MONASH University

MONASH BUSINESS SCHOOL

Forecasting using R

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1.2 The forecaster’s toolbox

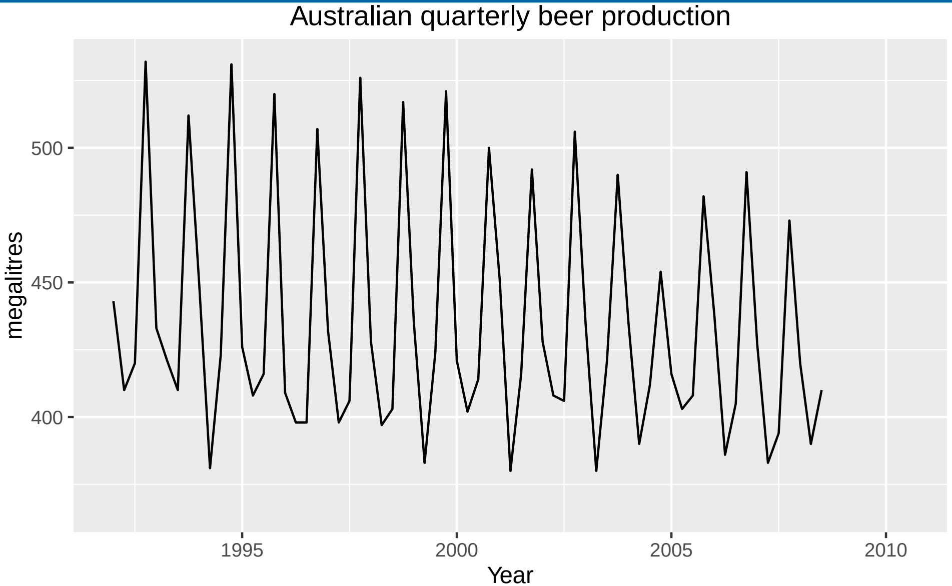
Outline

Forecasting

Forecasting is estimating how the sequence of observations will continue into the future.

- We usually think probabilistically about future sample paths
- What range of values covers the possible sample paths with 80% probability?

Australian beer production



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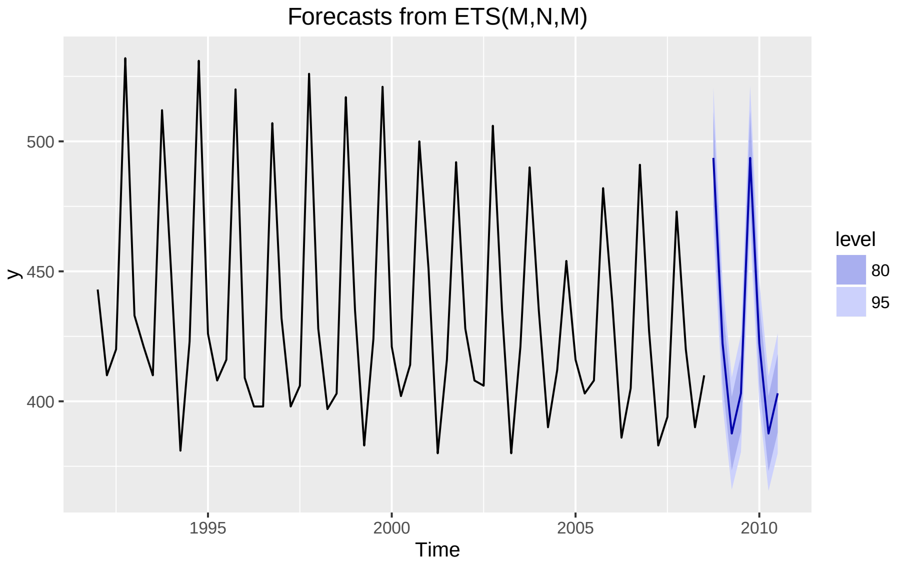
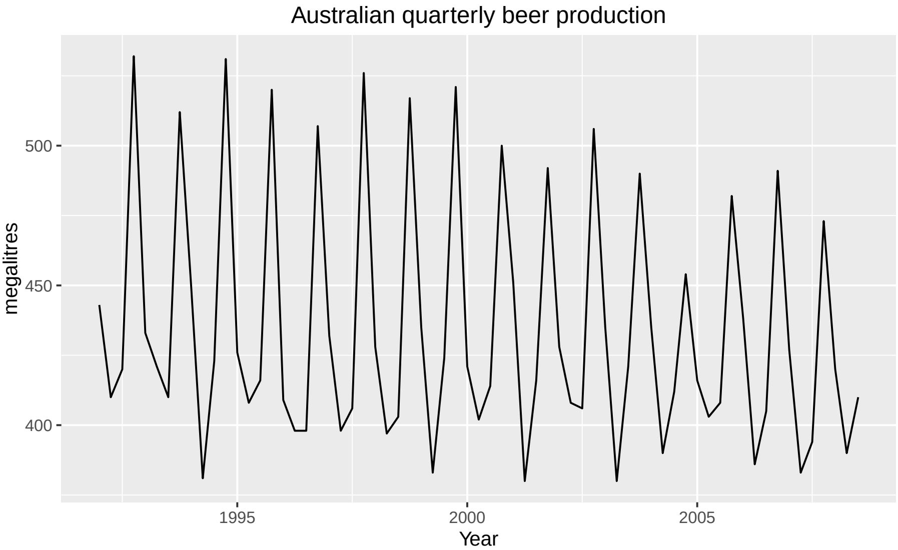


