

Forecasting & Predictive Analytics

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1st set of slides
Forecasting Principles

Aims of this course and logistics

Aims

- Provide a comprehensive understanding of forecasting & predictive analytics, principles and methods.
- Focus will be somewhat on time series, i.e. forecasting from an econometrics/statistics viewpoint.
- To learn how to produce forecasts yourselves as well as how to critically consider the forecasts of others.
- Provide tools to assess uncertainty and evaluate forecasts in R.
- Textbook references are mentioned in the lecture notes.

Forecasting Principles

Definition (Forecasting)

Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the object being forecast.

It is related but different from

- “Goals”: what you would like to happen,
- “Planning”: appropriate actions that are required to achieve your goals.

Definition (Predictive Analytics – Wikipedia)

Predictive analytics is an area of data mining that deals with extracting information from data and using it to predict trends and behavior patterns. Often the unknown event of interest is in the future, but predictive analytics can be applied to any type of unknown whether it be in the past, present or future.

Course overview

Material: slides, lecture notes, R scripts, on the Moodle website.

Labs with Arkadiy Voronkin: starting today (October 5) at 4:30pm.

Evaluation:

- Midterm written exam (50% of overall assessment), on November 16.
- Quizzes (15% of overall assessment), due on October 26, on November 9.
- Projects (35% of overall assessment), groups of 4, starting mid-November, due at the end of course.

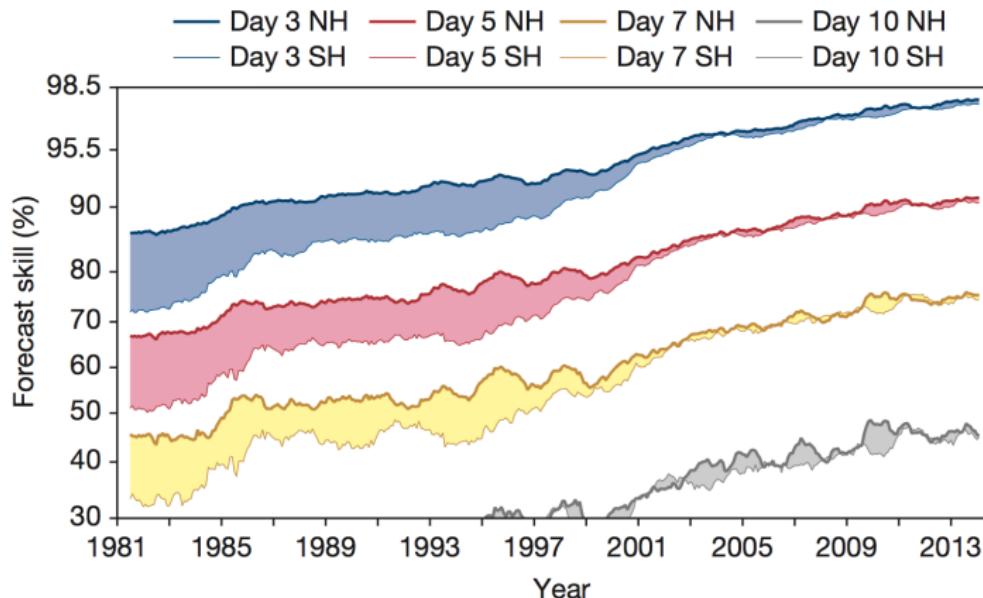
Examples of forecasting

Example: forecasting sales

I think there is a world market for maybe five computers.
(Chairman of IBM, 1943)

There is no reason anyone would want a computer in their home.
(President of DEC, 1977)

Example: weather forecasting



Source: *The quiet revolution of numerical weather prediction*, P. Bauer, A. Thorpe, G. Brunet (2015)

