



MONASH
University

MONASH
BUSINESS
SCHOOL

ETC3550/ETC5550 Applied forecasting

Ch11. Advanced methods

af.numbat.space

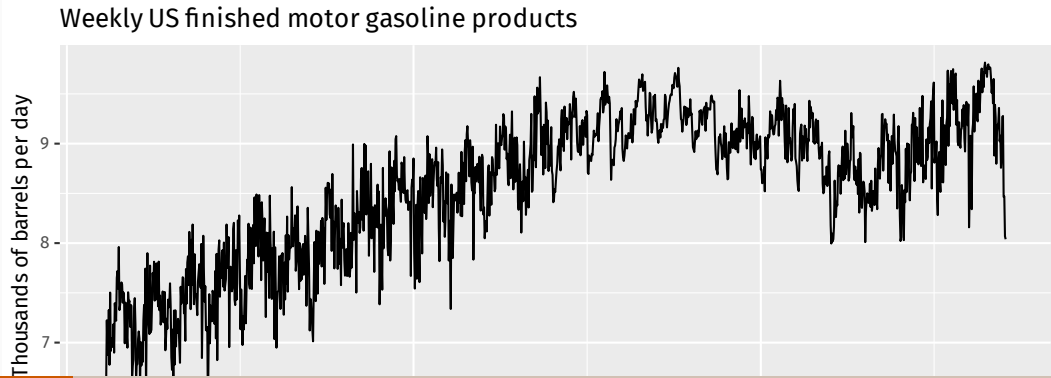


Outline

- 1 Complex seasonality
- 2 Vector autoregression
- 3 Neural network models
- 4 Bootstrapping and bagging

Examples

```
us_gasoline |> autoplot(Barrels) +  
  labs(  
    x = "Year", y = "Thousands of barrels per day",  
    title = "Weekly US finished motor gasoline products"  
  )
```



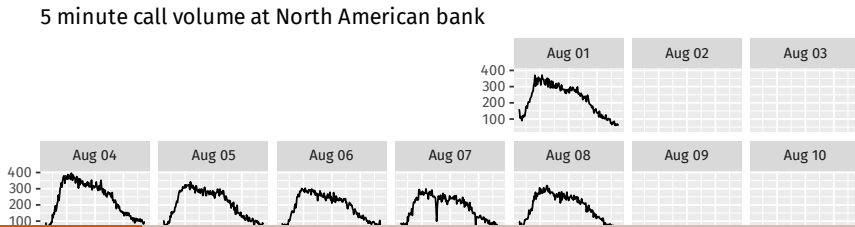
Examples

```
calls <- read_tsv("http://robjhyndman.com/data/callcenter.txt") |>
  rename(time = `...1`) |>
  pivot_longer(-time, names_to = "date", values_to = "volume") |>
  mutate(
    date = as.Date(date, format = "%d/%m/%Y"),
    datetime = as_datetime(date) + time
  ) |>
  as_tsibble(index = datetime)
calls |>
  fill_gaps() |>
  autoplot(volume) +
  labs(
    x = "Weeks", y = "Call volume",
    title = "5 minute call volume at North American bank"
  )
```

5 minute call volume at North American bank

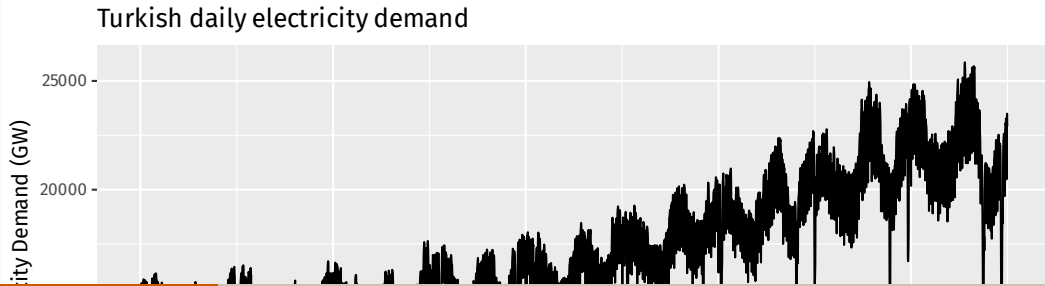
Examples

```
library(sugrrants)
calls |>
  filter(yearmonth(date) == yearmonth("2003 August")) |>
  ggplot(aes(x = time, y = volume)) +
  geom_line() +
  facet_calendar(date) +
  labs(
    x = "Weeks", y = "Call volume",
    title = "5 minute call volume at North American bank"
  )
```



Examples

```
turkey_elec <- read_csv("data/turkey_elec.csv", col_names = "Demand") |>
  mutate(Date = seq(ymd("2000-01-01"), ymd("2008-12-31"), by = "day")) |>
  as_tsibble(index = Date)
turkey_elec |> autoplot(Demand) +
  labs(
    title = "Turkish daily electricity demand",
    x = "Year", y = "Electricity Demand (GW)"
  )
```



