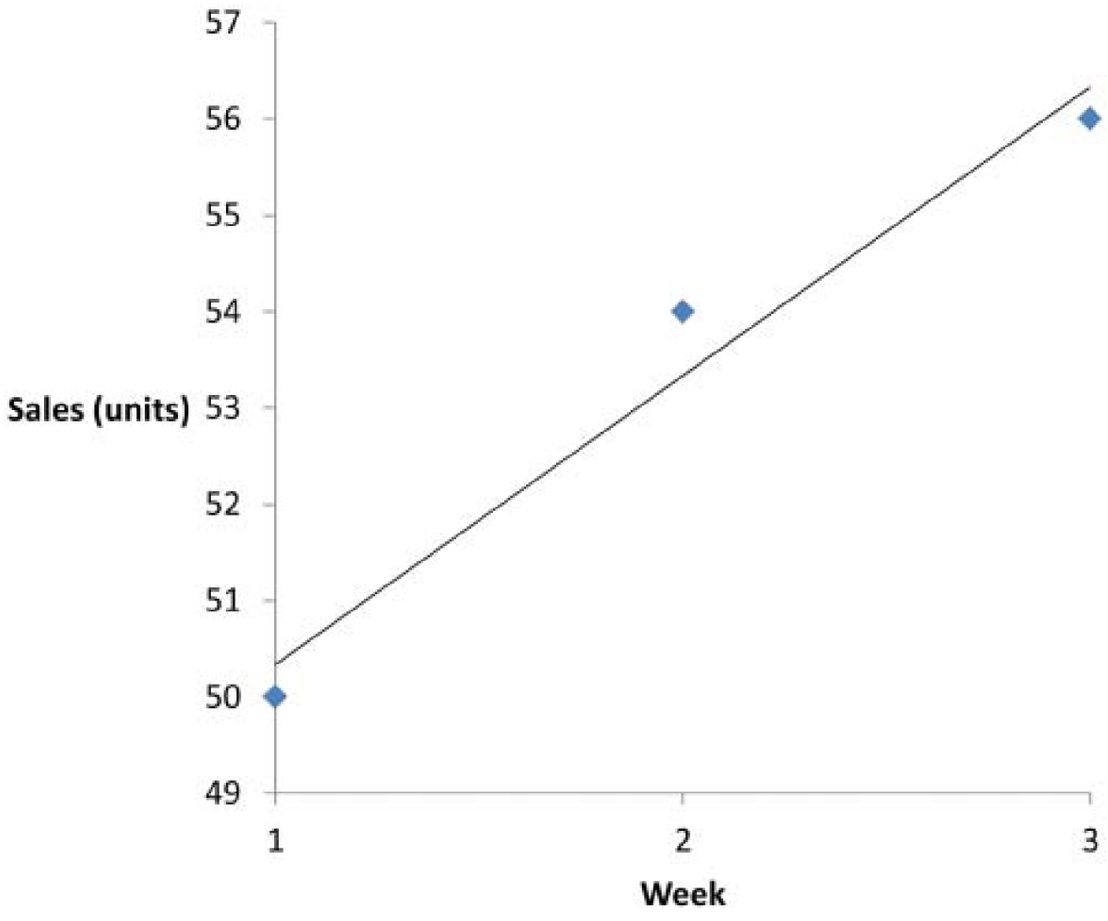
How much past data?