Example: elections



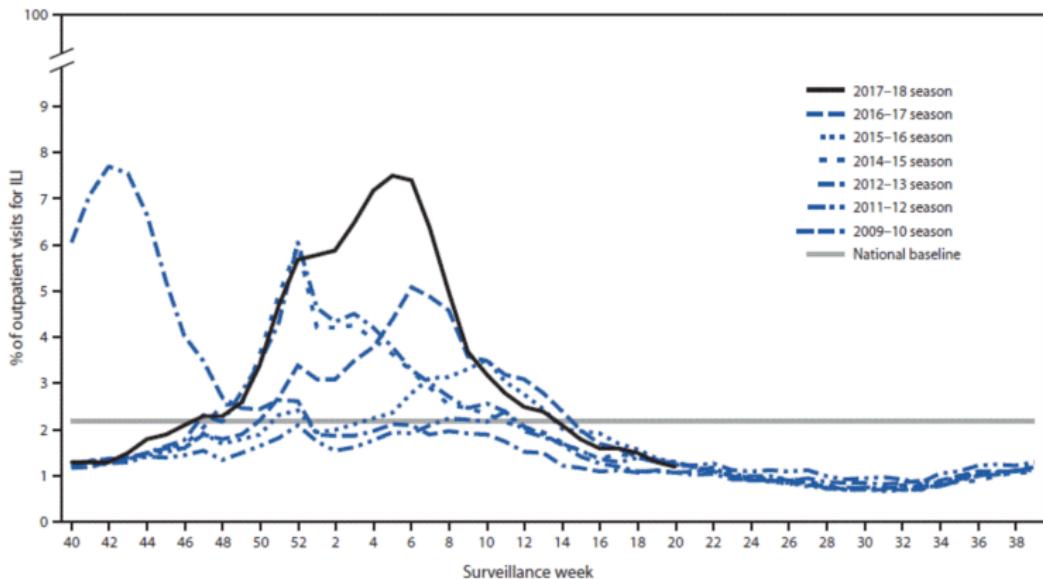
Projected Popular Vote Margin

Once a state has counted all its results, our estimated margin and the reported margin will match. As a rule, when our estimated margin is steady, our forecast is more trustworthy.

ESTIMATED VOTE MARGIN	95%
Best guess	50% of outcomes
	5%

Source: New York Times 2016 Election Forecasts

Example: influenza



Week-by-week percentage of outpatient visits for influenza-like illnesses, displayed by season. Source: Centers for Disease Control and Prevention,

<https://www.cdc.gov/mmwr/volumes/67/wr/mm6722a4.htm>.

Example: natural disasters



Source: "Hundreds Missing and Scores Dead as Raging Floods Strike Western Europe", The New York Times, July 15, 2021.
Photo: Harald Tittel/DPA, via Associated Press.

Can we forecast anything?



Source: Paleofuture. Postcard from 1925.

Types of forecast

- Point prediction.
- Point prediction + standard deviation.
- Prediction interval.
- Probabilistic forecast / predictive distributions.

In each case, how to assess accuracy?

Uncertainty

Alan Greenspan, former Chairman of the Federal Reserve Board:

Given our inevitably incomplete knowledge about key structural aspects of an ever-changing economy and the sometimes asymmetric costs or benefits of particular outcomes, a central bank needs to consider not only the most likely future path for the economy but also the distribution of possible outcomes about that path. The decision makers then need to reach a judgment about the probabilities, costs, and benefits of the various possible outcomes under alternative choices for policy.

Uncertainty

Chart 1.3: Unemployment projection based on market interest rate expectations, other policy measures as announced

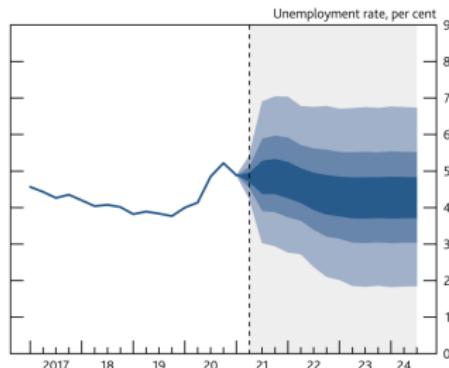


Chart 1.4: CPI inflation projection based on market interest rate expectations, other policy measures as announced

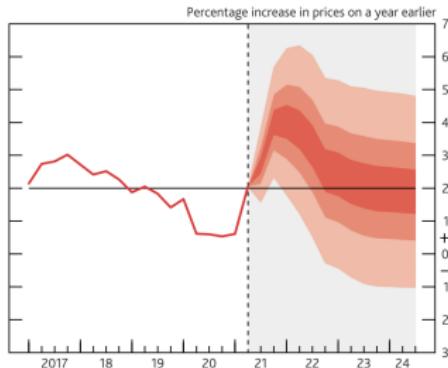


Figure: Source: Bank of England, Monetary Policy Report, August 2021.
<https://www.bankofengland.co.uk/monetary-policy-report/2021/august-2021>

Predictability and interpretability

Predictability

Predictability comes from

- knowledge/ignorance e.g. about initial conditions,
- inherent stochasticity of the phenomenon under study,
- influence of our future actions, possibly informed by our forecast.