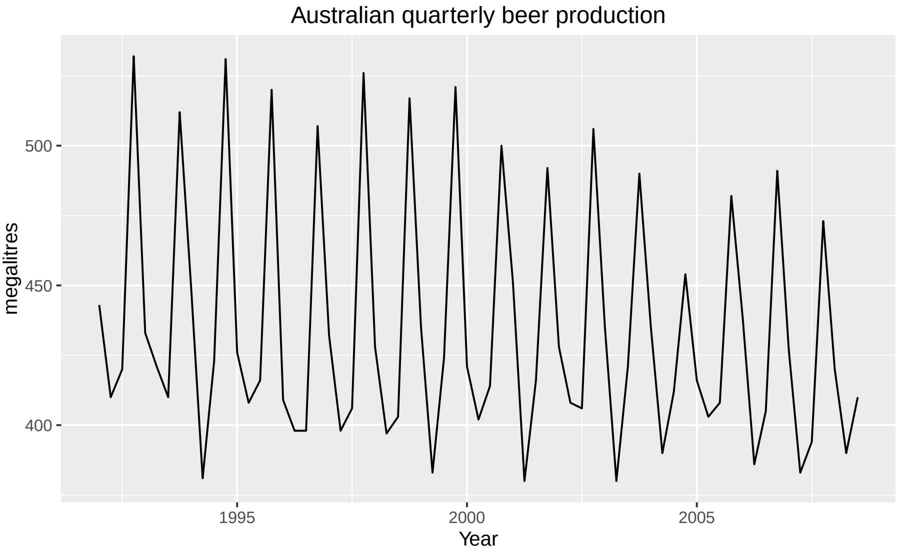
Outline

Some simple forecasting methods



Can you think of any forecasting methods for these data?

Some simple forecasting methods



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Some simple forecasting methods

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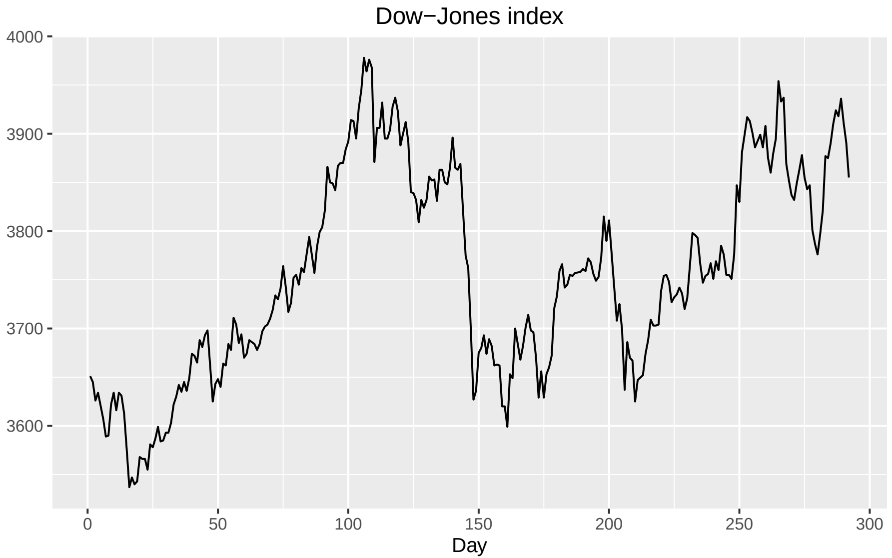

