

MA 5124 Financial Time Series Analysis & Forecasting

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Course Syllabus

Module Code: MA 5124

Title: Financial Time Series Analysis & Forecasting

Credits: 4

Pre-requiites

None

Learning Objectives

- The purpose of this course is to provide students with introductory tools for the time series analysis of financial time series.
- Analyze of data series based on stochastic and non stochastic models

Learning Outcomes

- On successful completion of this course, students will be able to provide more than an introductory treatment of the topics.
- Students are encouraged to pursue further study in this area if they find that the topics covered in this course.

Outline Syllabus

- Definition and examples of time series
- back-shift and differencing-operators, - strong and weak stationarity, definition of ACF, PACF.

- Definitions and properties of the $MA(q)$, $MA(\infty)$, $AR(p)$, $AR(\infty)$ and $ARMA(p, q)$, in particular their acf's
- causal stationarity of AR
- invertibility of MA models and causal stationarity and invertibility of ARMA; - concept of spectral density function and its applications
- definition and properties of integrated $ARIMA(p, d, q)$ processes
- definition and properties of random walks with or without drift.
- Model selection following the AIC and BIC
- brief introduction to linear prediction and calculation of forecasting intervals for normal ARMA models
- point and interval forecasts for normal random walks with or without drift.
- Definition and properties of the VAR (vector autoregressive) model, arrange a univariate time series as a multivariate Markov model.
- Nonlinear properties of financial time series
- definition and properties of the well known ARCH, GARCH etc.
- Cointegration in Single Equations, Modeling and Forecasting Financial Time Series.

Method of Assessment

- Assignment 30%
- End-semester examination 70%

Lecturer

Dr. Priyanga D. Talagala

Schedule

Lectures:

- Sunday [9.00am -12.00 noon]

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Chapter 1

Intordution to Time Series Forecasting

CHAPTER 1. INTRODUCTION TO TIME SERIES FORECASTING

Chapter 2

ARIMA models

- **AR**: autoregressive (lagged observations as inputs)
- **I**: integrated (differencing to make series stationary)
- **MA**: moving average (lagged errors as inputs)

An ARIMA model is rarely interpretable in terms of visible data structures like trend and seasonality. But it can capture a huge range of time series patterns.

2.1 Stationarity and differencing

2.1.1 Stationarity

Definition

If $\{y_t\}$ is a stationary time series, then for all s , the distribution of (y_t, \dots, y_{t+s}) does not depend on t .

A **stationary series** is:

- roughly horizontal
- constant variance
- no patterns predictable in the long-term
- Transformations help to stabilize the variance.
- For ARIMA modelling, we also need to stabilize the mean.

Identifying non-stationary series

- time plot.
- The ACF of stationary data drops to zero relatively quickly
- The ACF of non-stationary data decreases slowly.
- For non-stationary data, the value of r_1 is often large and positive.



- A time series, $\{Y_t, t = 0, \pm 1, \dots\}$ is said to be **strict stationary**, if (Y_1, \dots, Y_n) and $(Y_{1+h}, \dots, Y_{n+h})$ have the same joint distribution for all integers h and $n > 0$.

2.1.1.1 Weak Stationarity

Definition: Covariance function (in (Brockwell et al., 2016), p. 15; the notations have been changed for consistency within this note)

Let $\{Y_t\}$ be a time series with $E(Y_t^2) < \infty$. The **mean function** of $\{Y_t\}$ is

$$\mu_Y(t) = E(Y_t)$$

The **covariance function** of $\{Y_t\}$ is

$$\gamma_Y(r, s) = Cov(Y_r, Y_s) = E[(Y_r - \mu_Y(r))(Y_s - \mu_Y(s))]$$

for all integers r and s .

Definition: Weakly stationary (in (Brockwell et al., 2016), p. 15; the notations have been changed for consistency within this note)

$\{Y_t\}$ is **weakly stationary** if

1. $\mu_Y(t)$ is independent of t ,

and

2. $\gamma_Y(t+h, t)$ is independent of t for each h .

- Unless specifically indicate otherwise, whenever we use the term *stationary* we shall mean *weakly stationary*.

2.1.2 Differencing

- Differencing helps to **stabilize the mean**.
- The differenced series is the *change* between each observation in the original series: $y'_t = y_t - y_{t-1}$.
- The differenced series will have only $T - 1$ values since it is not possible to calculate a difference y'_1 for the first observation.

2.1.2.1 Second-order differencing

Occasionally the differenced data will not appear stationary and it may be necessary to difference the data a second time:

$$\begin{aligned} y_t'' &= y_t' - y_{t-1}' \\ &= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\ &= y_t - 2y_{t-1} + y_{t-2}. \end{aligned}$$

- y_t'' will have $T - 2$ values.
- In practice, it is almost never necessary to go beyond second-order differences.

2.1.2.2 Seasonal differencing

A seasonal difference is the difference between an observation and the corresponding observation from the previous year.

$$y_t' = y_t - y_{t-m}$$

where m = number of seasons.

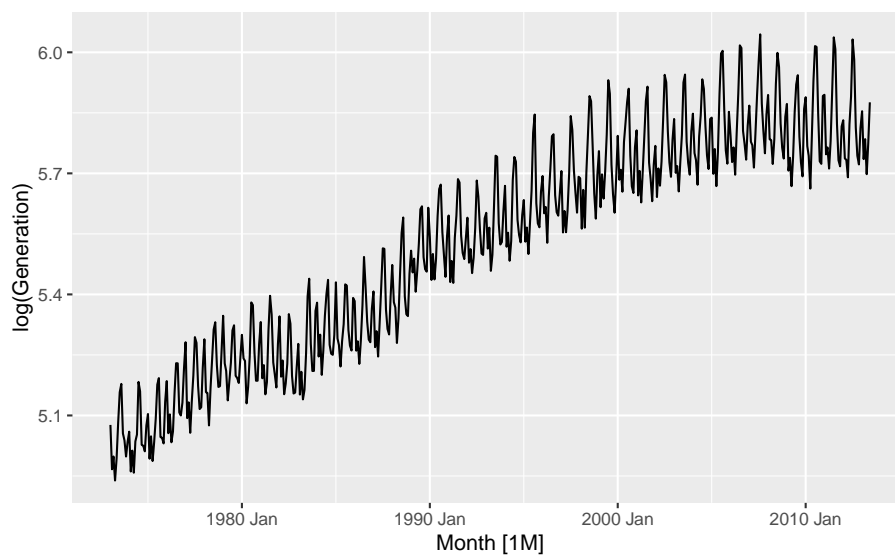
- For monthly data $m = 12$.
- For quarterly data $m = 4$.

Example : Electricity production

```
usmelec %>% autoplot(Generation)
```



```
usmelec %>% autoplot(log(Generation))
```



```
usmelec %>% autoplot(log(Generation) %>% difference(12))
```



```
usmelec %>% autoplot(log(Generation) %>% difference(12) %>% difference())
```



- Seasonally differenced series is closer to being stationary.
- Remaining non-stationarity can be removed with further first difference.

If $y'_t = y_t - y_{t-12}$ denotes seasonally differenced series, then twice-differenced series is

$$\begin{aligned} y_t^* &= y'_t - y'_{t-1} \\ &= (y_t - y_{t-12}) - (y_{t-1} - y_{t-13}) \\ &= y_t - y_{t-1} - y_{t-12} + y_{t-13}. \end{aligned}$$

When both seasonal and first differences are applied ...

- it makes no difference which is done first—the result will be the same.
- If seasonality is strong, we recommend that seasonal differencing be done first because sometimes the resulting series will be stationary and there will be no need for further first difference.

It is important that if differencing is used, the differences are interpretable.

2.1.2.3 Interpretation of differencing

- first differences are the change between one observation and the next;
- seasonal differences are the change between one year to the next.

But taking lag 3 differences for yearly data, for example, results in a model which cannot be sensibly interpreted.

2.1.3 Backshift notation

A very useful notational device is the backward shift operator, B , which is used as follows:

$$By_t = y_{t-1}$$

In other words,

- B , operating on y_t , has the effect of **shifting the data back one period**.
- Two applications of B to y_t **shifts the data back two periods**:

$$B(By_t) = B^2y_t = y_{t-2}$$

- For monthly data, if we wish to shift attention to “the same month last year”, then B^{12} is used, and the notation is

$$B^{12}y_t = y_{t-12}$$

2.2. NON-SEASONAL ARIMA MODELS CHAPTER 2. ARIMA MODELS

- The backward shift operator is convenient for describing the process of *differencing*.
- A first difference can be written as

$$y'_t = y_t - y_{t-1} = y_t - By_t = (1 - B)y_t$$

- Note that a first difference is represented by $(1 - B)$.
- Similarly, if second-order differences (i.e., first differences of first differences) have to be computed, then:

$$y''_t = y_t - 2y_{t-1} + y_{t-2} = (1 - B)^2 y_t$$

- Second-order difference is denoted $(1 - B)^2$.
- *Second-order difference* is not the same as a *second difference*, which would be denoted $1 - B^2$;
- In general, a d th-order difference can be written as

$$(1 - B)^d y_t$$

* A seasonal difference followed by a first difference can be written as

$$(1 - B)(1 - B^m)y_t$$

- The “backshift” notation is convenient because the terms can be multiplied together to see the combined effect.

$$\begin{aligned}(1 - B)(1 - B^m)y_t &= (1 - B - B^m + B^{m+1})y_t \\ &= y_t - y_{t-1} - y_{t-m} + y_{t-m-1}.\end{aligned}$$

- For monthly data, $m = 12$ and we obtain the same result as earlier.

2.2 Non-seasonal ARIMA models

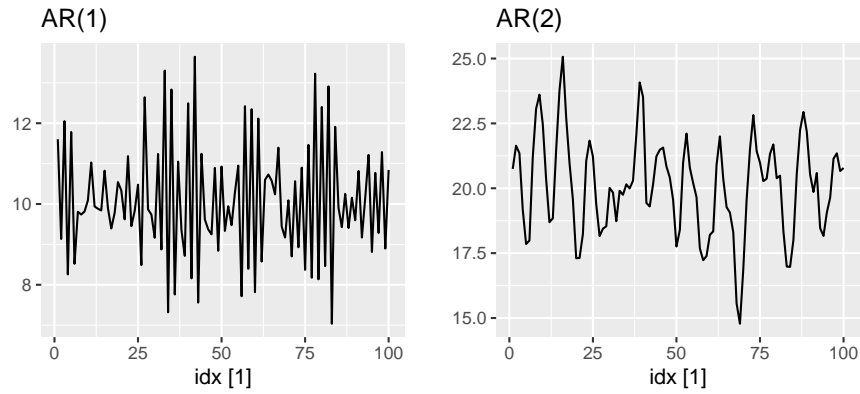
2.2.1 Autoregressive models

Autoregressive (AR) models:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t,$$

where ε_t is white noise. This is a multiple regression with **lagged values** of y_t as predictors.

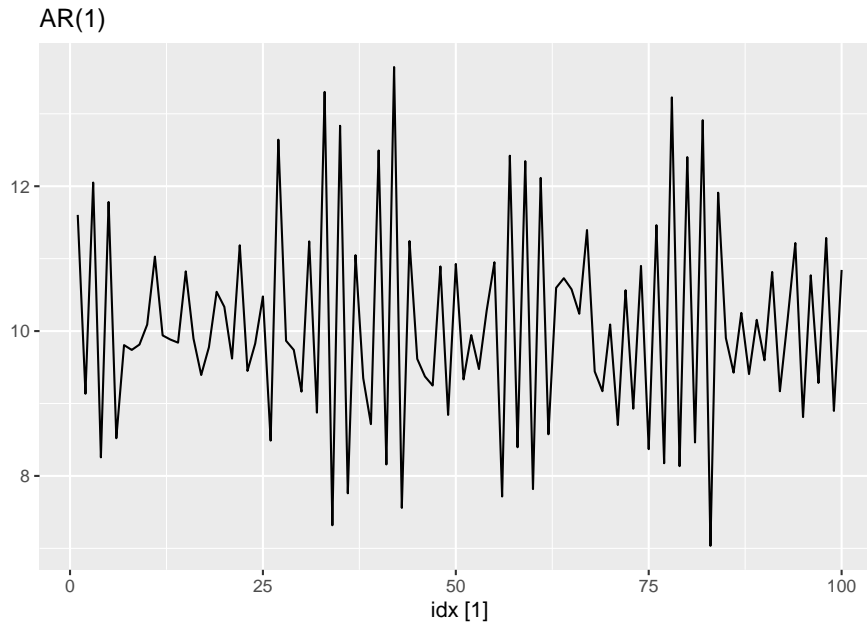
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2.2.1.1 AR(1) model

$$y_t = 18 - 0.8y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



$$y_t = c + \phi_1 y_{t-1} + \varepsilon_t$$

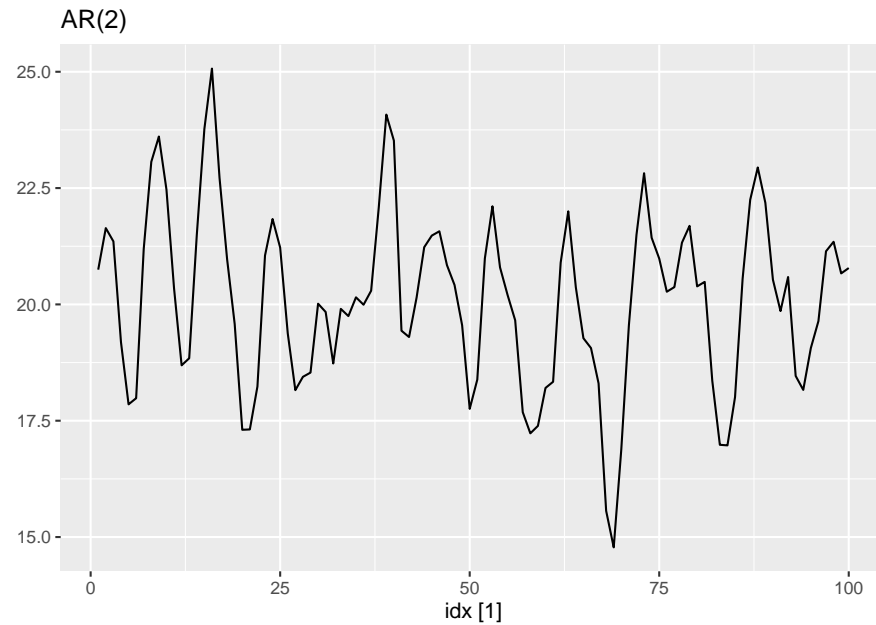
- When $\phi_1 = 0$, y_t is **equivalent to WN**

2.2. NON-SEASONAL ARIMA MODELS CHAPTER 2. ARIMA MODELS

- When $\phi_1 = 1$ and $c = 0$, y_t is **equivalent to a RW**
- When $\phi_1 = 1$ and $c \neq 0$, y_t is **equivalent to a RW with drift**
- When $\phi_1 < 0$, y_t tends to **oscillate between positive and negative values**.

2.2.1.2 AR(2) model

$$y_t = 8 + 1.3y_{t-1} - 0.7y_{t-2} + \varepsilon_t$$
$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



2.2.1.3 Stationarity conditions

- We normally restrict autoregressive models to stationary data, and then some constraints on the values of the parameters are required.

General condition for stationarity

Complex roots of $1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p$ lie outside the unit circle on the complex plane.

- For $p = 1$: $-1 < \phi_1 < 1$.
- For $p = 2$:
 $-1 < \phi_2 < 1 \quad \phi_2 + \phi_1 < 1 \quad \phi_2 - \phi_1 < 1$.

- More complicated conditions hold for $p \geq 3$.
- Estimation software takes care of this.

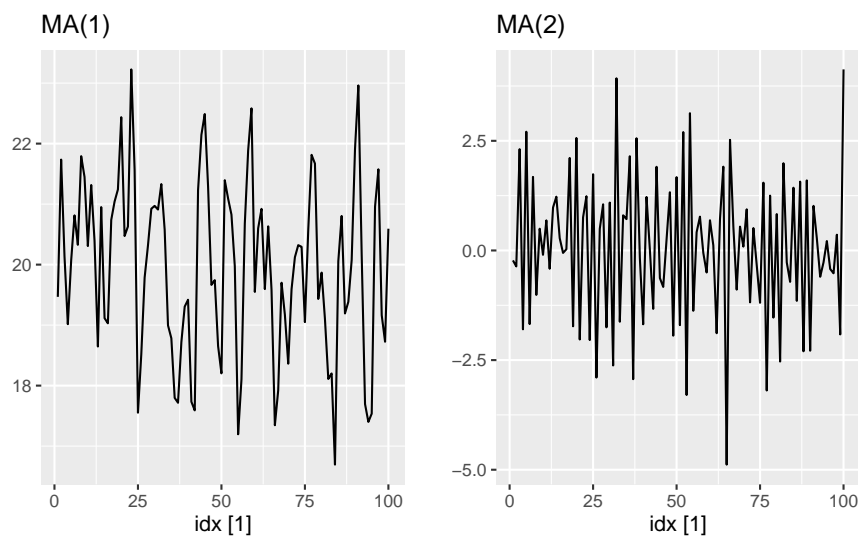
2.2.2 Moving Average (MA) models

Moving Average (MA) models:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q},$$

where ε_t is white noise. This is a multiple regression with **past errors** as predictors.

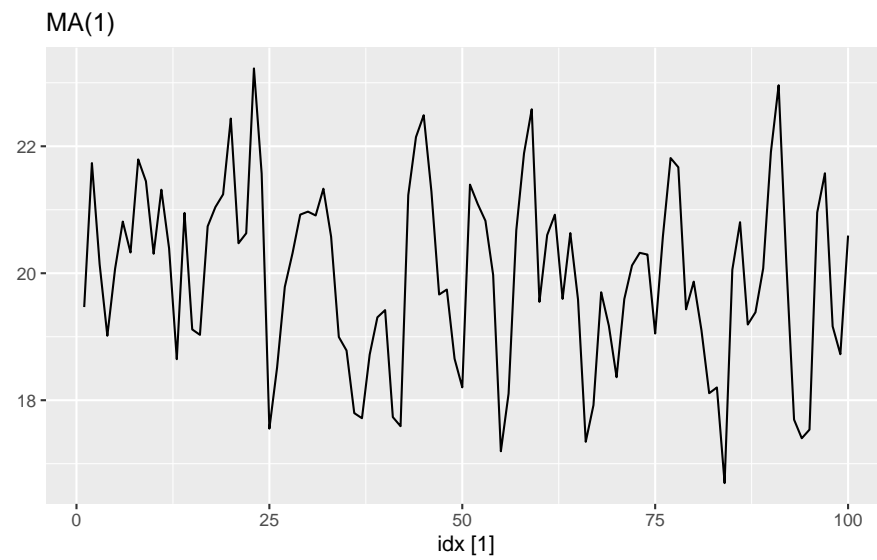
- Don't confuse this with moving average smoothing!



