



Tidy Time Series & Forecasting in R



2. Time series graphics

Outline

- 1 Seasonal plots
- 2 Lab Session 3
- 3 Seasonal or cyclic?
- 4 Lag plots and autocorrelation
- 5 Lab Session 4
- 6 White noise
- 7 Lab Session 5

Outline

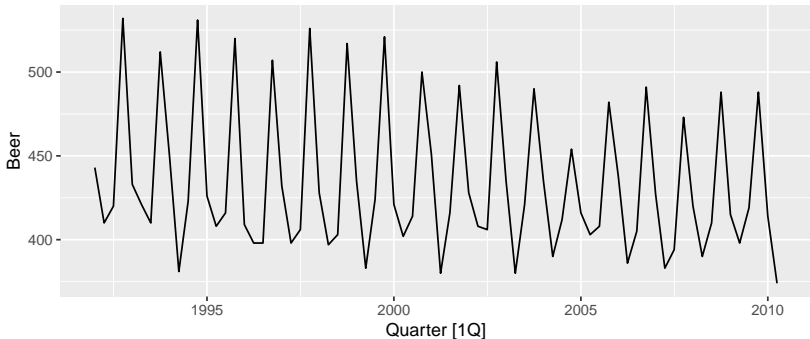
- 1 Seasonal plots
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Seasonal plots

- Data plotted against the individual “seasons” in which the data were observed. (In this case a “season” is a month.)
- Something like a time plot except that the data from each season are overlapped.
- Enables the underlying seasonal pattern to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified.
- In R: `gg_season()`

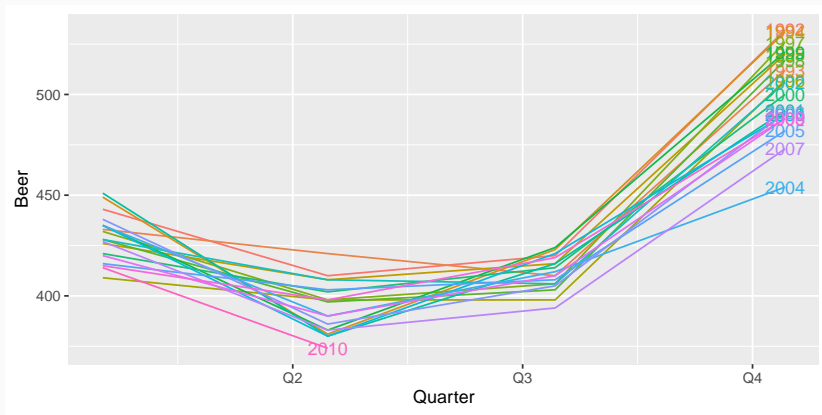
Quarterly Australian Beer Production

```
beer <- aus_production %>%  
  select(Quarter, Beer) %>%  
  filter(year(Quarter) >= 1992)  
beer %>% autoplot(Beer)
```



Quarterly Australian Beer Production

```
beer %>% gg_season(Beer, labels="right")
```



Multiple seasonal periods

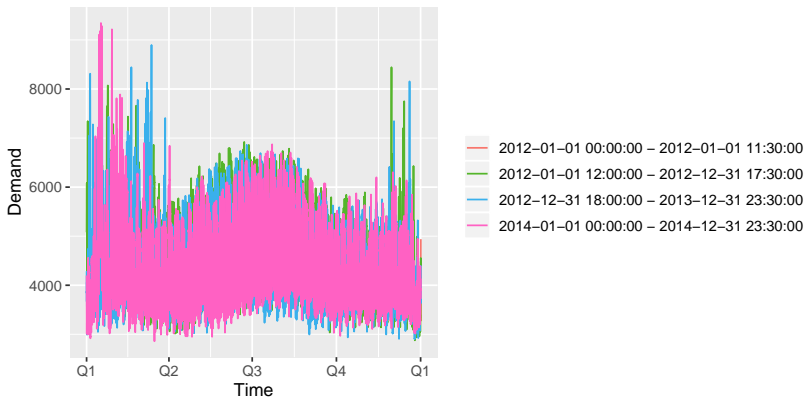
```
vic_elec
```

```
## # A tsibble: 52,608 x 5 [30m] <UTC>
```