Example: learning the odds associated with a coin versus predicting the next coin flip; time of sunrise versus lottery numbers; elections.

Predictability

Coin flips are predictable given initial velocity and rate of spin.

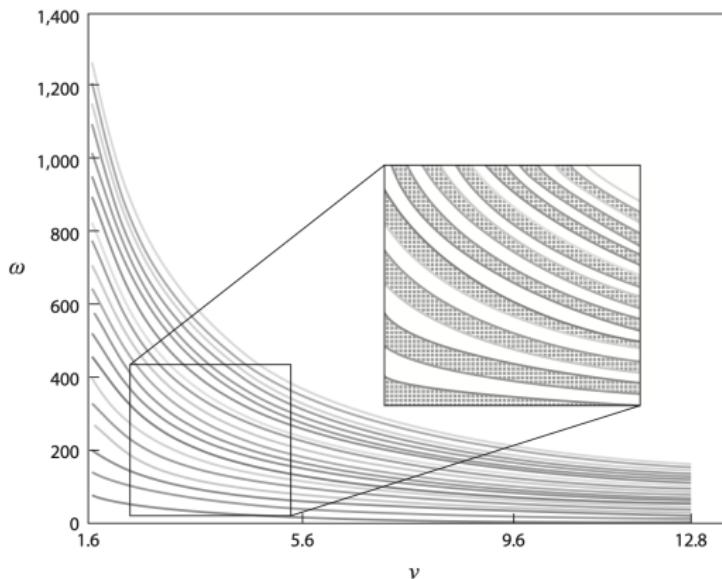


Figure 1.5. The hyperbolas separating heads from tails in part of phase space. Initial conditions leading to heads are hatched, tails are left white, and ω is measured in s^{-1} .

Figure: Source: Brian Skyrms & Persi Diaconis, "Ten Great Ideas about Chance", 2017.

Predictability

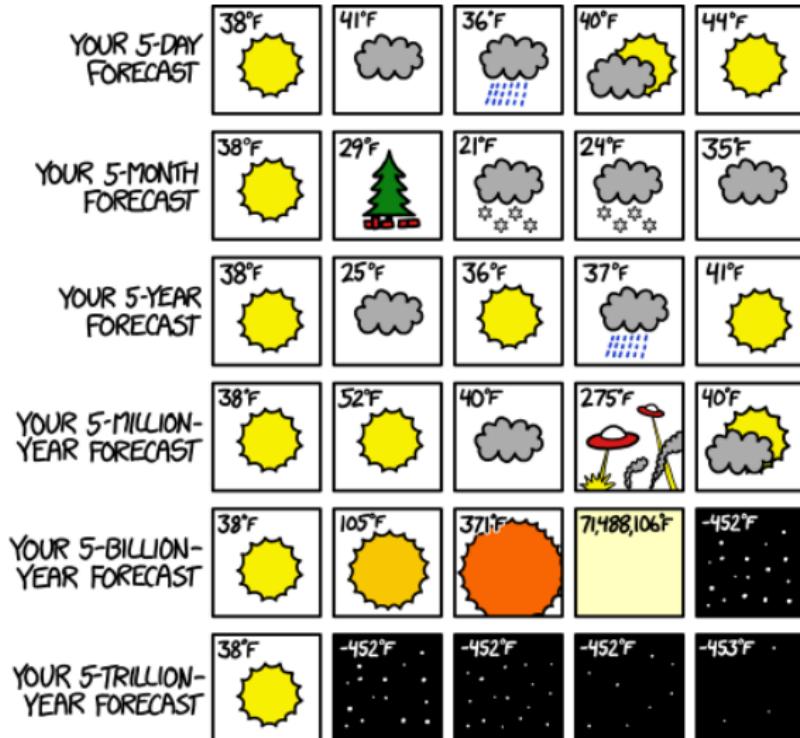


Figure: Source: XKCD, November 20, 2015.

Predictability and time horizon

We expect prediction accuracy to decrease for longer time horizons.