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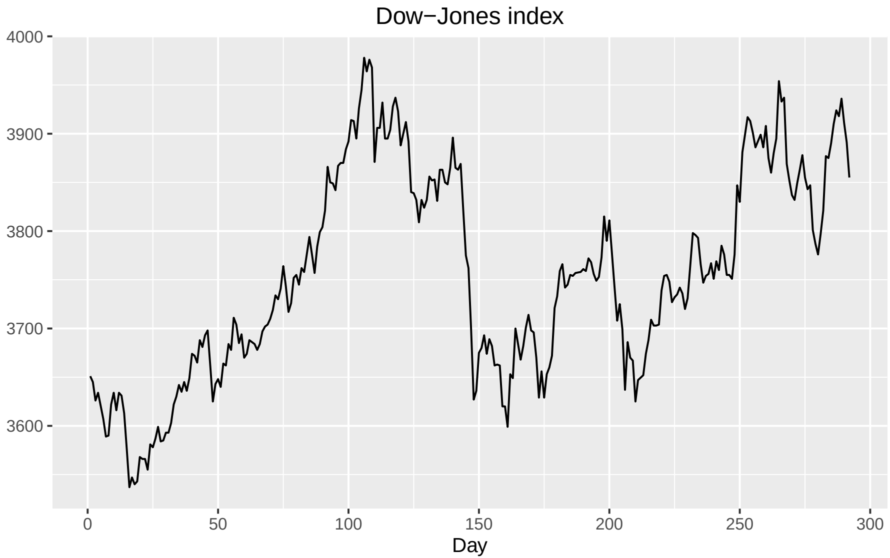

How would you forecast these data?

Some simple forecasting methods

Average method

- Forecast of all future values is equal to mean of historical data $\{y_1, \dots, y_T\}$.
- Forecasts: $\hat{y}_{T+h|T} = \bar{y} = (y_1 + \cdots + y_T)/T$

Naïve method

- Forecasts equal to last observed value.
- Forecasts: $\hat{y}_{T+h|T} = y_T$.
- Consequence of efficient market hypothesis.

Seasonal naïve method

- Forecasts equal to last value from same season.
- Forecasts: $\hat{y}_{T+h|T} = y_{T+h-km}$ where m = seasonal period and $k = \lfloor (h-1)/m \rfloor + 1$.

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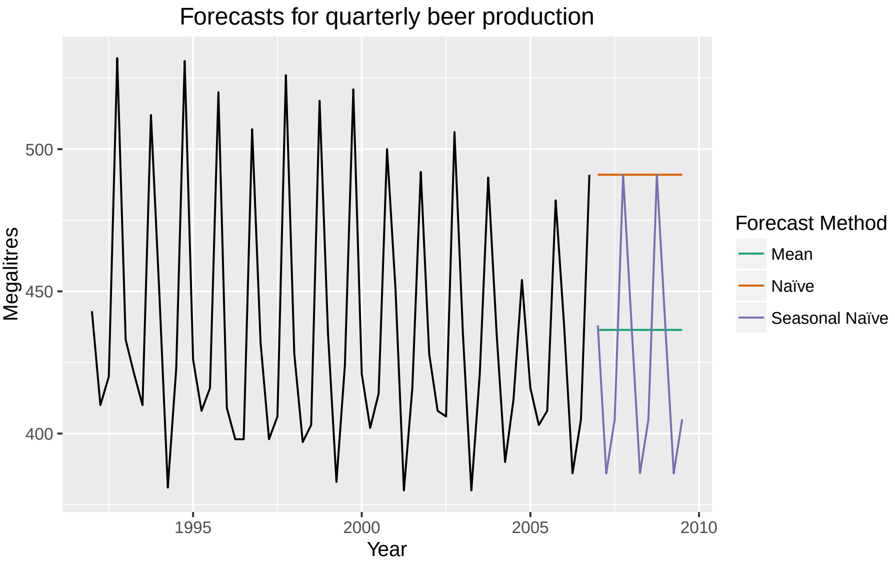