##	Time	Demand	Temperature	Date	Holiday
##	<dtm>	<dbl>	<dbl>	<date>	<lgl>
##	1 2012-01-01 00:00:00	4263.	21.0	2012-01-01	TRUE
##	2 2012-01-01 00:30:00	4049.	20.7	2012-01-01	TRUE
##	3 2012-01-01 01:00:00	3878.	20.6	2012-01-01	TRUE
##	4 2012-01-01 01:30:00	4036.	20.4	2012-01-01	TRUE
##	5 2012-01-01 02:00:00	3866.	20.2	2012-01-01	TRUE
##	6 2012-01-01 02:30:00	3694.	20.1	2012-01-01	TRUE
##	7 2012-01-01 03:00:00	3562.	19.6	2012-01-01	TRUE
##	8 2012-01-01 03:30:00	3433.	19.1	2012-01-01	TRUE
##	9 2012-01-01 04:00:00	3359.	19.0	2012-01-01	TRUE
##	10 2012-01-01 04:30:00	3331.	18.8	2012-01-01	TRUE
##	# ... with 52,598 more rows				

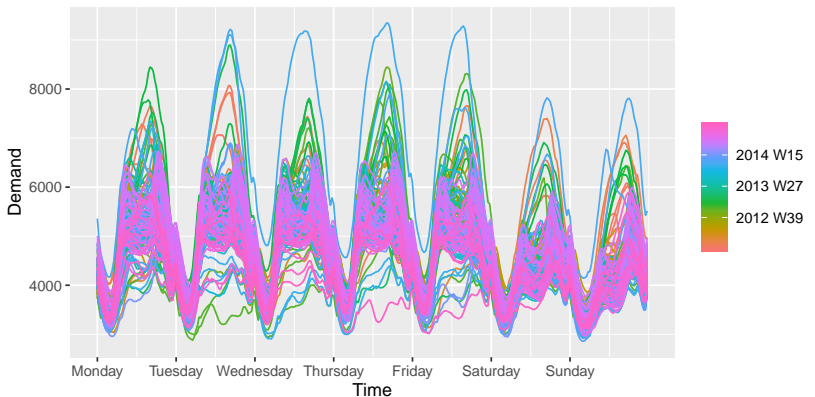
Multiple seasonal periods

```
vic_elec %>% gg_season(Demand)
```



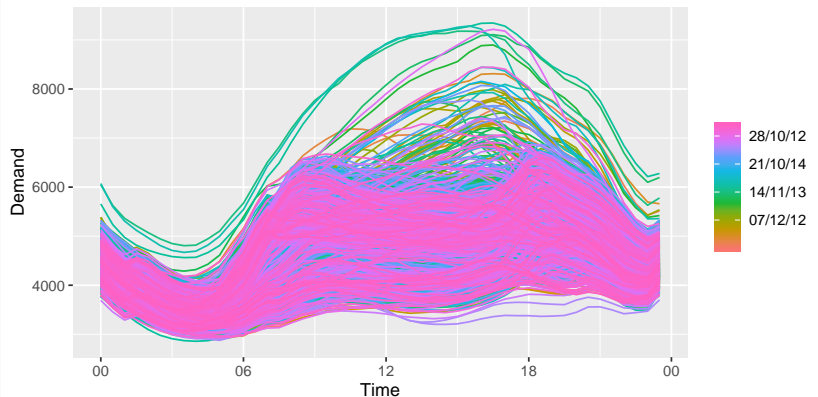
Multiple seasonal periods

```
vic_elec %>% gg_season(Demand, period="week")
```