Possible uses also change with the time horizon. Examples:

- Short-term demand forecasts to schedule personnel, production and transportation.
- Medium-term forecasts to determine future resource requirements, purchase raw materials, buy machinery.
- Long-term forecasts that are used in strategic planning and take into account market opportunities and environmental factors.

Interpretability and communication

Accuracy is an important requirement in forecasting. Relatively simple approaches can provide remarkable improvements over the most naive baselines.

Forecasting methods can get complicated, with numerous sensitive tuning parameters, leading to partly unexplained behavior and unstable results.

Interpretation (of the output, of the input-output relation) is as critical as accuracy.

- Todd Tomalak's "Communicating Forecasts to the C-Suite: A Six-Step Survival Guide".
- Cynthia Rudin's "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead".

Overview of a forecast

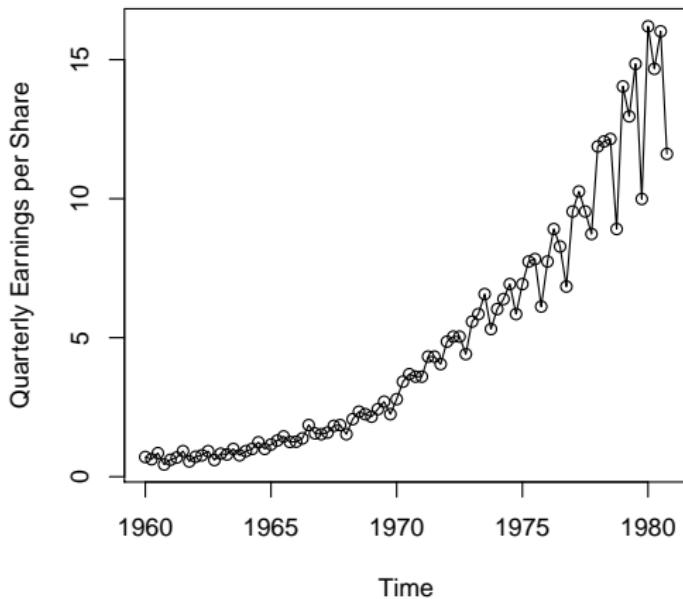
- 1 Identifying the problem: what for? who? when? how?
- 2 Gathering information: what are the available data? Are they reliable? Can they help address our original question?
- 3 Exploratory analysis: graphs to see trends, seasonality, breaks, outliers, volatility, etc.
- 4 Selecting appropriate methods and compare them
- 5 Evaluating and refining forecasting methods over time.
- 6 Output final forecast in desired format.

Time series data

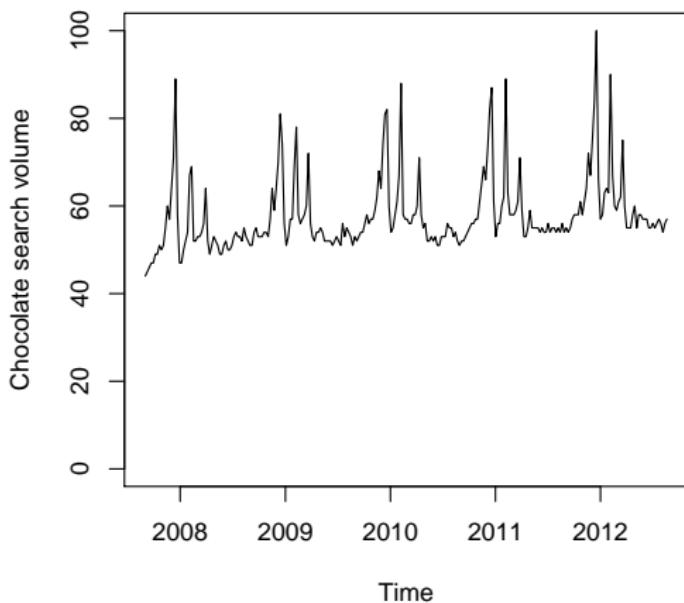
What are time series?

- Data (Y_1, \dots, Y_T) collected over time. Each Y_t could be an integer, a real value, a vector, etc.
- But all data are collected over time.
- Time series: data for which the time element is important.
Sometimes, this is a subjective assessment.
- Data for which we consider that
 Y_t is *related* to Y_s , if t is close to s .