2.2.2.1 MA(1) model

$$y_t = 20 + \varepsilon_t + 0.8\varepsilon_{t-1}$$

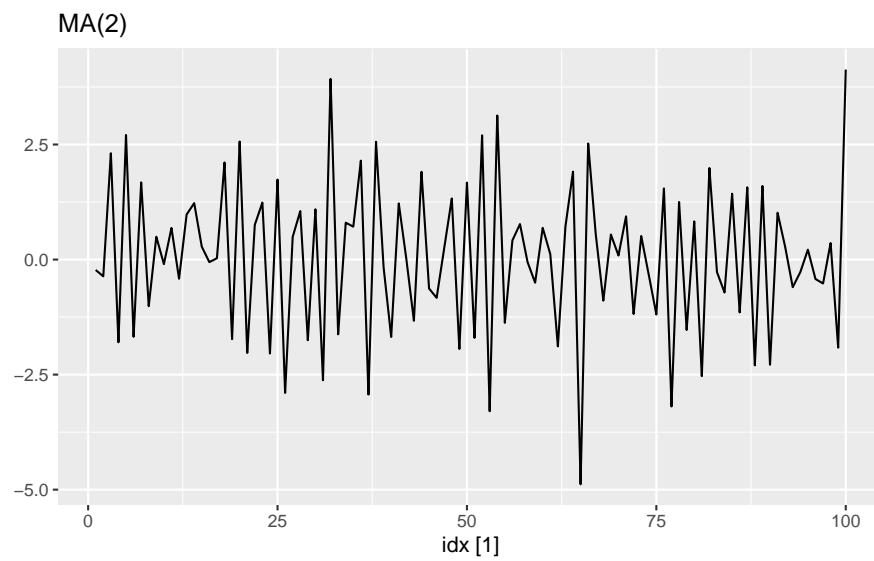
$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



2.2.2.2 MA(2) model

$$y_t = \varepsilon_t - \varepsilon_{t-1} + 0.8\varepsilon_{t-2}$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



2.2.2.3 MA(∞) models

It is possible to write any stationary AR(p) process as an MA(∞) process.

Example: AR(1)

$$\begin{aligned} y_t &= \phi_1 y_{t-1} + \varepsilon_t \\ &= \phi_1(\phi_1 y_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= \phi_1^2 y_{t-2} + \phi_1 \varepsilon_{t-1} + \varepsilon_t \\ &= \phi_1^3 y_{t-3} + \phi_1^2 \varepsilon_{t-2} + \phi_1 \varepsilon_{t-1} + \varepsilon_t \\ &\quad \dots \end{aligned}$$

Provided $-1 < \phi_1 < 1$:

$$y_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_1^2 \varepsilon_{t-2} + \phi_1^3 \varepsilon_{t-3} + \dots$$

2.2.3 Invertibility

- Any MA(q) process can be written as an AR(∞) process if we impose some constraints on the MA parameters.
- Then the MA model is called “invertible”.
- Invertible models have some mathematical properties that make them easier to use in practice.
- Invertibility of an ARIMA model is equivalent to forecastability of an ETS model.

General condition for invertibility

Complex roots of $1 + \theta_1 z + \theta_2 z^2 + \dots + \theta_q z^q$ lie outside the unit circle on the complex plane.

- For $q = 1$: $-1 < \theta_1 < 1$.
- For $q = 2$:
 $-1 < \theta_2 < 1 \quad \theta_2 + \theta_1 > -1 \quad \theta_1 - \theta_2 < 1$.
- More complicated conditions hold for $q \geq 3$.
- Estimation software takes care of this.

2.2.4 ARIMA models

Autoregressive Moving Average models:

$$\begin{aligned} y_t &= c + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} \\ &\quad + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \end{aligned}$$

2.2. NON-SEASONAL ARIMA MODELS CHAPTER 2. ARIMA MODELS

- Predictors include both **lagged values of y_t** and **lagged errors**.
- Conditions on coefficients ensure stationarity.
- Conditions on coefficients ensure invertibility.

Autoregressive Integrated Moving Average models

- Combine ARMA model with **differencing**.
- $(1 - B)^d y_t$ follows an ARMA model.

Autoregressive Integrated Moving Average models

ARIMA(p, d, q) model

- **AR:** p = order of the autoregressive part
- **I:** d = degree of first differencing involved
- **MA:** q = order of the moving average part.
 - White noise model: ARIMA(0,0,0)
 - Random walk: ARIMA(0,1,0) with no constant
 - Random walk with drift: ARIMA(0,1,0) with const.
 - AR(p): ARIMA($p,0,0$)
 - MA(q): ARIMA(0,0, q)

2.2.5 Backshift notation for ARIMA

- **ARMA model:**

$$y_t = c + \phi_1 B y_t + \cdots + \phi_p B^p y_t + \varepsilon_t + \theta_1 B \varepsilon_t + \cdots + \theta_q B^q \varepsilon_t$$

$$\text{or } (1 - \phi_1 B - \cdots - \phi_p B^p) y_t = c + (1 + \theta_1 B + \cdots + \theta_q B^q) \varepsilon_t$$

ARIMA(1,1,1) model:

$$(1 - \phi_1 B)(1 - B)y_t = c + (1 + \theta_1 B)\varepsilon_t$$

NOTE:

Written out:

$$y_t = c + y_{t-1} + \phi_1 y_{t-1} - \phi_1 y_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

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2.3 Estimation and order selection

2.3.1 Maximum likelihood estimation

Having identified the model order, we need to estimate the parameters $c, \phi_1, \dots, \phi_p, \theta_1, \dots, \theta_q$.

- MLE is very similar to least squares estimation obtained by minimizing

$$\sum_{t=1}^T e_t^2$$

- The `ARIMA()` function allows CLS or MLE estimation.
- Non-linear optimization must be used in either case.
- Different software will give different estimates.

2.3.2 Partial autocorrelations

Partial autocorrelations measure relationship between y_t and y_{t-k} , when the effects of other time lags — $1, 2, 3, \dots, k-1$ — are removed.

$\alpha_k = k$ th partial autocorrelation coefficient

= equal to the estimate of ϕ_k in regression:

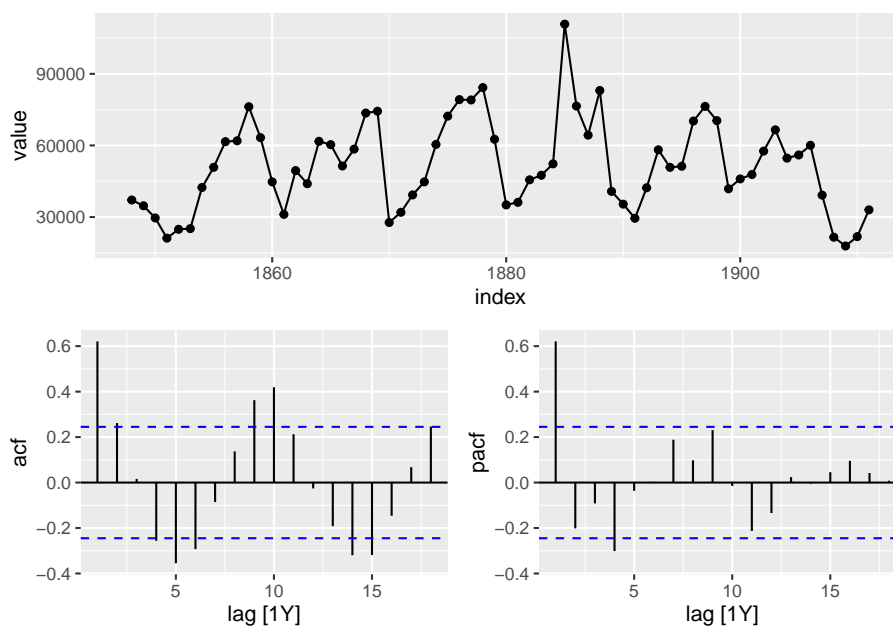
$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_k y_{t-k}.$$

- Varying number of terms on RHS gives α_k for different values of k .
- $\alpha_1 = \rho_1$
- same critical values of $\pm 1.96/\sqrt{T}$ as for ACF.
- Last significant α_k indicates the order of an AR model.

2.3.2.1 Example: Mink trapping



```
mink %>% gg_tsdisplay(value, plot_type='partial')
```



2.3.3 ACF and PACF interpretation

AR(1)

$$\rho_k = \phi_1^k \quad \text{for } k = 1, 2, \dots;$$

$$\alpha_1 = \phi_1 \quad \alpha_k = 0 \quad \text{for } k = 2, 3, \dots.$$

So we have an AR(1) model when

- autocorrelations exponentially decay
- there is a single significant partial autocorrelation.

AR(p)

- ACF dies out in an exponential or damped sine-wave manner
- PACF has all zero spikes beyond the p th spike

So we have an AR(p) model when

- the ACF is exponentially decaying or sinusoidal

- there is a significant spike at lag p in PACF, but none beyond p

MA(1)

$$\rho_1 = \theta_1 \quad \rho_k = 0 \quad \text{for } k = 2, 3, \dots;$$

$$\alpha_k = -(-\theta_1)^k$$

So we have an MA(1) model when

- the PACF is exponentially decaying and
- there is a single significant spike in ACF

MA(q)

- PACF dies out in an exponential or damped sine-wave manner
- ACF has all zero spikes beyond the q th spike

So we have an MA(q) model when

- the PACF is exponentially decaying or sinusoidal
- there is a significant spike at lag q in ACF, but none beyond q

2.3.4 Information criteria

Akaike's Information Criterion (AIC)

$$\text{AIC} = -2 \log(L) + 2(p + q + k + 1),$$

where L is the likelihood of the data, $k = 1$ if $c \neq 0$ and $k = 0$ if $c = 0$.

Corrected AIC:

$$\text{AICc} = \text{AIC} + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}.$$

Bayesian Information Criterion:

$$\text{BIC} = \text{AIC} + [\log(T) - 2](p + q + k + 1).$$

- Good models are obtained by minimizing either the AIC, AICc or BIC.
- Our preference is to use the AICc.

2.4 Seasonal ARIMA models

ARIMA	$\underbrace{(p, d, q)}$	$\underbrace{(P, D, Q)_m}$
	↑	↑
	Non-seasonal part of the model	Seasonal part of of the model

where m = number of observations per year.

Example: ARIMA(1, 1, 1)(1, 1, 1)₄ model (without constant)

$$(1 - \phi_1 B)(1 - \Phi_1 B^4)(1 - B)(1 - B^4)y_t = (1 + \theta_1 B)(1 + \Theta_1 B^4)\varepsilon_t.$$

All the factors can be multiplied out and the general model written as follows:

$$y_t = (1 + \phi_1)y_{t-1} - \phi_1 y_{t-2} + (1 + \Phi_1)y_{t-4} - (1 + \phi_1 + \Phi_1 + \phi_1 \Phi_1)y_{t-5} + (\phi_1 + \phi_1 \Phi_1)y_{t-6} \\ - \Phi_1 y_{t-8} + (\Phi_1 + \phi_1 \Phi_1)y_{t-9} - \phi_1 \Phi_1 y_{t-10} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \Theta_1 \varepsilon_{t-4} + \theta_1 \Theta_1 \varepsilon_{t-5}.$$

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2.5. THEORETICAL PROPERTIES OF THE COMMON ARIMA MODELS

2.4.1 Common ARIMA models

The US Census Bureau uses the following models most often:

ARIMA(0,1,1)(0,1,1) _m	with log transformation
ARIMA(0,1,2)(0,1,1) _m	with log transformation
ARIMA(2,1,0)(0,1,1) _m	with log transformation
ARIMA(0,2,2)(0,1,1) _m	with log transformation
ARIMA(2,1,2)(0,1,1) _m	with no transformation

2.4.2 Seasonal ARIMA models

The seasonal part of an AR or MA model will be seen in the seasonal lags of the PACF and ACF.

ARIMA(0,0,0)(0,0,1)₁₂ will show:

- a spike at lag 12 in the ACF but no other significant spikes.
- The PACF will show exponential decay in the seasonal lags; that is, at lags 12, 24, 36,

ARIMA(0,0,0)(1,0,0)₁₂ will show:

- exponential decay in the seasonal lags of the ACF
- a single significant spike at lag 12 in the PACF.

2.5 Theoretical properties of the models

2.5.1 Autoregressive (AR) models

2.5.1.1 Properties of AR(1) model

Consider the following $AR(1)$ model.

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t \quad (2.1)$$

where ϵ_t is white noise.

2.5.1.1.1 Mean

Assuming that the series is weak stationary, we have $E(Y_t) = \mu$, $Var(Y_t) = \gamma_0$, and $Cov(Y_t, Y_{t-k}) = \gamma_k$, where μ and γ_0 are constants. Given that ϵ_t is a white noise, we have $E(\epsilon_t) = 0$. The mean of $AR(1)$ process can be computed as follows:

$$\begin{aligned} E(Y_t) &= E(\phi_0 + \phi_1 Y_{t-1}) \\ &= E(\phi_0) + E(\phi_1 Y_{t-1}) \\ &= \phi_0 + \phi_1 E(Y_{t-1}). \end{aligned}$$

Under the stationarity condition, $E(Y_t) = E(Y_{t-1}) = \mu$. Thus we get

$$\mu = \phi_0 + \phi_1 \mu.$$

Solving for μ yields

$$E(Y_t) = \mu = \frac{\phi_0}{1 - \phi_1}. \quad (2.2)$$

The results has two constraints for Y_t . First, the mean of Y_t exists if $\phi_1 \neq 1$. The mean of Y_t is zero if and only if $\phi_0 = 0$.

2.5.1.1.2 Variance and the stationary condition of AR (1) process

First take variance of both sides of Equation (2.1)

$$Var(Y_t) = Var(\phi_0 + \phi_1 Y_{t-1} + \epsilon_t)$$

The Y_{t-1} occurred before time t . The ϵ_t does not depend on any past observation. Hence, $cov(Y_{t-1}, \epsilon_t) = 0$. Furthermore, ϵ_t is a white noise. This gives

$$Var(Y_t) = \phi_1^2 Var(Y_{t-1}) + \sigma^2.$$

Under the stationarity condition, $Var(Y_t) = Var(Y_{t-1})$. Hence,

$$Var(Y_t) = \frac{\sigma^2}{1 - \phi_1^2}.$$

provided that $\phi_1^2 < 1$ or $|\phi_1| < 1$ (The variance of a random variable is bounded and non-negative). The necessary and sufficient condition for the $AR(1)$ model in Equation (2.1) to be weakly stationary is $|\phi_1| < 1$. This condition is equivalent to saying that the root of $1 - \phi_1 B = 0$ must lie outside the unit circle. This can be explained as below

2.5. THEORETICAL PROPERTIES OF THE ARIMA MODELS

Using the backshift notation we can write $AR(1)$ process as

$$Y_t = \phi_0 + \phi_1 BY_t + \epsilon_t.$$

Then we get

$$(1 - \phi_1 B)Y_t = \phi_0 + \epsilon_t.$$

The $AR(1)$ process is said to be stationary if the roots of $(1 - \phi_1 B) = 0$ lie outside the unit circle.

2.5.1.1.3 Covariance

The covariance $\gamma_k = Cov(Y_t, Y_{t-k})$ is called the lag- k autocovariance of Y_t . The two main properties of γ_k : (a) $\gamma_0 = Var(Y_t)$ and (b) $\gamma_{-k} = \gamma_k$.

The lag- k autocovariance of Y_t is

$$\begin{aligned}\gamma_k &= Cov(Y_t, Y_{t-k}) \\ &= E[(Y_t - \mu)(Y_{t-k} - \mu)] \\ &= E[Y_t Y_{t-k} - Y_t \mu - \mu Y_{t-k} + \mu^2] \\ &= E(Y_t Y_{t-k}) - \mu^2.\end{aligned}\tag{2.3}$$

Now we have

$$E(Y_t Y_{t-k}) = \gamma_k + \mu^2\tag{2.4}$$

2.5.1.1.4 Autocorrelation function of an AR(1) process

To derive autocorrelation function of an $AR(1)$ process we first multiply both sides of Equation (2.1) by Y_{t-k} and take expected values:

$$E(Y_t Y_{t-k}) = \phi_0 E(Y_{t-k}) + \phi_1 E(Y_{t-1} Y_{t-k}) + E(\epsilon_t Y_{t-k})$$

Since ϵ_t and Y_{t-k} are independent and using the results in Equation (2.4)

$$\gamma_k + \mu^2 = \phi_0 \mu + \phi_1 (\gamma_{k-1} + \mu^2)$$

Substituting the results in Equation (2.2) to Equation (2.4) we get

$$\gamma_k = \phi_1 \gamma_{k-1}.\tag{2.5}$$

The autocorrelation function, ρ_k , is defined as

$$\rho_k = \frac{\gamma_k}{\gamma_0}$$

Setting $k = 1$, we get $\gamma_1 = \phi_1 \gamma_0$. Hence,

$$\rho_1 = \phi_1.$$

Similarly with $k = 2$, $\gamma_2 = \phi_1 \gamma_1$. Dividing both sides by γ_0 and substituting with $\rho_1 = \phi_1$ we get

$$\rho_2 = \phi_1^2.$$

Now it is easy to see that in general

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \phi_1^k \quad (2.6)$$

for $k = 0, 1, 2, 3, \dots$

Since $|\phi_1| < 1$, the autocorrelation function is an exponentially decreasing as the number of lags k increases. There are two features in the ACF of AR(1) process depending on the sign of ϕ_1 . They are,

1. If $0 < \phi_1 < 1$, all correlations are positive.
2. if $-1 < \phi_1 < 0$, the lag 1 autocorrelation is negative ($\rho_1 = \phi_1$) and the signs of successive autocorrelations alternate from positive to negative with their magnitudes decreasing exponentially.

2.5.1.2 Properties of AR(2) model

Now consider a second-order autoregressive process (AR(2))

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \epsilon_t. \quad (2.7)$$

2.5.1.2.1 Mean

Question 1: Using the same technique as that of the AR(1), show that

$$E(Y_t) = \mu = \frac{\phi_0}{1 - \phi_1 - \phi_2}$$

and the mean of Y_t exists if $\phi_1 + \phi_2 \neq 1$.

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2.5.1.2.2 Variance

Question 2: Show that

$$\text{Var}(Y_t) = \frac{(1 - \phi_2)\sigma^2}{(1 + \phi_2)((1 + \phi_2)^2 - \phi_1^2)}.$$

Here is a guide to the solution

Start with

$$\text{Var}(Y_t) = \text{Var}(\phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \epsilon_t)$$

Solve it until you obtain the Eq. (a) as shown below.

$$\gamma_0(1 - \phi_1^2 - \phi_2^2) = 2\phi_1\phi_2\gamma_1 + \sigma^2. \quad (\text{a})$$

Next multiply both sides of Equation (2.7) by Y_{t-1} and obtain an expression for γ_1 . Let's call this Eq. (b).

Solve Eq. (a) and (b) for γ_0 .

2.5.1.2.3 Stationarity of AR(2) process

To discuss the stationarity condition of the $AR(2)$ process we use the roots of the characteristic polynomial. Here is the illustration.

