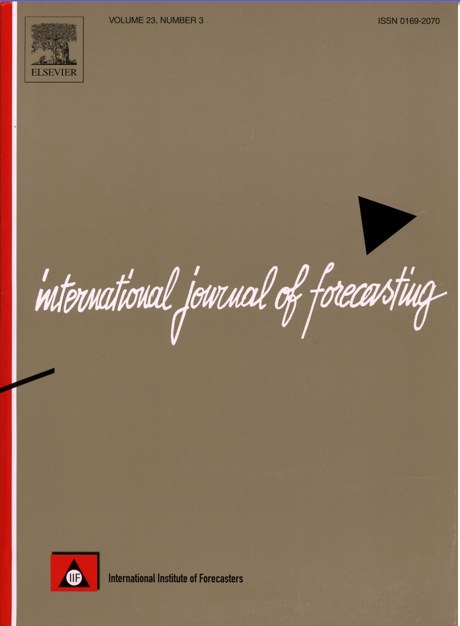
Extreme Forecasting

Rob J Hyndman

Business & Economic Forecasting Unit

MONASH University

My perspective



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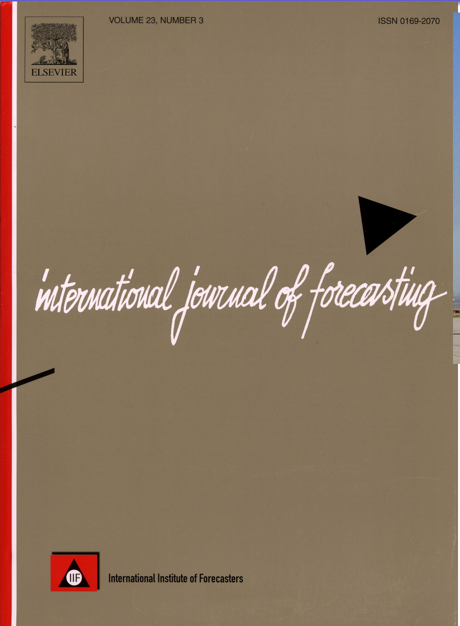

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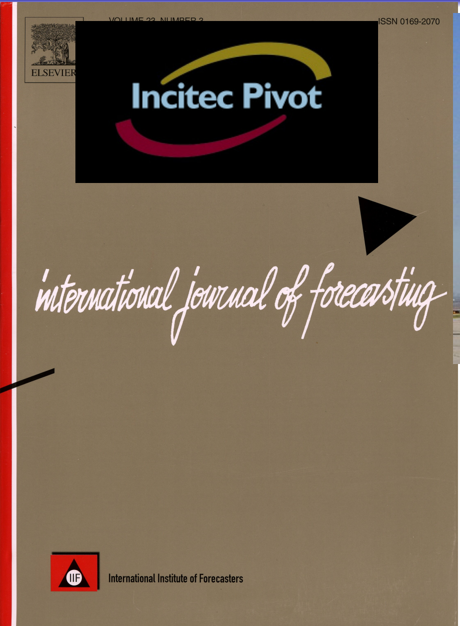

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- Real-world problems are often much more difficult than existing forecasting methods can handle.
- Many research papers tackle “small” problems rather than the “big” problems that arise in commercial forecasting.
- Commercial forecasting problems can (and should) motivate research.

Three case studies

1. Weekly airline passenger traffic: Ansett Australia.

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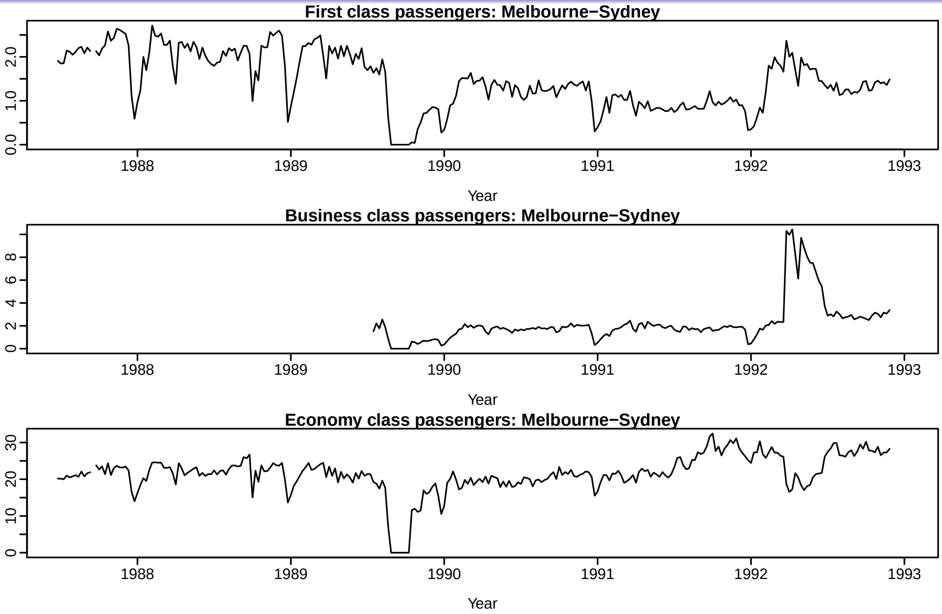
- Highly complex data for which no standard models were suitable.
- Real-world complications that textbooks (and often journals) don't cover.
- Problems motivated some of my research papers.

Outline

1. **Extremely messy data**
2. Extremely expensive forecast errors
3. Extreme electricity demand
4. Extremely useful conclusions

Airline passenger traffic

Airline passenger traffic



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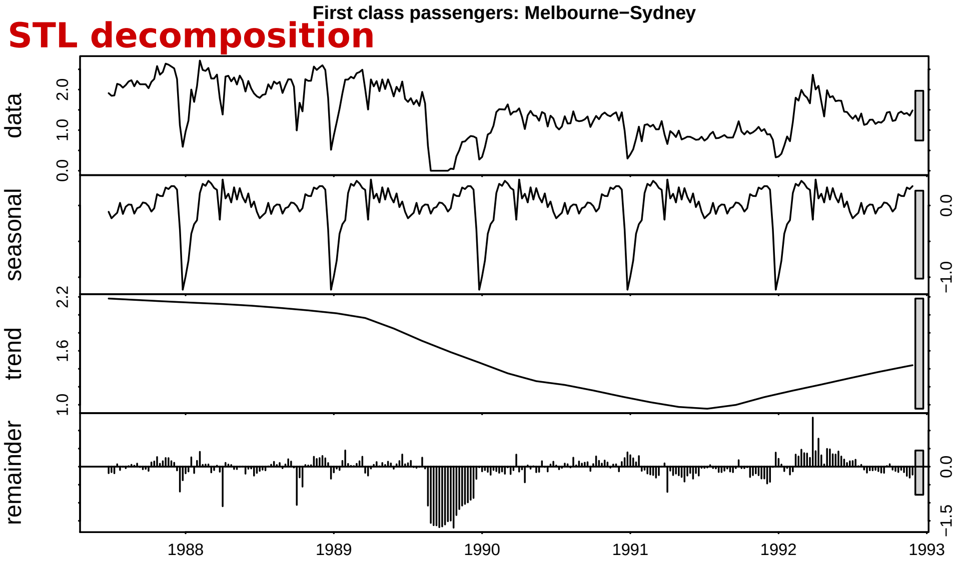
STL decomposition



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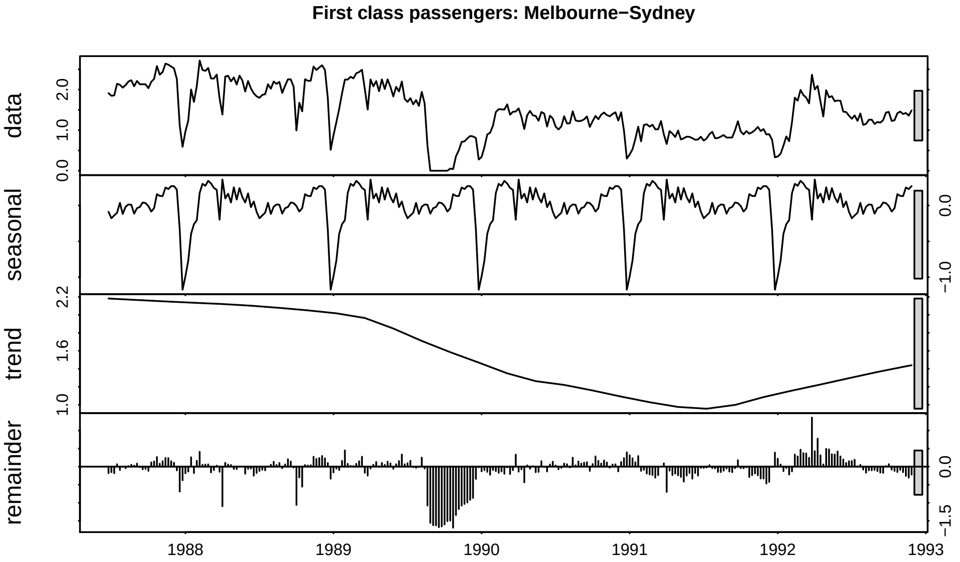

