Forecasting and the importance of being uncertain

Rob J Hyndman

MONASH University

Speaker introduction

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- Co-author of textbook, *Forecasting: methods and applications*.

Forecasters are to blame!

News report on 16 August 2006

A Russian woman is suing weather forecasters for wrecking her holiday. A court in Uljanovsk heard that Alyona Gabitova had been promised 28 degrees and sunshine when she planned a camping trip to a local nature reserve, newspaper *Nowyje Iswestija* said.
But it did nothing but pour with rain the whole time, leaving her with a cold. Gabitova has asked the court to order the weather service to pay the cost of her travel.

Outline

What is it?

What is it?

Clay model of sheep's liver

Used by Babylonian forecasters approximately 600 B.C.

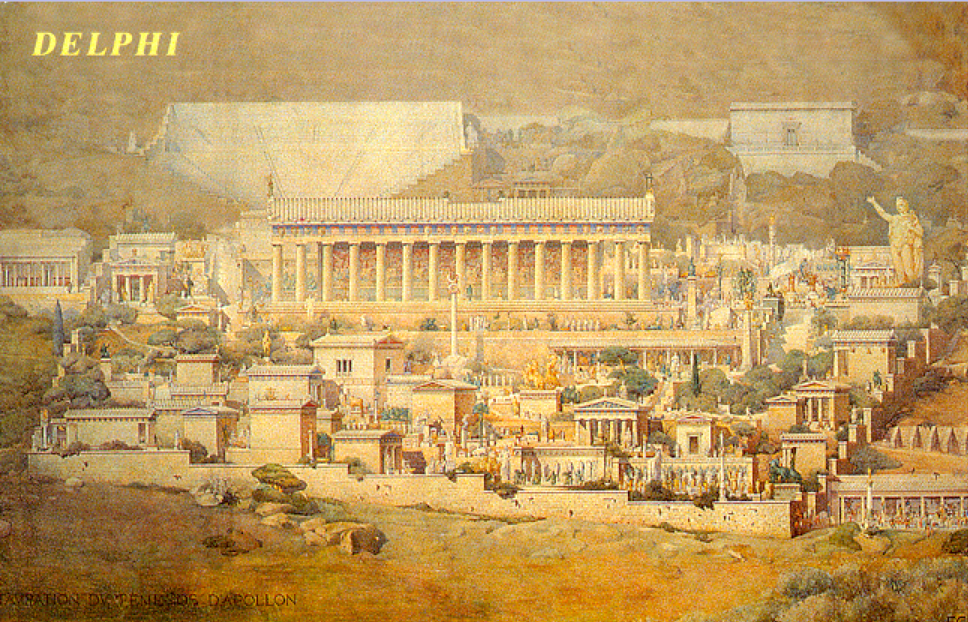
Now in British Museum.

Delphic oracle

Delphic oracle

Delphic oracle

Temple of Apollo



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Vagrant forecasters

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Punishment: a fine or three months' imprisonment with hard labour.

Reputations can be made and lost

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- "There are four ways economists can lose their reputation. Gambling is the quickest, sex is the most pleasurable and drink the slowest. But forecasting is the surest." (Max Walsh, *The Age*, 1993)

Those "unforeseen events"

Precautions should be taken against running into unforeseen occurrences or events. (Horoscope, New York Times)

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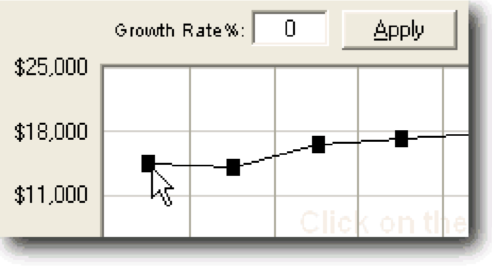
We are ready for any unforeseen event which may or may not occur.

(Dan Quayle)

Standard business practice today

Graphic Forecaster

Create forecasts visually with a "drag and drop" graphic forecaster. The Graphic Forecaster is a simple and powerful tool to streamline the forecasting process. You can change your sales and expenses estimates by simply clicking your mouse button to move the line on your forecast chart or apply a specific growth rate to the whole year. Build forecasts using visual common sense.



View More Detail

Standard business practice today

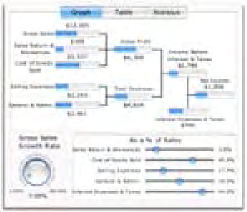
Crystal Xcelsius Showcase

Examples of what you can build with Crystal Xcelsius.

Free Trial Buy Now

If you cannot open these demos, download the latest version of Macromedia's Flash Player.

Featured Example: Profitability Analysis



Profitability Analysis

This profitability model allows you to create "what-if" scenarios by modifying sales growth rate and all other relevant accounts measured as a percentage of total sales. This example, built with fictitious data, depicts the most relevant accounts of a profit and loss statement, and shows the impact of changes on net income. The results change immediately, allowing you to create endless what-if scenarios.

Download as PowerPoint
Download as Flash
Download as PDF
Download Source Files
Download as Word

Standard business practice today

Budget Maestro by Centage

Budget Maestro by Centage

Click here for a free demo FREE!

Application: Business Intelligence and Analytics

Price Range: Solutions start at $5K

A huge advance over spreadsheet-based systems, Budget Maestro is a complete solution for budgeting, forecasting, what-if scenario planning, reporting and analysis. Budget Maestro takes the pain out of the budgeting process (no tedious data entry and formula verification) while providing you a tool to more accurately analyze and measure business performance and profitability. Budget Maestro's capabilities include:

Budgeting and Forecasting: Budget Maestro utilizes database technology for real-time data collection and reporting. A common interface for all users fosters collaboration and increases the accuracy of data entry. There are no formulas or macros to create, no tedious re-keying of data and no mystery links to chase down and fix. Budget Maestro's built-in "financial intelligence and business rules" builds the formulas for you ensuring 100% accuracy.

Standard business practice today

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Is this any better than a sheep's liver or hallucinogens?

The rise of stochastic models

1959 exponential smoothing (Brown)

1970 ARIMA models (Box, Jenkins)

1980 VAR models (Sims, Granger)

1980 non-linear models (Granger, Tong, Hamilton, Teräsvirta, . . .)

1982 ARCH/GARCH (Engle, Bollerslev)

1986 neural networks (Rumelhart)

1989 state space models (Harvey, West, Harrison)

1994 nonparametric forecasting (Tjøstheim, Härdle, Tsay,. . .)

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- Objective measure of uncertainty
- Able to compute prediction intervals

Outline

Forecasting the PBS

ABC News Online
AUSTRALIAN BROADCASTING CORPORATION

This Bulletin: Wed, May 30 2001 6:22 PM AEST

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.

Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme

Department of Health and Aging

- \$5 billion budget. Underforecasted by \$500–\$800 million in 2000 and 2001.

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- Subject to covert marketing, volatile products, uncontrollable expenditure.
- All forecasts being done with the `FORECAST` function in MS-Excel applied to 10 year old data!

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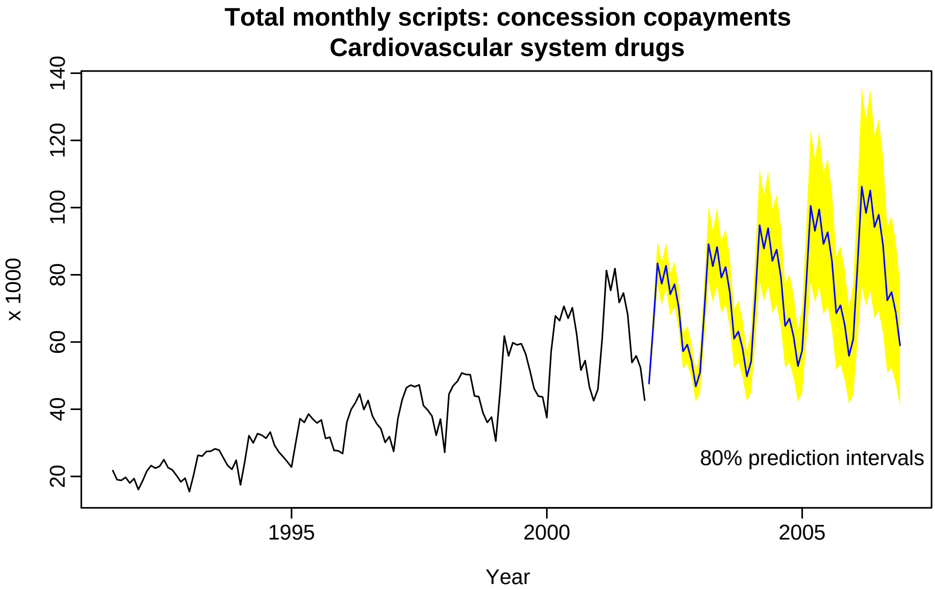
- Forecast error now a few $million per year.