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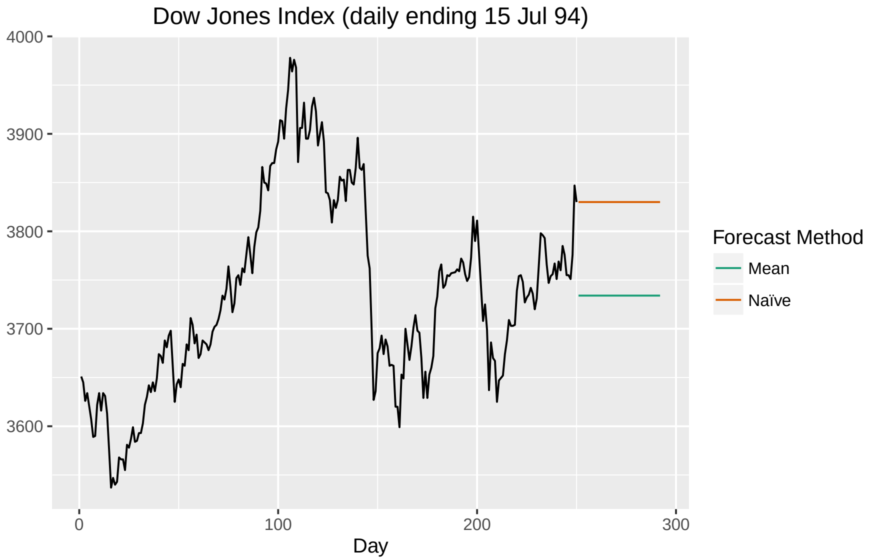

Some simple forecasting methods

- Mean: `meanf(y, h=20)`
- Naïve: `naive(y, h=20)`
- Seasonal naïve: `snaive(y, h=20)`
- Linear trend: `forecast(tslm(y ~ trend))`
- Linear trend with seasonal dummies: `forecast(tslm(y ~ trend + season))`

Outline

Forecasting residuals

Residuals in forecasting: difference between observed value and its forecast based on all previous observations: $e_t = y_t - \hat{y}_{t|t-1}$.

Assumptions

1. $\{e_t\}$ uncorrelated. If they aren't, then information left in residuals that should be used in computing forecasts.
2. $\{e_t\}$ have mean zero. If they don't, then forecasts are biased.

Useful properties (for prediction intervals)

3. $\{e_t\}$ have constant variance.
4. $\{e_t\}$ are normally distributed.

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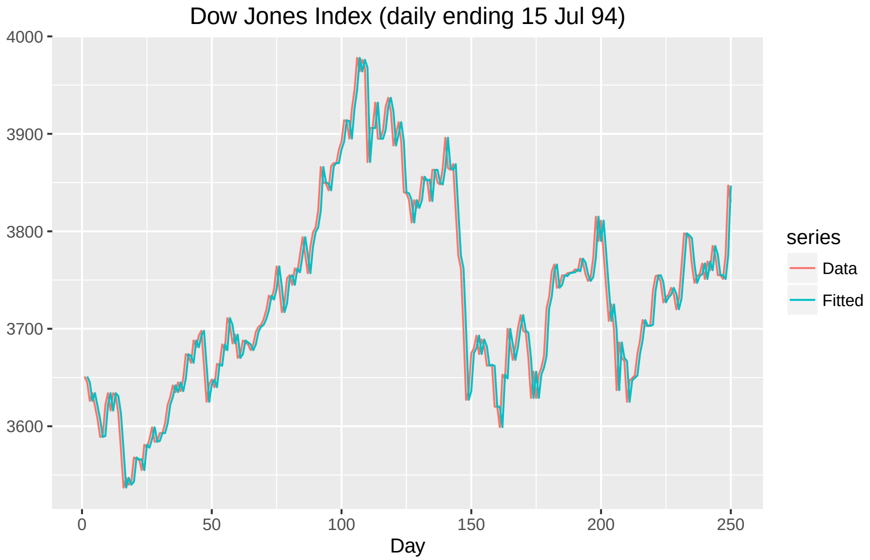
Example: Dow-Jones index