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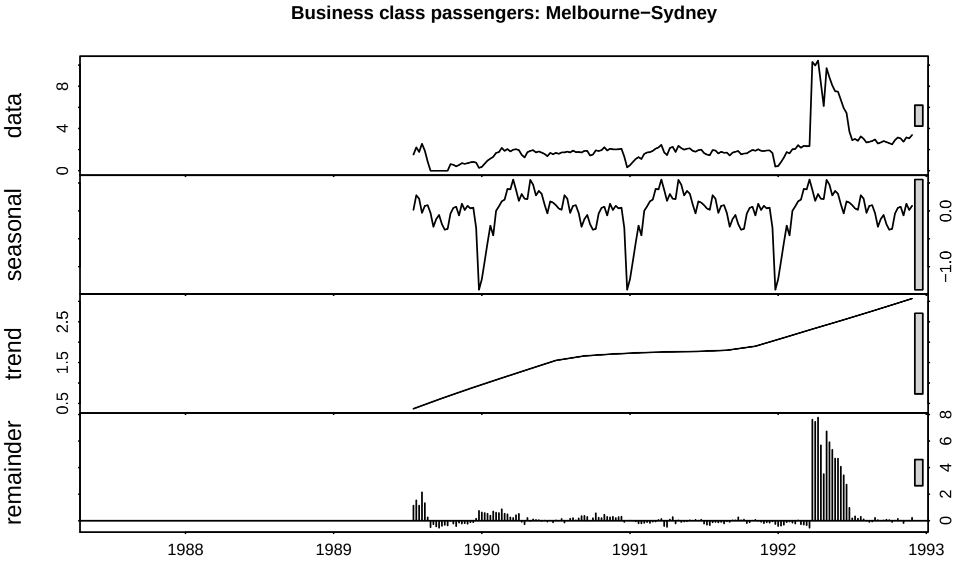

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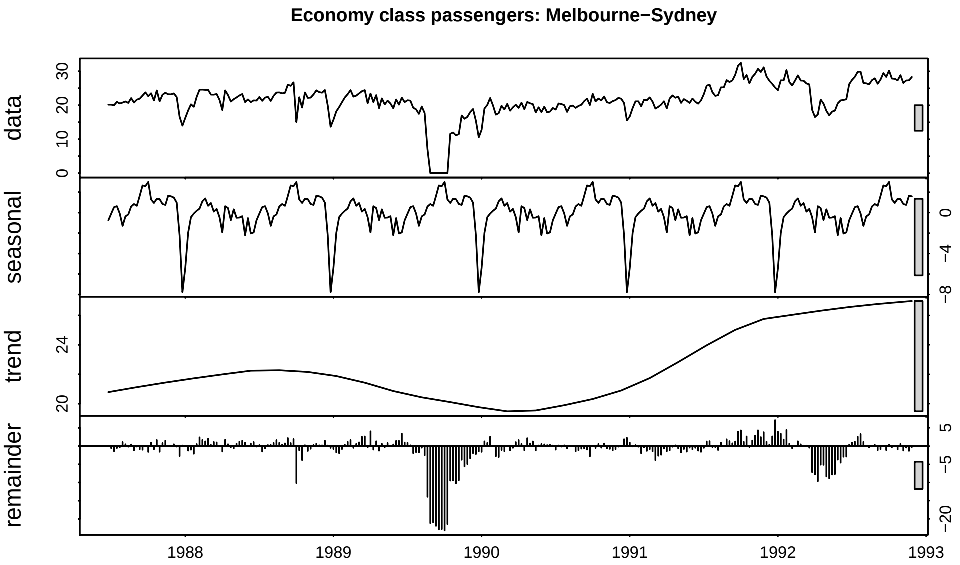

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- Statistical models tend not to be able to allow for the effects seen in these data.
- A common approach is to use “cleaned” data where the time series are reconstructed to look like what might have been if there were no strikes, no changes of definition, etc.
- Probably has small effect on point forecasts, but may have large effect on prediction intervals.

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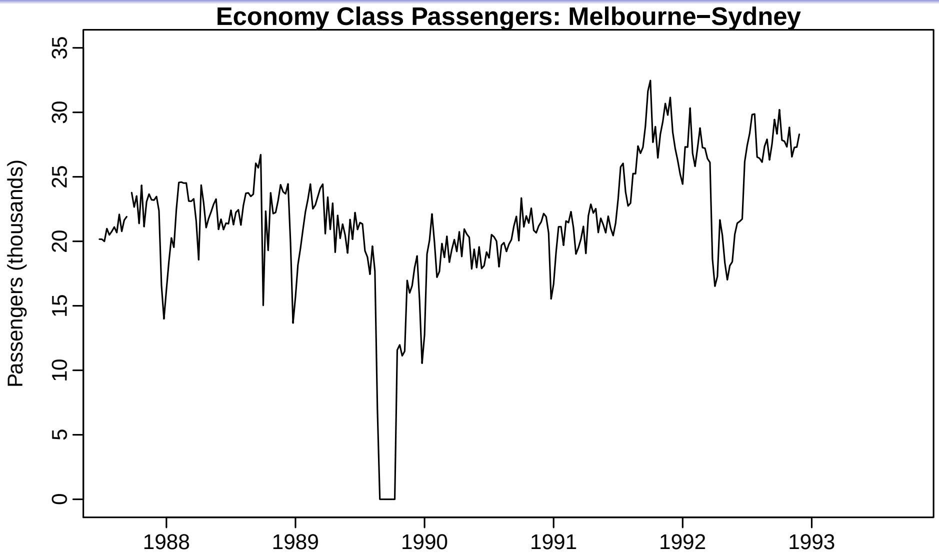

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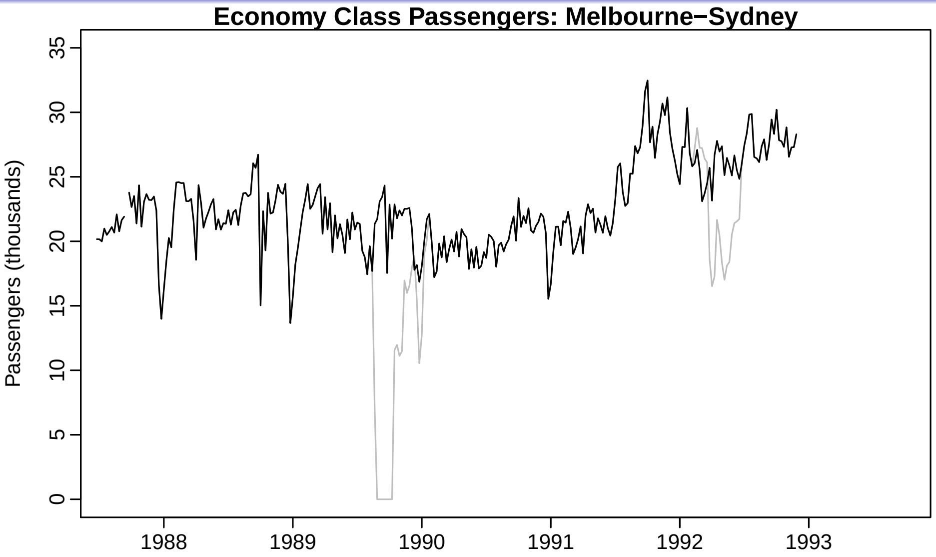

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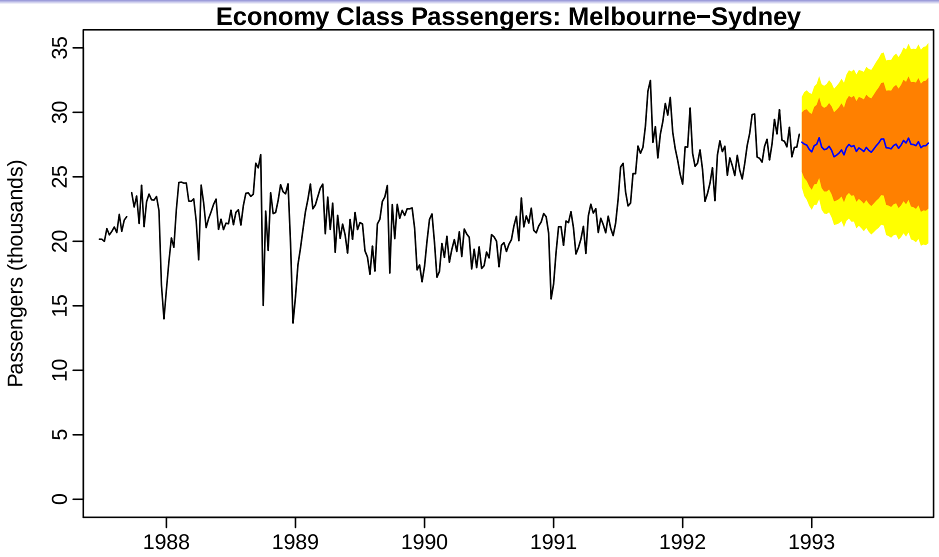

Possible model

$$Y_t = Y_t^* + Z_t$$

$$Y_t^* = \beta_0 + \sum_j \beta_j x_{t,j} + N_t$$

- Y_t = observed data for one passenger class.
- Y_t^* = reconstructed data.
- Z_t = latent process (usually equal to zero).
- $x_{t,j}$ are covariates and dummy variables.
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Research issues

How to model Z_t in the presence of industrial action and changing definitions?