Using the backshift notation we can write $AR(2)$ process as

$$Y_t = \phi_0 + \phi_1 B Y_t + \phi_2 B^2 Y_t + \epsilon_t.$$

Furthermore, we get

$$(1 - \phi_1 B - \phi_2 B^2)Y_t = \phi_0 + \epsilon_t.$$

The **characteristic polynomial** of $AR(2)$ process is

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2.$$

and the corresponding **AR characteristic equation**

$$1 - \phi_1 B - \phi_2 B^2 = 0.$$

For stationarity, the roots of AR characteristic equation must lie outside the unit circle. The two roots of the AR characteristic equation are

$$\frac{\phi_1 \pm \sqrt{\phi_1^2 + 4\phi_2}}{-2\phi_2}$$

Using algebraic manipulation, we can show that these roots will exceed 1 in modulus if and only if simultaneously $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$, and $|\phi_2| < 1$. This is called the stationarity condition of $AR(2)$ process.

2.5.1.2.4 Autocorrelation function of an $AR(2)$ process

To derive autocorrelation function of an $AR(2)$ process we first multiply both sides of Equation (2.7) by Y_{t-k} and take expected values:

$$E(Y_t Y_{t-k}) = E(\phi_0 Y_{t-k} + \theta_1 Y_{t-1} Y_{t-k} + \theta_2 Y_{t-2} Y_{t-k} + \epsilon_t Y_{t-k}) \quad (2.8)$$

$$= \phi_0 E(Y_{t-k}) + \phi_1 E(Y_{t-1} Y_{t-k}) + \phi_2 E(Y_{t-2} Y_{t-k}) + E(\epsilon_t Y_{t-k}). \quad (2.9)$$

Using the independence between ϵ_t and Y_{t-1} , $E(\epsilon_t Y_{t-k}) = 0$ and the results in Equation (2.4) (This is valid for $AR(2)$) we have

$$\gamma_k + \mu^2 = \phi_0 \mu + \theta_1 (\gamma_{k-1} + \mu^2) + \phi_2 (\gamma_{k-2} + \mu^2).$$

(Note that $E(X_{t-1} X_{t-k}) = E(X_{t-1} X_{(t-1)-(k-1)}) = \gamma_{k-1}$)

Solving for γ_k we get

$$\gamma_k = \phi_1 \gamma_{k-1} + \phi_2 \gamma_{k-2}. \quad (2.10)$$

By dividing both sides of Equation (2.10) by γ_0 , we have

$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2}. \quad (2.11)$$

for $k > 0$.

Setting $k = 1$ and using $\rho_0 = 1$ and $\rho_{-1} = \rho_1$, we get **the Yule-Walker equation for $AR(2)$ process.**

$$\rho_1 = \phi_1 + \phi_2 \rho_1$$

or

$$\rho_1 = \frac{\phi_1}{1 - \phi_2}.$$

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Similarly, we can show that

$$\rho_2 = \frac{\phi_2(1 - \phi_2) + \phi_1^2}{(1 - \phi_2)}.$$

2.5.1.3 Properties of AR(p) model

The p th order autoregressive model can be written as

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \epsilon_t. \quad (2.12)$$

The AR characteristic equation is

$$1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p = 0.$$

For stationarity of $AR(p)$ process, the p roots of the AR characteristic must lie outside the unit circle.

2.5.1.3.1 Mean

Question 3: Find $E(Y_t)$ of $AR(p)$ process.

2.5.1.3.2 Variance

Question 4: Find $Var(Y_t)$ of $AR(p)$ process.

2.5.1.3.3 Autocorrelation function (ACF) of an AR(p) process

Question 5: Similar to the results in Equation (2.11) for $AR(2)$ process, obtain the following recursive relationship for $AR(p)$.

$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \dots + \phi_p \rho_{k-p}. \quad (2.13)$$

Setting $k = 1, 2, \dots, p$ into Equation (2.13) and using $\rho_0 = 1$ and $\rho_{-k} = \rho_k$, we get the Yule-Walker equations for $AR(p)$ process

$$\begin{aligned} \rho_1 &= \phi_1 + \phi_2 \rho_1 + \dots + \phi_p \rho_{p-1} \\ \rho_2 &= \phi_1 \rho_1 + \phi_2 + \dots + \phi_p \rho_{p-2} \\ &\dots \\ \rho_p &= \phi_1 \rho_{p-1} + \phi_2 \rho_{p-2} + \dots + \phi_p \end{aligned} \quad (2.14)$$

The Yule-Walker equations in (2.14) can be written in matrix form as below.

$$\begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \vdots \\ \rho_p \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdot & \cdot & \cdot & \rho_{p-1} \\ \rho_1 & 1 & \rho_1 & \cdot & \cdot & \cdot & \rho_{p-2} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \rho_{p-1} & \rho_{p-2} & \rho_{p-3} & \cdot & \cdot & \cdot & 1 \end{bmatrix} \begin{bmatrix} \phi_1 \\ \phi_2 \\ \cdot \\ \cdot \\ \cdot \\ \phi_p \end{bmatrix}$$

or

$$\rho_p = P_p \phi.$$

where,

$$\rho_p = \begin{bmatrix} \rho_1 \\ \rho_2 \\ \cdot \\ \cdot \\ \cdot \\ \rho_p \end{bmatrix}, P_p = \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdot & \cdot & \cdot & \rho_{p-1} \\ \rho_1 & 1 & \rho_1 & \cdot & \cdot & \cdot & \rho_{p-2} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \rho_{p-1} & \rho_{p-2} & \rho_{p-3} & \cdot & \cdot & \cdot & 1 \end{bmatrix}, \phi = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \cdot \\ \cdot \\ \cdot \\ \phi_p \end{bmatrix}$$

The parameters can be estimated using

$$\phi = P_p^{-1} \rho_p.$$

Question 6: Obtain the parameters of an $AR(3)$ process whose first autocorrelations are $\rho_1 = 0.9$; $\rho_2 = 0.9$; $\rho_3 = 0.5$. Is the process stationary?

2.5.1.3.4 The partial autocorrelation function (PACF)

Let ϕ_{kj} , the j th coefficient in an $AR(k)$ model. Then, ϕ_{kk} is the last coefficient. From Equation (2.13), the ϕ_{kj} satisfy the set of equations

$$\rho_j = \phi_{k1}\rho_{j-1} + \dots + \phi_{k(k-1)}\rho_{j-k+1} + \phi_{kk}\rho_{j-k}, \quad (2.15)$$

for $j = 1, 2, \dots, k$, leading to the Yule-Walker equations which may be written

$$\begin{bmatrix} \rho_1 \\ \rho_2 \\ \cdot \\ \cdot \\ \cdot \\ \rho_k \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdot & \cdot & \cdot & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdot & \cdot & \cdot & \rho_{k-2} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdot & \cdot & \cdot & 1 \end{bmatrix} \begin{bmatrix} \phi_{k1} \\ \phi_{k2} \\ \cdot \\ \cdot \\ \cdot \\ \phi_{kk} \end{bmatrix} \quad (2.16)$$

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or

$$\boldsymbol{\rho}_k = \mathbf{P}_k \boldsymbol{\phi}_k.$$

where

$$\boldsymbol{\rho}_k = \begin{bmatrix} \rho_1 \\ \rho_2 \\ \cdot \\ \cdot \\ \cdot \\ \rho_k \end{bmatrix}, \mathbf{P}_k = \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdot & \cdot & \cdot & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdot & \cdot & \cdot & \rho_{k-2} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdot & \cdot & \cdot & 1 \end{bmatrix}, \boldsymbol{\phi}_k = \begin{bmatrix} \phi_{k1} \\ \phi_{k2} \\ \cdot \\ \cdot \\ \cdot \\ \phi_{kk} \end{bmatrix}$$

For each k , we compute the coefficients ϕ_{kk} . Solving the equations for $k = 1, 2, 3, \dots$ successively, we obtain

For $k = 1$,

$$\phi_{11} = \rho_1. \quad (2.17)$$

For $k = 2$,

$$\phi_{22} = \frac{\begin{bmatrix} 1 & \rho_1 \\ \rho_1 & \rho_2 \end{bmatrix}}{\begin{bmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{bmatrix}} = \frac{\rho_2 - \rho_1^2}{1 - \rho_1^2} \quad (2.18)$$

For $k = 3$,

$$\phi_{33} = \frac{\begin{bmatrix} 1 & \rho_1 & \rho_2 \\ \rho_1 & 1 & \rho_1 \\ \rho_2 & \rho_1 & \rho_3 \end{bmatrix}}{\begin{bmatrix} 1 & \rho_1 & \rho_2 \\ \rho_1 & 1 & \rho_1 \\ \rho_2 & \rho_1 & 1 \end{bmatrix}} \quad (2.19)$$

The quantity ϕ_{kk} is called the partial autocorrelation at lag k and can be defined as

$$\phi_{kk} = \text{Corr}(Y_t Y_{t-k} | Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}).$$

The partial autocorrelation between Y_t and Y_{t-k} is the correlation between Y_t and Y_{t-k} after removing the effect of the intermediate variables $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}$.

In general the determinant in the numerator of Equations (2.17), (2.18) and (2.19) has the same elements as that in the denominator, but replacing the last column with $\boldsymbol{\rho}_k = (\rho_1, \rho_2, \dots, \rho_k)$.

2.5.1.3.5 PACF for AR(1) models

From Equation (2.6) we have

$$\rho_k = \phi_1^k \text{ for } k = 0, 1, 2, 3, \dots$$

Hence, for $k = 1$, the first partial autocorrelation coefficient is

$$\phi_{11} = \rho_1 = \phi_1.$$

From (2.18) for $k = 2$, the second partial autocorrelation coefficient is

$$\phi_{22} = \frac{\rho_2 - \rho_1^2}{1 - \rho_1^2} = \frac{\phi_1^2 - \phi_1^2}{1 - \phi_1^2} = 0$$

Similarly, for $AR(1)$ we can show that $\phi_{kk} = 0$ for all $k > 1$. Hence, for $AR(1)$ process the partial autocorrelation is non-zero for lag 1 which is the order of the process, but is zero for lags beyond the order 1.

2.5.1.3.6 PACF for AR(2) model

Question 7: For $AR(2)$ process show that $\phi_{kk} = 0$ for all $k > 2$. Sketch the PACF of $AR(2)$ process.

2.5.1.3.7 PACF for AR(P) model

In general for $AR(p)$ process, the partial autocorrelation function ϕ_{kk} is non-zero for k less than or equal to p (the order of the process) and zero for all k greater than p . In other words, the partial autocorrelation function of a $AR(p)$ process has a cut-off after lag p .

2.5.2 Moving average (MA) models

We first derive the properties of $MA(1)$ and $MA(2)$ models and then give the results for the general $MA(q)$ model.

2.5.2.1 Properties of MA(1) model

The general form for $MA(1)$ model is

$$Y_t = \theta_0 + \theta_1 \epsilon_{t-1} + \epsilon_t \quad (2.20)$$

where θ_0 is a constant and ϵ_t is a white noise series.

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2.5.2.1.1 Mean

Question 8: Show that $E(Y_t) = \theta_0$.

2.5.2.1.2 Variance

Question 9: Show that $Var(Y_t) = (1 + \theta_1^2)\sigma^2$.

We can see both mean and variance are time-invariant. MA models are finite linear combinations of a white noise sequence. Hence, MA processes are always weakly stationary.

2.5.2.1.3 Autocorrelation function of an $MA(1)$ process

Method 1

To obtain the autocorrelation function of $MA(1)$, we first multiply both sides of Equation (2.20) by Y_{t-k} and take the expectation.

$$\begin{aligned} E[Y_t Y_{t-k}] &= E[\theta_0 Y_{t-k} + \theta_1 \epsilon_{t-1} Y_{t-k} + \epsilon_t Y_{t-k}] \\ &= \theta_0 E(Y_{t-k}) + \theta_1 E(\epsilon_{t-1} Y_{t-k}) + E(\epsilon_t Y_{t-k}) \end{aligned} \quad (2.21)$$

Using the independence between ϵ_t and Y_{t-k} (future error and past observation) $E(\epsilon_t Y_{t-k}) = 0$. Now we have

$$E[Y_t Y_{t-k}] = \theta_0^2 + \theta_1 E(\epsilon_{t-1} Y_{t-k}) \quad (2.22)$$

Now let's obtain an expression for $E[Y_t Y_{t-k}]$.

$$\begin{aligned} \gamma_k &= Cov(Y_t, Y_{t-k}) \\ &= E[(Y_t - \theta_0)(Y_{t-k} - \theta_0)] \\ &= E[Y_t Y_{t-k} - Y_t \theta_0 - \theta_0 Y_{t-k} + \theta_0^2] \\ &= E(Y_t Y_{t-k}) - \theta_0^2. \end{aligned} \quad (2.23)$$

Now we have

$$E(Y_t Y_{t-k}) = \gamma_k + \theta_0^2. \quad (2.24)$$

Using the Equations (2.22) and (2.24) we have

$$\gamma_k = \theta_0^2 - \theta_0^2 + \theta_1 E(\epsilon_{t-1} Y_{t-k}). \quad (2.25)$$

Now let's consider the case $k = 1$.

$$\gamma_1 = \theta_0^2 - \theta_0^2 + \theta_1 E(\epsilon_{t-1} Y_{t-1}) \quad (2.26)$$

Today's error and today's value are dependent. Hence, $E(\epsilon_{t-1} Y_{t-1}) \neq 0$. We first need to identify $E(\epsilon_{t-1} Y_{t-1})$.

$$E(\epsilon_{t-1} Y_{t-1}) = E(\theta_0 \epsilon_{t-1} + \theta_1 \epsilon_{t-2} \epsilon_{t-1} + \epsilon_{t-1}^2) \quad (2.27)$$

Since, $\{\epsilon_t\}$ is a white noise process $E(\epsilon_{t-1}) = 0$ and $E(\epsilon_{t-2} \epsilon_{t-1}) = 0$. Hence, we have

$$E(\epsilon_{t-1} Y_{t-1}) = E(\epsilon_{t-1}^2) = \sigma^2 \quad (2.28)$$

Substituting (2.28) in (2.26) we get

$$\gamma_1 = \theta_1 \sigma^2$$

Furthermore, $\gamma_0 = Var(Y_t) = (1 + \theta_1^2) \sigma^2$. Hence

$$\rho_1 = \frac{\gamma_1}{\gamma_0} = \frac{\theta_1}{1 + \theta_1^2}.$$

When $k = 2$, from Equation (2.26) and $E(\epsilon_{t-1} Y_{t-2}) = 0$ (future error and past observation) we get $\gamma_2 = 0$. Hence $\rho_2 = 0$. Similarly, we can show that

$$\gamma_k = \rho_k = 0$$

for all $k \geq 2$.

We can see that the ACF of $MA(1)$ process is zero, beyond the order of 1 of the process.

Method 2: By using the definition of covariance

$$\begin{aligned} \gamma_1 &= Cov(Y_t, Y_{t-1}) = Cov(\epsilon_t + \theta_1 \epsilon_{t-1} + \theta_0, \epsilon_{t-1} + \theta_1 \epsilon_{t-2} + \theta_0) \\ &= Cov(\theta_1 \epsilon_{t-1}, \epsilon_{t-1}) \\ &= \theta_1 \sigma^2. \end{aligned} \quad (2.29)$$

$$\begin{aligned} \gamma_2 &= Cov(Y_t, Y_{t-2}) = Cov(\epsilon_t + \theta_1 \epsilon_{t-1} + \theta_0, \epsilon_{t-2} + \theta_1 \epsilon_{t-3} + \theta_0) \\ &= 0. \end{aligned} \quad (2.30)$$

We have $\gamma_0 = \sigma^2(1 + \theta_1^2)$, (Using the variance).

Hence

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$$\rho_1 = \frac{\gamma_1}{\gamma_0} = \frac{\theta_1}{1 + \theta_1^2}.$$

Similarly we can show $\gamma_k = \rho_k = 0$ for all $k \geq 2$.

2.5.2.2 Properties of MA(2) model

An $MA(2)$ model is in the form

$$Y_t = \theta_0 + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \epsilon_t \quad (2.31)$$

where θ_0 is a constant and ϵ_t is a white noise series.

2.5.2.2.1 Mean

Question 10: Show that $E(Y_t) = \theta_0$.

2.5.2.2.2 Variance

Question 11: Show that $Var(Y_t) = \sigma^2(1 + \theta_1^2 + \theta_2^2)$.

2.5.2.2.3 Autocorrelation function of an MA(2) process

Question 12: For $MA(2)$ process show that,

$$\rho_1 = \frac{\theta_1(1 + \theta_2)}{1 + \theta_1^2 + \theta_2^2},$$
$$\rho_2 = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2},$$

and $\rho_k = 0$ for all $k \geq 3$.

2.5.2.3 Properties of MA(q) model

$$Y_t = \theta_0 + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \dots + \theta_q\epsilon_{t-q} + \epsilon_t \quad (2.32)$$

where θ_0 is a constant and ϵ_t is a white noise series.

2.5.2.3.1 Mean

Question 13: Show that the constant term of an MA model is the mean of the series (i.e. $E(Y_t) = \theta_0$).

2.5.2.3.2 Variance

Question 14: Show that the variance of an MA model is

$$\text{Var}(Y_t) = (1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2)\sigma^2.$$

2.5.2.3.3 Autocorrelation function of an $MA(q)$ process

Question 15: Show that the autocorrelation function of a $MA(q)$ process is zero, beyond the order of q of the process. In other words, the autocorrelation function of a moving average process has a cutoff after lag q .

2.5.2.3.4 Partial autocorrelation function of an $MA(q)$ process

The partial autocorrelation functions for $MA(q)$ models behave very much like the autocorrelation functions of $AR(p)$ models. The PACF of MA models decays exponentially to zero, rather like ACF for AR model.

2.5.3 Dual relation between AR and MA process

Dual relation 1

First we consider the relation $AR(p) \leftrightarrow MA(\infty)$

Let $AR(p)$ be a **stationary** AR model with order p . Then,

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \epsilon_t,$$

where $\epsilon_t \sim WN(0, \sigma^2)$.

Using the backshift operator we can write the $AR(p)$ model as

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)Y_t = \epsilon_t.$$

Then

$$\phi(B)Y_t = \epsilon_t,$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$. Furthermore, Y_t can be written as infinite sum of previous ϵ 's as below

$$Y_t = \phi^{-1}(B)\epsilon_t,$$

where $\phi(B)\psi(B) = 1$ and $\psi(B) = 1 + \psi_1 B + \psi_2 B^2 + \dots$. Then

$$Y_t = \psi(B)\epsilon_t.$$

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This is a representation of $MA(\infty)$ process.