Forecasting the PBS



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- Models allowed for time-changing trend and seasonal patterns.
- Stochastic models provide prediction intervals which give a sense of uncertainty.
- Class of models was based on exponential smoothing.
- At the time, exponential smoothing methods were not thought to be based on stochastic models.

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

Since 2002. . .

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- new results on the admissible parameter space.

Taxonomy of models

		Seasonal Component		
Trend Component		N (None)	A (Additive)	M (Multiplicative)
N	(None)	N,N	N,A	N,M
A	(Additive)	A,N	A,A	A,M
A_d	(Additive damped)	A_d,N	A_d,A	A_d,M
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General notation **ETS**(*Error,Trend,Seasonal*)

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ETS(A,N,N): Simple exponential smoothing with additive errors

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ETS(A,A,N): Holt's linear method with additive errors

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ETS(A,A,A): Additive Holt-Winters' method with additive errors

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ETS(M,A,M): Multiplicative Holt-Winters' method with multiplicative errors

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ETS(A,A_d,N): Damped trend method with additive errors

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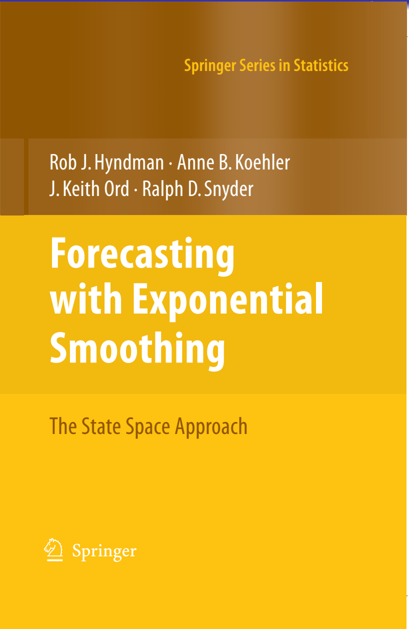
Exponen**T**ial **S**moothing

There are 30 separate models in the ETS framework

New book!



- State space modeling framework
- Prediction intervals
- Model selection
- Maximum likelihood estimation
- All the important research results in one place with consistent notation
- Many new results
- 375 pages but only

US$54.95 / £28.50 / €36.95

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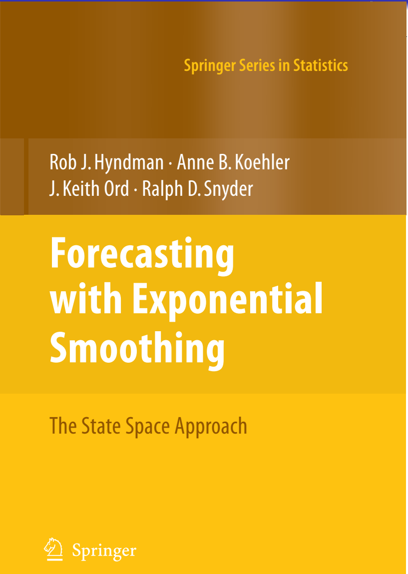

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www.exponentialsmoothing.net

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Australian Greenhouse Office

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- Solution: Use **judgmental methods**

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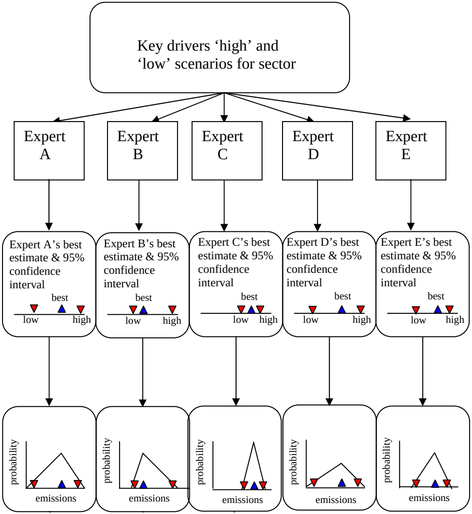

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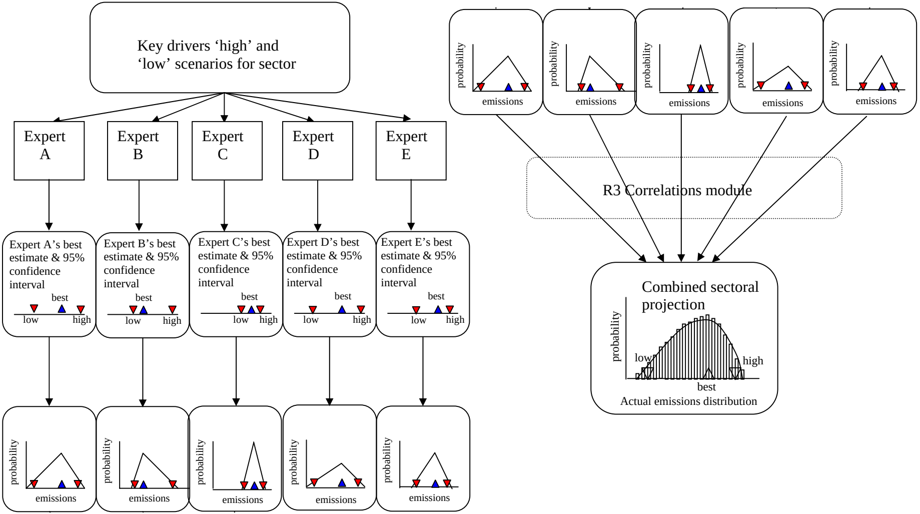

Outline

ABS population projections

The Australian Bureau of Statistics provide population "projections".

"The projections are not intended as predictions or forecasts, but are illustrations of growth and change in the population that would occur if assumptions made about future demographic trends were to prevail over the projection period.
While the assumptions are formulated on the basis of an assessment of past demographic trends, both in Australia and overseas, there is no certainty that any of the assumptions will be realised. In addition, no assessment has been made of changes in non-demographic conditions."

ABS 3222.0 - Population Projections, Australia, 2004 to 2101

ABS population projections

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- Based on assumed mortality, fertility and migration rates

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- Based on assumed mortality, fertility and migration rates
- No objectivity.
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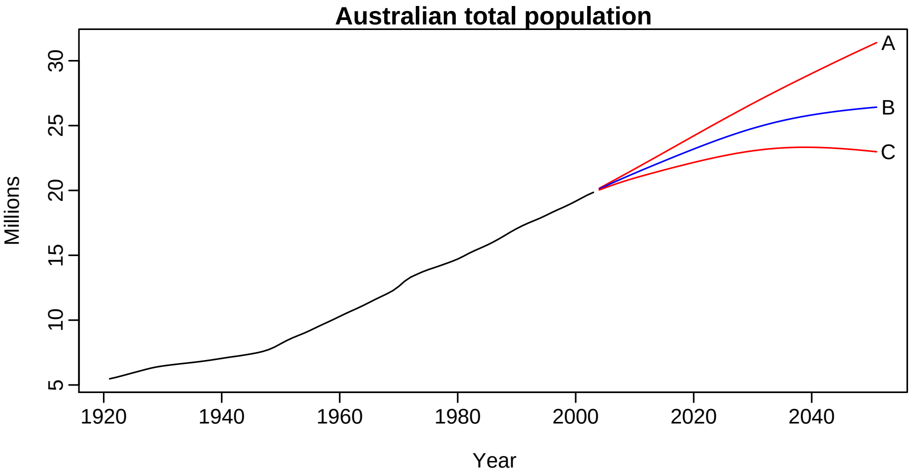
- Most users use the “Medium” projection, but it is unrelated to the mean, median or mode of the future distribution.

ABS population projections



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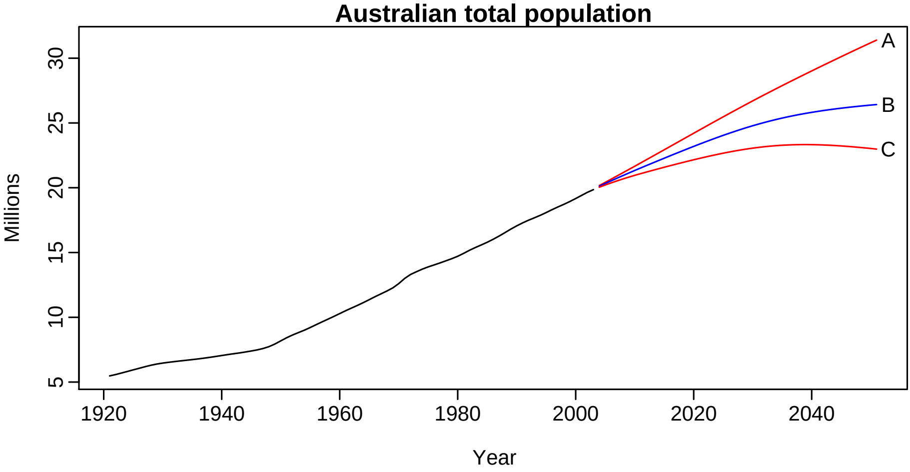

What do these projections mean?