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What to do with the non-integer seasonality? (average 52.19)?

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Research issues

How to deal with the correlations between classes and between routes?

Outline

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- The total cost is budgeted based on forecasts of drug usage.

Forecasting the PBS

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POLITICS

Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost $800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from $220 to $22 after it was listed on the PBS.

the Public Record
For full election coverage

FEATURES

the Public Record
Federal Election 2001

For a fresh perspective on the federal election, reach into ABC Online's campaign weblog, The Poll Vault.

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- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- Although monthly data available for 10 years, data are aggregated to annual values, and only the first three years are used in estimating the forecasts.
- All forecasts being done with the `FORECAST` function in MS-Excel!

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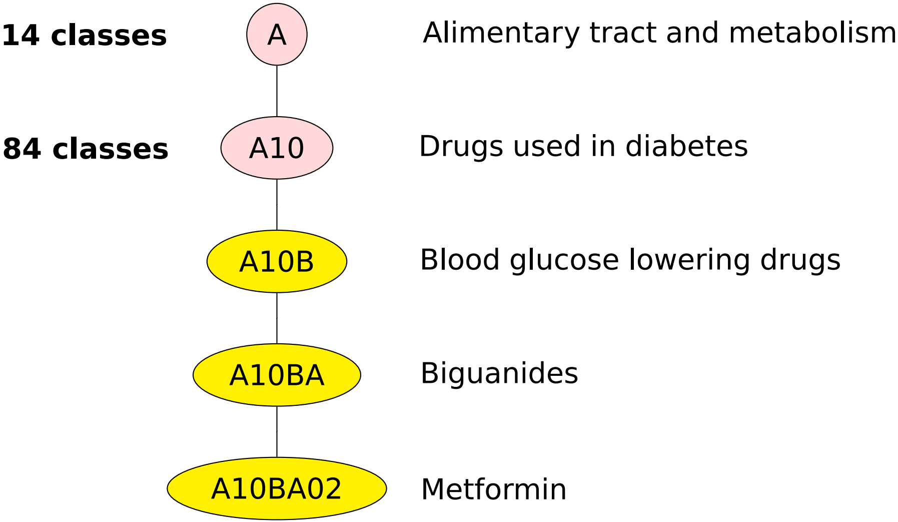
- Monthly data on thousands of drug groups and 4 concession types available from 1991.
- Method needs to be automated and implemented within Excel.
- Exponential smoothing seems appropriate (monthly data with changing trends and seasonal patterns), but in 2001, *automated* exponential smoothing was not well-developed.

ATC drug classification

A	Alimentary tract and metabolism
B	Blood and blood forming organs
C	Cardiovascular system
D	Dermatologicals
G	Genito-urinary system and sex hormones
H	Systemic hormonal preparations, excluding sex hormones and insulins
J	Anti-infectives for systemic use
L	Antineoplastic and immunomodulating agents
M	Musculo-skeletal system
N	Nervous system
P	Antiparasitic products, insecticides and repellents
R	Respiratory system
S	Sensory organs
V	Various

ATC drug classification



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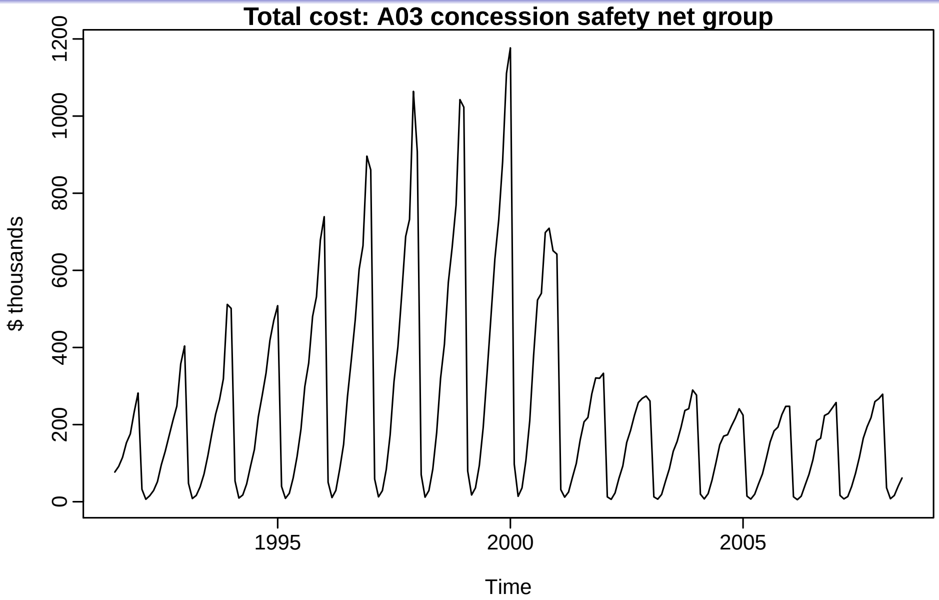
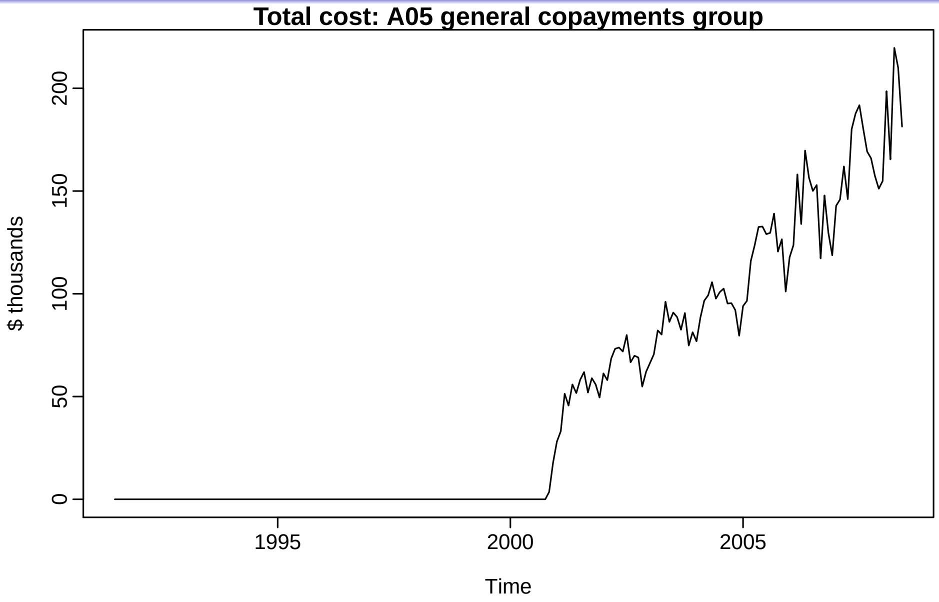
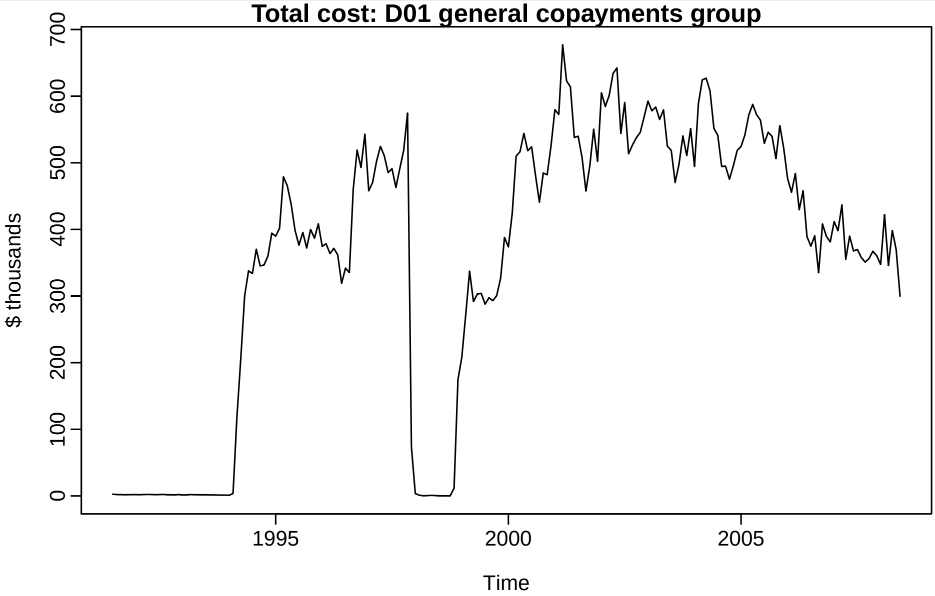
PBS data


Total cost: A03 concession safety net group
$ thousands
0
200
400
600
800
1000
1200
1995
2000
2005
Time