Next, we consider the relation $MA(q) \leftrightarrow AR(\infty)$

Let $MA(q)$ be **invertible** moving average process

$$Y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_p \epsilon_{t-p}.$$

Using the backshift operator we can write the $MA(q)$ process as

$$Y_t = (1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q) \epsilon_t.$$

Then,

$$Y_t = \theta(B) \epsilon_t,$$

where $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$. Hence, for an **invertible** moving average process, Y_t can be represented as a finite weighted sum of previous error terms, ϵ . Furthermore, since the process is invertible ϵ_t can be represented as an infinite weighted sum of previous Y 's as below

$$\epsilon_t = \theta^{-1}(B) Y_t,$$

where $\pi(B)\theta(B) = 1$, and $\pi(B) = 1 + \pi_1 B + \pi_2 B^2 + \dots$. Hence,

$$\epsilon_t = \pi(B) Y_t.$$

This is an representation of a $AR(\infty)$ process.

Dual relation 2

An $MA(q)$ process has an ACF function that is zero beyond lag q and its PACF is decays exponentially to 0. Consequently, an $AR(p)$ process has an PACF that is zero beyond lag- p , but its ACF decays exponentially to 0.

Dual relation 3

For an $AR(p)$ process the roots of $\phi(B) = 0$ must lie outside the unit circle to satisfy the condition of stationarity. However, the parameters of the $AR(p)$ are not required to satisfy any conditions to ensure invertibility. Conversely, the parameters of the MA process are not required to satisfy any condition to ensure stationarity. However, to ensure the condition of invertibility, the roots of $\theta(B) = 0$ must lie outside the unit circle.

2.5.4 Autoregressive and Moving-average (ARMA) models

current value = linear combination of past values + linear combination of past error + current error

The $ARMA(p, q)$ can be written as

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

where $\{\epsilon_t\}$ is a white noise process.

Using the back shift operator

$$\phi(B)Y_t = \theta(B)\epsilon_t,$$

where $\phi(\cdot)$ and $\theta(\cdot)$ are the p th and q th degree polynomials,

$$\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p,$$

and

$$\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q.$$

2.5.4.1 Stationary condition

Roots of

$$\phi(B) = 0$$

lie outside the unit circle.

2.5.4.2 Invertible condition

Roots of

$$\theta(B) = 0$$

lie outside the unit circle.

2.5.4.3 Autocorrelation function and Partial autocorrelation function

The ACF of an ARMA model exhibits a pattern similar to that of an AR model. The PACF of ARMA process behaves like the PACF of a MA process. Hence, the ACF and PACF are not informative in determining the order of an ARMA model.

2.6 Unit root tests

- Many financial time series are with trending behavior or nonstationarity in the mean.
- Two common trend removal or de-trending procedures
 - First differencing (appropriate for $I(1)$ time series).
 - time-trend regression (appropriate for trend stationary $I(0)$ time series).
- Unit root tests are statistical tests to determine the required order of differencing or whether it should be regressed on deterministic functions of time to render the data stationary.

2.6.1 Dickey-Fuller test

- Consider the model

$$\Delta y_t = c + \beta y_{t-1} + \epsilon_t$$

- Hypothesis to be tested $H_0 : \beta = 0$ and $H_1 : \beta < 0$
- Test statistics = $\frac{\hat{\beta}}{SE(\hat{\beta})}$

2.6.2 Augmented Dickey-Fuller test

- The Dickey-Fuller Unit Root Test is valid if the time series y_t is well characterized by an AR(1) model with white noise errors.
- Many financial time series have a more complicated dynamic structures
- The Augmented Dickey-Fuller (ADF) test allows for higher-order autoregressive processes by including Δy_{t-p} in the model.
- The number of lags included in the model should be just sufficient to remove any autocorrelation in errors.
- Consider the model:

$$\Delta y_t = c + \beta y_{t-1} + \alpha_1 \Delta y_{t-1} + \cdots + \alpha_p \Delta y_{t-p} + \epsilon_t$$

- Hypothesis to be tested $H_0 : \beta = 0$ and $H_1 : \beta < 0$
- ADF test: null hypothesis is that the data are non-stationary and non-seasonal.
- DF and ADF tests are not suitable when there is a deterministic trend

- Alternative tests:
 - Phillips-Perron Unit Root Tests
- The main difference between Phillips-Perron (PP) unit root tests and the ADF tests is in the way they deal with serial correlation and heteroskedasticity in the errors.

2.6.3 Stationarity Tests

- The ADF unit root test tests the null hypothesis that a time series y_t is $I(1)$.
- In contrast, Stationarity tests are for the null that y_t is $I(0)$.
- Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the most commonly used stationarity test that tests the null hypothesis that the data are stationary and non-seasonal.
- Other tests available for seasonal data

2.6.3.1 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test

```
google_2018 %>%
  features(Close, unitroot_kpss)

## # A tibble: 1 x 3
##   Symbol kpss_stat kpss_pvalue
##   <chr>      <dbl>      <dbl>
## 1 GOOG      0.573      0.0252

google_2018 %>%
  mutate(diff_close = difference(Close)) %>%
  features(diff_close, unitroot_kpss)

## # A tibble: 1 x 3
##   Symbol kpss_stat kpss_pvalue
##   <chr>      <dbl>      <dbl>
## 1 GOOG      0.0955      0.1

google_2018 %>%
  features(Close, unitroot_ndiffs)

## # A tibble: 1 x 2
##   Symbol ndiffs
##   <chr>   <int>
## 1 GOOG     1
```

2.6.3.2 Automatically selecting differences

STL decomposition: $y_t = T_t + S_t + R_t$

Seasonal strength $F_s = \max(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(S_t + R_t)})$

If $F_s > 0.64$, do one seasonal difference.

```
usmelec %>% mutate(log_gen = log(Generation)) %>%
  features(log_gen, list(unitroot_nsdiffs, feat_stl))
```

```
## # A tibble: 1 x 10
##   nsdiffs trend_strength seasonal_streng~ seasonal_peak_y~
##   <int>         <dbl>         <dbl>         <dbl>
## 1         1         0.994         0.941         7
## # ... with 6 more variables: seasonal_trough_year <dbl>,
## #   spikiness <dbl>, linearity <dbl>, curvature <dbl>,
## #   stl_e_acf1 <dbl>, stl_e_acf10 <dbl>
```

```
usmelec %>% mutate(log_gen = log(Generation)) %>%
  features(log_gen, unitroot_nsdiffs)
```

```
## # A tibble: 1 x 1
##   nsdiffs
##   <int>
## 1         1
```

```
usmelec %>% mutate(d_log_gen = difference(log(Generation), 12)) %>%
  features(d_log_gen, unitroot_ndiffs)
```

```
## # A tibble: 1 x 1
##   ndiffs
##   <int>
## 1         1
```

2.7 ARIMA modelling in R

2.7.1 How does ARIMA() work?

A non-seasonal ARIMA process

$$\phi(B)(1 - B)^d y_t = c + \theta(B)\varepsilon_t$$

Need to select appropriate orders: p, q, d

Hyndman and Khandakar (JSS, 2008) algorithm:

- Select no. differences d and D via KPSS test and seasonal strength measure.
- Select p, q by minimising AICc.
- Use step-wise search to traverse model space.

$$\text{AICc} = -2\log(L) + 2(p + q + k + 1) \left[1 + \frac{(p + q + k + 2)}{T - p - q - k - 2} \right].$$

where L is the maximised likelihood fitted to the *differenced* data, $k = 1$ if $c \neq 0$ and $k = 0$ otherwise.

Step1: Select current model (with smallest AICc) from:

ARIMA(2, d , 2)

ARIMA(0, d , 0)

ARIMA(1, d , 0)

ARIMA(0, d , 1)

Step 2: Consider variations of current model:

- vary one of p, q , from current model by ± 1 ;
- p, q both vary from current model by ± 1 ;
- Include/exclude c from current model.

Model with lowest AICc becomes current model.

Repeat Step 2 until no lower AICc can be found.

2.7.2 Choosing your own model

```
web_usage <- as_tsibble(WWWusage)
web_usage %>% gg_tsdisplay(value, plot_type = 'partial')
```



```
web_usage %>% mutate(diff = difference(value)) %>%
  gg_tsdisplay(diff, plot_type = 'partial')
```



```
fit <- web_usage %>%
  model(arima = ARIMA(value ~ pdq(3, 1, 0)))
report(fit)
```

```
## Series: value
```

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```
## Model: ARIMA(3,1,0)
##
## Coefficients:
##          ar1      ar2      ar3
##          1.151 -0.6612  0.3407
## s.e.    0.095   0.1353  0.0941
##
## sigma^2 estimated as 9.656:  log likelihood=-252
## AIC=512   AICc=512.4   BIC=522.4
```

```
web_usage %>%
  model(ARIMA(value ~ pdq(d=1))) %>%
  report()
```

```
## Series: value
## Model: ARIMA(1,1,1)
##
## Coefficients:
##          ar1      ma1
##          0.6504  0.5256
## s.e.    0.0842  0.0896
##
## sigma^2 estimated as 9.995:  log likelihood=-254.2
## AIC=514.3   AICc=514.5   BIC=522.1
```

```
web_usage %>%
  model(ARIMA(value ~ pdq(d=1),
    stepwise = FALSE, approximation = FALSE)) %>%
  report()
```

```
## Series: value
## Model: ARIMA(3,1,0)
##
## Coefficients:
##          ar1      ar2      ar3
##          1.151 -0.6612  0.3407
## s.e.    0.095   0.1353  0.0941
##
## sigma^2 estimated as 9.656:  log likelihood=-252
## AIC=512   AICc=512.4   BIC=522.4
```

```
gg_tsresiduals(fit)
```



```
augment(fit) %>%
  features(.resid, ljung_box, lag = 10, dof = 3)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
##   <chr>    <dbl>    <dbl>
## 1 arima      4.49      0.722
```

```
fit %>% forecast(h = 10) %>%
  autoplot(web_usage)
```



2.7.3 Modelling procedure with ARIMA()

1. Plot the data. Identify any unusual observations.
2. If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.
3. If the data are non-stationary: take first differences of the data until the data are stationary.
4. Examine the ACF/PACF: Is an $AR(p)$ or $MA(q)$ model appropriate?
5. Try your chosen model(s), and use the $AICc$ to search for a better model.
6. Check the residuals from your chosen model by plotting the ACF of the residuals, and doing a portmanteau test of the residuals. If they do not look like white noise, try a modified model.
7. Once the residuals look like white noise, calculate forecasts.

2.7.4 Automatic modelling procedure with ARIMA()

1. Plot the data. Identify any unusual observations.
2. If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.
3. Use ARIMA to automatically select a model.
6. Check the residuals from your chosen model by plotting the ACF of the residuals, and doing a portmanteau test of the residuals. If they do not look like white noise, try a modified model.
7. Once the residuals look like white noise, calculate forecasts.

2.7.5 Example in R

Seasonally adjusted electrical equipment

```
elecequip <- as_tsibble(fpp2::elecequip)
dcmp <- elecequip %>%
  model(STL(value ~ season(window = "periodic"))) %>%
  components() %>% select(-.model)
dcmp %>% as_tsibble %>%
  autoplot(season_adjust) + xlab("Year") +
  ylab("Seasonally adjusted new orders index")
```



```
dcmp %>% mutate(diff = difference(season_adjust)) %>%
  gg_tsdisplay(diff, plot_type = 'partial')
```



```
fit <- dcmp %>%
  model(arima = ARIMA(season_adjust))
report(fit)
```

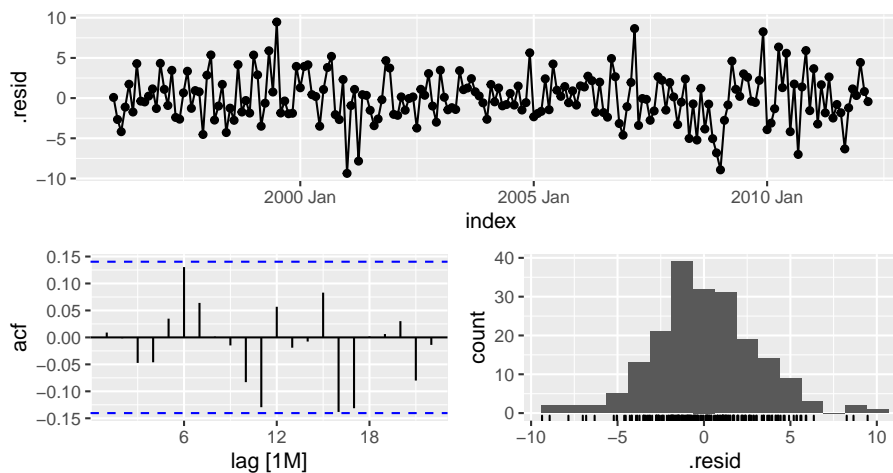
```
## Series: season_adjust
## Model: ARIMA(3,1,0)
##
## Coefficients:
##      ar1      ar2      ar3
```

```
##      -0.3418  -0.0426  0.3185
## s.e.   0.0681   0.0725  0.0682
##
## sigma^2 estimated as 9.639:  log likelihood=-493.8
## AIC=995.6   AICc=995.8   BIC=1009
```

```
fit <- dcmp %>%
  model(arima = ARIMA(season_adjust, approximation=FALSE))
report(fit)
```

```
## Series: season_adjust
## Model: ARIMA(3,1,1)
##
## Coefficients:
##      ar1      ar2      ar3      ma1
##      0.0044  0.0916  0.3698 -0.3921
## s.e.   0.2201  0.0984  0.0669  0.2426
##
## sigma^2 estimated as 9.577:  log likelihood=-492.7
## AIC=995.4   AICc=995.7   BIC=1012
```