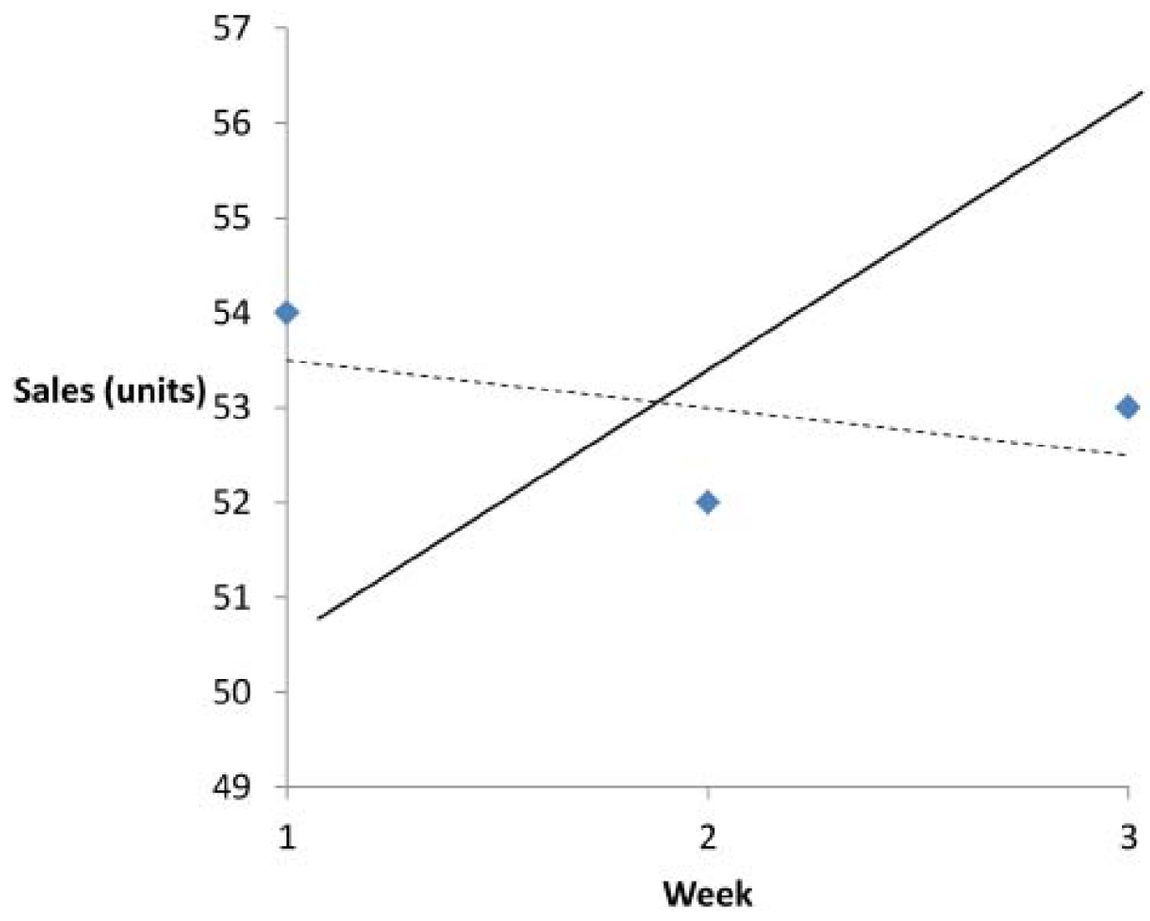
- Which method do we want to apply?
- Consider only fundamental changes to discard past data.
  - Remember that methods (like exponential smoothing) adapt to changes.
  - Data storage is cheap.
- Short (or no) histories? Consider analogous products.
- If one has to rely on forecasting based on past observations:
  - Complexity → number of parameters.
  - Randomness.

Number of parameters (table 8.1)

Method	Minimum Number of Data points
Fitted straight line	3
Quadratic curve	4
Exponential curve	3
Simple exponential smoothing	3
Holt's method	5
Damped Holt's method	6
Holt-Winters method (monthly)	17
Holt-Winters method (quarterly)	9
ARIMA(1,0,0) or ARIMA(0,0,1)	3
ARIMA(1,1,0) or ARIMA(0,1,1)	4
ARIMA(0,1,1)(0,1,1)12	16
ARIMA(0,1,1)(0,1,1)4	8

The effect of randomness (figures 8.1a and 8.1b)





- The width of the interval is proportional to the square root of the number of observations: four times more observations, you will halve the width of the interval.

Are complex methods better?

- Not necessarily.
- They can handle more elaborate patterns in past data…
- …but they also tend to overfit.
- Always test the performance on out-of-sample data.
- “Forecasters should use simple methods – no more complex than is needed for accuracy and usefulness.” Armstrong and Green
- Multiple seasonal cycles? Consider methods that can handle these.
- Always explore the forecast-value-added…
- …and the additional computational cost!