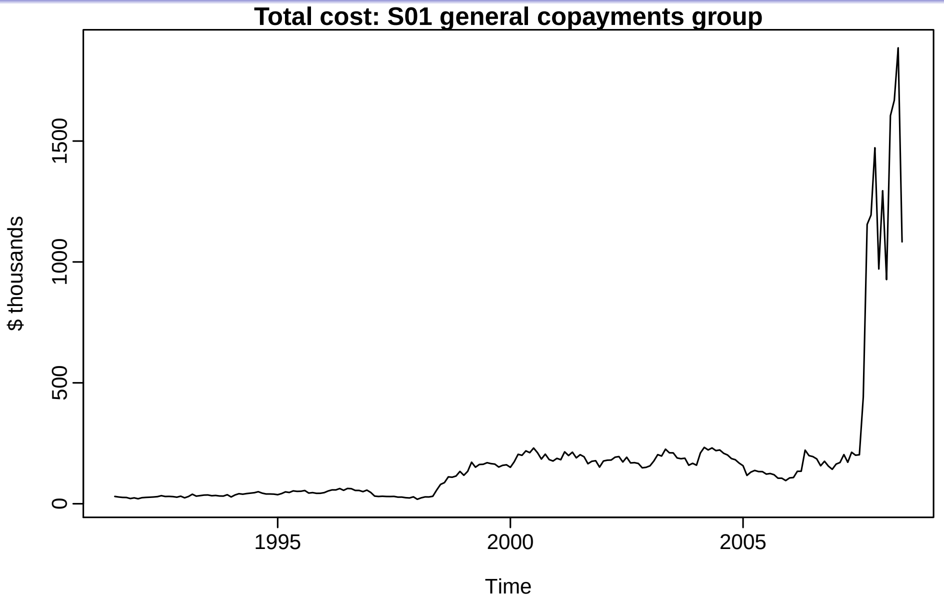
PBS data


Total cost: A05 general copayments group
$ thousands
0
50
100
150
200
1995
2000
2005
Time

PBS data

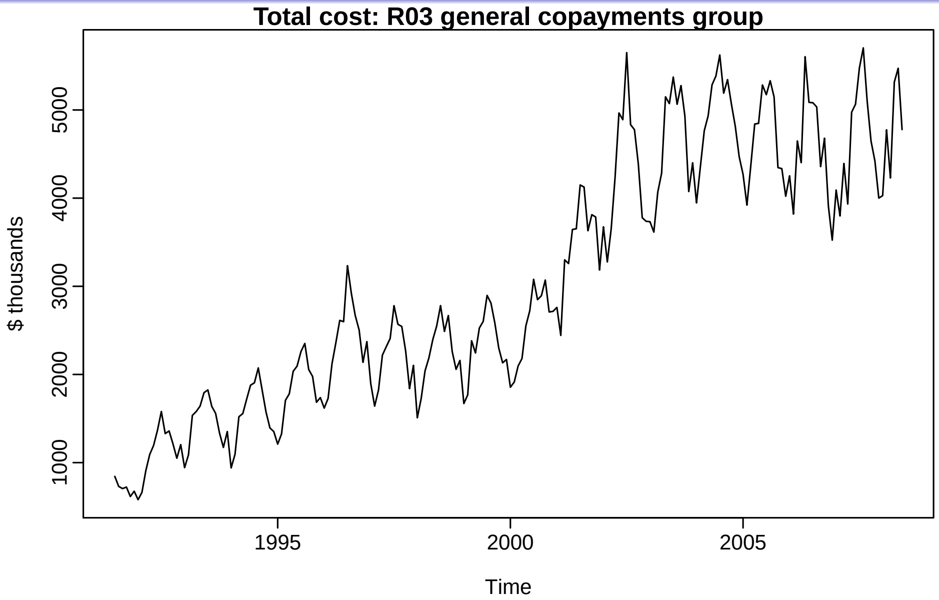

Total cost: D01 general copayments group
$ thousands
0
100
200
300
400
500
600
700
1995
2000
2005
Time

PBS data



Total cost: S01 general copayments group
$ thousands
0
500
1000
1500
1995
2000
2005
Time

PBS data


Total cost: R03 general copayments group
$ thousands
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2000
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Exponential smoothing

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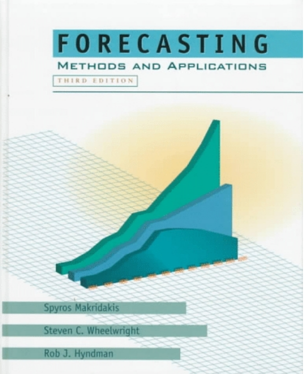

"Unfortunately, exponential smoothing methods do not allow easy calculation of prediction intervals."

Makridakis, Wheelwright and Hyndman, p.177. (Wiley, 3rd ed., 1998)

Exponential smoothing

Estimation and Prediction for a Class of Dynamic Nonlinear Statistical Models

J. K. ORD, A. B. KOEHLER, and R. D. SNYDER

A class of nonlinear state-space models, characterized by a single source of randomness, is introduced. A special case, the model underpinning the multiplicative Holt–Winters method of forecasting, is identified. Maximum likelihood estimation based on exponential smoothing instead of a Kalman filter, and with the potential to be applied in contexts involving non-Gaussian disturbances, is considered. A method for computing prediction intervals is proposed and evaluated on both simulated and real data.

KEY WORDS: Forecasting; Holt–Winters method; Maximum likelihood estimation; State-space models.

1. INTRODUCTION

The fact that business and economic time series often possess seasonal cycles with increasing amplitudes together with random fluctuations dependent on movements in underlying levels is a compelling reason to study nonlinear statistical models. Most nonlinear behavior commonly observed in time series plots can be represented by nonlinear state-space models. Being dynamic, the latter have the capacity to reflect many forms of inter temporal dependency encountered in economic time series. Like their linear counterparts (Ansley and Kohn 1985; Harvey and Todd 1983), nonlinear state-space models can be adapted to accommodate the nonstationary features of most economic time series surable quantity y_t in typical period t is governed by the following model:

Model 1:

$$y_t = h(\mathbf{x}_{t-1}, \boldsymbol{\theta}) + k(\mathbf{x}_{t-1}, \boldsymbol{\theta})e_t,$$
$$\text{where} \quad \mathbf{x}_t = \mathbf{f}(\mathbf{x}_{t-1}, \boldsymbol{\theta}) + \mathbf{g}(\mathbf{x}_{t-1}, \boldsymbol{\theta})\mathbf{e}_t.$$

The p vector $\mathbf{x}_{t-1}$ represents the state of the underlying process at the beginning of period t, $\boldsymbol{\theta}$ is a vector of parameters, e_t is from an iid$(0, \sigma^2)$ series of disturbances, h and k are known continuous functions with continuous derivatives mapping from $\Re^p \rightarrow \Re$, and $\mathbf{f}$ and $\mathbf{g}$ are known continuous mappings with continuous derivatives from $\Re^p \rightarrow \Re^p$. It is assumed that the e_t are independent of $\{y_{t-i}, \mathbf{x}_{t-i}, i \geq 1\}$. Although the functions h, k, $\mathbf{f}$, and $\mathbf{g}$ can potentially be in-

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- Forecast MAPE reduced from 15–20% to about 0.6%.

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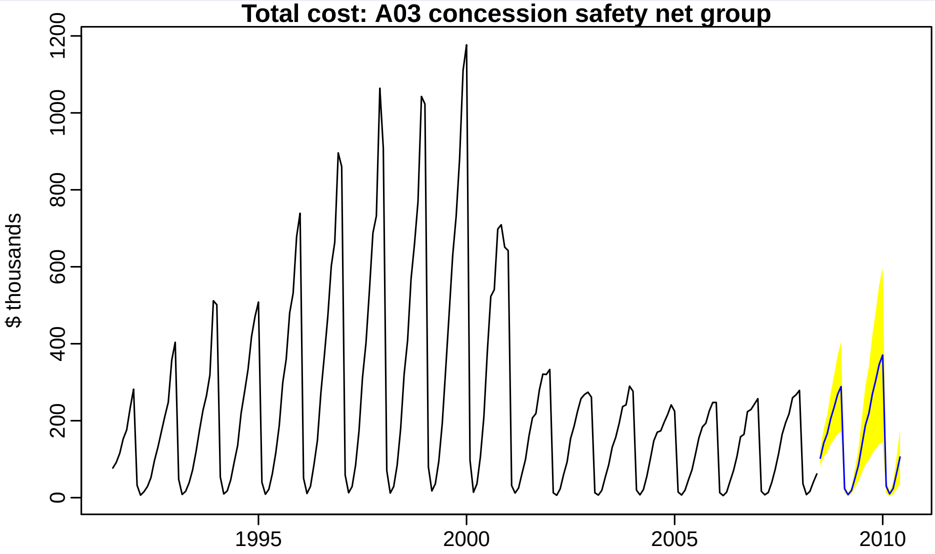