Annual age-specific population

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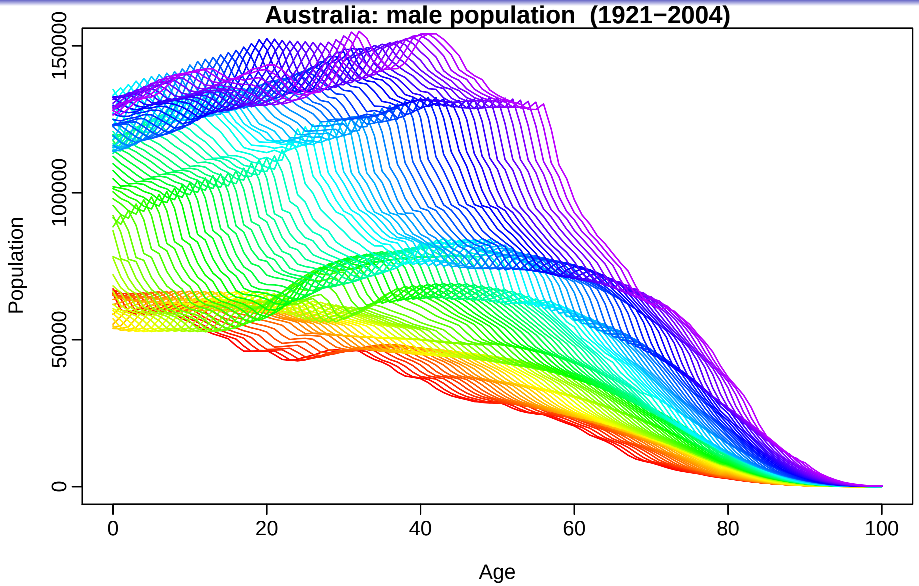

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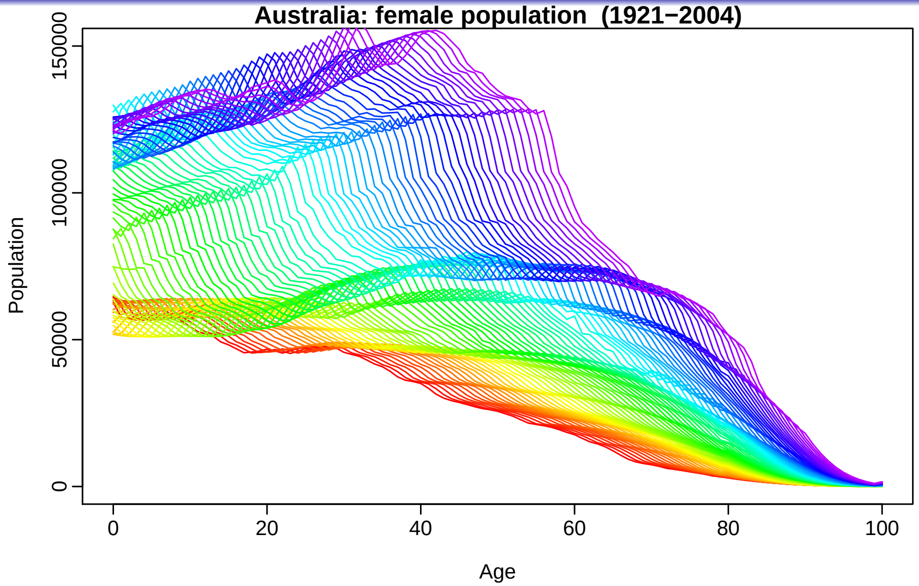

Stochastic population forecasts

Key ideas

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- Combine the results to get **age-specific stochastic population forecasts**.

Mortality rates

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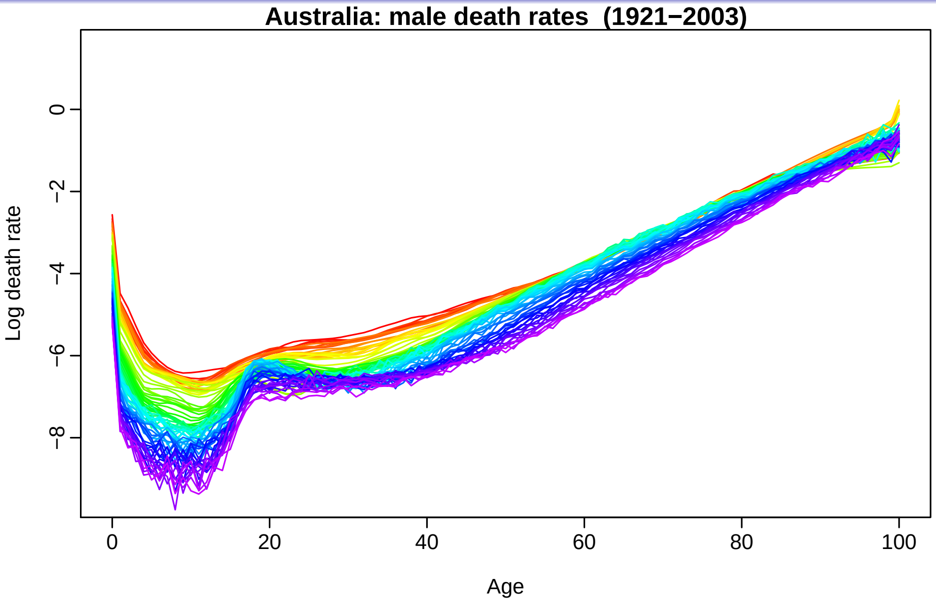
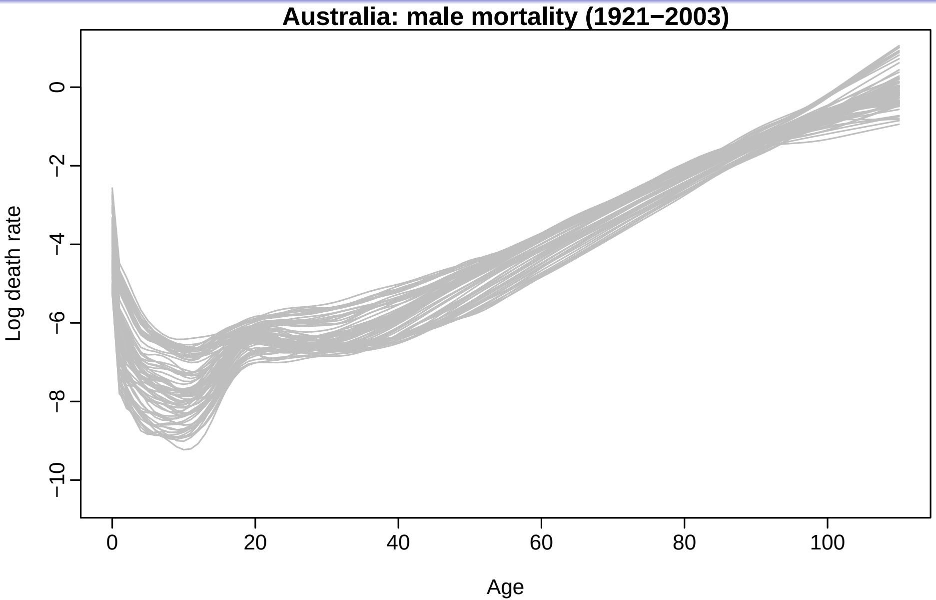


Mortality rates



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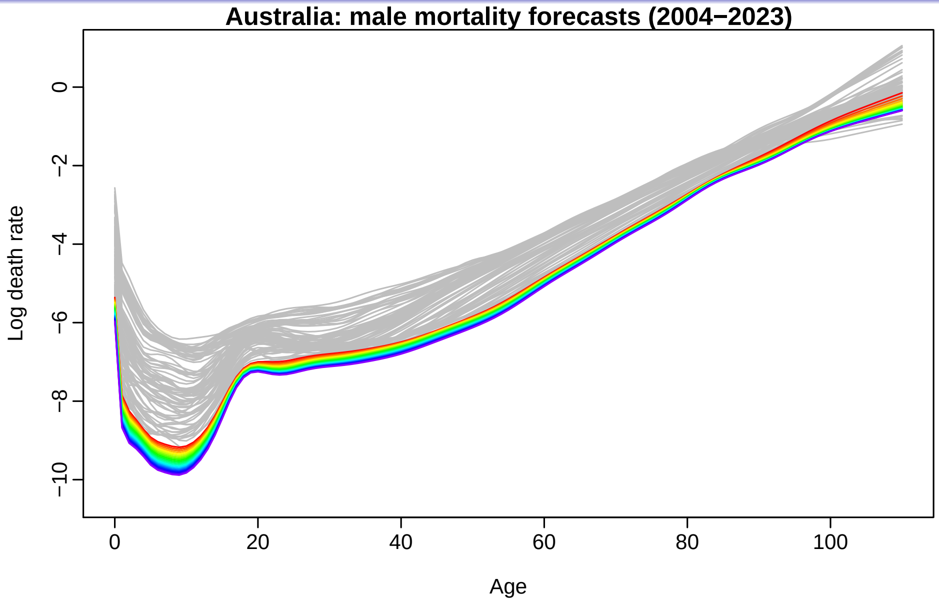