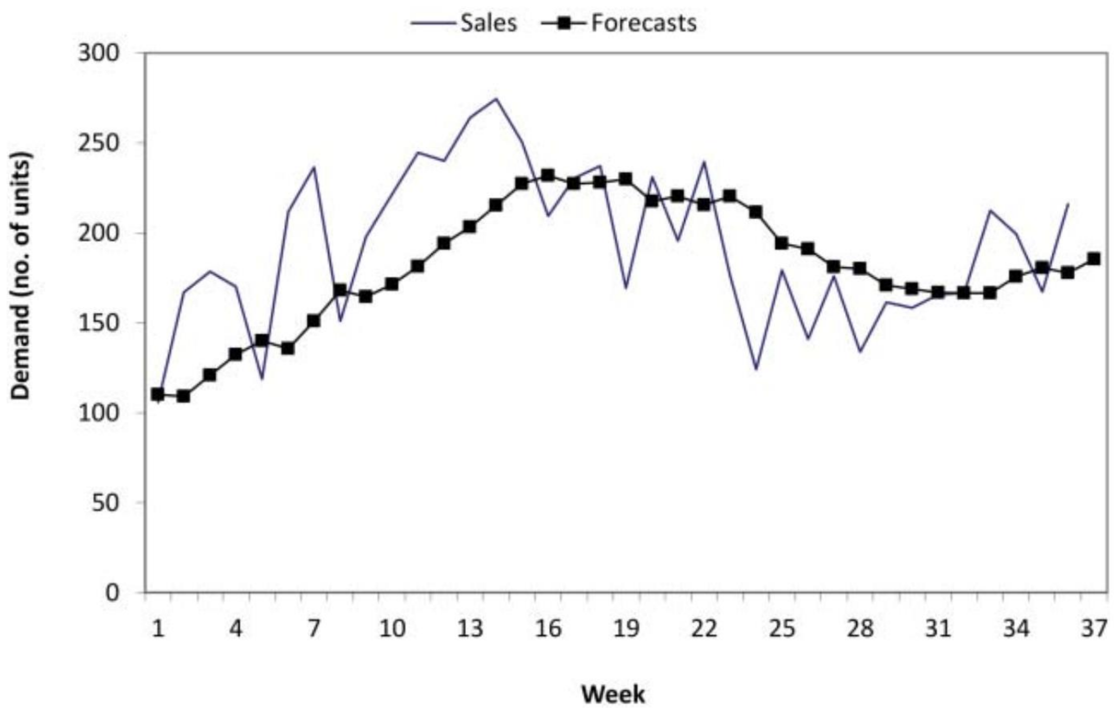
When it’s best to automate?

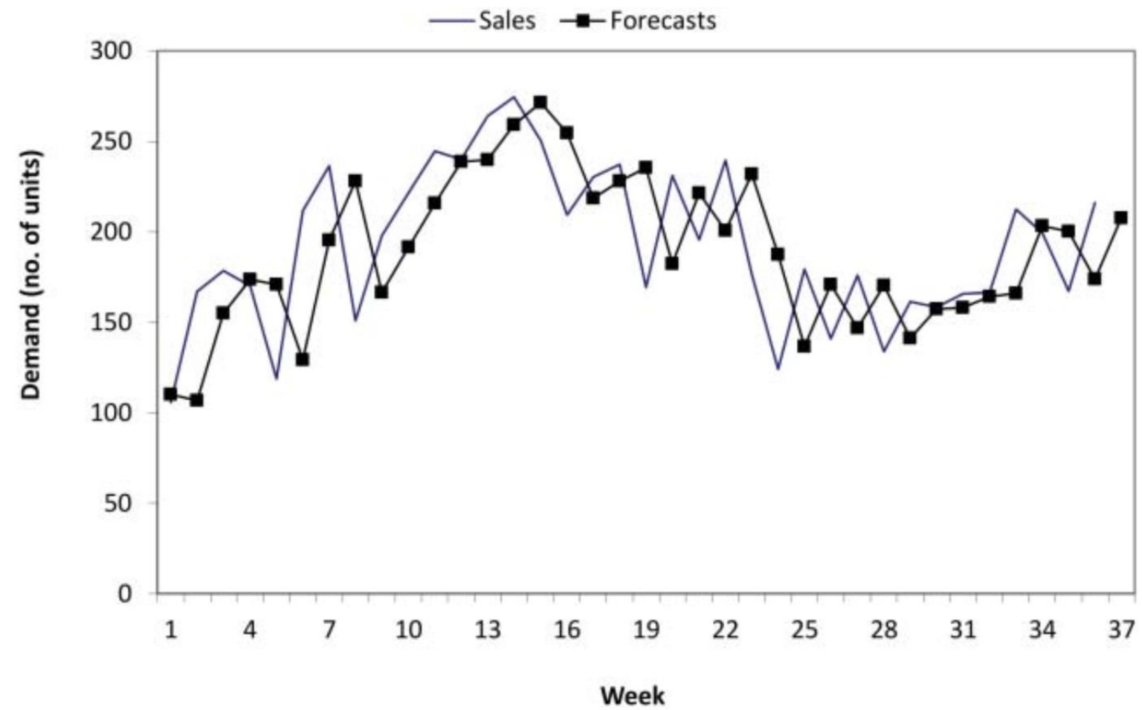
- Large number of forecasts to be produced.
  - Automation in tandem with management by exception.
  - Take advantage of system’s automated reports and flags.
  - Tracking signal → manual interventions to correct biasedness.
- When the system is transparent about the automated choices.
  - Good-quality expert systems will provide reasons on why a method is chosen.
  - Judgment could lead to confusing signal with noise.