Example: Johnson and Johnson earnings per share

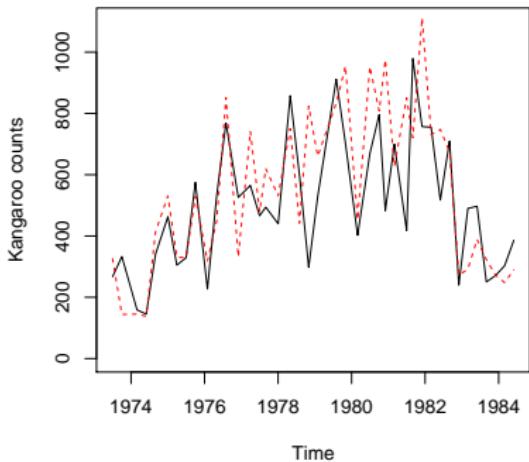


Example: “chocolate” search volume



Source: Google Trends.

Example: red kangaroos



Source: *Kangaroos, their ecology and management in the sheep rangelands of Australia*, Caughley, G., N. Shepherd, and J. Short (1987).

Features

Time series can exhibit

- trends (linear, polynomial, exponential, etc),
- variability around the trend, of constant or varying magnitude,
- seasonality (highs and lows occurring very regularly in time),
- cycles (highs and lows that can have a changing period).

These features change when we perform transformations to the data.

Specificity of time series data analysis

Contrarily to the setting of linear regression, time series observations cannot be assumed exchangeable.

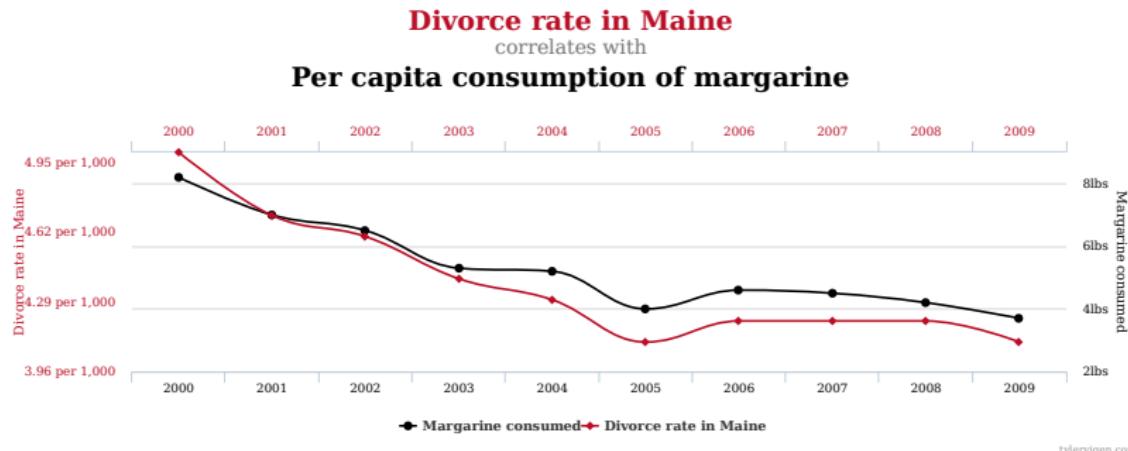
Can we do statistical analysis without assuming that the observations are exchangeable, “i.i.d.”?

A time series = a single trajectory, but possibly a long one.
So is it like having a single observation, or many observations?

Concept of stationarity, “time average” versus “population average”.

Specificity of multivariate time series

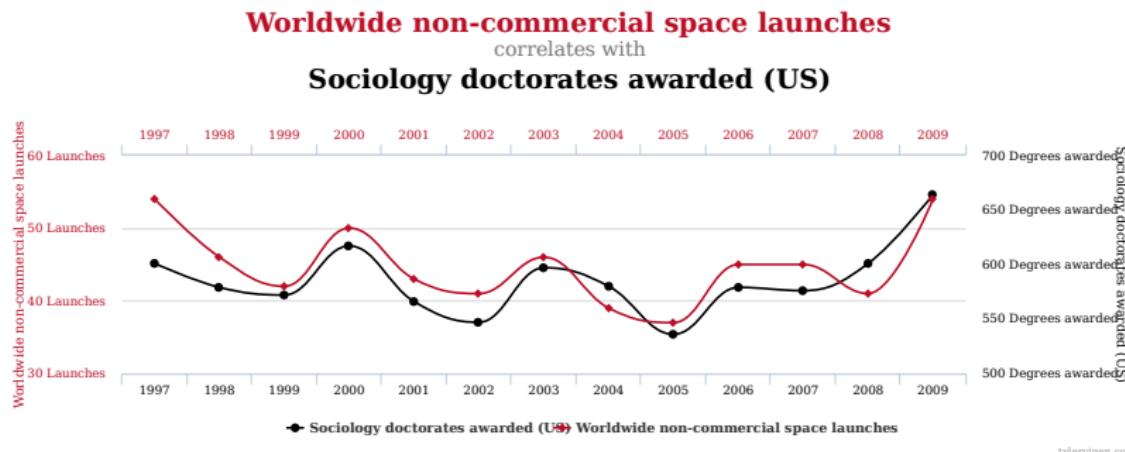
With multiple series, we can consider the predictability of one given others.