TBATS model

TBATS

Trigonometric terms for seasonality

Box-Cox transformations for heterogeneity

ARMA errors for short-term dynamics

Trend (possibly damped)

Seasonal (including multiple and

non-integer periods)

TBATS model

y_t = observation at time t

$$y_t^{(\omega)} = \begin{cases} (y_t^\omega - 1)/\omega & \text{if } \omega \neq 0; \\ \log y_t & \text{if } \omega = 0. \end{cases}$$

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^M s_{t-m_i}^{(i)} + d_t$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t$$

$$b_t = (1 - \phi)b + \phi b_{t-1} + \beta d_t$$

$$d_t = \sum_{i=1}^p \phi_i d_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$s_{j,t}^{(i)} = \sum_{k_i=1}^{k_i} s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t$$

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M seasonal periods

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^M s_{t-m_i}^{(i)} + d_t$$

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global and local trend

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t$$

$$b_t = (1 - \phi)b + \phi b_{t-1} + \beta d_t$$

$$d_t = \sum_{i=1}^p \phi_i d_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$s_{j,t}^{(i)} = \sum_{k_i} s_{j,t-k_i}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t$$

TBATS model

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global and local trend

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t$$

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ARMA error

$$d_t = \sum_{i=1}^p \phi_i d_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t$$

$$s_{j,t}^{(i)} = \sum_{k=1}^{k_i} s_{j,t}^{(i,k)}$$

TBATS model

y_t = observation at time t

Box-Cox transformation

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global and local trend

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t$$

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ARMA error

$$d_t = \sum_{i=1}^p \phi_i d_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Fourier-like seasonal terms

$$s_{j,t}^{(i)} = \sum_{k_i=1}^{k_i} s_{j,t-1}^{(i)}$$

TBATS model

y_t = observation at time t

Box-Cox transformation

$$y_t^{(\omega)} = \begin{cases} \text{TBATS} \\ \text{Trigonometric} \end{cases}$$

M seasonal periods

$$y_t^{(\omega)} = \ell_t b_t d_t$$

Box-Cox

d_t

global and local trend

$$\ell_t = \ell$$

ARMA

$$b_t = (1 - \beta B)^d$$

Trend

ARMA error

$$d_t = \sum_{i=1}^M \cos\left(\frac{2\pi i t}{M}\right)$$

Seasonal

Fourier-like seasonal terms

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\left(\frac{2\pi i}{M}\right)$$

Complex seasonality

```
gasoline |>  
  tbats() |>  
  forecast() |>  
  autoplot()
```

Complex seasonality

```
calls |>  
  tbats() |>  
  forecast() |>  
  autoplot()
```


Complex seasonality

```
telec |>  
  tbats() |>  
  forecast() |>  
  autoplot()
```

TBATS model

TBATS

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ARMA errors for short-term dynamics

Trend (possibly damped)

Seasonal (including multiple and non-integer periods)

- Handles non-integer seasonality, multiple seasonal periods.
- Entirely automated
- Prediction intervals often too wide
- Very slow on long series

Outline

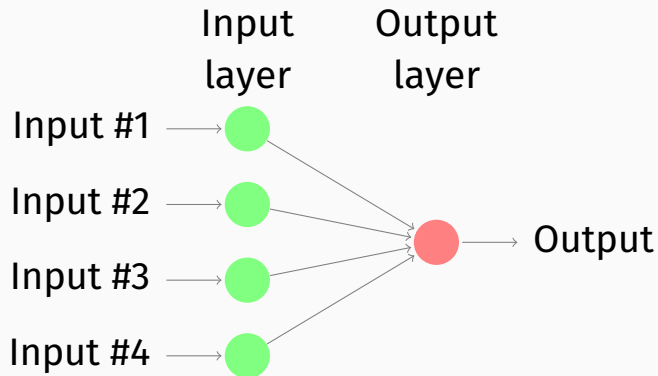
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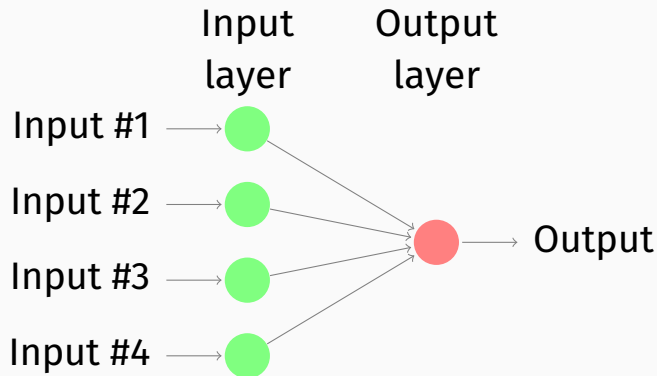
Neural network models