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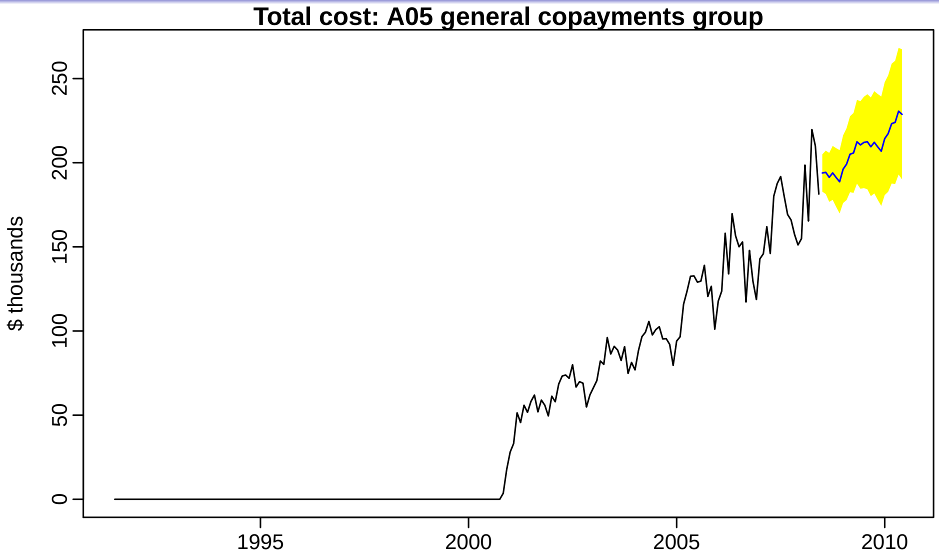

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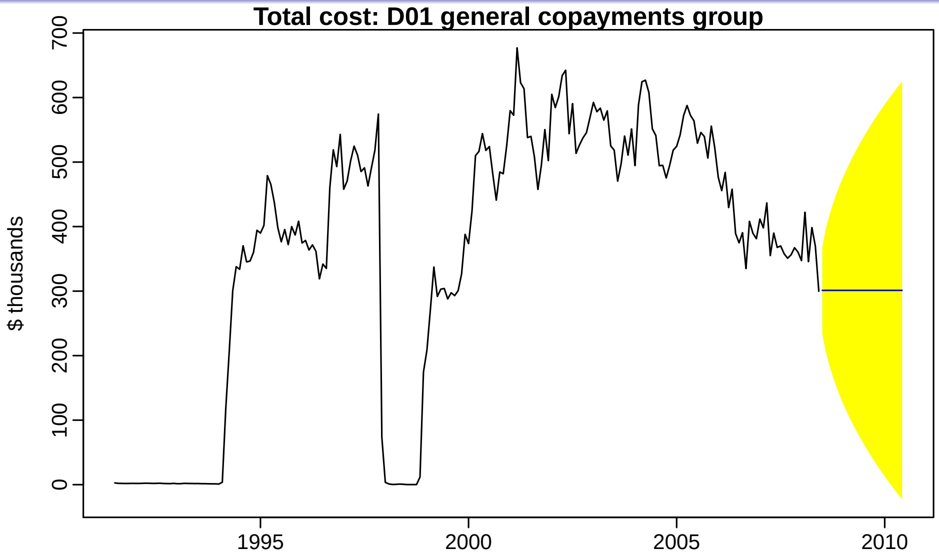

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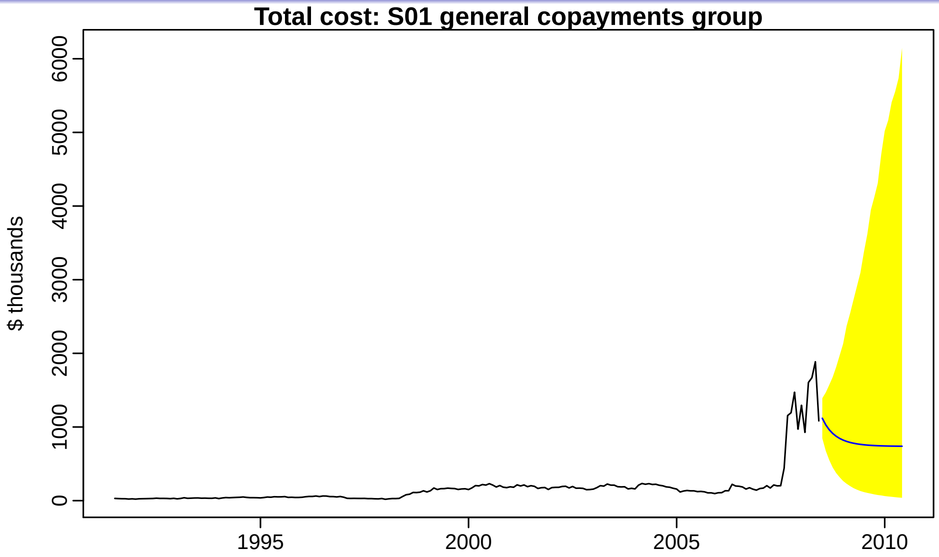

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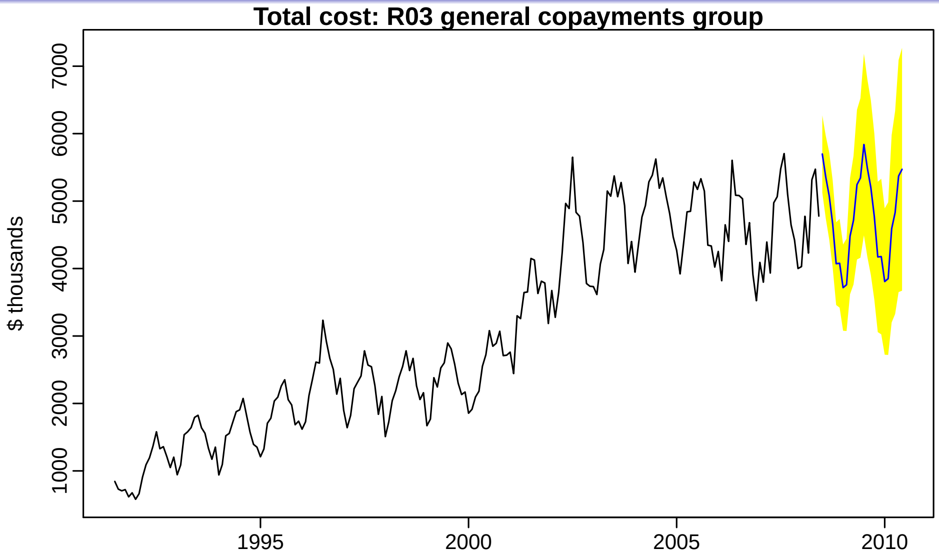

Exponential smoothing

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- a general class of state space models proposed underlying all the common exponential smoothing methods.

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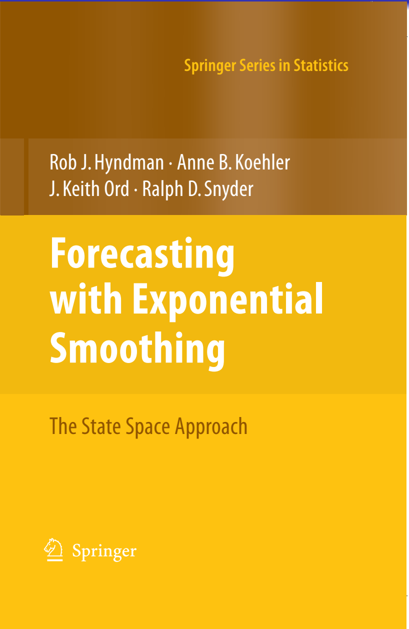
- new results on admissible parameter space.
- algorithm now part of **forecast** package in **R**.

Recent book



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- Prediction intervals
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- All the important research results in one place with consistent notation
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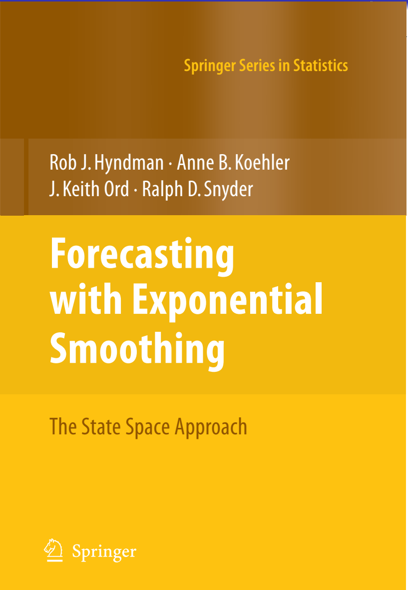

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www.exponentialsmoothing.net

Forecasting the PBS

Research issues

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2. How to generate prediction intervals for all varieties of exponential smoothing forecasts?
3. Data can be disaggregated at five levels of a drug hierarchy. At what level of disaggregation should we forecast?
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3. **Extreme electricity demand**
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Extreme electricity demand

Joint work with
Dr Shu Fan

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- We have twelve years of half-hourly electricity data, temperature data and some economic and demographic data.
- The location is South Australia: home to the most volatile electricity demand in the world.

The problem

- We want to forecast the peak electricity demand in a half-hour period in ten years time.
- We have twelve years of half-hourly electricity data, temperature data and some economic and demographic data.
- The location is South Australia: home to the most volatile electricity demand in the world.