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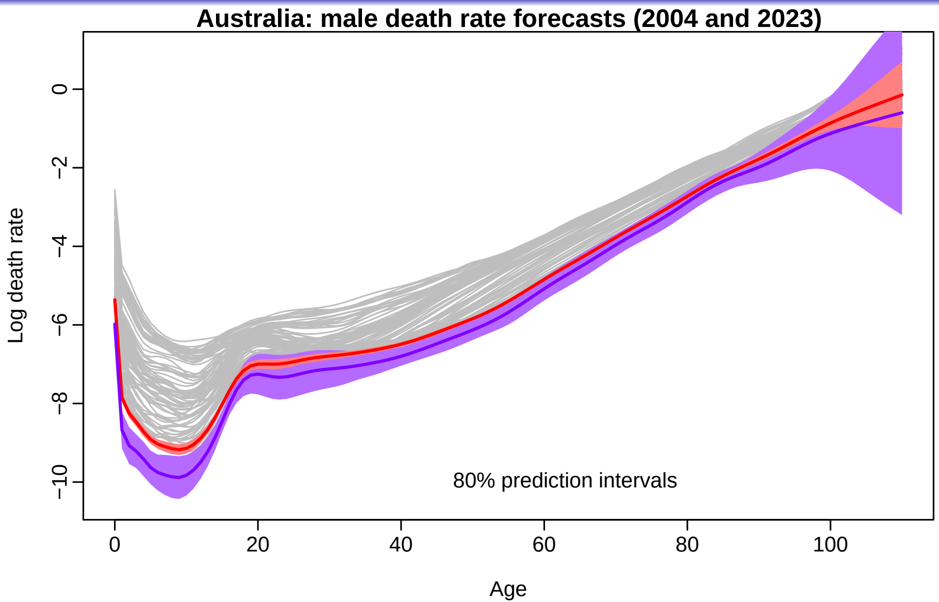
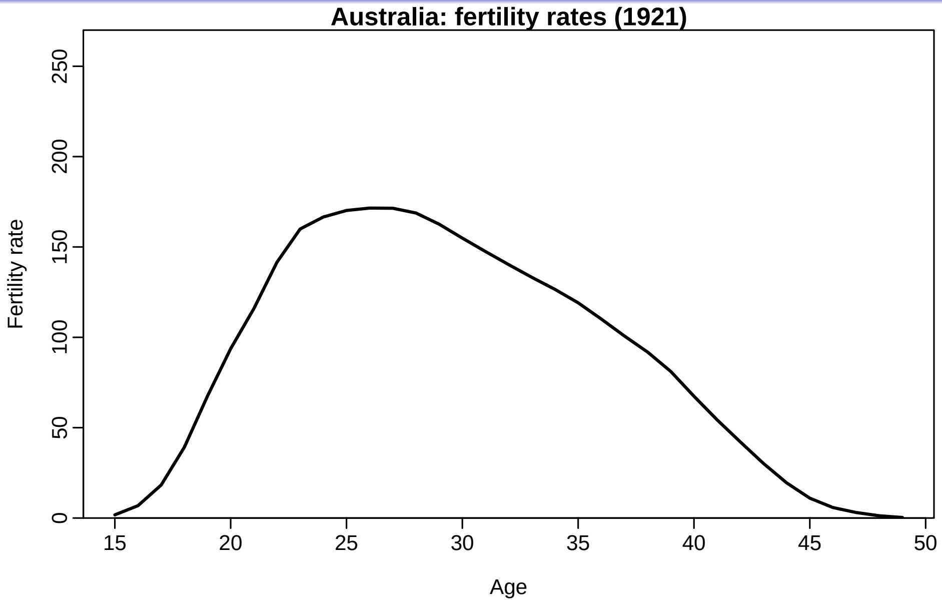