Simplest version: linear regression



Neural network models

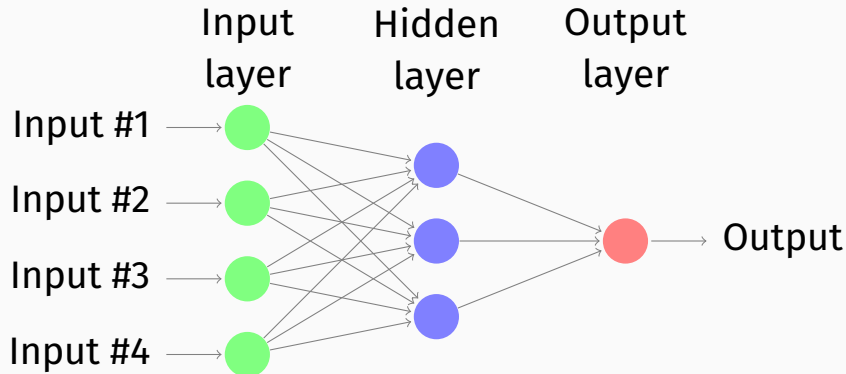
Simplest version: linear regression



- Coefficients attached to predictors are called “weights”.
- Forecasts are obtained by a linear combination of inputs

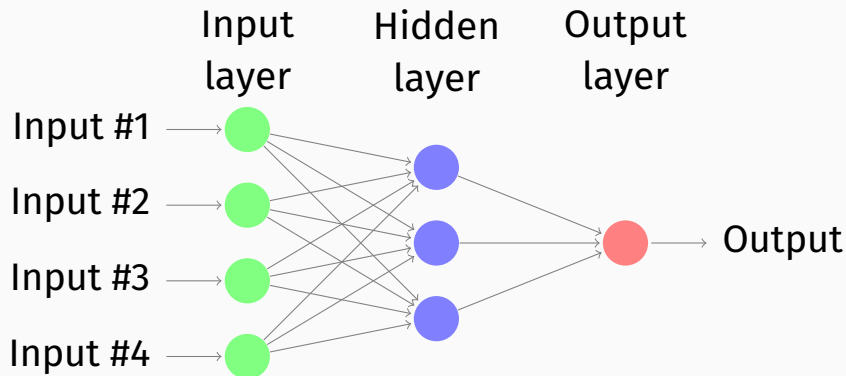
Neural network models

Nonlinear model with one hidden layer



Neural network models

Nonlinear model with one hidden layer



- A **multilayer feed-forward network** where each layer of nodes receives inputs from the previous layers

Neural network models

Inputs to hidden neuron j linearly combined:

$$z_j = b_j + \sum_{i=1}^4 w_{i,j} x_i.$$

Modified using nonlinear function such as a sigmoid:

$$s(z) = \frac{1}{1 + e^{-z}},$$

This tends to reduce the effect of extreme input values, thus making the network somewhat robust to outliers.

Neural network models

- Weights take random values to begin with, which are then updated using the observed data.
- There is an element of randomness in the predictions. So the network is usually trained several times using different random starting points, and the results are averaged.
- Number of hidden layers, and the number of nodes in each hidden layer, must be specified in advance.

NNAR models

- Lagged values of the time series can be used as inputs to a neural network.
- $NNAR(p, k)$: p lagged inputs and k nodes in the single hidden layer.
- $NNAR(p, 0)$ model is equivalent to an $ARIMA(p, 0, 0)$ model but without stationarity restrictions.
- Seasonal $NNAR(p, P, k)$: inputs $(y_{t-1}, y_{t-2}, \dots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-Pm})$ and k neurons in the hidden layer.
- $NNAR(p, P, 0)_m$ model is equivalent to an $ARIMA(p, 0, 0)(P, 0, 0)_m$ model but without stationarity restrictions.