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Naïve forecast:

$$\hat{y}_{t|t-1} = y_{t-1}$$

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Note: e_t are one-step-forecast residuals

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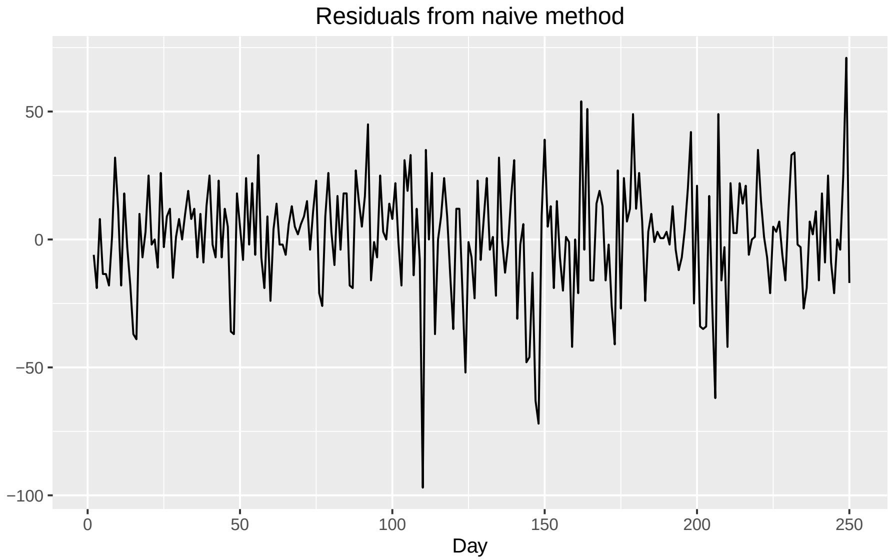

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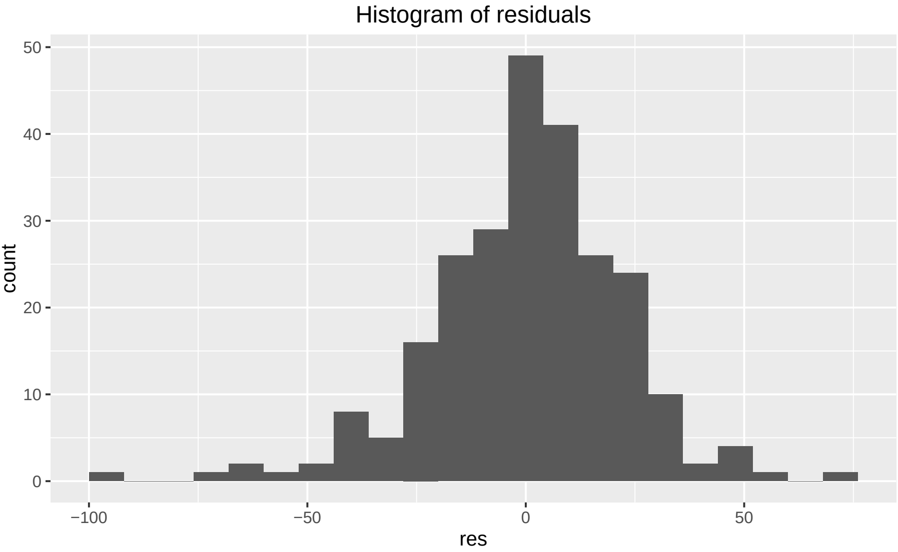