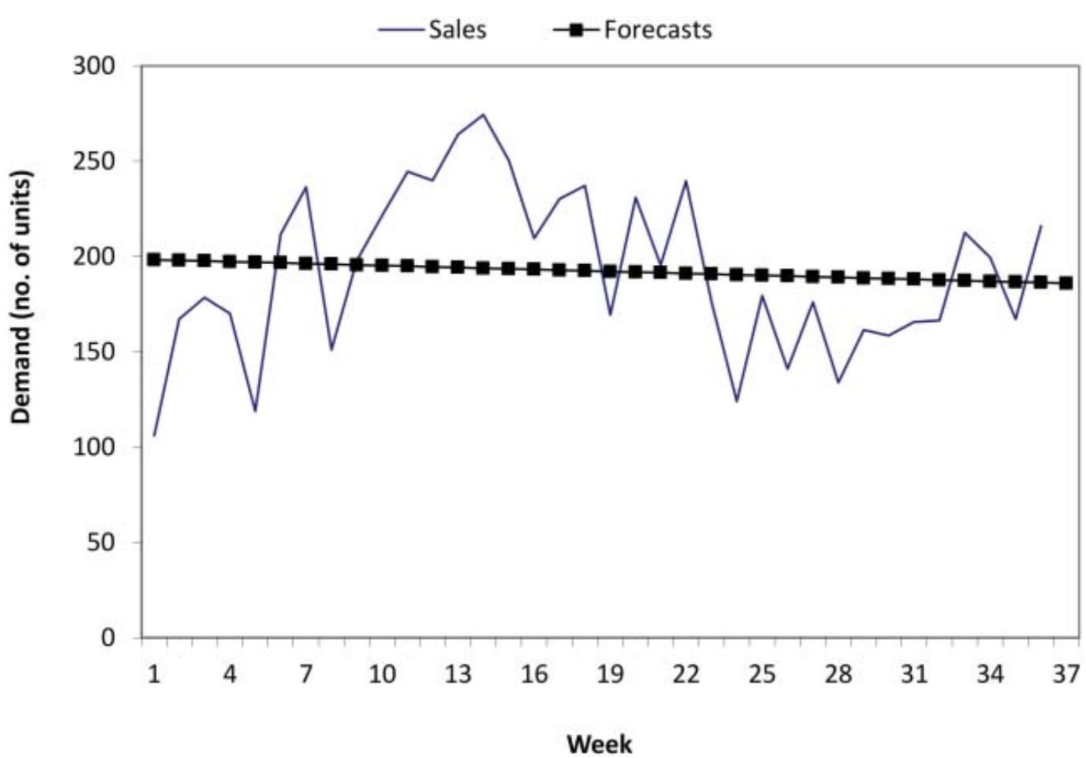
When it’s best to automate? (continued)