```
gg_tsresiduals(fit)
```



```
augment(fit) %>%
  features(.resid, ljung_box, lag = 24, dof = 4)
```

```
## # A tibble: 1 x 3
##   .model lb_stat lb_pvalue
```

```
## <chr> <dbl> <dbl>
## 1 arima 24.0 0.241
```

```
fit %>% forecast %>% autoplot(dcmp)
```



2.8 Forecasting

2.8.1 Point forecasts

1. Rearrange ARIMA equation so y_t is on LHS.
2. Rewrite equation by replacing t by $T + h$.
3. On RHS, replace future observations by their forecasts, future errors by zero, and past errors by corresponding residuals.

Start with $h = 1$. Repeat for $h = 2, 3, \dots$

Example:

ARIMA(3,1,1) forecasts: Step 1

$$(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3)(1 - B)y_t = (1 + \theta_1 B)\varepsilon_t,$$

$$[1 - (1 + \phi_1)B + (\phi_1 - \phi_2)B^2 + (\phi_2 - \phi_3)B^3 + \phi_3B^4]y_t = (1 + \theta_1B)\varepsilon_t$$

$$y_t - (1 + \phi_1)y_{t-1} + (\phi_1 - \phi_2)y_{t-2} + (\phi_2 - \phi_3)y_{t-3} + \phi_3y_{t-4} = \varepsilon_t + \theta_1\varepsilon_{t-1}.$$

$$y_t = (1 + \phi_1)y_{t-1} - (\phi_1 - \phi_2)y_{t-2} - (\phi_2 - \phi_3)y_{t-3} - \phi_3y_{t-4} + \varepsilon_t + \theta_1\varepsilon_{t-1}.$$

2.8.1.1 Point forecasts (h=1)

$$y_t = (1 + \phi_1)y_{t-1} - (\phi_1 - \phi_2)y_{t-2} - (\phi_2 - \phi_3)y_{t-3} - \phi_3y_{t-4} + \varepsilon_t + \theta_1\varepsilon_{t-1}.$$

ARIMA(3,1,1) forecasts: Step 2

$$y_{T+1} = (1 + \phi_1)y_T - (\phi_1 - \phi_2)y_{T-1} - (\phi_2 - \phi_3)y_{T-2} - \phi_3y_{T-3} + \varepsilon_{T+1} + \theta_1\varepsilon_T.$$

ARIMA(3,1,1) forecasts: Step 3

$$\hat{y}_{T+1|T} = (1 + \phi_1)y_T - (\phi_1 - \phi_2)y_{T-1} - (\phi_2 - \phi_3)y_{T-2} - \phi_3y_{T-3} + \theta_1\varepsilon_T.$$

2.8.1.2 Point forecasts (h=2)

$$y_t = (1 + \phi_1)y_{t-1} - (\phi_1 - \phi_2)y_{t-2} - (\phi_2 - \phi_3)y_{t-3} - \phi_3y_{t-4} + \varepsilon_t + \theta_1\varepsilon_{t-1}.$$

ARIMA(3,1,1) forecasts: Step 2

$$y_{T+2} = (1 + \phi_1)y_{T+1} - (\phi_1 - \phi_2)y_T - (\phi_2 - \phi_3)y_{T-1} - \phi_3y_{T-2} + \varepsilon_{T+2} + \theta_1\varepsilon_{T+1}.$$

ARIMA(3,1,1) forecasts: Step 3

$$\hat{y}_{T+2|T} = (1 + \phi_1)\hat{y}_{T+1|T} - (\phi_1 - \phi_2)y_T - (\phi_2 - \phi_3)y_{T-1} - \phi_3y_{T-2}.$$

2.8.2 Prediction intervals

95% prediction interval

$$\hat{y}_{T+h|T} \pm 1.96\sqrt{v_{T+h|T}}$$

where $v_{T+h|T}$ is estimated forecast variance.

- $v_{T+1|T} = \hat{\sigma}^2$ for all ARIMA models regardless of parameters and orders.
- Multi-step prediction intervals for $ARIMA(0, 0, q)$:

$$y_t = \varepsilon_t + \sum_{i=1}^q \theta_i \varepsilon_{t-i}.$$

$$\hat{\sigma}_h = \hat{\sigma}^2 \left[1 + \sum_{i=1}^{h-1} \theta_i^2 \right], \quad \text{for } h = 2, 3, \dots$$

- AR(1): Rewrite as MA(∞) and use above result.
- Other models beyond scope of this subject.
- Prediction intervals **increase in size with forecast horizon**.
- Prediction intervals can be difficult to calculate by hand
- Calculations assume residuals are **uncorrelated** and **normally distributed**.
- Prediction intervals tend to be too narrow.
 - the uncertainty in the parameter estimates has not been accounted for.
 - the ARIMA model assumes historical patterns will not change during the forecast period.
 - the ARIMA model assumes uncorrelated future errors.

2.9 References:

- Brockwell, P. J., Brockwell, P. J., Davis, R. A., & Davis, R. A. (2016). Introduction to time series and forecasting. springer.
- Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.
- Zivot, E., & Wang, J. (2006). Unit root tests. Modeling Financial Time Series with S-PLUS®, 111-139.

Chapter 3

Exponential Smoothing

3.1 Introduction

3.1.1 Historical perspective

- Developed in the 1950s and 1960s as methods (algorithms) to produce point forecasts.
- Combine a “level”, “trend” (slope) and “seasonal” component to describe a time series.
- The rate of change of the components are controlled by “smoothing parameters”: α , β and γ respectively.
- Need to choose best values for the smoothing parameters (and initial states).
- Equivalent ETS state space models developed in the 1990s and 2000s.

3.1.2 Big idea: control the rate of change

α controls the flexibility of the **level**

- If $\alpha = 0$, the level never updates (mean)
- If $\alpha = 1$, the level updates completely (naive)

β controls the flexibility of the **trend**

- If $\beta = 0$, the trend is linear (regression trend)
- If $\beta = 1$, the trend updates every observation

γ controls the flexibility of the **seasonality**

3.2. ~~SIMPLE EXPONENTIAL SMOOTHING~~ SIMPLE EXPONENTIAL SMOOTHING

- If $\gamma = 0$, the seasonality is fixed (seasonal means)
- If $\gamma = 1$, the seasonality updates completely (seasonal naive)

3.1.3 A model for levels, trends, and seasonalities

We want a model that captures the level (ℓ_t), trend (b_t) and seasonality (s_t).

How do we combine these elements?

- Additively?

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$

- Multiplicatively?

$$y_t = \ell_{t-1} b_{t-1} s_{t-m} (1 + \varepsilon_t)$$

- Perhaps a mix of both?

$$y_t = (\ell_{t-1} + b_{t-1}) s_{t-m} + \varepsilon_t$$

How do the level, trend and seasonal components evolve over time?

General notation:

ETS: **E**xponen**T**ial **S**MOOTHING

Error: Additive ("A") or multiplicative ("M")

Trend: None ("N"), additive ("A"), multiplicative ("M"), or damped ("Ad" or "Md").

Seasonality: None ("N"), additive ("A") or multiplicative ("M")

3.2 Simple exponential smoothing

Time series y_1, y_2, \dots, y_T .

Random walk forecasts

$$\hat{y}_{T+h|T} = y_T$$

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Average forecasts

$$\hat{y}_{T+h|T} = \frac{1}{T} \sum_{t=1}^T y_t$$

- Want something in between these methods.
- Most recent data should have more weight.

Forecast equation

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1 - \alpha)y_{T-1} + \alpha(1 - \alpha)^2 y_{T-2} + \dots$$

where $0 \leq \alpha \leq 1$

Observation	Weights assigned to observations for:			
	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$
y_T	0.2	0.4	0.6	0.8
y_{T-1}	0.16	0.24	0.24	0.16
y_{T-2}	0.128	0.144	0.096	0.032
y_{T-3}	0.1024	0.0864	0.0384	0.0064
y_{T-4}	$(0.2)(0.8)^4$	$(0.4)(0.6)^4$	$(0.6)(0.4)^4$	$(0.8)(0.2)^4$
y_{T-5}	$(0.2)(0.8)^5$	$(0.4)(0.6)^5$	$(0.6)(0.4)^5$	$(0.8)(0.2)^5$

Component form

- Forecast equation $\hat{y}_{t+h|t} = \ell_t$
- Smoothing equation $\ell_t = \alpha y_t + (1 - \alpha)\ell_{t-1}$
- ℓ_t is the level (or the smoothed value) of the series at time t.
- $\hat{y}_{t+1|t} = \alpha y_t + (1 - \alpha)\hat{y}_{t|t-1}$
Iterate to get exponentially weighted moving average form.

Weighted average form

$$\hat{y}_{T+1|T} = \sum_{j=0}^{T-1} \alpha(1 - \alpha)^j y_{T-j} + (1 - \alpha)^T \ell_0$$

3.2.1 Optimising smoothing parameters

- Need to choose best values for α and ℓ_0 .
 - Similarly to regression, choose optimal parameters by minimising SSE:

$$\text{SSE} = \sum_{t=1}^T (y_t - \hat{y}_{t|t-1})^2.$$

3.2. SIMPLE EXPONENTIAL SMOOTHING

- Unlike regression there is no closed form solution — use numerical optimization.
- For Algerian Exports example:

- $\hat{\alpha} = 0.8400$
- $\hat{\ell}_0 = 39.54$



3.2.2 Models and methods

3.2.2.1 Methods

- Algorithms that return point forecasts.

3.2.2.2 Models

- Generate same point forecasts but can also generate forecast distributions.
- A stochastic (or random) data generating process that can generate an entire forecast distribution.
- Allow for “proper” model selection.

3.2.3 ETS(A,N,N): A model for SES

Component form

- Forecast equation: $\hat{y}_{t+h|t} = \ell_t$
- Smoothing equation: $\ell_t = \alpha y_t + (1 - \alpha)\ell_{t-1}$

Forecast error: $e_t = y_t - \hat{y}_{t|t-1} = y_t - \ell_{t-1}$

Error correction form

$$\begin{aligned} y_t &= \ell_{t-1} + e_t \\ \ell_t &= \ell_{t-1} + \alpha(y_t - \ell_{t-1}) \end{aligned}$$

$$\ell_t = \ell_{t-1} + \alpha e_t$$

Specify probability distribution for e_t , we assume $e_t = \varepsilon_t \sim \text{NID}(0, \sigma^2)$.

3.2.4 ETS(A,N,N)

- Measurement equation: $y_t = \ell_{t-1} + \varepsilon_t$
- State equation: $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$

where $\varepsilon_t \sim \text{NID}(0, \sigma^2)$.

- “innovations” or “single source of error” because equations have the same error process, ε_t .
 - Measurement equation: relationship between observations and states.
 - State equation(s): evolution of the state(s) through time.

3.2.5 ETS(M,N,N)

SES with multiplicative errors.

- Specify relative errors $\varepsilon_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}} \sim \text{NID}(0, \sigma^2)$
 - Substituting $\hat{y}_{t|t-1} = \ell_{t-1}$ gives:
 - * $y_t = \ell_{t-1} + \ell_{t-1} \varepsilon_t$
 - * $e_t = y_t - \hat{y}_{t|t-1} = \ell_{t-1} \varepsilon_t$
- Measurement equation: $y_t = \ell_{t-1}(1 + \varepsilon_t)$
- State equation: $\ell_t = \ell_{t-1}(1 + \alpha \varepsilon_t)$
- Models with additive and multiplicative errors with the same parameters generate the same point forecasts but different prediction intervals.

3.2.6 ETS(A,N,N): Specifying the model

```
ETS(y ~ error("A") + trend("N") + season("N"))
```

By default, an optimal value for α and ℓ_0 is used.

α can be chosen manually in `trend()`.

3.2. SIMPLE EXPONENTIAL SMOOTHING

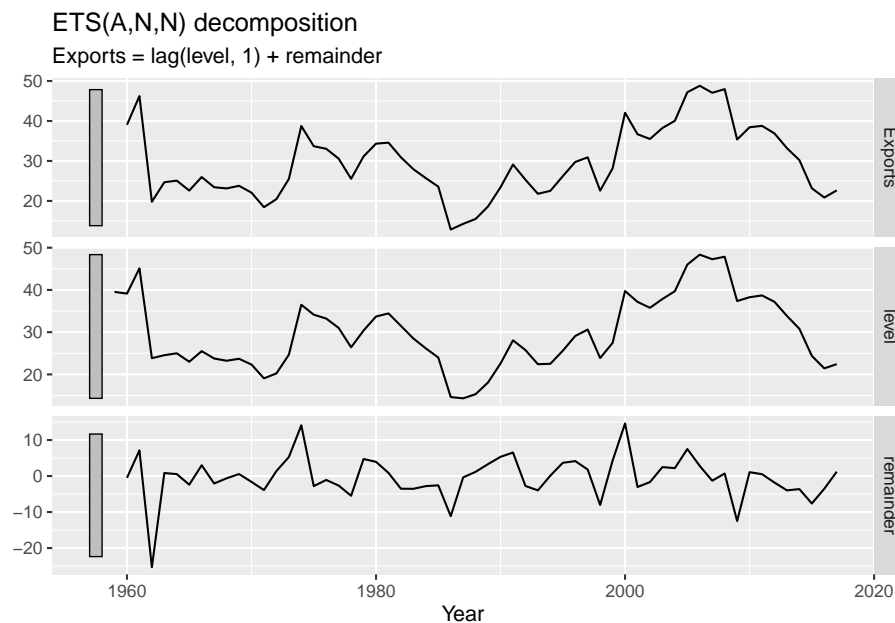
```
trend("N", alpha = 0.5)
trend("N", alpha_range = c(0.2, 0.8))
```

3.2.7 Example: Algerian Exports

```
algeria_economy <- global_economy %>%
  filter(Country == "Algeria")
fit <- algeria_economy %>%
  model(ANN = ETS(Exports ~ error("A") + trend("N") + season("N")))
report(fit)
```

```
## Series: Exports
## Model: ETS(A,N,N)
## Smoothing parameters:
##   alpha = 0.84
##
## Initial states:
##   1
## 39.54
##
## sigma^2: 35.63
##
## AIC AICc BIC
## 446.7 447.2 452.9
```

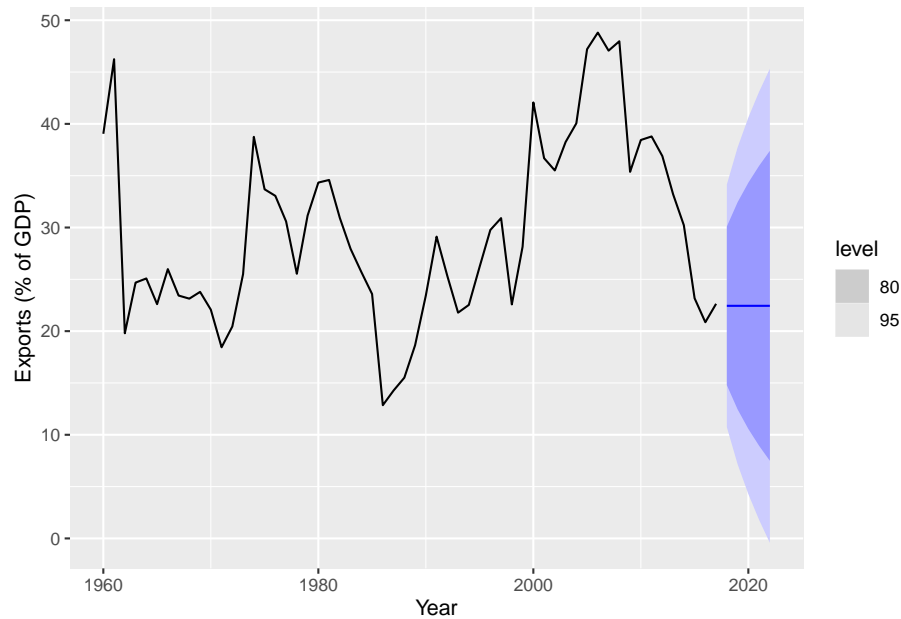
```
components(fit) %>% autoplot()
```

```
components(fit) %>%
  left_join(fitted(fit), by = c("Country", ".model", "Year"))
```

```
## # A dable:                59 x 7 [1Y]
## # Key:                  Country, .model [1]
## # ETS(A,N,N) Decomposition: Exports = lag(level, 1) +
## #   remainder
##   Country .model Year Exports level remainder .fitted
##   <fct>   <chr> <dbl> <dbl> <dbl>      <dbl> <dbl>
## 1 Algeria ANN  1959    NA    39.5     NA      NA      NA
## 2 Algeria ANN  1960    39.0   39.1  -0.496   39.5
## 3 Algeria ANN  1961    46.2   45.1    7.12    39.1
## 4 Algeria ANN  1962    19.8   23.8  -25.3    45.1
## 5 Algeria ANN  1963    24.7   24.6    0.841   23.8
## 6 Algeria ANN  1964    25.1   25.0    0.534   24.6
## 7 Algeria ANN  1965    22.6   23.0   -2.39    25.0
## 8 Algeria ANN  1966    26.0   25.5    3.00    23.0
## 9 Algeria ANN  1967    23.4   23.8   -2.07    25.5
## 10 Algeria ANN 1968    23.1   23.2   -0.630   23.8
## # ... with 49 more rows
```

```
fit %>%
  forecast(h = 5) %>%
  autoplot(algeria_economy) +
  ylab("Exports (% of GDP)") + xlab("Year")
```



3.3 Models with trend

3.3.1 Holt's linear trend

Component form

- Forecast $\hat{y}_{t+h|t} = \ell_t + hb_t$
- Level $\ell_t = \alpha y_t + (1 - \alpha)(\ell_{t-1} + b_{t-1})$
- Trend $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$
- Two smoothing parameters α and β^* ($0 \leq \alpha, \beta^* \leq 1$).
- ℓ_t level: weighted average between y_t and one-step ahead forecast for time t , ($\ell_{t-1} + b_{t-1} = \hat{y}_{t|t-1}$)
- b_t slope: weighted average of $(\ell_t - \ell_{t-1})$ and b_{t-1} , current and previous estimate of slope.
- Choose $\alpha, \beta^*, \ell_0, b_0$ to minimise SSE.

3.3.2 ETS(A,A,N)

Holt's linear method with additive errors.

- Assume $\varepsilon_t = y_t - \ell_{t-1} - b_{t-1} \sim \text{NID}(0, \sigma^2)$.

- Substituting into the error correction equations for Holt's linear method

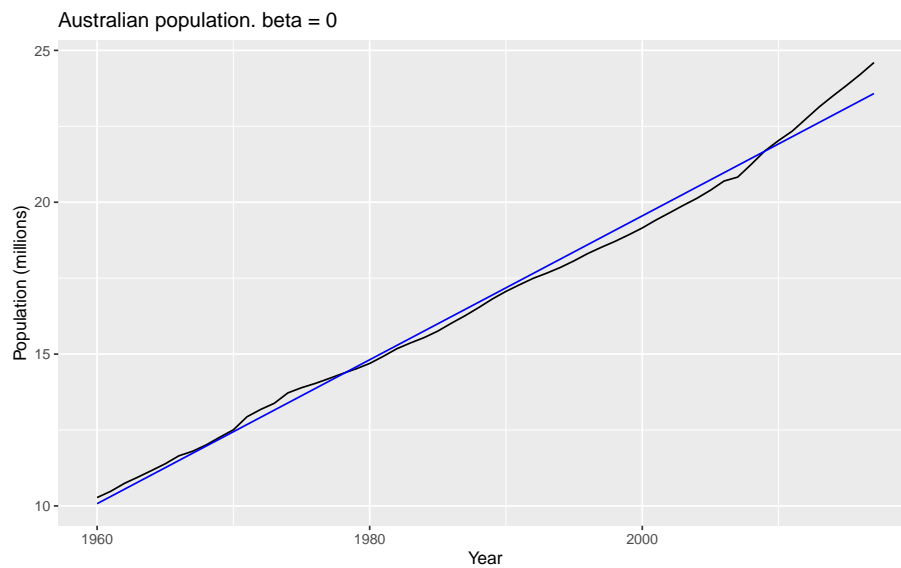
$$y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$$

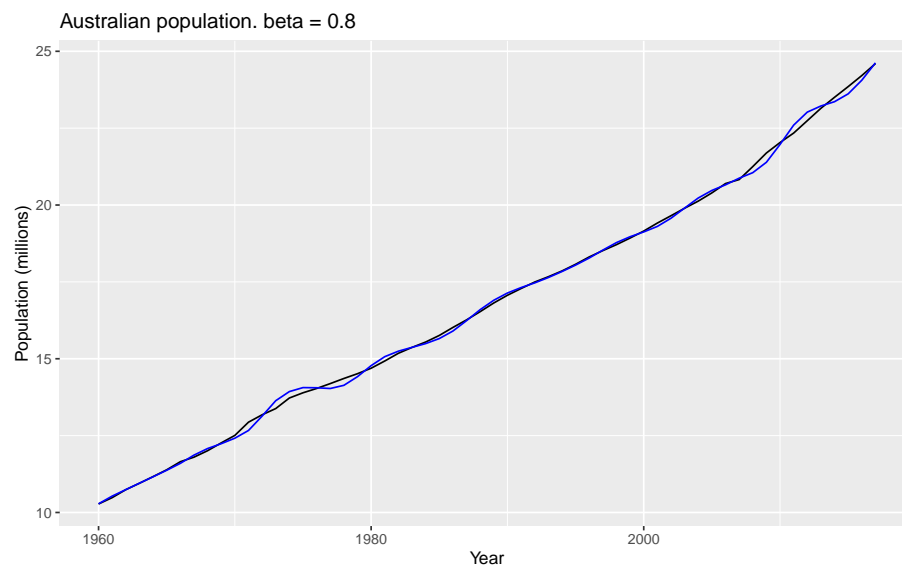
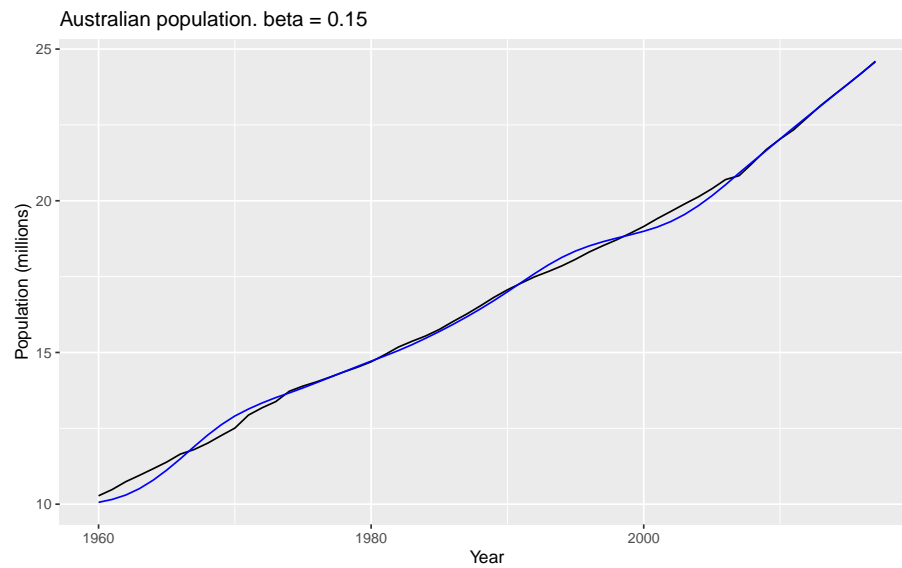
$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t$$

$$b_t = b_{t-1} + \alpha \beta^* \varepsilon_t$$

- For simplicity, set $\beta = \alpha \beta^*$.

3.3.3 Exponential smoothing: trend/slope





3.3.4 ETS(M,A,N)

Holt's linear method with multiplicative errors.

- Assume $\varepsilon_t = \frac{y_t - (\ell_{t-1} + b_{t-1})}{(\ell_{t-1} + b_{t-1})}$
- Following a similar approach as above, the innovations state space model underlying Holt's linear method with multiplicative errors is specified as

$$\begin{aligned}y_t &= (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t) \\ \ell_t &= (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t) \\ b_t &= b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t\end{aligned}$$

where again $\beta = \alpha\beta^*$ and $\varepsilon_t \sim \text{NID}(0, \sigma^2)$.

3.3.5 ETS(A,A,N): Specifying the model