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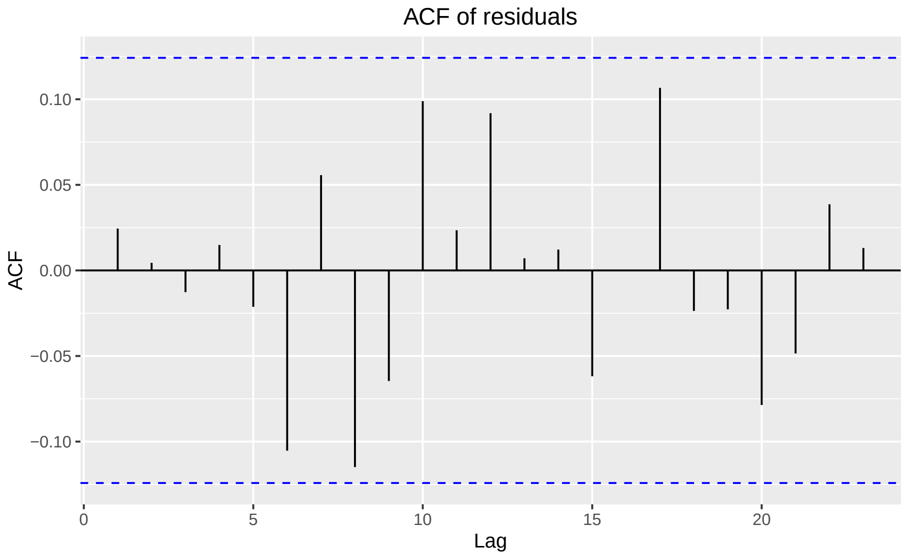

Example: Dow-Jones index

```r
fc <- naive(dj)
res <- residuals(fc)
autoplot(res)
hist(res,breaks="FD")
ggAcf(res,main="")
```

ACF of residuals

- We assume that the residuals are white noise (uncorrelated, mean zero, constant variance). If they aren't, then there is information left in the residuals that should be used in computing forecasts.
- So a standard residual diagnostic is to check the ACF of the residuals of a forecasting method.
- We *expect* these to look like white noise.

Portmanteau tests

Consider a *whole set* of r_k values, and develop a test to see whether the set is significantly different from a zero set.

Box-Pierce test

$$Q = T\sum_{k=1}^{h} r_k^2$$

where h is max lag being considered and T is number of observations.

- My preferences: $h = 10$ for non-seasonal data, $h = 2m$ for seasonal data.
- If each r_k close to zero, Q will be **small**.
- If some r_k values large (positive or negative), Q will be **large**.

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Ljung-Box test

$$Q^* = T(T+2)\sum_{k=1}^{h}(T-k)^{-1}r_k^2$$

where h is max lag being considered and T is number of observations.

- My preferences: $h = 10$ for non-seasonal data, $h = 2m$ for seasonal data.
- Better performance, especially in small samples.

Portmanteau tests

- If data are WN, Q^* has χ^2 distribution with $(h - K)$ degrees of freedom where K = no. parameters in model.
- When applied to raw data, set $K = 0$.
- For the Dow-Jones example,

```
res <- residuals(naive(dj))

# lag=h and fitdf=K

> Box.test(res, lag=10, fitdf=0)
  Box-Pierce test
X-squared = 14.0451, df = 10, p-value = 0.1709
> Box.test(res, lag=10, fitdf=0, type="Lj")
  Box-Ljung test
X-squared = 14.4615, df = 10, p-value = 0.153
```

Outline

Lab Session 3

Outline

Measures of forecast accuracy

Let y_t denote the tth observation and $\hat{y}_{t|t-1}$ denote its forecast based on all previous data, where $t = 1, \dots, T$. Then the following measures are useful.

$$\text{MAE} = T^{-1}\sum_{t=1}^{T}|y_t - \hat{y}_{t|t-1}|$$

$$\text{MSE} = T^{-1}\sum_{t=1}^{T}(y_t - \hat{y}_{t|t-1})^2 \qquad \text{RMSE} = \sqrt{T^{-1}\sum_{t=1}^{T}(y_t - \hat{y}_{t|t-1})^2}$$

$$\text{MAPE} = 100T^{-1}\sum_{t=1}^{T}|y_t - \hat{y}_{t|t-1}|/|y_t|$$

- MAE, MSE, RMSE are all scale dependent.
- MAPE is scale independent but is only sensible if $y_t \gg 0$ for all t, and y has a natural zero.

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Measures of forecast accuracy

Mean Absolute Scaled Error

$$\text{MASE} = T^{-1} \sum_{t=1}^{T} |y_t - \hat{y}_{t|t-1}|/Q$$

where Q is a stable measure of the scale of the time series $\{y_t\}$.