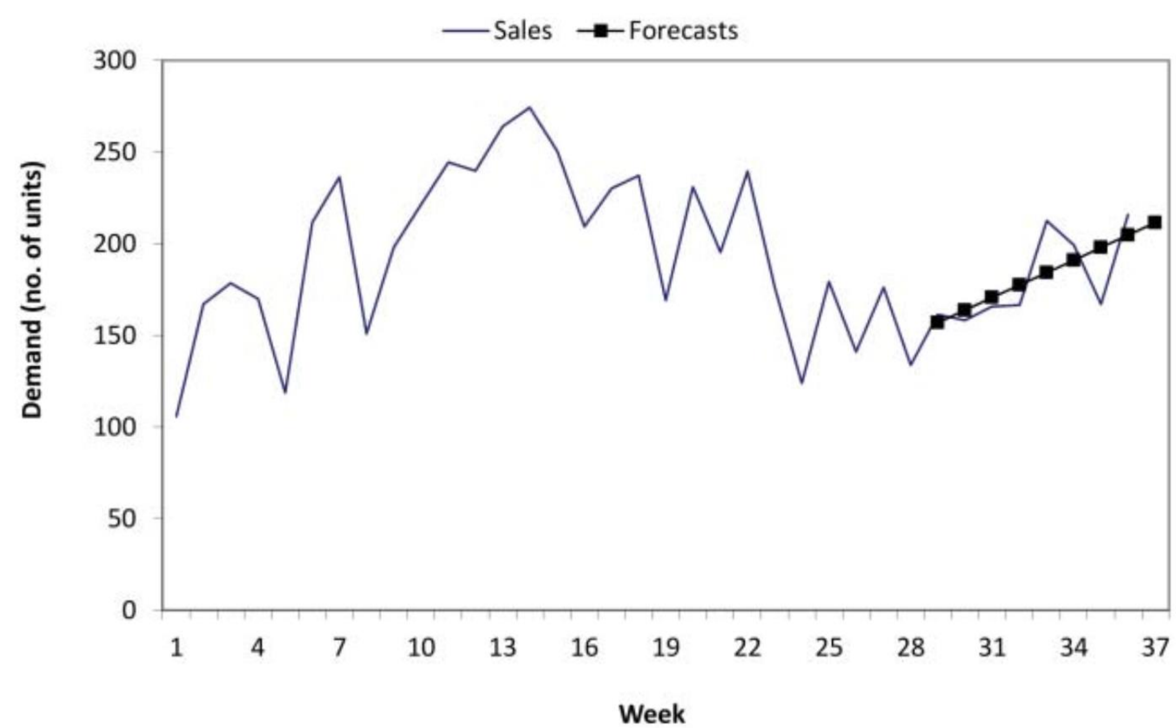
- Avoiding judgmental forecasting by the back door
  - System manipulation.
  - More “acceptable” forecasts.
  - Political pressures.
  - Example of system manipulation: adjust the smoothing parameters of an exponential smoothing method.
  - Modified forecast: “computer-system forecast”.
  - Large error? Blame the software!

When it's best to automate? (continued)