```
ETS(y ~ error("A") + trend("A") + season("N"))
```

By default, optimal values for β and b_0 are used.

β can be chosen manually in `trend()`.

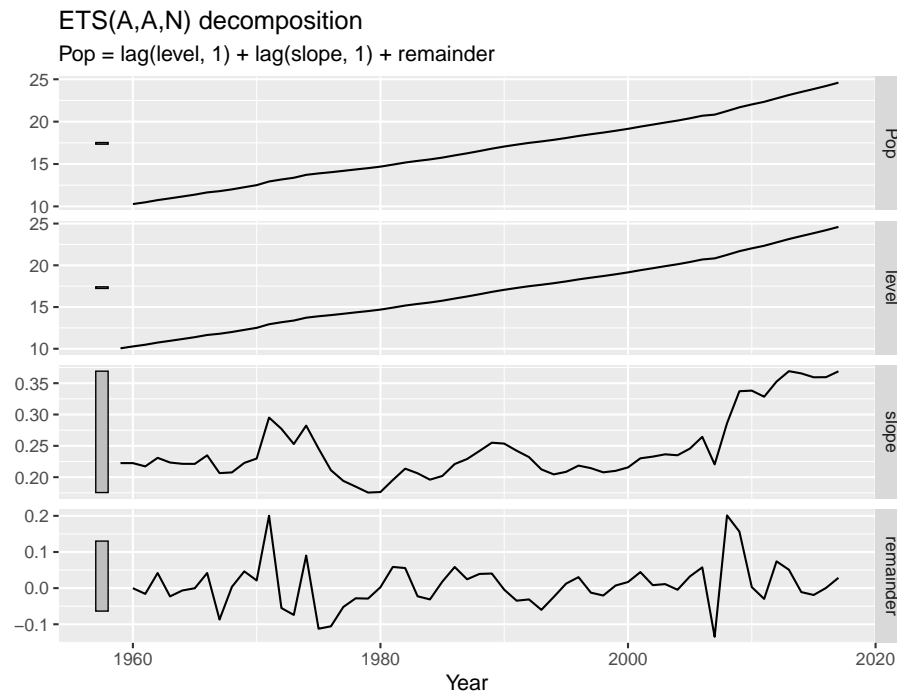
```
trend("A", beta = 0.004)
trend("A", beta_range = c(0, 0.1))
```

3.3.6 Example: Australian population

```
aus_economy <- global_economy %>% filter(Code == "AUS") %>%
  mutate(Pop = Population/1e6)
fit <- aus_economy %>%
  model(AAN = ETS(Pop ~ error("A") + trend("A") + season("N")))
report(fit)
```

```
## Series: Pop
## Model: ETS(A,A,N)
## Smoothing parameters:
##   alpha = 0.9999
##   beta  = 0.3266
##
## Initial states:
##   l      b
## 10.05 0.2225
##
## sigma^2: 0.0041
##
##   AIC   AICc   BIC
## -76.99 -75.83 -66.68
```

```
components(fit) %>% autoplot()
```

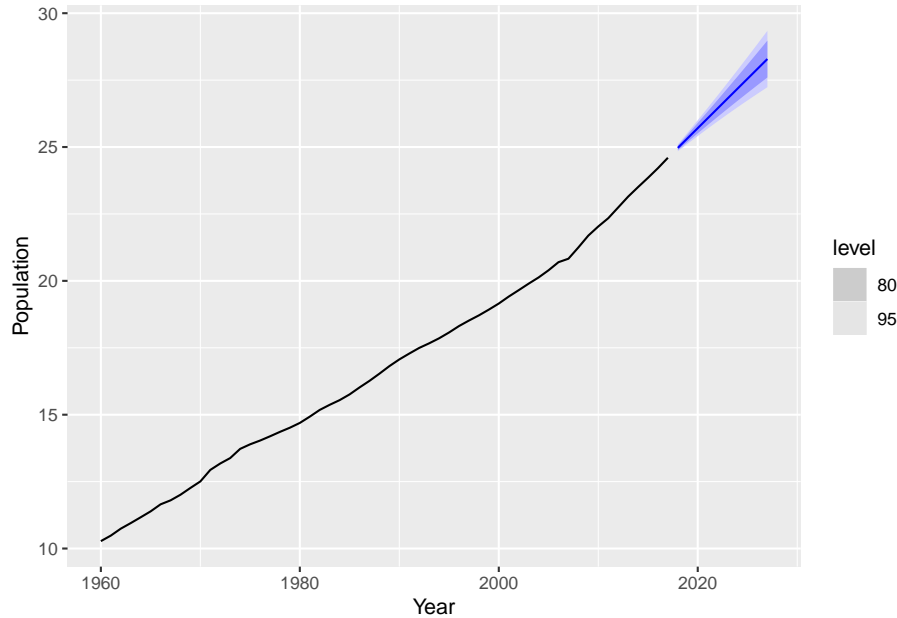


```
components(fit) %>%
  left_join(fitted(fit), by = c("Country", ".model", "Year"))
```

```
## # A dable:              59 x 8 [1Y]
## # Key:                Country, .model [1]
## # ETS(A,A,N) Decomposition: Pop = lag(level, 1) +
## #   lag(slope, 1) + remainder
##   Country .model Year  Pop level slope remainder .fitted
##   <fct>    <chr> <dbl> <dbl> <dbl> <dbl>      <dbl>   <dbl>
## 1 Austral~ AAN    1959  NA    10.1 0.222 NA         NA
## 2 Austral~ AAN    1960  10.3  10.3 0.222 -0.000145  10.3
## 3 Austral~ AAN    1961  10.5  10.5 0.217 -0.0159    10.5
## 4 Austral~ AAN    1962  10.7  10.7 0.231  0.0418    10.7
## 5 Austral~ AAN    1963  11.0  11.0 0.223 -0.0229    11.0
## 6 Austral~ AAN    1964  11.2  11.2 0.221 -0.00641   11.2
## 7 Austral~ AAN    1965  11.4  11.4 0.221 -0.000314  11.4
## 8 Austral~ AAN    1966  11.7  11.7 0.235  0.0418    11.6
## 9 Austral~ AAN    1967  11.8  11.8 0.206 -0.0869    11.9
## 10 Austral~ AAN    1968  12.0  12.0 0.208  0.00350   12.0
## # ... with 49 more rows
```

```
fit %>%
  forecast(h = 10) %>%
```

```
autoplot(aus_economy) +  
ylab("Population") + xlab("Year")
```



3.3.7 Damped trend method

Component form

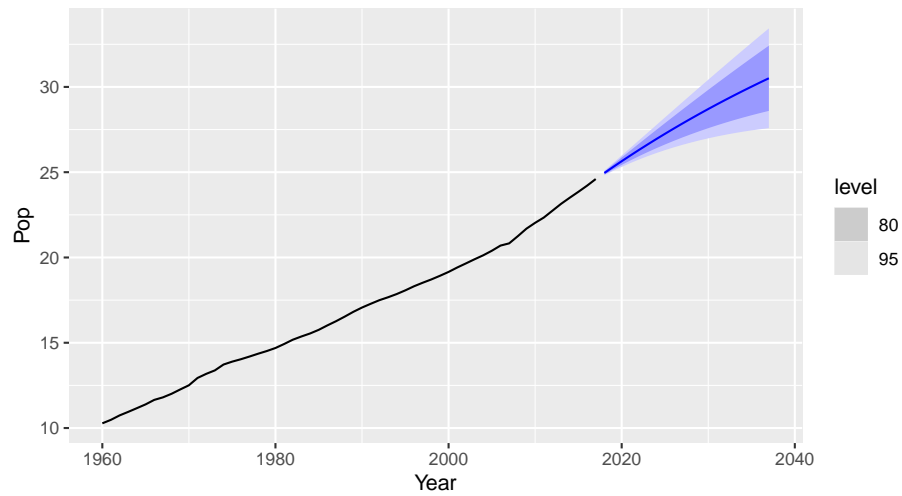
$$\begin{aligned}\hat{y}_{t+h|t} &= \ell_t + (\phi + \phi^2 + \dots + \phi^h)b_t \\ \ell_t &= \alpha y_t + (1 - \alpha)(\ell_{t-1} + \phi b_{t-1}) \\ b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)\phi b_{t-1}.\end{aligned}$$

- Damping parameter $0 < \phi < 1$.
- If $\phi = 1$, identical to Holt's linear trend.
- As $h \rightarrow \infty$, $\hat{y}_{T+h|T} \rightarrow \ell_T + \phi b_T / (1 - \phi)$.
- Short-run forecasts trended, long-run forecasts constant.

3.3.8 Example: Australian population

- Write down the model for ETS(A, A_d, N)

```
aus_economy %>%  
model(holt = ETS(Pop ~ error("A") + trend("Ad") + season("N"))) %>%  
forecast(h = 20) %>%  
autoplot(aus_economy)
```



```
fit <- aus_economy %>%
  filter(Year <= 2010) %>%
  model(
    ses = ETS(Pop ~ error("A") + trend("N") + season("N")),
    holt = ETS(Pop ~ error("A") + trend("A") + season("N")),
    damped = ETS(Pop ~ error("A") + trend("Ad") + season("N"))
  )

tidy(fit)
accuracy(fit)
```

	term	SES	Linear trend	Damped trend
	alpha	1.00	1.00	1.00
	beta*		0.30	0.40
	phi			0.98
	l_0	10.28	10.05	10.04
	b_0		0.22	0.25
	Training RMSE	0.24	0.06	0.07
	Test RMSE	1.63	0.15	0.21
	Test MASE	6.18	0.55	0.75
	Test MAPE	6.09	0.55	0.74
	Test MAE	1.45	0.13	0.18

3.4 Models with seasonality

3.4.1 Holt-Winters additive method

Holt and Winters extended Holt's method to capture seasonality.

Prepared by Dr. Priyanga D. Talagala (Copyright 2021 Priyanga D. Talagala)

Component form

$$\begin{aligned}\hat{y}_{t+h|t} &= \ell_t + hb_t + s_{t+h-m(k+1)} \\ \ell_t &= \alpha(y_t - s_{t-m}) + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \\ b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1} \\ s_t &= \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}\end{aligned}$$

- $k = \text{integer part of } (h - 1)/m$. Ensures estimates from the final year are used for forecasting.

– Parameters: $0 \leq \alpha \leq 1$, $0 \leq \beta^* \leq 1$, $0 \leq \gamma \leq 1 - \alpha$ and $m = \text{period of seasonality}$ (e.g. $m = 4$ for quarterly data).

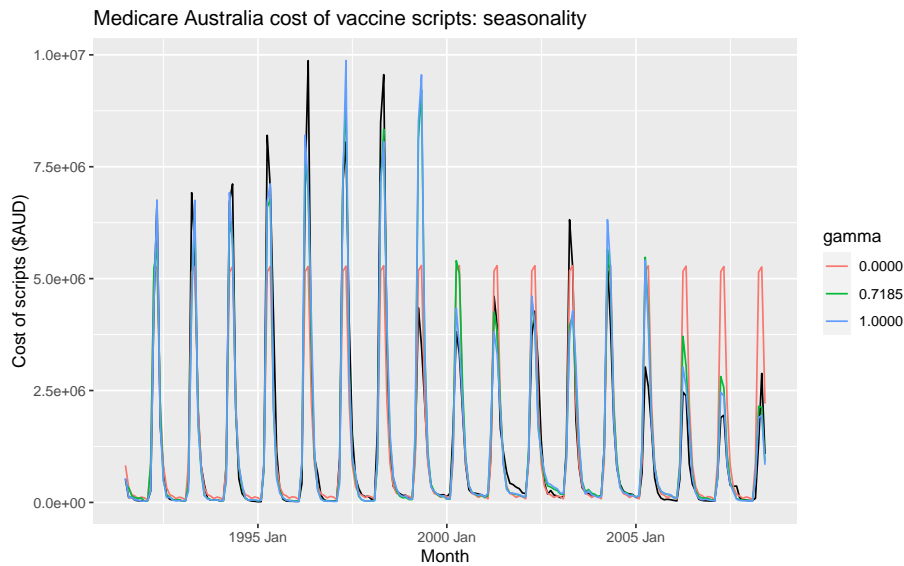
- Seasonal component is usually expressed as

$$s_t = \gamma^*(y_t - \ell_t) + (1 - \gamma^*)s_{t-m}.$$

- Substitute in for ℓ_t :

$$s_t = \gamma^*(1 - \alpha)(y_t - \ell_{t-1} - b_{t-1}) + [1 - \gamma^*(1 - \alpha)]s_{t-m}$$

- We set $\gamma = \gamma^*(1 - \alpha)$.
- The usual parameter restriction is $0 \leq \gamma^* \leq 1$, which translates to $0 \leq \gamma \leq (1 - \alpha)$.



3.4.2 ETS(A,A,A)

Holt-Winters additive method with additive errors.

- Forecast equation $\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)}$
- Observation equation $y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$
- State equations

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

$$b_t = b_{t-1} + \beta\varepsilon_t$$

$$s_t = s_{t-m} + \gamma\varepsilon_t$$

- Forecast errors: $\varepsilon_t = y_t - \hat{y}_{t|t-1}$
- k is integer part of $(h-1)/m$

Activity

- Write down the model for ETS(A,N,A)

3.4.3 Holt-Winters multiplicative method

For when seasonal variations are changing proportional to the level of the series.

Component form

$$\hat{y}_t + ht = (\ell_t + hb_t)s_{t+h-m(k+1)}$$

$$\ell_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1})$$

$b_{\{t\}} \&=$

$$\beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$$

$$s_t = \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}$$

- k is integer part of $(h-1)/m$.
- With additive method s_t is in absolute terms:
within each year $\sum_i s_i \approx 0$.
- With multiplicative method s_t is in relative terms:
within each year $\sum_i s_i \approx m$.

3.4.4 ETS(M,A,M)

Holt-Winters multiplicative method with multiplicative errors.

- Forecast equation $\hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t+h-m(k+1)}$
- Observation equation $y_t = (\ell_{t-1} + b_{t-1})s_{t-m}(1 + \varepsilon_t)$

- State equations

$$\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$$

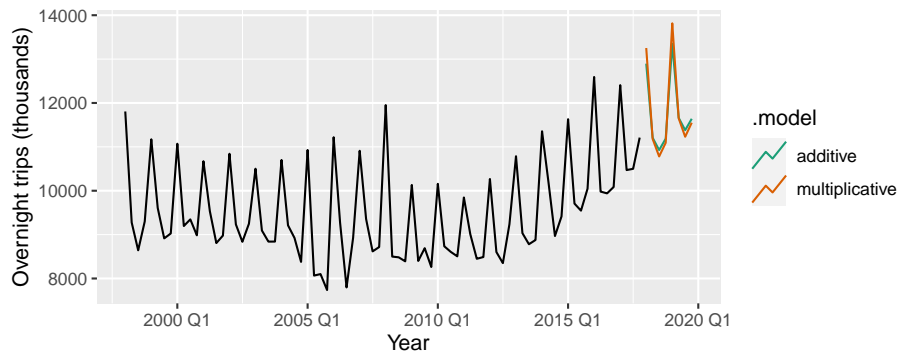
$$b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$$

$$s_t = s_{t-m}(1 + \gamma\varepsilon_t)$$

- Forecast errors: $\varepsilon_t = (y_t - \hat{y}_{t|t-1})/\hat{y}_{t|t-1}$
- k is integer part of $(h-1)/m$.

3.4.5 Example: Australian holiday tourism

```
aus_holidays <- tourism %>%
  filter(Purpose == "Holiday") %>%
  summarise(Trips = sum(Trips))
fit <- aus_holidays %>%
  model(
    additive = ETS(Trips ~ error("A") + trend("A") + season("A")),
    multiplicative = ETS(Trips ~ error("M") + trend("A") + season("M"))
  )
fc <- fit %>% forecast()
```

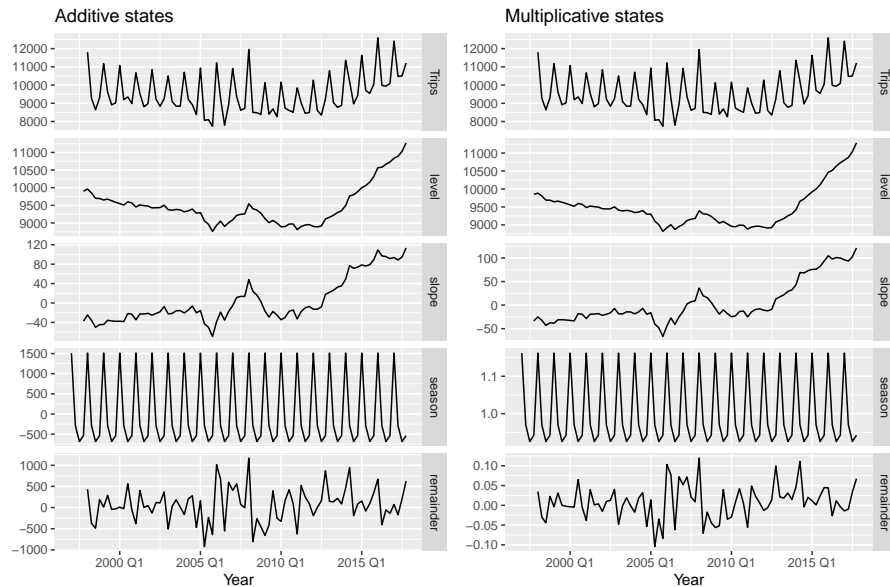


Estimated components

```
components(fit)
```

```
## # A tibble: 168 x 7 [1Q]
## # Key: .model [2]
## # ETS(A,A,A) & ETS(M,A,M) Decomposition: Trips = lag(level,
## # 1) + lag(slope, 1) + lag(season, 4) + remainder
##   .model  Quarter Trips level slope season remainder
##   <chr>    <qtr>   <dbl> <dbl> <dbl> <dbl>      <dbl>
## 1 additive 1997 Q1    NA     NA    NA    1512.      NA
## 2 additive 1997 Q2    NA     NA    NA   -290.      NA
## 3 additive 1997 Q3    NA     NA    NA   -684.      NA
```