Fertility rates



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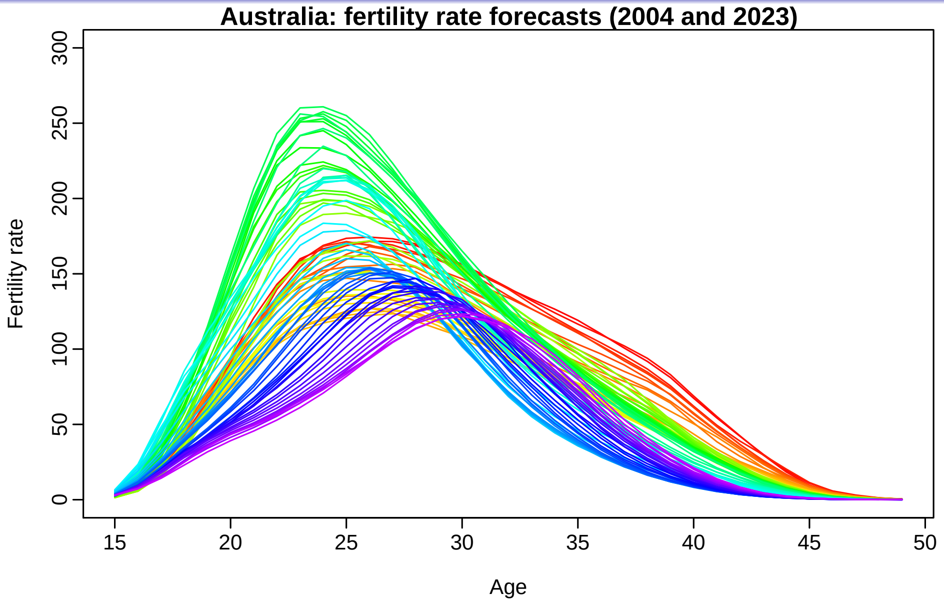
Australia: fertility rate forecasts (2004 and 2023)
Fertility rate
0
50
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150
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250
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Age
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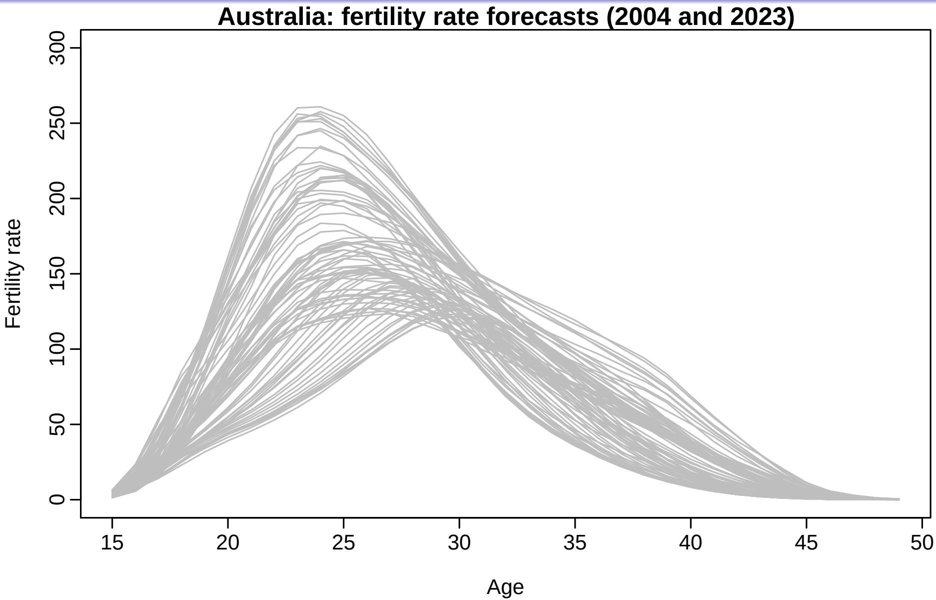
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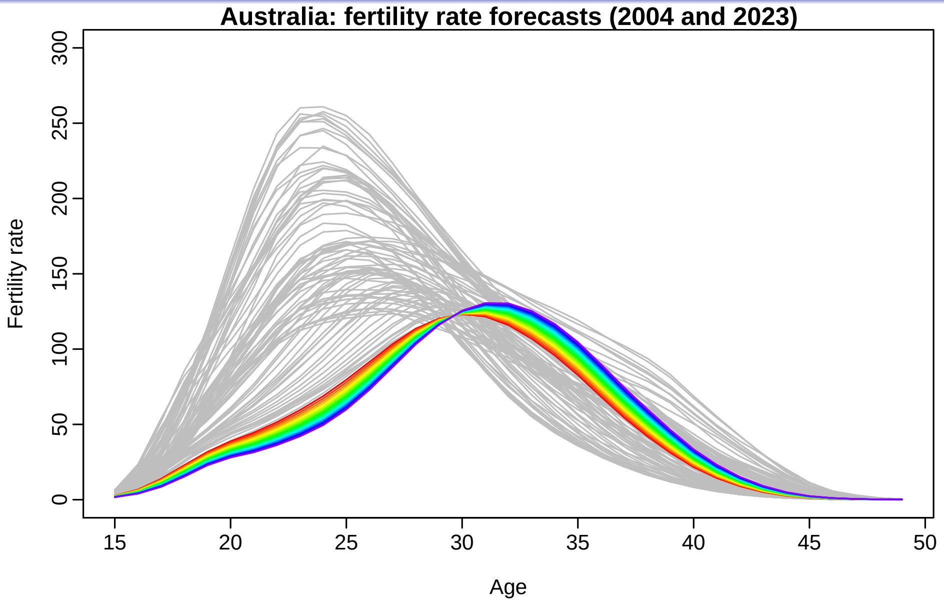
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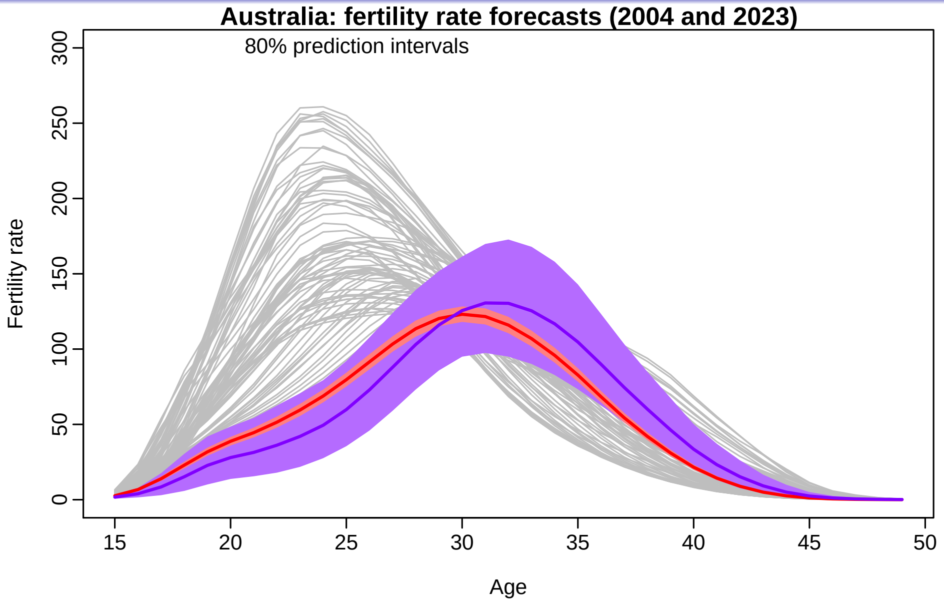
Australia: fertility rate forecasts (2004 and 2023)
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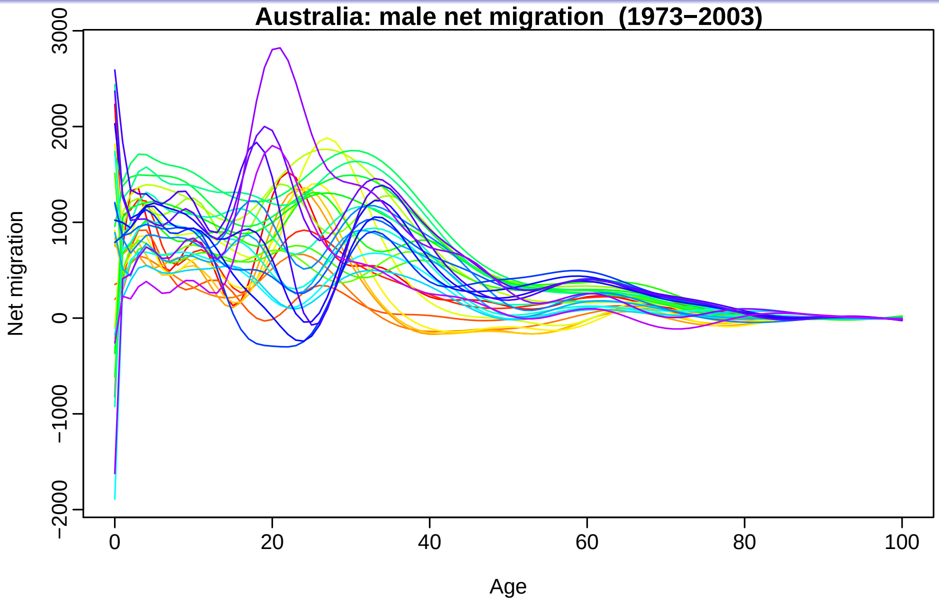
Migration: male



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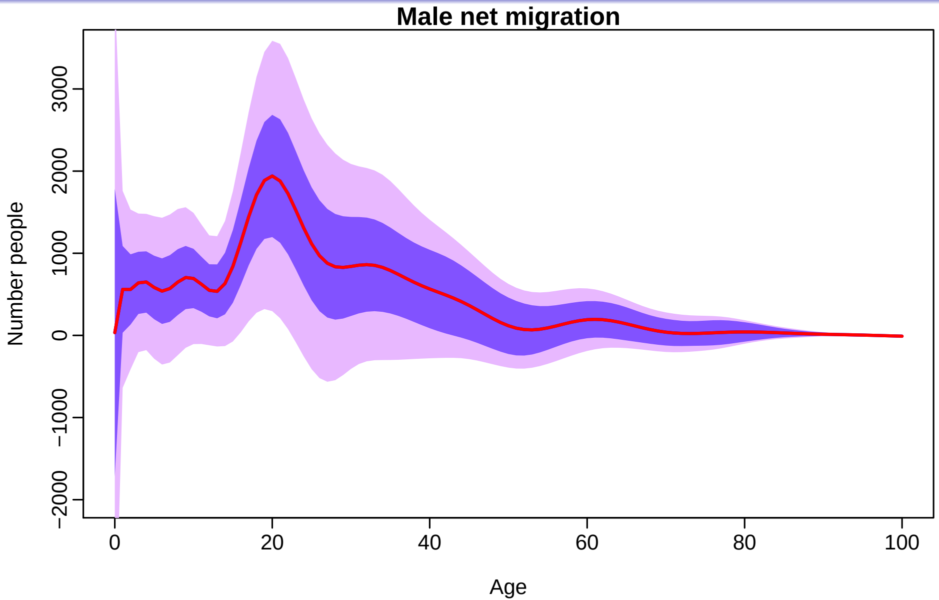
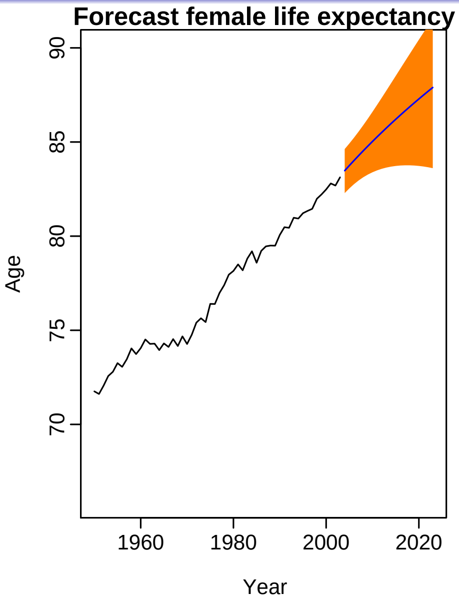
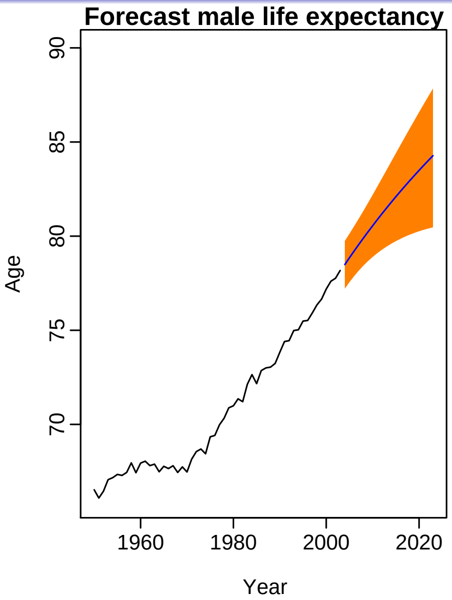
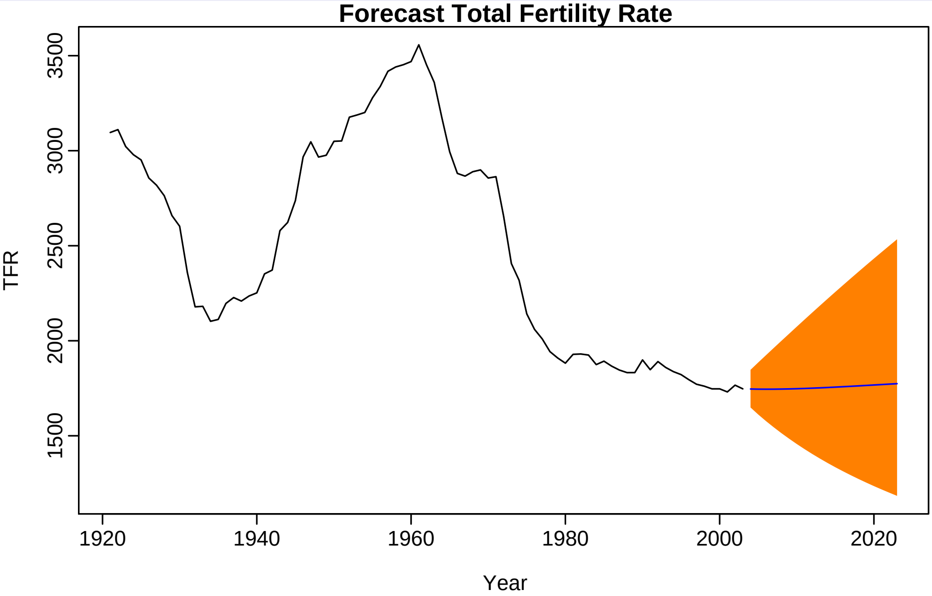