NNAR models in R

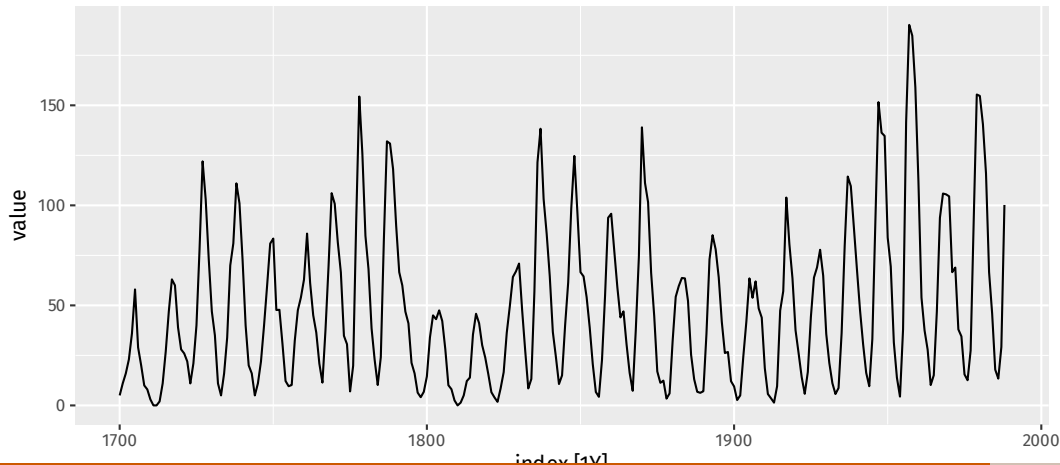
- The `nnetar()` function fits an $NNAR(p, P, k)_m$ model.
- If p and P are not specified, they are automatically selected.
- For non-seasonal time series, default p = optimal number of lags (according to the AIC) for a linear $AR(p)$ model.
- For seasonal time series, defaults are $P = 1$ and p is chosen from the optimal linear model fitted to the seasonally adjusted data.
- Default $k = (p + P + 1)/2$ (rounded to the nearest integer).

Sunspots

- Surface of the sun contains magnetic regions that appear as dark spots.
- These affect the propagation of radio waves and so telecommunication companies like to predict sunspot activity in order to plan for any future difficulties.
- Sunspots follow a cycle of length between 9 and 14 years.

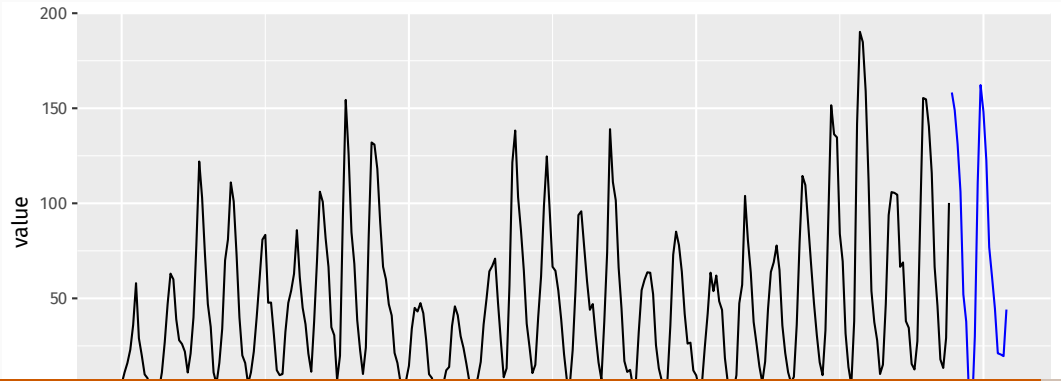
Sunspots

```
sunspots <- sunspot.year |> as_tsibble()  
sunspots |> autoplot(value)
```



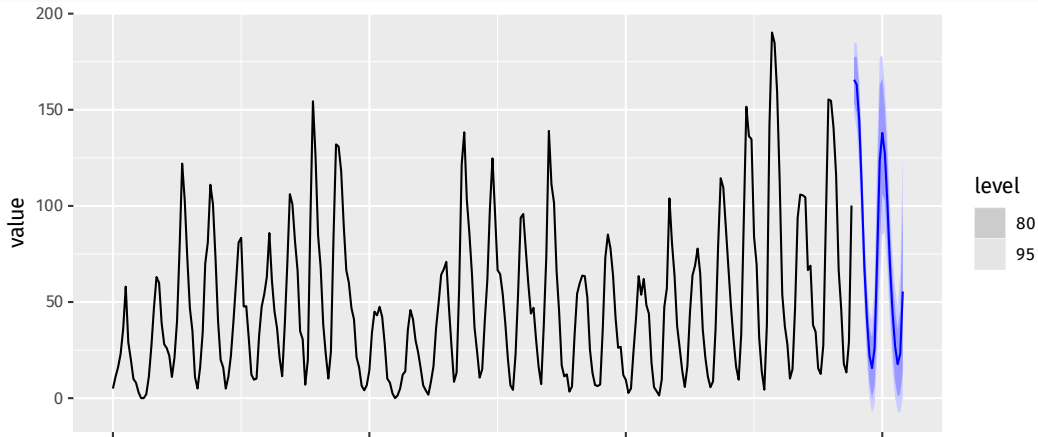
NNAR(9,5) model for sunspots

```
sunspots <- sunspot.year |> as_tsibble()  
fit <- sunspots |> model(NNETAR(value))  
fit |>  
  forecast(h = 20, times = 1) |>  
  autoplot(sunspots, level = NULL)
```



Prediction intervals by simulation

```
fit |>  
  forecast(h = 20) |>  
  autoplot(sunspots)
```



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