```
## 4 additive 1997 Q4 NA 9899. -37.4 -538. NA
## 5 additive 1998 Q1 11806. 9964. -24.5 1512. 433.
## 6 additive 1998 Q2 9276. 9851. -35.6 -290. -374.
## 7 additive 1998 Q3 8642. 9700. -50.2 -684. -489.
## 8 additive 1998 Q4 9300. 9694. -44.6 -538. 188.
## 9 additive 1999 Q1 11172. 9652. -44.3 1512. 10.7
## 10 additive 1999 Q2 9608. 9676. -35.6 -290. 290.
## # ... with 158 more rows
```



3.4.6 Holt-Winters damped method

Often the single most accurate forecasting method for seasonal data:

$$\begin{aligned}\hat{y}_{t+h|t} &= [\ell_t + (\phi + \phi^2 + \dots + \phi^h)b_t]s_{t+h-m(k+1)} \\ \ell_t &= \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1} + \phi b_{t-1}) \\ b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1} \\ s_t &= \gamma \frac{y_t}{(\ell_{t-1} + \phi b_{t-1})} + (1-\gamma)s_{t-m}\end{aligned}$$

3.5 Innovations state space models

3.5.1 Exponential smoothing methods

	Trend Component	Seasonal 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)

- (N, N) : Simple exponential smoothing
- (A, N) : Holt's linear method
- (A_d, N) : Additive damped trend method
- (A, A) : Additive Holt-Winters' method
- (A, M) : Multiplicative Holt-Winters' method
- (A_d, M) : Damped multiplicative Holt-Winters' method

There are also multiplicative trend methods (not recommended).

3.5.2 ETS models

Additive Error

	Trend Component	Seasonal Component		
		N (None)	A (Additive)	M (Multiplicative)
N	(None)	(A, N, N)	(A, N, A)	(A, N, M)
A	(Additive)	(A, A, N)	(A, A, A)	(A, A, M)
A_d	(Additive damped)	(A, A_d, N)	(A, A_d, A)	(A, A_d, M)

Multiplicative Error

	Trend Component	Seasonal Component		
		N (None)	A (Additive)	M (Multiplicative)
N	(None)	(M, N, N)	(M, N, A)	(M, N, M)
A	(Additive)	(M, A, N)	(M, A, A)	(M, A, M)
A_d	(Additive damped)	(M, A_d, N)	(M, A_d, A)	(M, A_d, M)

3.5.3 Additive error models

Trend	Seasonal		
	N	A	M
N	$y_t = \ell_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$	$y_t = \ell_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$y_t = \ell_{t-1} s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha \varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma \varepsilon_t / \ell_{t-1}$
A	$y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t$ $b_t = b_{t-1} + \beta \varepsilon_t$	$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t$ $b_t = b_{t-1} + \beta \varepsilon_t$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1}) s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t / s_{t-m}$ $b_t = b_{t-1} + \beta \varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma \varepsilon_t / (\ell_{t-1} + b_{t-1})$
Ad	$y_t = \ell_{t-1} + \phi b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t$ $b_t = \phi b_{t-1} + \beta \varepsilon_t$	$y_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t$ $b_t = \phi b_{t-1} + \beta \varepsilon_t$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1}) s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t / s_{t-m}$ $b_t = \phi b_{t-1} + \beta \varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma \varepsilon_t / (\ell_{t-1} + \phi b_{t-1})$

3.5.4 Multiplicative error models

Trend	Seasonal		
	N	A	M
N	$y_t = \ell_{t-1}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha \varepsilon_t)$	$y_t = (\ell_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \alpha(\ell_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + s_{t-m})\varepsilon_t$	$y_t = \ell_{t-1} s_{t-m}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha \varepsilon_t)$ $s_t = s_{t-m}(1 + \gamma \varepsilon_t)$
A	$y_t = (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha \varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1}) s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha \varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma \varepsilon_t)$
Ad	$y_t = (\ell_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha \varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1}) s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha \varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma \varepsilon_t)$

3.5.5 Estimating ETS models

- Smoothing parameters α , β , γ and ϕ , and the initial states ℓ_0 , b_0 , s_0 , s_{-1}, \dots, s_{-m+1} are estimated by maximising the “likelihood” = the probability of the data arising from the specified model.
- For models with additive errors equivalent to minimising SSE.
- For models with multiplicative errors, **not** equivalent to minimising SSE.

3.5.6 Innovations state space models

Let $\mathbf{x}_t = (\ell_t, b_t, s_t, s_{t-1}, \dots, s_{t-m+1})$ and $\varepsilon_t \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$.

$$\begin{aligned} y_t &= \underbrace{h(\mathbf{x}_{t-1})}_{\mu_t} + \underbrace{k(\mathbf{x}_{t-1})\varepsilon_t}_{e_t} \\ \mathbf{x}_t &= f(\mathbf{x}_{t-1}) + g(\mathbf{x}_{t-1})\varepsilon_t \end{aligned}$$

Additive errors

$$k(x) = 1. \quad y_t = \mu_t + \varepsilon_t.$$

Multiplicative errors

$$\begin{aligned} k(\mathbf{x}_{t-1}) &= \mu_t. \quad y_t = \mu_t(1 + \varepsilon_t). \\ \varepsilon_t &= (y_t - \mu_t)/\mu_t \text{ is relative error.} \end{aligned}$$

3.5.7 Innovations state space models

Estimation

$$\begin{aligned} L^*(\cdot, \mathbf{x}_0) &= T \log \left(\sum_{t=1}^T \varepsilon_t^2 \right) + 2 \sum_{t=1}^T \log |k(\mathbf{x}_{t-1})| \\ &= -2 \log(\text{Likelihood}) + \text{constant} \end{aligned}$$

- Estimate parameters $(\alpha, \beta, \gamma, \phi)$ and initial states $\mathbf{x}_0 = (\ell_0, b_0, s_0, s_{-1}, \dots, s_{-m+1})$ by minimizing L^* .

3.5.8 Parameter restrictions

3.5.8.1 Usual region

- Traditional restrictions in the methods $0 < \alpha, \beta^*, \gamma^*, \phi < 1$ (equations interpreted as weighted averages).
- In models we set $\beta = \alpha\beta^*$ and $\gamma = (1 - \alpha)\gamma^*$.
- Therefore $0 < \alpha < 1$, $0 < \beta < \alpha$ and $0 < \gamma < 1 - \alpha$.
- $0.8 < \phi < 0.98$ — to prevent numerical difficulties.

3.5.8.2 Admissible region

- To prevent observations in the distant past having a continuing effect on current forecasts.
- Usually (but not always) less restrictive than the *traditional* region.
- For example for ETS(A,N,N):
traditional $0 < \alpha < 1$ — *admissible* is $0 < \alpha < 2$.

3.5.9 Model selection

Akaike's Information Criterion

$$\text{AIC} = -2 \log(L) + 2k$$

where L is the likelihood and k is the number of parameters initial states estimated in the model.

Corrected AIC

$$\text{AIC}_c = \text{AIC} + \frac{2(k+1)(k+2)}{T-k}$$

which is the AIC corrected (for small sample bias).

Bayesian Information Criterion

$$\text{BIC} = \text{AIC} + k(\log(T) - 2).$$

3.5.10 AIC and cross-validation

Minimizing the AIC assuming Gaussian residuals is asymptotically equivalent to minimizing one-step time series cross validation MSE.

3.5.11 Automatic forecasting

From Hyndman et al. (IJF, 2002):

- Apply each model that is appropriate to the data. Optimize parameters and initial values using MLE (or some other criterion).
- Select best method using AICc:
- Produce forecasts using best method.
- Obtain forecast intervals using underlying state space model.

Method performed very well in M3 competition.

3.5.12 Example: National populations

```
fit <- global_economy %>%
  mutate(Pop = Population / 1e6) %>%
  model(ets = ETS(Pop))
fit
```



```
## # A mable: 263 x 2
## # Key:      Country [263]
##      Country      ets
##      <fct>        <model>
## 1 Afghanistan    <ETS(A,A,N)>
## 2 Albania         <ETS(M,A,N)>
## 3 Algeria         <ETS(M,A,N)>
## 4 American Samoa <ETS(M,A,N)>
## 5 Andorra         <ETS(M,A,N)>
## 6 Angola          <ETS(M,A,N)>
## 7 Antigua and Barbuda <ETS(M,A,N)>
## 8 Arab World      <ETS(M,A,N)>
## 9 Argentina       <ETS(A,A,N)>
## 10 Armenia        <ETS(M,A,N)>
## # ... with 253 more rows
```

```
fit %>%
  forecast(h = 5)
```

```
## # A fable: 1,315 x 5 [1Y]
## # Key:      Country, .model [263]
##      Country .model Year      Pop .mean
##      <fct>   <chr>  <dbl>    <dist> <dbl>
## 1 Afghanistan ets    2018    N(36, 0.012) 36.4
## 2 Afghanistan ets    2019    N(37, 0.059) 37.3
## 3 Afghanistan ets    2020    N(38, 0.16) 38.2
## 4 Afghanistan ets    2021    N(39, 0.35) 39.0
## 5 Afghanistan ets    2022    N(40, 0.64) 39.9
## 6 Albania     ets    2018    N(2.9, 0.00012) 2.87
## 7 Albania     ets    2019    N(2.9, 6e-04) 2.87
## 8 Albania     ets    2020    N(2.9, 0.0017) 2.87
## 9 Albania     ets    2021    N(2.9, 0.0036) 2.86
## 10 Albania    ets    2022    N(2.9, 0.0066) 2.86
## # ... with 1,305 more rows
```

3.5.13 Example: Australian holiday tourism

```
holidays <- tourism %>%
  filter(Purpose == "Holiday")
fit <- holidays %>% model(ets = ETS(Trips))
fit
```

```
## # A mable: 76 x 4
## # Key:      Region, State, Purpose [76]
##      Region      State      Purpose      ets
##      <chr>        <chr>      <chr>        <model>
## 1 New South Wales New South Wales Holiday ETS(M,A,N)
```

3.5. INNOVATIONS STATE SPACE MODEL EXponential SMOOTHING

```
## 1 Adelaide          South Austral~ Holiday <ETS(A,N,A)>
## 2 Adelaide Hills    South Austral~ Holiday <ETS(A,A,N)>
## 3 Alice Springs     Northern Terr~ Holiday <ETS(M,N,A)>
## 4 Australia's Coral Co~ Western Austr~ Holiday <ETS(M,N,A)>
## 5 Australia's Golden O~ Western Austr~ Holiday <ETS(M,N,M)>
## 6 Australia's North We~ Western Austr~ Holiday <ETS(A,N,A)>
## 7 Australia's South We~ Western Austr~ Holiday <ETS(M,N,M)>
## 8 Ballarat          Victoria      Holiday <ETS(M,N,A)>
## 9 Barkly            Northern Terr~ Holiday <ETS(A,N,A)>
## 10 Barossa          South Austral~ Holiday <ETS(A,N,N)>
## # ... with 66 more rows
```

```
fit %>%
  filter(Region == "Snowy Mountains") %>%
  report()
```

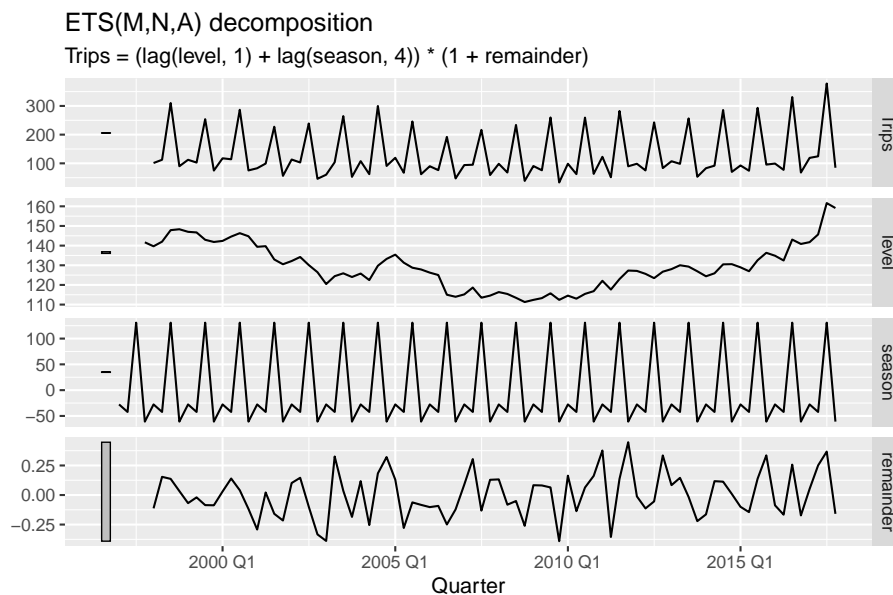
```
## Series: Trips
## Model: ETS(M,N,A)
## Smoothing parameters:
##   alpha = 0.1571
##   gamma = 0.0001001
##
## Initial states:
##   l      s1      s2      s3      s4
## 141.7 -60.96 130.9 -42.24 -27.66
##
## sigma^2: 0.0388
##
## AIC AICc BIC
## 852.0 853.6 868.7
```

```
fit %>%
  filter(Region == "Snowy Mountains") %>%
  components(fit)
```

```
## # A dable:              84 x 9 [1Q]
## # Key:                  Region, State, Purpose, .model
## #   [1]
## # ETS(M,N,A) Decomposition: Trips = (lag(level, 1) +
## #   lag(season, 4)) * (1 + remainder)
##   Region State Purpose .model Quarter Trips level season
##   <chr>   <chr> <chr>   <chr>   <qtr> <dbl> <dbl> <dbl>
## 1 Snowy~ New ~ Holiday ets    1997 Q1  NA     NA    -27.7
## 2 Snowy~ New ~ Holiday ets    1997 Q2  NA     NA    -42.2
## 3 Snowy~ New ~ Holiday ets    1997 Q3  NA     NA    131.
## 4 Snowy~ New ~ Holiday ets    1997 Q4  NA    142.  -61.0
## 5 Snowy~ New ~ Holiday ets    1998 Q1 101.   140.  -27.7
## 6 Snowy~ New ~ Holiday ets    1998 Q2 112.   142.  -42.2
```

```
## 7 Snowy~ New ~ Holiday ets    1998 Q3 310.   148.   131.
## 8 Snowy~ New ~ Holiday ets    1998 Q4  89.8  148.  -61.0
## 9 Snowy~ New ~ Holiday ets    1999 Q1 112.   147.  -27.7
## 10 Snowy~ New ~ Holiday ets   1999 Q2 103.   147.  -42.2
## # ... with 74 more rows, and 1 more variable:
## #   remainder <dbl>
```

```
fit %>%
  filter(Region == "Snowy Mountains") %>%
  components(fit) %>%
  autoplot()
```



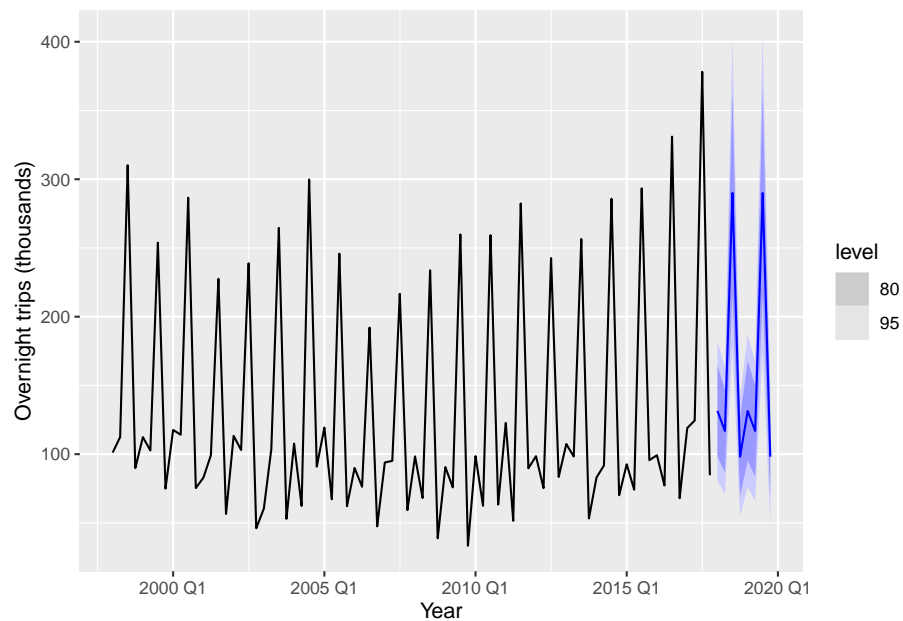
```
fit %>% forecast()
```

```
## # A tibble: 608 x 7 [1Q]
## # Key:   Region, State, Purpose, .model [76]
##   Region State Purpose .model Quarter      Trips .mean
##   <chr>   <chr>   <chr>   <chr>   <qtr>     <dist> <dbl>
## 1 Adelaide South ~ Holiday ets    2018 Q1 N(210, 457) 210.
## 2 Adelaide South ~ Holiday ets    2018 Q2 N(173, 473) 173.
## 3 Adelaide South ~ Holiday ets    2018 Q3 N(169, 489) 169.
## 4 Adelaide South ~ Holiday ets    2018 Q4 N(186, 505) 186.
## 5 Adelaide South ~ Holiday ets    2019 Q1 N(210, 521) 210.
## 6 Adelaide South ~ Holiday ets    2019 Q2 N(173, 537) 173.
## 7 Adelaide South ~ Holiday ets    2019 Q3 N(169, 553) 169.
## 8 Adelaide South ~ Holiday ets    2019 Q4 N(186, 569) 186.
## 9 Adelaid~ South ~ Holiday ets    2018 Q1  N(19, 36)  19.4
```

3.5. INNOVATIONS STATE SPACE MODEL: EXPONENTIAL SMOOTHING

```
## 10 Adelaide~ South ~ Holiday ets      2018 Q2      N(20, 36)  19.6
## # ... with 598 more rows
```

```
fit %>%
  forecast() %>%
  filter(Region == "Snowy Mountains") %>%
  autoplot(holidays) +
  xlab("Year") + ylab("Overnight trips (thousands)")
```



3.5.14 Some unstable models

- Some of the combinations of (Error, Trend, Seasonal) can lead to numerical difficulties; see equations with division by a state.
- These are: ETS(A,N,M), ETS(A,A,M), ETS(A,A_d,M).
- Models with multiplicative errors are useful for strictly positive data, but are not numerically stable with data containing zeros or negative values. In that case only the six fully additive models will be applied.

3.5.15 Exponential smoothing models

Additive Error

Prepared by Dr. Priyanga D. Talagala (Copyright 2021 Priyanga D. Talagala)

		Seasonal Component		
	Trend Component	N (None)	A (Additive)	M (Multiplicative)
N	(None)	(A, N, N)	(A, N, A)	
A	(Additive)	(A, A, N)	(A, A, A)	
A _d	(Additive damped)	(A, A _d , N)	(A, A _d , A)	

3.5. INNOVATIONS STATE SPACE MODEL EXponential SMOOTHING

Multiplicative Error

	Trend Component	Seasonal Component		
		N (None)	A (Additive)	M (Multiplicative)
N	(None)	(M, N, N)	(M, N, A)	(M, N, M)
A	(Additive)	(M, A, N)	(M, A, A)	(M, A, M)
A_d	(Additive damped)	(M, A_d, N)	(M, A_d, A)	(M, A_d, M)

3.5.16 Residuals

Response residuals

$$\hat{e}_t = y_t - \hat{y}_{t|t-1}$$

Innovation residuals

Additive error model:

$$\hat{\varepsilon}_t = y_t - \hat{y}_{t|t-1}$$

Multiplicative error model:

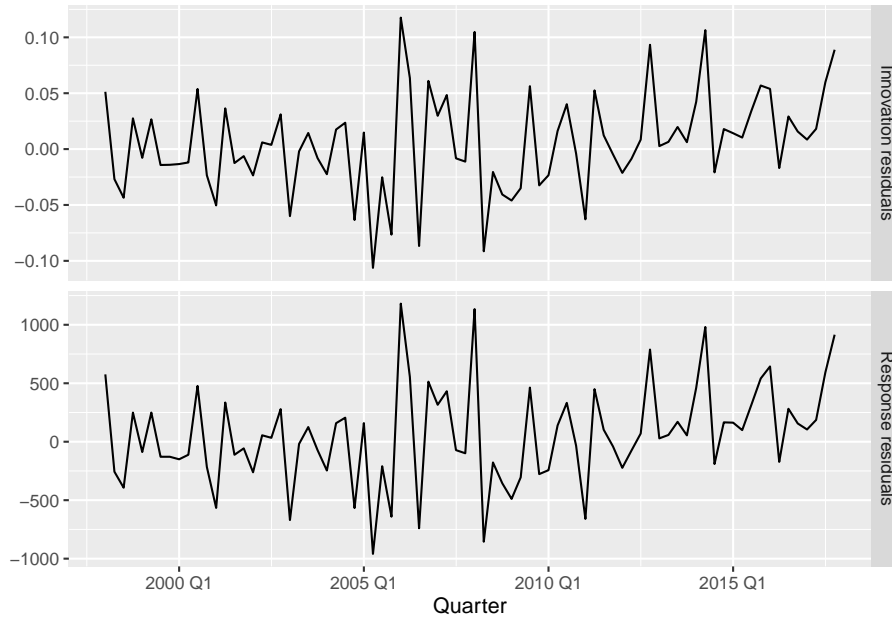
$$\hat{\varepsilon}_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}}$$

3.5.17 Example: Australian holiday tourism