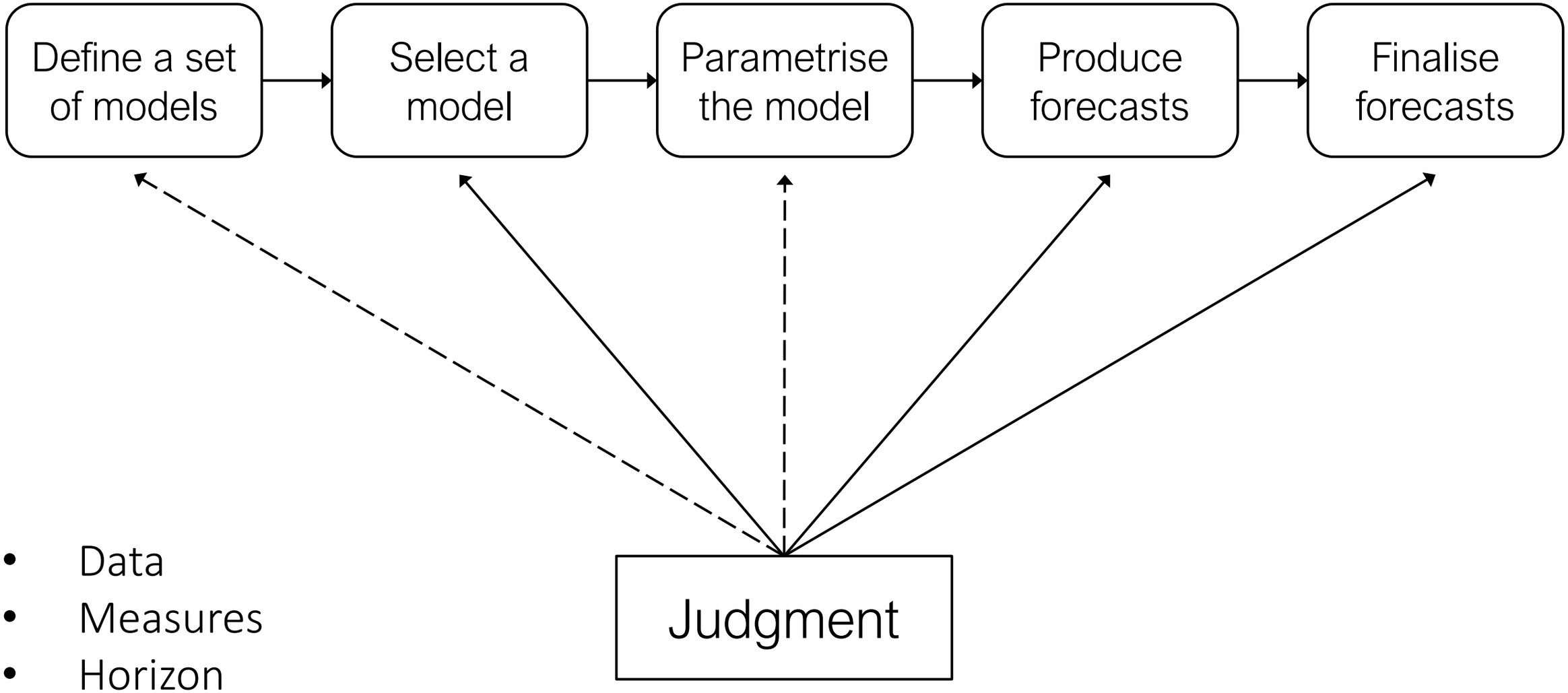




Chapter 9: Judgmental Interventions: When Are They Appropriate?

Judgment is everywhere

The forecasting process



- Data
- Measures
- Horizon

Adjustments are common

- Usually more than 60%, in some cases as often as 90%.

- **Why?**
  - Computer forecasts are not politically welcome.
  - What is your job, again? What do you do?
  - Confusion of the forecast with the target and the plan.
  - “I can improve it!”

Psychological biases

1. **Confuse noise with patterns**
    - Statistical forecasts aim only to predict the underlying pattern, filtering-out the randomness.
    - “A straight line forecast cannot be right!”
- Humans are pattern-seeking animals.
    - “The computer must have missed it!”
    - Illusory patterns.
- Humans are also story-telling animals.
    - We can invent stories to explain every little movement.

1 ABD Doları eşittir

8,00 Türk Lirası

26 Eki 06:26 UTC · Sorumluluk reddi beyanı

1G 5G 1A 1Y 5Y Maks.

Psychological biases

2. **Recency bias**

- Humans tend to focus on the very last movements.
  - "Back then, things were different!"
  - Over-reaction to recent movements.
  - Two-point regression line.
- Humans pay attention to high-profile events.
  - Remember the base rates.
  - Judgment distortion, due to the high impact of unlikely events.
  - Terrorist attacks, earthquakes, …

Psychological biases

3. **Hindsight bias**

- After an event happens, everyone is an expert.
- Humans believe that they have predicted the event before it happened, when they had not.
- “I knew it all along!”
- Illusion of expertise: “I am better than the system!”
- The world is not as predictable as we think.
- Humans often underestimate uncertainty.
- We need to learn from past forecast errors.

Psychological biases

4. **Optimism bias**

- Humans are optimistic by nature.
- Adjustments in the correct direction that are too large can still decrease forecast accuracy.
- Selectively paying attention to information that reinforces the biased view.
- Again: remember the base rates!
- “This time is different/special/unique”
- “The new product will definitely succeed, because…”