Proposed by Hyndman and Koehler (IJF, 2006).

For non-seasonal time series,

$$Q = (T-1)^{-1} \sum_{t=2}^{T} |y_t - y_{t-1}|$$

works well. Then MASE is equivalent to MAE relative to a naïve method.

Measures of forecast accuracy

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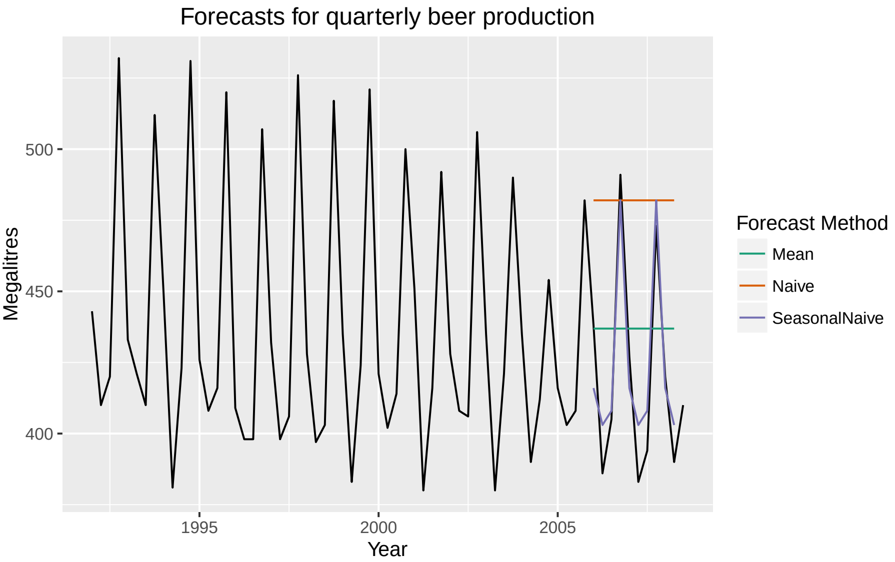
For seasonal time series,

$$Q = (T-m)^{-1}\sum_{t=m+1}^{T}|y_t - y_{t-m}|$$

works well. Then MASE is equivalent to MAE relative to a seasonal naïve method.

Measures of forecast accuracy



Measures of forecast accuracy

```r
beer3 <- window(ausbeer, start=2006)
accuracy(beerfit1, beer3)
accuracy(beerfit2, beer3)
accuracy(beerfit3, beer3)
```

	RMSE	MAE	MAPE	MASE
Mean method	38.95	34.46	8.33	2.35
Naïve method	70.80	63.10	15.71	4.29
Seasonal naïve method	13.59	12.20	2.95	0.83

Training and test sets

Available data

Training set (e.g., 80%)	Test set (e.g., 20%)

- The test set must not be used for *any* aspect of model development or calculation of forecasts.
- Forecast accuracy is based only on the test set.

Training and test sets

```
beer3 <- window(ausbeer,start=1992,end=c(2005,4))
beer4 <- window(ausbeer,start=2006)

fit1 <- meanf(beer3,h=20)
fit2 <- naive(beer3,h=20)

accuracy(fit1,beer4)
accuracy(fit2,beer4)
```

In-sample accuracy (one-step forecasts)

```
accuracy(fit1)
accuracy(fit2)
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Beware of over-fitting

- A model which fits the data well does not necessarily forecast well.
- A perfect fit can always be obtained by using a model with enough parameters. (Compare R^2)
- Over-fitting a model to data is as bad as failing to identify the systematic pattern in the data.
- Problems can be overcome by measuring true *out-of-sample* forecast accuracy. That is, total data divided into "training" set and "test" set. Training set used to estimate parameters. Forecasts are made for test set.
- Accuracy measures computed for errors in test set only.

Poll: true or false?

1. Good forecast methods should have normally distributed residuals.
2. A model with small residuals will give good forecasts.
3. The best measure of forecast accuracy is MAPE.
4. If your model doesn't forecast well, you should make it more complicated.
5. Always choose the model with the best forecast accuracy as measured on the test set.

Outline

Lab Session 4