Forecasts of life expectancy at age 0

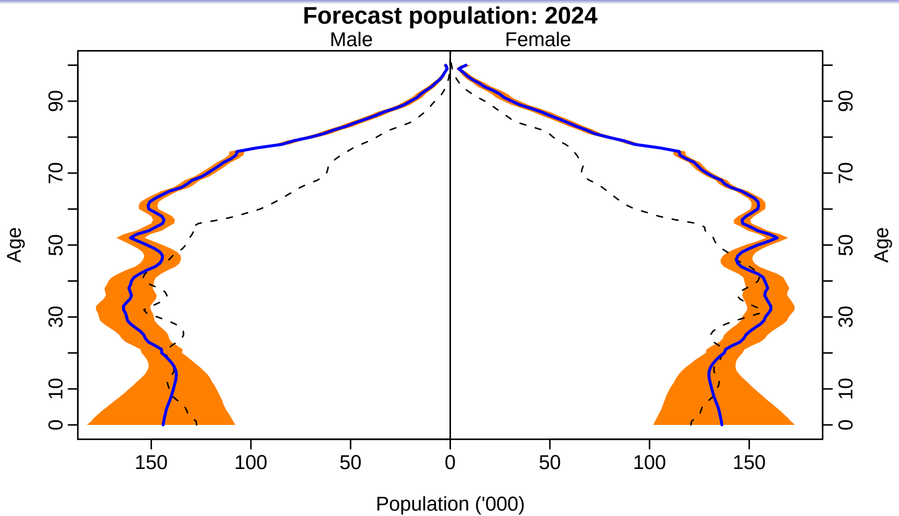




Forecasts of TFR

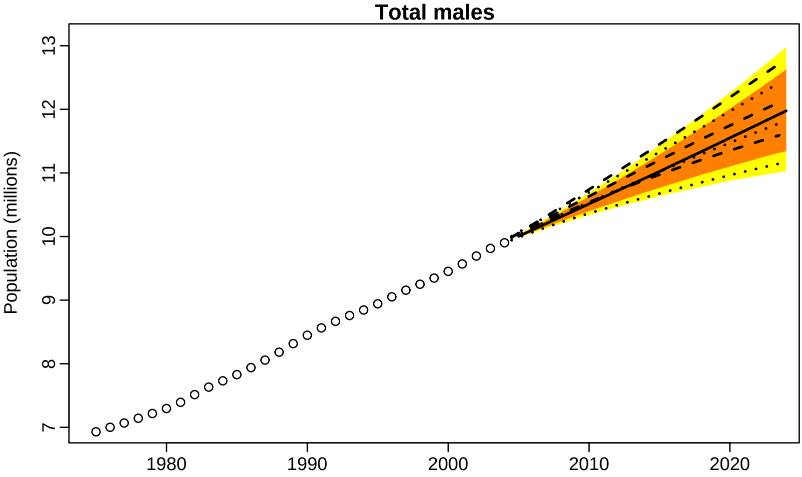


Population forecasts



Forecast population pyramid for 2024, along with 80% prediction intervals. Dashed: actual population pyramid for 2004.

Population forecasts



Twenty-year forecasts of total population along with 80% and 95% prediction intervals. Dashed: ABS (2006) projections. Dotted: ABS (2003) projections.

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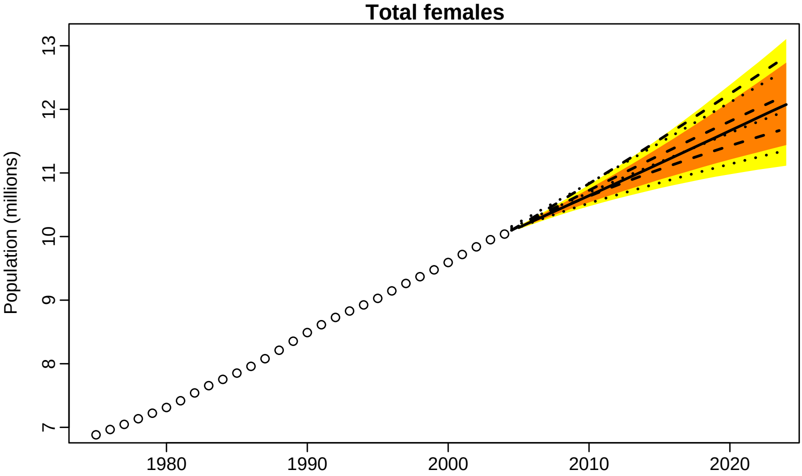

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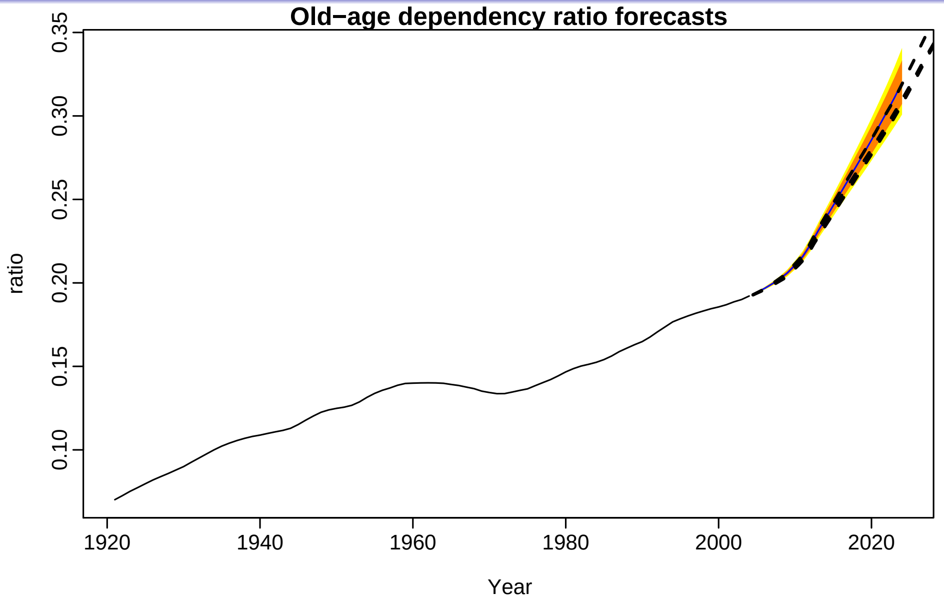
Old-age dependency ratio