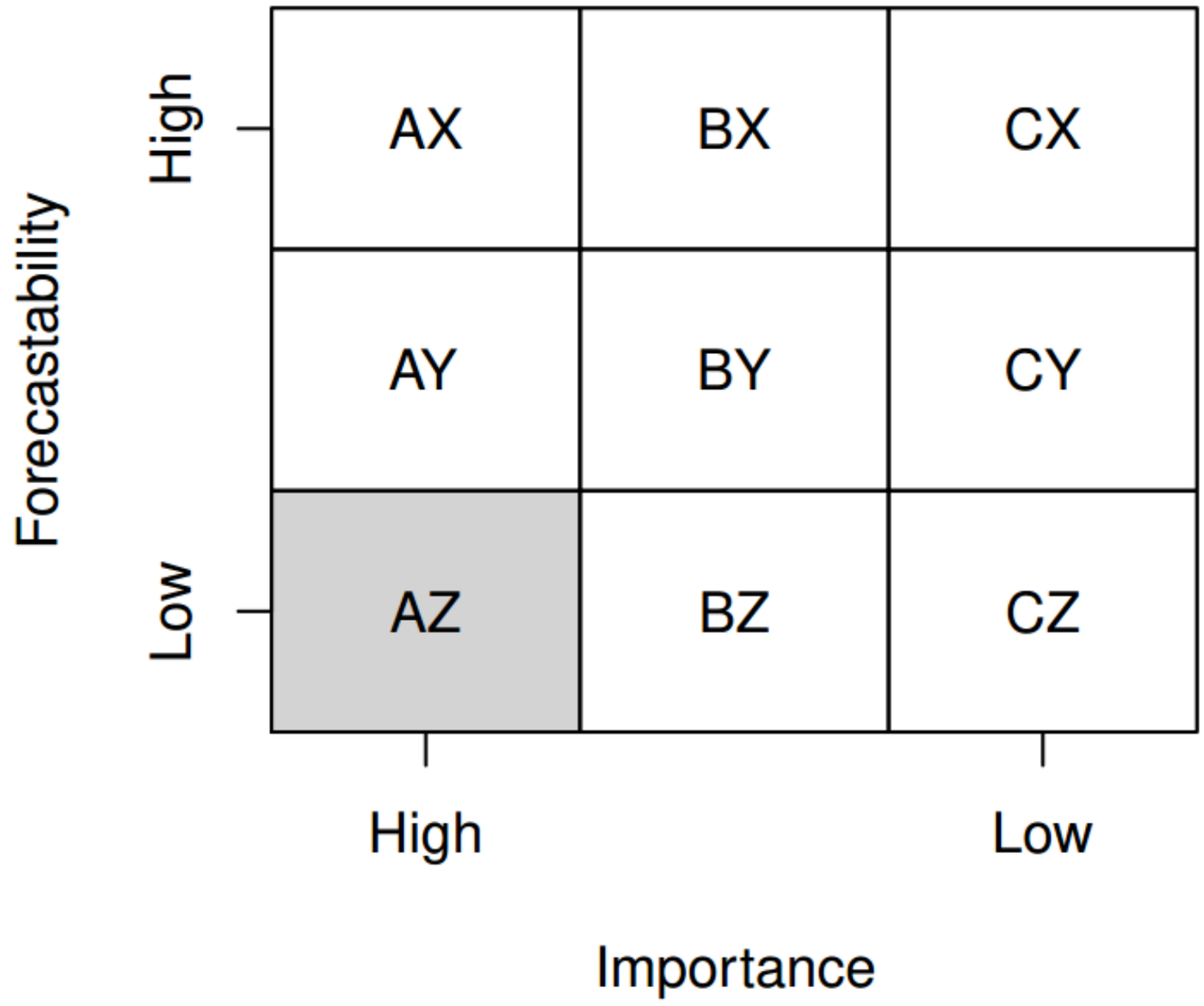
Restricting interventions

1. **Large adjustments are better**

- Empirical evidence suggests that usually large adjustments improve accuracy.
- Large adjustment show commitment, skin in the game.
- Usually incorporate/reflect reliable information, such as promotions, price changes, government policies, etc.
- Double-check that this information is not taken into account by the statistical forecast.
- What is large enough? Possibly something beyond the average forecast error…

Restricting interventions

2. Focus on what matters



Making effective interventions

1. **Divide and conquer**

- The world is complex, and sometimes it is challenging to make multicriteria judgments and decisions.
- Split the problem into smaller, manageable parts.
- Try to avoid raw holistic judgment.
- Try to account for each effect separately.
- Try to account for interaction effects.
- This will give you a documented rationale for your adjusted forecast.
- This will allow trackability, and further enhancements or adjustments where needed.