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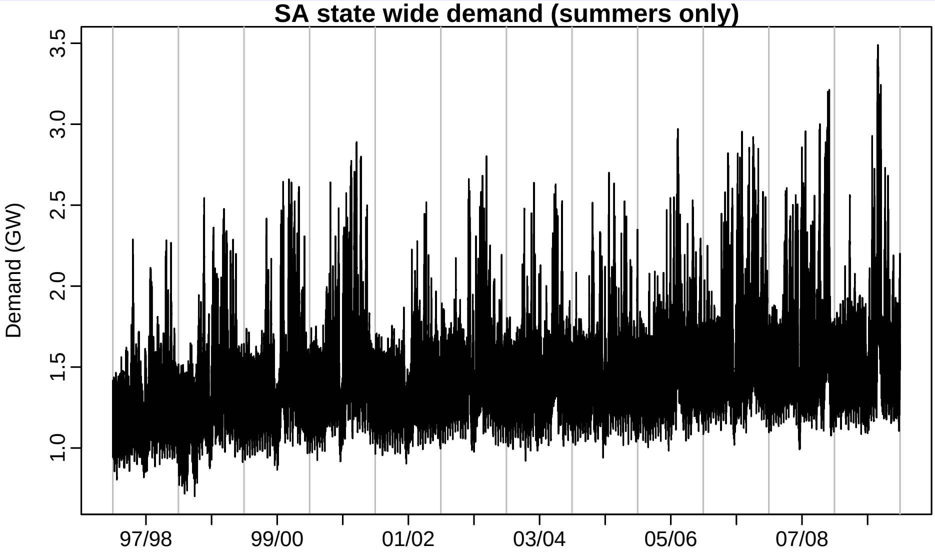
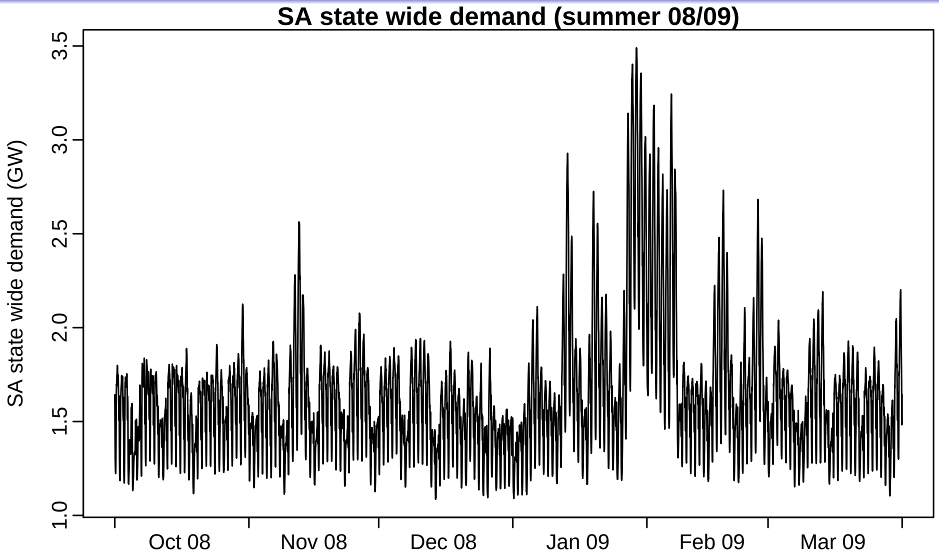
Sounds impossible?

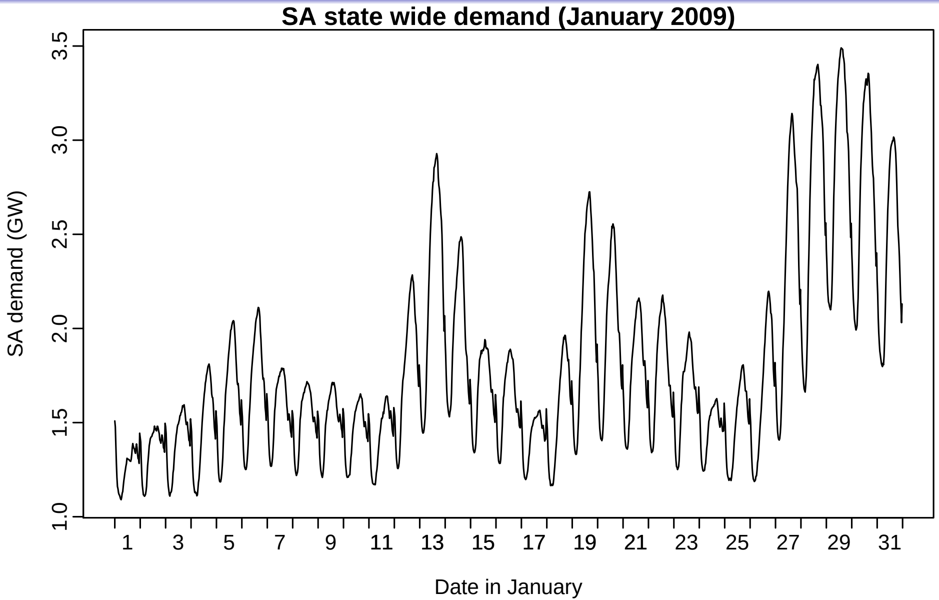
Demand data


SA state wide demand (summers only)
Demand (GW)
1.0
1.5
2.0
2.5
3.0
3.5
97/98
99/00
01/02
03/04
05/06
07/08

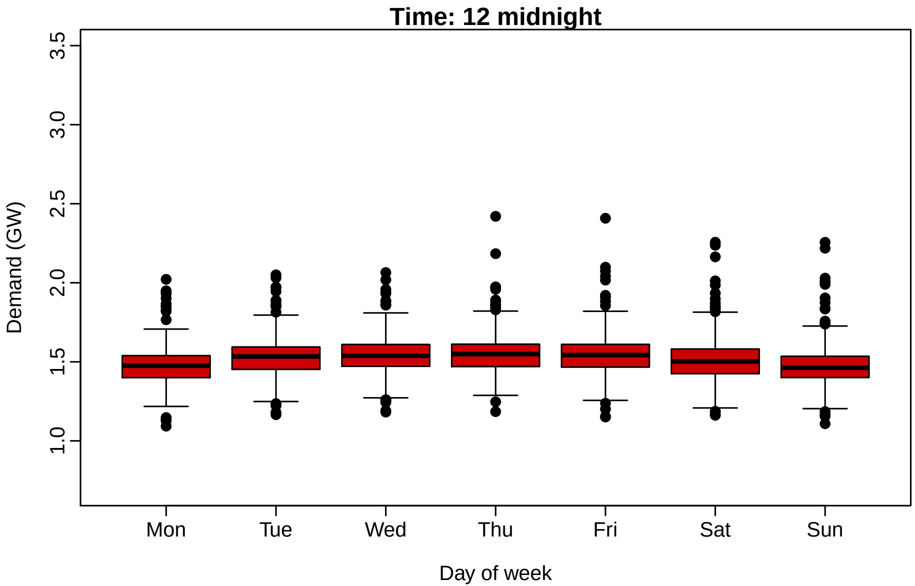
Demand data


SA state wide demand (summer 08/09)
SA state wide demand (GW)
1.0
1.5
2.0
2.5
3.0
3.5
Oct 08
Nov 08
Dec 08
Jan 09
Feb 09
Mar 09

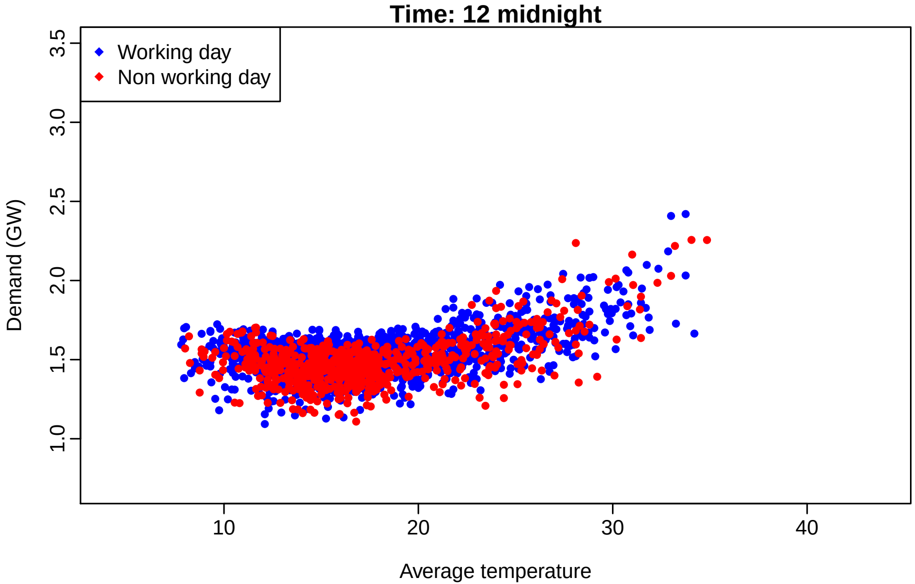
Demand data


SA state wide demand (January 2009)
SA demand (GW)
1.0
1.5
2.0
2.5
3.0
3.5
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
Date in January

Demand boxplots



Temperature data



Demand drivers

- calendar effects

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- calendar effects
- prevailing and recent weather conditions

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Modelling framework

- **Semi-parametric additive models** with correlated errors.