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Outline

The problem

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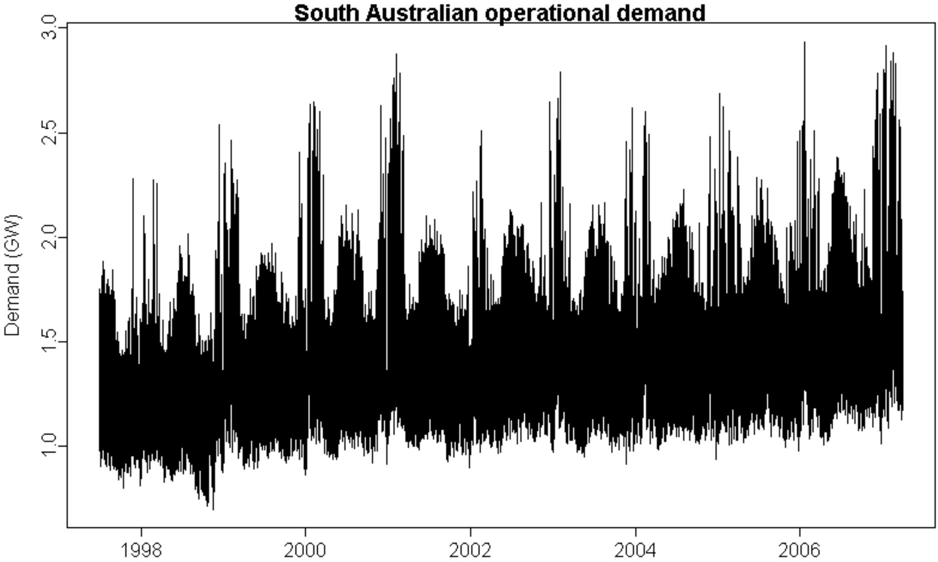
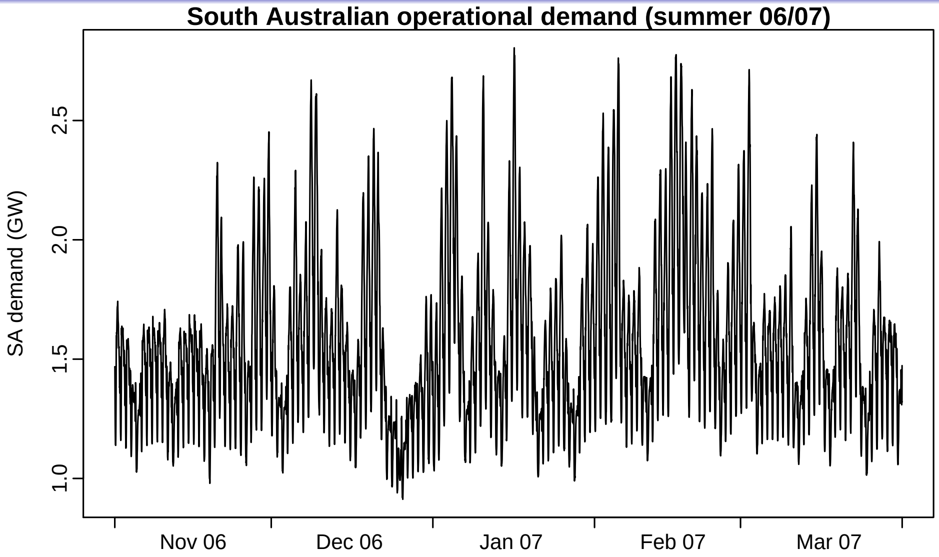
Sounds impossible?

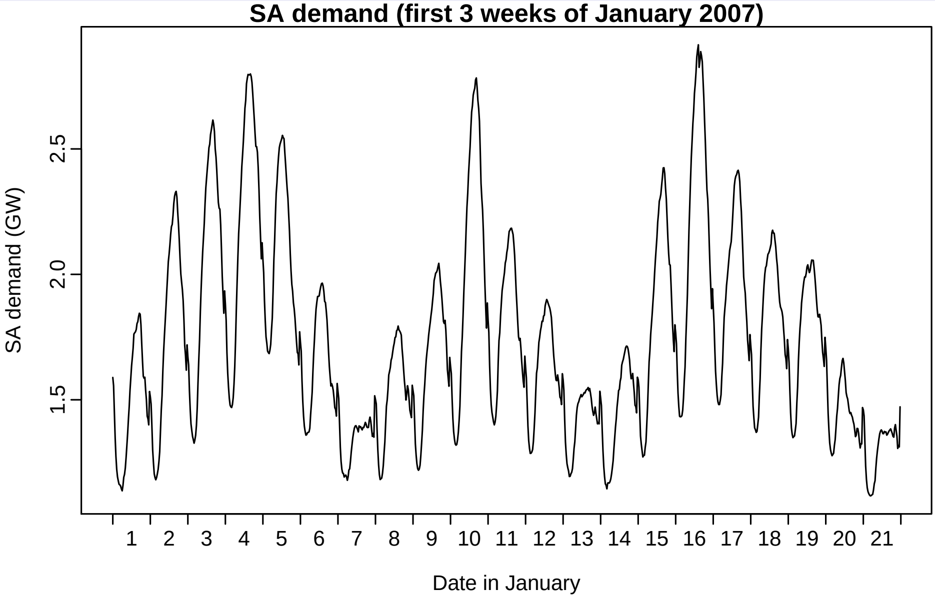
Demand data


South Australian operational demand
Demand (GW)
1.0
1.5
2.0
2.5
3.0
1998
2000
2002
2004
2006

Demand data


South Australian operational demand (summer 06/07)
SA demand (GW)
1.0
1.5
2.0
2.5
Nov 06
Dec 06
Jan 07
Feb 07
Mar 07

Demand data


SA demand (first 3 weeks of January 2007)
SA demand (GW)
1.5
2.0
2.5
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
Date in January

Demand drivers

- calendar effects

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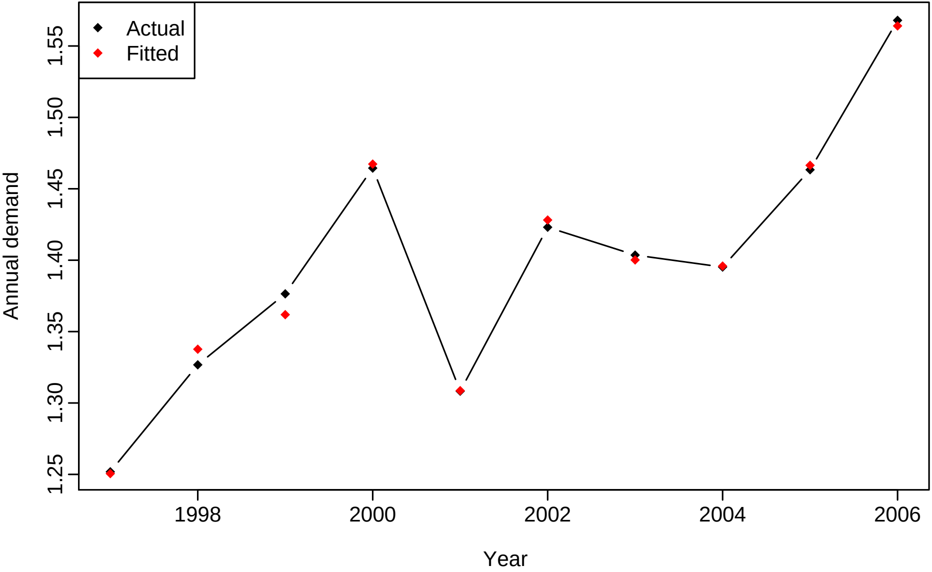
- Variables selected to provide best out-of-sample predictions for 2005/06 summer.

Predictions



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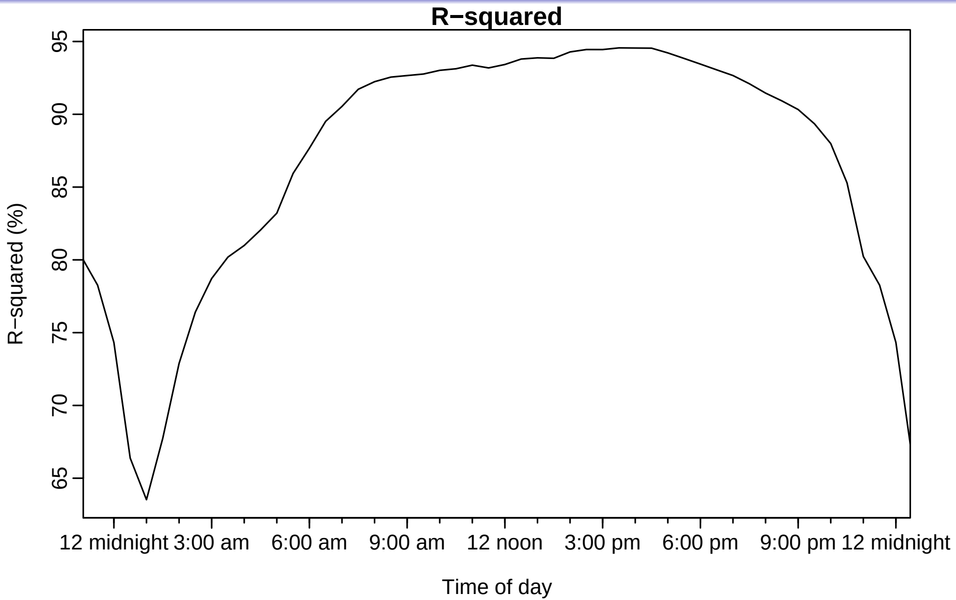