Source: Spurious Correlations.

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Stochastic processes and models

Stochastic processes

- A stochastic process is a collection of random variables.
 (Y_1, \dots, Y_T) , also denoted $Y_{1:T}$.
- From now on, uppercase for random variables, lowercase for realizations of it.
- We can define a stochastic process as (Y_t) where $t \in \mathbb{T}$.
In discrete time, $\mathbb{T} = \mathbb{N}$ or $\mathbb{T} = \mathbb{Z}$.
In continuous time, \mathbb{T} might be $[0, 1]$ or \mathbb{R} .
- Existence of (infinitely long) stochastic processes:
Obtained from finite-dimensional specification through Kolmogorov's extension theorem.

Some stochastic processes

Consider $(W_t)_{t=1}^T$, a collection of i.i.d. Normal variables, with mean 0 and variance $\sigma^2 > 0$.

Simplest model: $Y_t = \alpha + W_t$ with $\alpha \in \mathbb{R}$.

A model for real-valued time series with a trend could be

$$\forall t \in \{1, \dots, T\} \quad Y_t = \beta_1 + \beta_2 t + W_t. \quad (1)$$

Another model with a trend: the random walk model with drift,

$$Y_1 = W_1 \quad \text{and} \quad \forall t \in \{2, \dots, T\} \quad Y_t = \delta + Y_{t-1} + W_t. \quad (2)$$

A simple “autoregressive” model, with $\rho \in \mathbb{R}$.

$$Y_1 = W_1 \quad \text{and} \quad \forall t \in \{2, \dots, T\} \quad Y_t = \mu + \rho Y_{t-1} + W_t. \quad (3)$$

Trajectories and marginal distributions

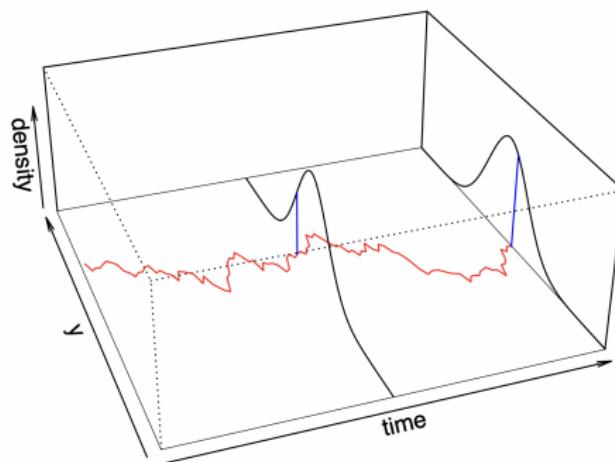


Figure: Trajectory of a stochastic process, along with curves representing two marginal distributions at different times.

From stochastic processes to statistical models

Having considered multiple models,

- we can “fit” them (preferably avoiding “overfitting”),
i.e. use available data to estimate parameters,
method of moments, maximum likelihood, Bayesian
inference . . .
- we can compare model performance, see in which way models
might be improved,
- we can combine models, discard some of them.

Take Aways This Week

- 1 We aim for probabilistic forecasting: with random variables, not only deterministic variables.
- 2 Each forecast problem is an individual problem – but there is something like “good practice”.
- 3 Define your aims and plot your data! Are there trends, obvious breaks, seasonality?
- 4 Is the quality of the data sufficiently high to address your forecasting questions?
- 5 For whom do you produce the forecast and how will you communicate it?
- 6 Test, revise, combine models to avoid overfitting.