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- Each half-hour period modelled separately.

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Modelling framework

- **Semi-parametric additive models** with correlated errors.
- Each half-hour period modelled separately.
- Variables selected to provide best out-of-sample predictions using cross-validation on each summer.

Equations

$$\log(y_{t,p}) = h_p(t) + f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t$$

- $y_{t,p}$ denotes per capita demand at time t (measured in half-hourly intervals) during period p, $p = 1, \dots, 48$;

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- n_t denotes the model error at time t.

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$h_p(t)$ includes handle annual, weekly and daily seasonal patterns as well as public holidays:

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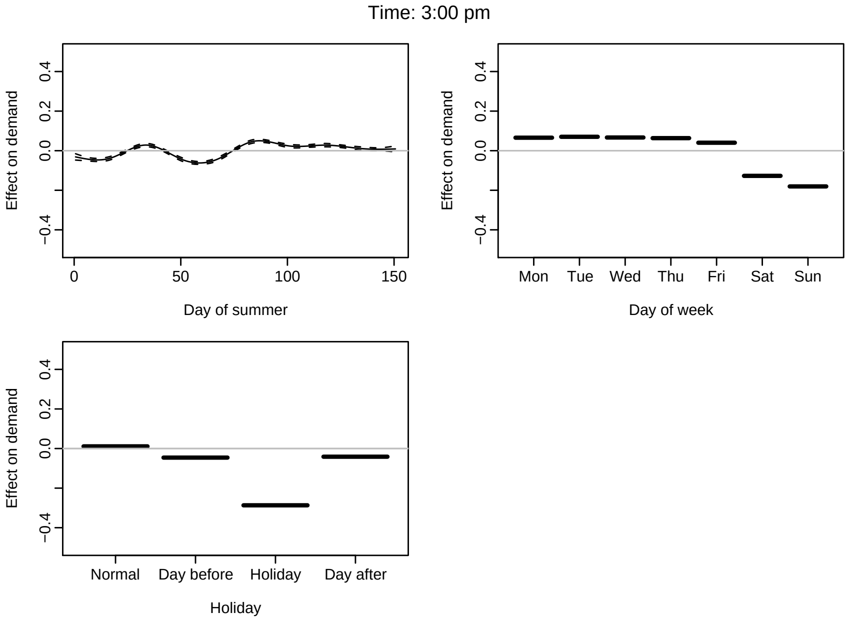
Fitted results (3pm)



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Each function is smooth and estimated using regression splines.

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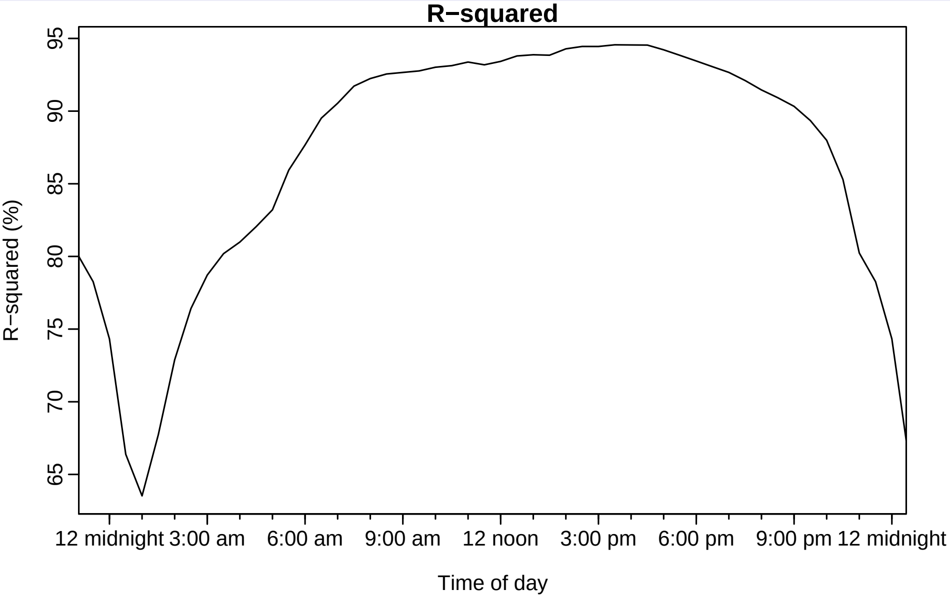
Variable	Coefficient	Std. Error	P value
Per-capita GSP	18.56	1.174	0.000
Lag Price	-0.0179	0.00491	0.002
Cooling Degree Days ($\times$1000)	0.1002	0.00456	0.043

Predictions



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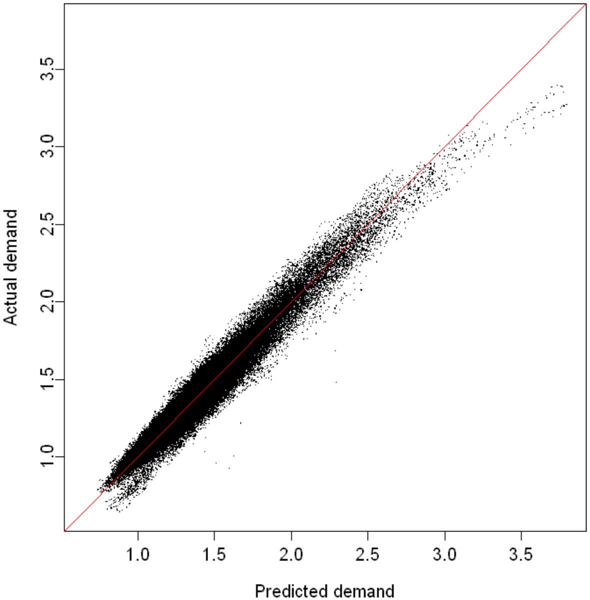

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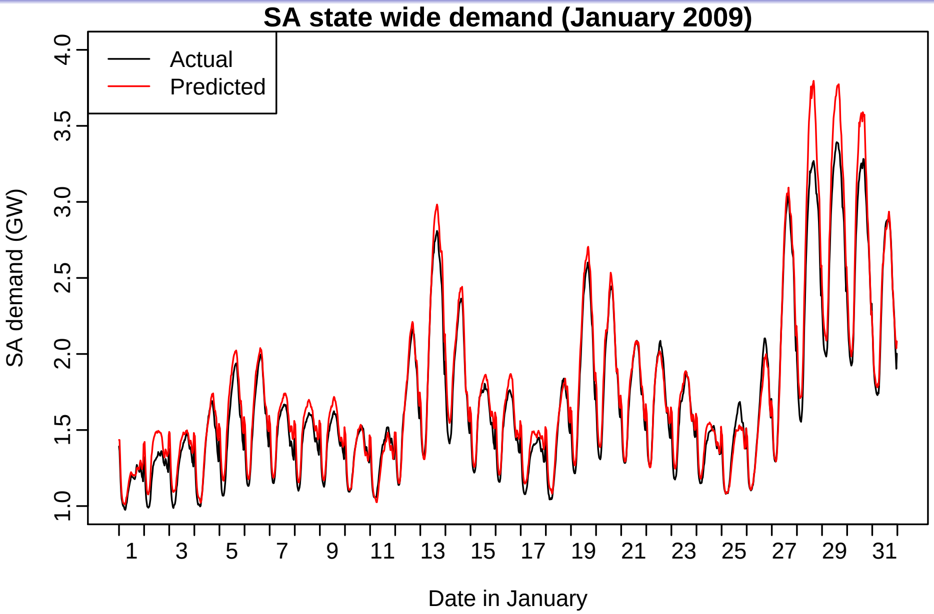
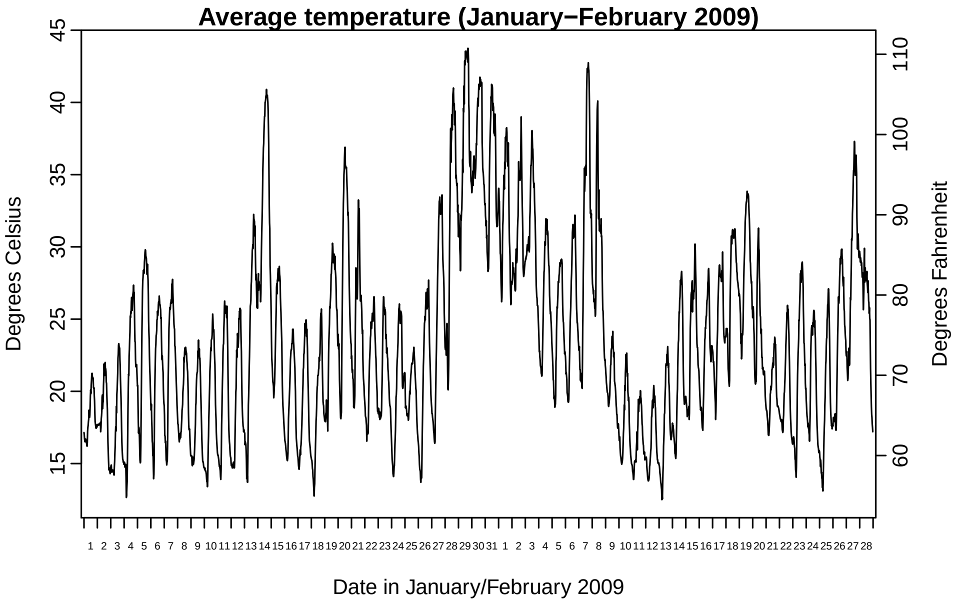