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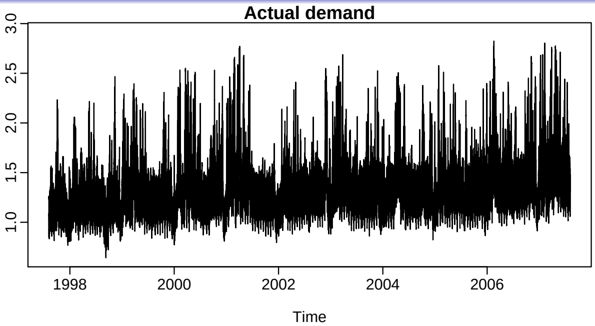

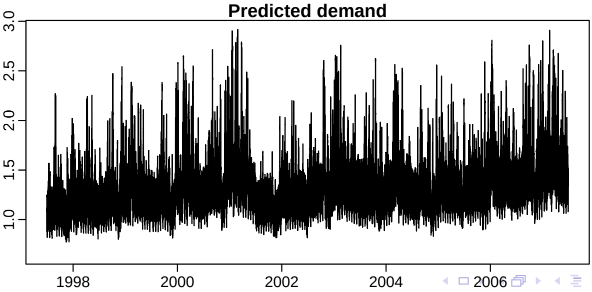

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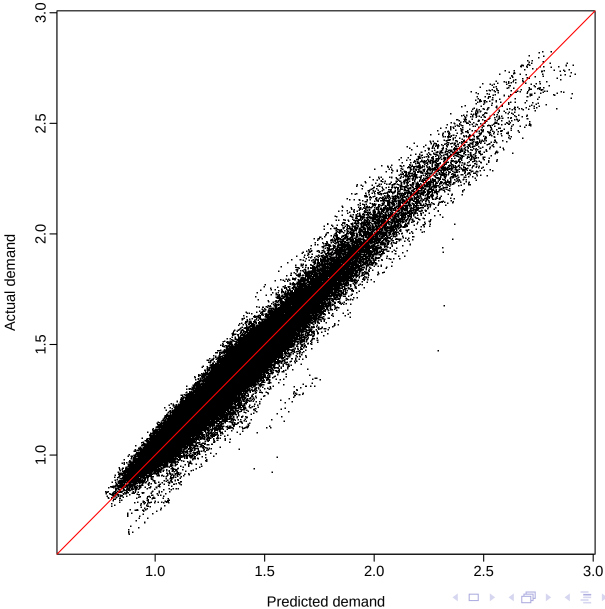
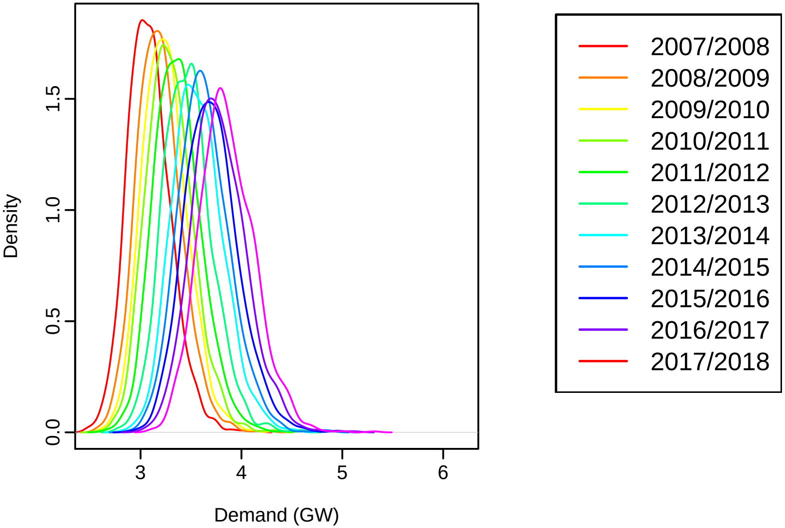


Peak demand distribution

Annual maximum demand



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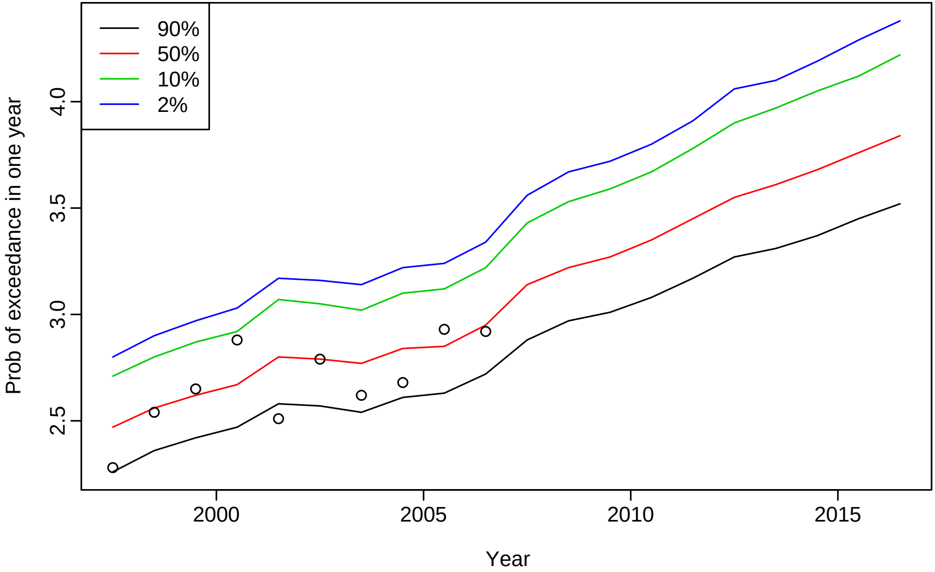

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- Provides way to analyse probability of coincident peaks across different interconnected markets.
- Could be extended to whole year, providing probabilistic forecasts of total energy requirements.

Outline

Forecast evaluation

- Ensure you have a systematic evaluation process.

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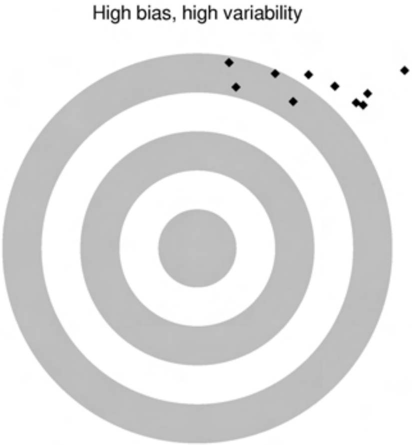
Bias and variability



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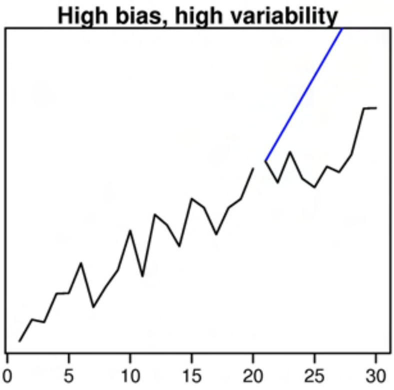

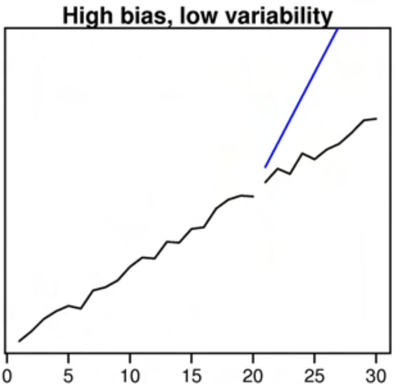

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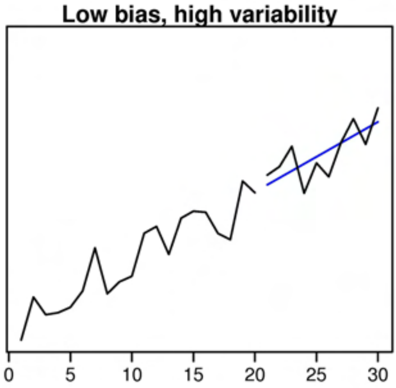

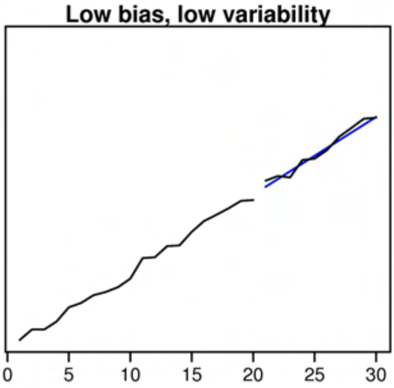

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Bias and variability

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Average of forecast errors.

Bias and variability

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Average of absolute (or squared) forecast errors.

Bias and variability

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If you don't use systematic forecast evaluation, you will never learn from your mistakes!

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Applied Forecasting Journal

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Slides available from

www.robjhyndman.com