Making effective interventions

2. **Use analogies**

- Special event? Limited information?
- Try to recall as many similar instances as possible: reduce recency bias.
- Try to look inside, but also outside: what has happened in other companies.
- Record what happened, and what is the similarity to the current case.
- Make an informed judgment, using past similar outcomes and weighting among them based on their similarity.

Making effective interventions

3. **Counteracting optimism bias**

- Track and monitor your bias.
- Learn by feedback, don't discard the performance of your past forecasts.
- Access to past data and forecasts? Mechanically adjust and correct for future biased forecasts.
- Keep in mind that…
  - …bias might change over time.
  - …people might attempt to counteract the correction.
- Devil's advocate: start a debate.
- Inside versus outside view: pay attention to the base rates.

Making effective interventions

4. **Harnessing the power of the (small) crowds**

- Assuming important items, the input from several managers (with diverse responsibilities) could enhance the accuracy.
- Beware: domination of views, groupthink effect,
- Structured ways to elicit knowledge from groups…
- **Delphi method.**
  - Anonymous judgments, feedback, repeat.
  - Less dynamic exchanges, not much skin in the game.
- **Prediction markets:** financial incentive, react to new information, no exchange of reasons and arguments.

Making effective interventions

5. **Record your rationale behind adjustments**

- Discourages gratuitous adjustments.
- Look back and check.
- Free-form text: records must be understandable and clear.
- Drop-down lists: “NGR”

Combining formal with judgmental forecasts

- Statistical algorithms and humans have complementary strengths and weaknesses.
- Humans: biases and inconsistent; but adaptable.
- Algorithms: robust and powerful but less flexible.
- Produce independent forecasts and then combine.
- Combining has proved to be very beneficial in forecasting, especially when forecasts are diverse.
- Beware of humans trying to counteract mechanical corrections (such as combinations).

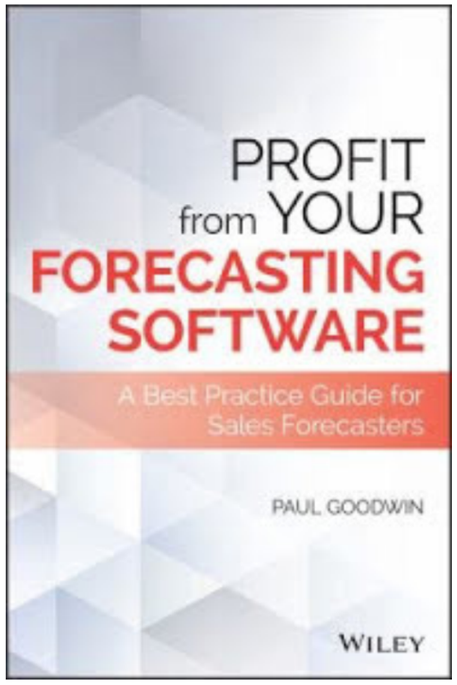
My review of the book

Petropoulos F. (2018) Book review of “Profit from Your Forecasting Software: A Best-Practice Guide for Sales Forecasters” (Paul Goodwin, 2018). In: Foresight: The International Journal of Applied Forecasting, Issue 51 (Fall 2018), pp. 5-7

BOOK REVIEW

Profit from Your Forecasting Software: A Best-Practice Guide for Sales Forecasters by Paul Goodwin

REVIEWED BY FOTIOS PETROPOULOS



Paul Goodwin’s newest book, *Profit from Your Forecasting Software*, focuses on the effective use of forecasting support systems. As the subtitle reveals, it is a guide of best practices for sales forecasters. While aimed at forecasting practitioners and demand managers, it could equally serve as the text in an MBA forecasting module. The book will also be appealing to those who are interested in learning the theoretical basics of forecasting methods without grinding through unpredictable nature of noise (also briefly outlining why a straight-line forecast makes sense). Correlation and autocorrelation are explained clearly, while the author provides examples of the dangers of focusing on the correlation coefficient as opposed to examining graphs. Interestingly, autocorrelation is presented prior to correlation (sections 2.3 and 2.6 respectively). The reader is also introduced to intermittent demand data, outliers and special

Thank you!

fotios@bath.edu http://fpetropoulos.eu @fotpetr