The heatwave



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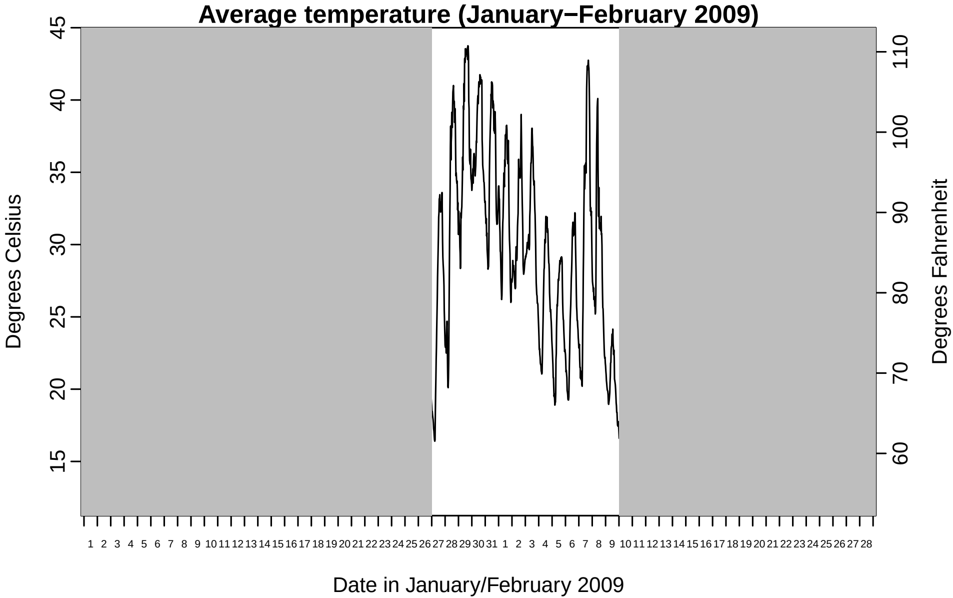

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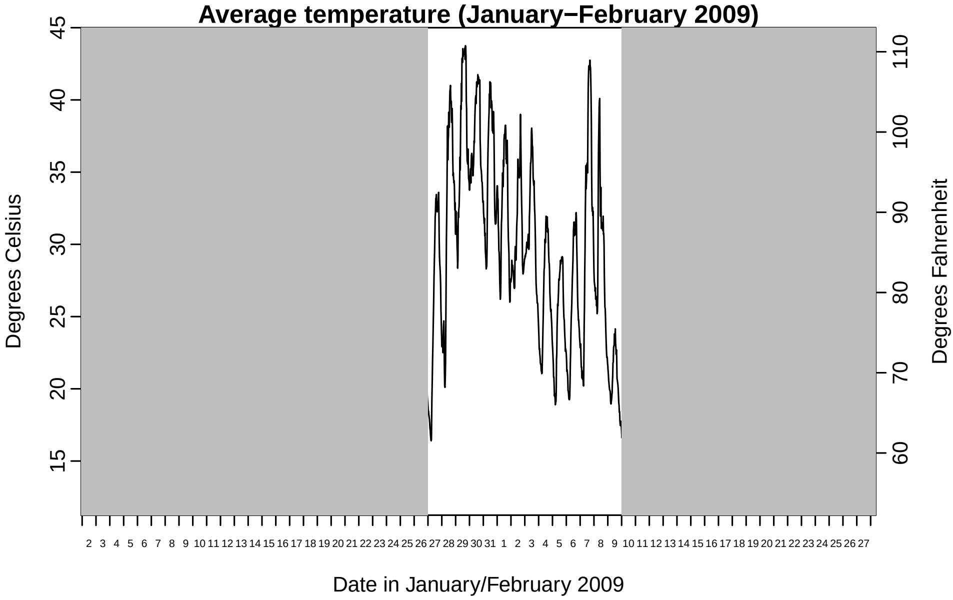

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Model allowing saturated usage

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$$\log(y_{t,p}) = \begin{cases} q_{t,p} & \text{if } q_{t,p} \le \tau; \\ \tau + k(q_{t,p} - \tau) & \text{if } q_{t,p} > \tau. \end{cases}$$

Peak demand forecasting

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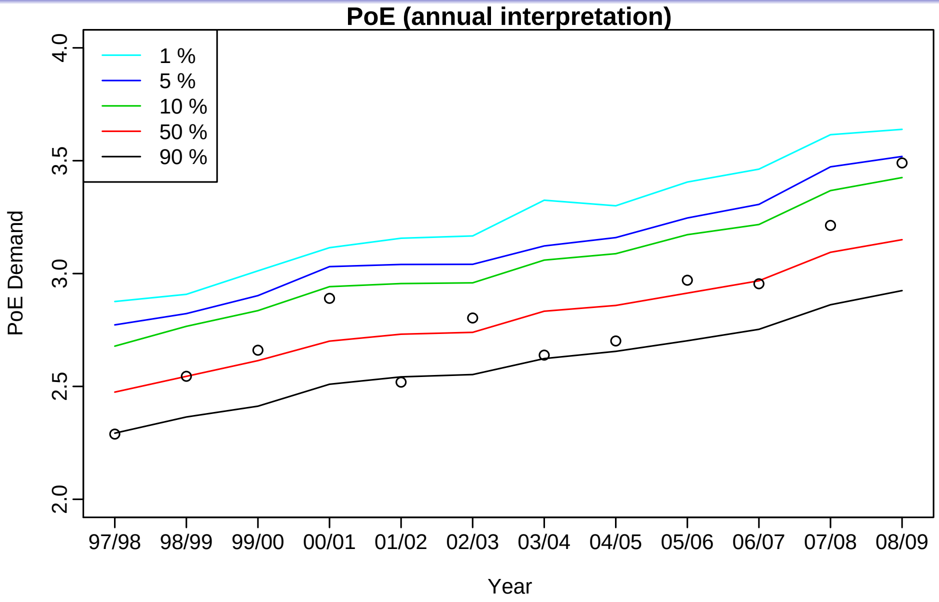
- use assumed values for GSP and Price.

Peak demand distribution



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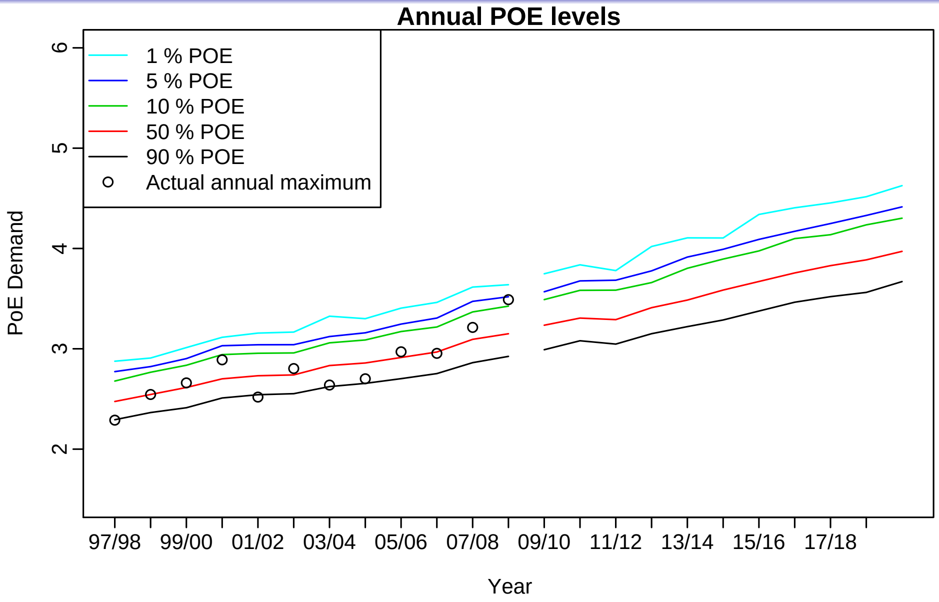

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- How to measure forecast accuracy for a 1-in-10 year event?

Outline

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- If only academics and practitioners talked more . . .

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- Choose methods to model all the information available, but no more.

Stationarity and structural change

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- Uncertainty is not always easy to measure, is not always easy to compute, but is often the thing of most interest.

Go forth and forecast

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(Anonymous)

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Slides available from

www.robjhyndman.com