```
aus_holidays <- tourism %>%
  filter(Purpose == "Holiday") %>%
  summarise(Trips = sum(Trips))
fit <- aus_holidays %>%
  model(ets = ETS(Trips)) %>%
  report()
```

```
## Series: Trips
## Model: ETS(M,N,M)
## Smoothing parameters:
##   alpha = 0.3578
##   gamma = 0.0009686
##
## Initial states:
##   l    s1    s2    s3    s4
## 9667 0.943 0.9268 0.9684 1.162
##
## sigma^2: 0.0022
##
## AIC AICc BIC
## 1331 1333 1348
```

```
residuals(fit)
residuals(fit, type = "response")
```



3.6 Forecasting with exponential smoothing

3.6.1 Forecasting with ETS models

Point forecasts: iterate the equations for $t = T + 1, T + 2, \dots, T + h$ and set all $\varepsilon_t = 0$ for $t > T$.

- Not the same as $E(y_{t+h}|\mathbf{x}_t)$ unless trend and seasonality are both additive.
- Point forecasts for ETS(A,,) are identical to ETS(M,,) if the parameters are the same.

3.6.2 Example: ETS(A,A,N)

$$\begin{aligned}
 y_{T+1} &= \ell_T + b_T + \varepsilon_{T+1} \\
 \hat{y}_{T+1|T} &= \ell_T + b_T \\
 y_{T+2} &= \ell_{T+1} + b_{T+1} + \varepsilon_{T+2} \\
 &= (\ell_T + b_T + \alpha\varepsilon_{T+1}) + (b_T + \beta\varepsilon_{T+1}) + \varepsilon_{T+2} \\
 \hat{y}_{T+2|T} &= \ell_T + 2b_T
 \end{aligned}$$

etc.

3.6.3 Example: ETS(M,A,N)

$$\begin{aligned}
 y_{T+1} &= (\ell_T + b_T)(1 + \varepsilon_{T+1}) \\
 \hat{y}_{T+1|T} &= \ell_T + b_T. \\
 y_{T+2} &= (\ell_{T+1} + b_{T+1})(1 + \varepsilon_{T+2}) \\
 &= \{(\ell_T + b_T)(1 + \alpha\varepsilon_{T+1}) + [b_T + \beta(\ell_T + b_T)\varepsilon_{T+1}]\} (1 + \varepsilon_{T+2}) \\
 \hat{y}_{T+2|T} &= \ell_T + 2b_T
 \end{aligned}$$

etc.

3.6.4 Forecasting with ETS models

Prediction intervals: can only generated using the models.

- The prediction intervals will differ between models with additive and multiplicative errors.
- Exact formulae for some models.
- More general to simulate future sample paths, conditional on the last estimate of the states, and to obtain prediction intervals from the percentiles of these simulated future paths.

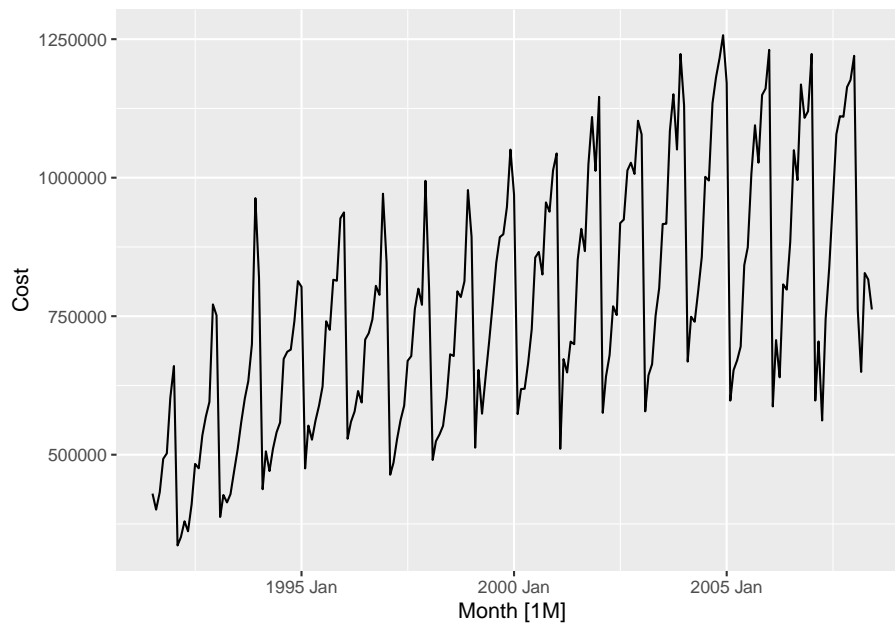
3.6.5 Prediction intervals

PI for most ETS models: $\hat{y}_{T+h|T} \pm c\sigma_h$, where c depends on coverage probability and σ_h is forecast standard deviation.

(A,N,N)	$\sigma_h = \sigma^2 [1 + \alpha^2(h-1)]$
(A,A,N)	$\sigma_h = \sigma^2 \left[1 + (h-1) \left\{ \alpha^2 + \alpha\beta h + \frac{1}{6}\beta^2 h(2h-1) \right\} \right]$
(A,A _d ,N)	$\sigma_h = \sigma^2 \left[1 + \alpha^2(h-1) + \frac{\beta\phi h}{(1-\phi)^2} \{2\alpha(1-\phi) + \beta\phi\} \right. \\ \left. - \frac{\beta\phi(1-\phi^h)}{(1-\phi)^2(1-\phi^2)} \{2\alpha(1-\phi^2) + \beta\phi(1+2\phi-\phi^h)\} \right]$
(A,N,A)	$\sigma_h = \sigma^2 [1 + \alpha^2(h-1) + \gamma k(2\alpha + \gamma)]$
(A,A,A)	$\sigma_h = \sigma^2 \left[1 + (h-1) \left\{ \alpha^2 + \alpha\beta h + \frac{1}{6}\beta^2 h(2h-1) \right\} + \gamma k \{2\alpha + \gamma + \beta m(k+1)\} \right]$
(A,A _d ,A)	$\sigma_h = \sigma^2 \left[1 + \alpha^2(h-1) + \frac{\beta\phi h}{(1-\phi)^2} \{2\alpha(1-\phi) + \beta\phi\} \right. \\ \left. - \frac{\beta\phi(1-\phi^h)}{(1-\phi)^2(1-\phi^2)} \{2\alpha(1-\phi^2) + \beta\phi(1+2\phi-\phi^h)\} \right. \\ \left. + \gamma k(2\alpha + \gamma) + \frac{2\beta\gamma\phi}{(1-\phi)(1-\phi^m)} \{k(1-\phi^m) - \phi^m(1-\phi^{mk})\} \right]$

3.6.6 Example: Corticosteroid drug sales

```
h02 <- PBS %>%
  filter(ATC2 == "H02") %>%
  summarise(Cost = sum(Cost))
h02 %>%
  autoplot(Cost)
```



```
h02 %>%
  model(ETS(Cost)) %>%
  report()
```

```
## Series: Cost
## Model: ETS(M,Ad,M)
## Smoothing parameters:
##   alpha = 0.3071
##   beta  = 0.0001007
##   gamma = 0.0001007
##   phi   = 0.9775
##
## Initial states:
##   l      b      s1      s2      s3      s4      s5      s6      s7
## 417269 8206 0.8717 0.826 0.7563 0.7733 0.6872 1.284 1.325
##   s8      s9      s10     s11     s12
## 1.18 1.164 1.105 1.048 0.9806
```

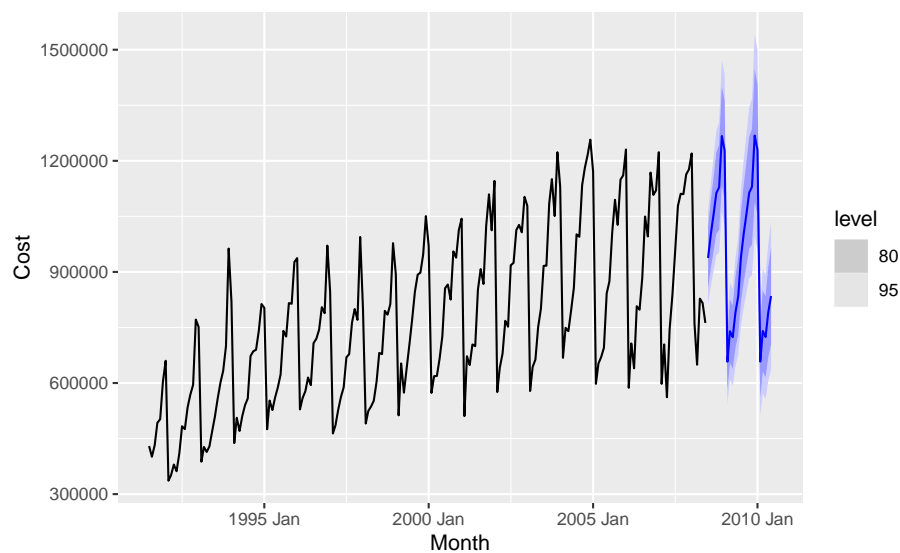
3.6. FORECASTING WITH ~~EXPONENTIAL~~ SMOOTHING

```
##
##   sigma^2:  0.0046
##
##   AIC AICc  BIC
## 5515 5519 5575

h02 %>%
  model(ETS(Cost ~ error("A") + trend("A") + season("A"))) %>%
  report()

## Series: Cost
## Model: ETS(A,A,A)
##   Smoothing parameters:
##     alpha = 0.1702
##     beta  = 0.006311
##     gamma = 0.4546
##
##   Initial states:
##      l      b      s1      s2      s3      s4      s5      s6
## 409706 9097 -99075 -136602 -191496 -174531 -241437 210644
##      s7      s8      s9      s10     s11     s12
## 244644 145368 130570 84458 39132 -11674
##
##   sigma^2:  3.499e+09
##
##   AIC AICc  BIC
## 5585 5589 5642

h02 %>% model(ETS(Cost)) %>% forecast() %>% autoplot(h02)
```

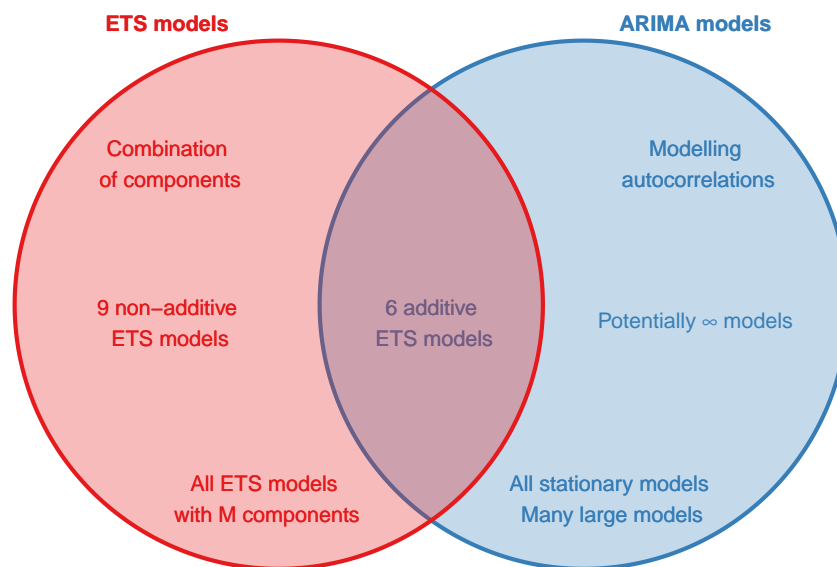


```
h02 %>%
  model(
    auto = ETS(Cost),
    AAA = ETS(Cost ~ error("A") + trend("A") + season("A"))
  ) %>%
  accuracy()
```

Model	ME	MAE	RMSE	MAPE	MASE
auto	2461	38649	51102	4.989	0.6376
AAA	-5780	43378	56784	6.048	0.7156

3.7 ARIMA vs ETS

- Myth that ARIMA models are more general than exponential smoothing.
- Linear exponential smoothing models all special cases of ARIMA models.
- Non-linear exponential smoothing models have no equivalent ARIMA counterparts.
- Many ARIMA models have no exponential smoothing counterparts.
- ETS models all non-stationary. Models with seasonality or non-damped trend (or both) have two unit roots; all other models have one unit root.



3.7.1 Equivalences

ETS model	ARIMA model	Parameters
ETS(A,N,N)	ARIMA(0,1,1)	$\theta_1 = \alpha - 1$
ETS(A,A,N)	ARIMA(0,2,2)	$\theta_1 = \alpha + \beta - 2$ $\theta_2 = 1 - \alpha$
ETS(A,A _d ,N)	ARIMA(1,1,2)	$\phi_1 = \phi$ $\theta_1 = \alpha + \phi\beta - 1 - \phi$ $\theta_2 = (1 - \alpha)\phi$
ETS(A,N,A)	ARIMA(0,0,m)(0,1,0) _m	
ETS(A,A,A)	ARIMA(0,1,m + 1)(0,1,0) _m	
ETS(A,A _d ,A)	ARIMA(1,0,m + 1)(0,1,0) _m	

3.8 References:

- Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.

Chapter 4

Volatility Models

4.1 Introduction

- Anything that is observed sequentially over time is a time series.
- **Financial time series** analysis focuses on the theory and practice of asset valuation over time.
- In finance, the data can be collected much more frequently – High frequency data.
- Many financial time series also exhibit changing variance and this can have important consequences in formulating financial decisions.

Example: Financial time series

- Typically, when we analyze assets, we look at the percentage change in prices or returns.

```
# Tidy financial analysis
library(tidyquant)

sp500 <- tq_get("^GSPC", from = "1995-01-04", to = "2021-02-25" )
print(sp500)
```

```
## # A tibble: 6,582 x 8
##   symbol date       open  high   low close volume adjusted
##   <chr>   <date>   <dbl> <dbl> <dbl> <dbl>   <dbl>   <dbl>
## 1 ^GSPC  1995-01-04  459.  461.  458.  461.  3.20e8  461.
## 2 ^GSPC  1995-01-05  461.  461.  460.  460.  3.09e8  460.
## 3 ^GSPC  1995-01-06  460.  462.  459.  461.  3.08e8  461.
```

```
## 4 ^GSPC 1995-01-09 461. 462. 460. 461. 2.79e8 461.
## 5 ^GSPC 1995-01-10 461. 465. 461. 462. 3.52e8 462.
## 6 ^GSPC 1995-01-11 462. 464. 459. 462. 3.46e8 462.
## 7 ^GSPC 1995-01-12 462. 462. 461. 462. 3.13e8 462.
## 8 ^GSPC 1995-01-13 462. 466. 462. 466. 3.37e8 466.
## 9 ^GSPC 1995-01-16 466. 470. 466. 469. 3.16e8 469.
## 10 ^GSPC 1995-01-17 469. 470. 468. 470. 3.32e8 470.
## # ... with 6,572 more rows
```

```
# Convert each assets raw adjusted closing prices to returns
sp500_return <- sp500 %>%
  tq_transmute(select = adjusted,
               mutate_fun = periodReturn,
               period = "daily")

sp500_return %>%
  as_tsibble(index = date) %>%
  autoplot(daily.returns) +
  labs(x = "Day", y = "Daily return")
```

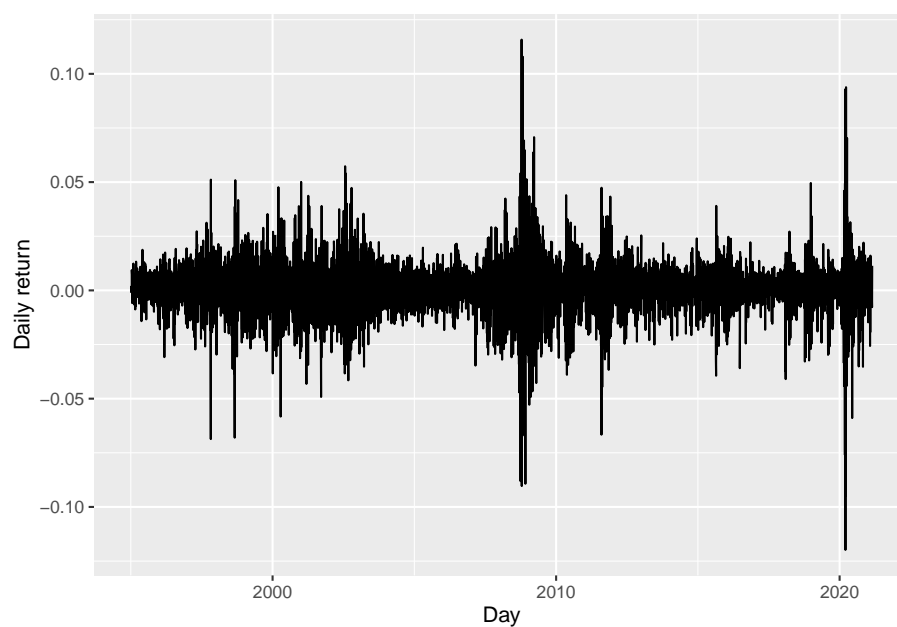


Figure 4.1: Daily returns of the adjusted closing prices of the S&P500 index from January 4, 1995 to February 25, 2021

4.2 References:

- Chatfield, C., & Xing, H. (2019). The analysis of time series: an introduction with R. CRC press.

Chapter 5

Multivariate Time Series Modeling

5.1 References:

- Chatfield, C., & Xing, H. (2019). The analysis of time series: an introduction with R. CRC press.

Bibliography

Brockwell, P. J., Brockwell, P. J., Davis, R. A., and Davis, R. A. (2016). *Introduction to time series and forecasting*. Springer.