Multiple seasonal periods

```
vic_elec %>% gg_season(Demand, period="day")
```

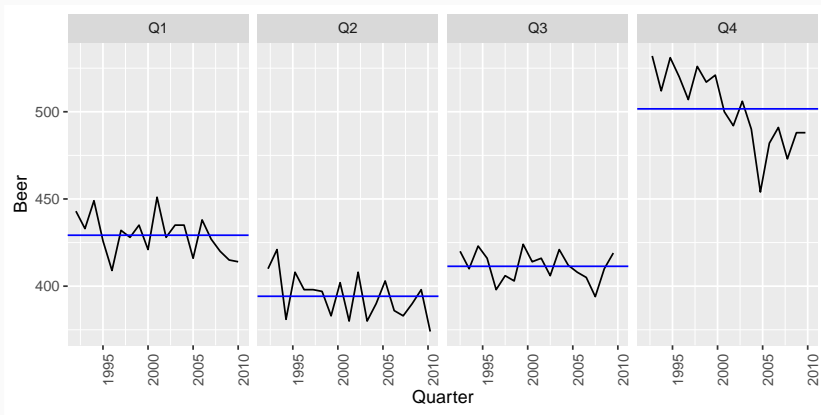


Seasonal subseries plots

- Data for each season collected together in time plot as separate time series.
- Enables the underlying seasonal pattern to be seen clearly, and changes in seasonality over time to be visualized.
- In R: `gg_subseries()`

Quarterly Australian Beer Production

```
beer %>% gg_subseries(Beer)
```



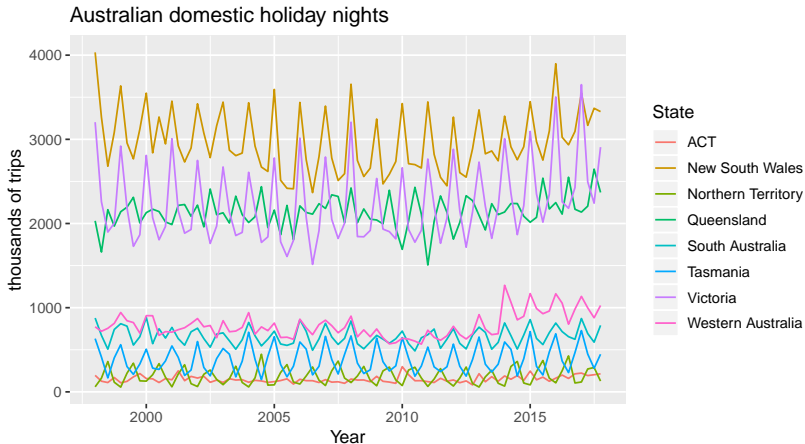
Australian holidays

```
holidays <- tourism %>%  
  filter(Purpose=="Holiday") %>%  
  group_by(State) %>%  
  summarise(Trips = sum(Trips))
```

```
## # A tsibble: 640 x 3 [1Q]  
## # Key:           State [8]  
##   State Quarter Trips  
##   <chr>   <qtr> <dbl>  
## 1 ACT    1998 Q1  196.  
## 2 ACT    1998 Q2  127.  
## 3 ACT    1998 Q3  111.  
## 4 ACT    1998 Q4  170.  
## 5 ACT    1999 Q1  108.  
## 6 ACT    1999 Q2  125.  
## 7 ACT    1999 Q3  178.  
## 8 ACT    1999 Q4  218.  
## 9 ACT    2000 Q1  158.  
## 10 ACT   2000 Q2  155.
```

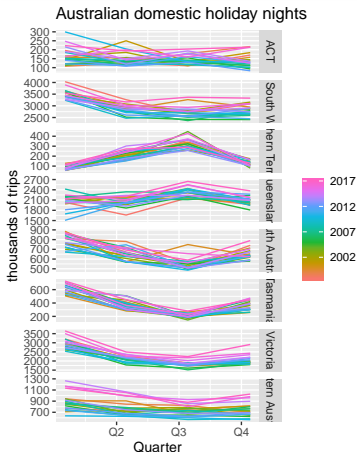
Australian holidays

```
holidays %>% autoplot(Trips) +  
  ylab("thousands of trips") + xlab("Year") +  
  ggtitle("Australian domestic holiday nights")
```



Seasonal plots

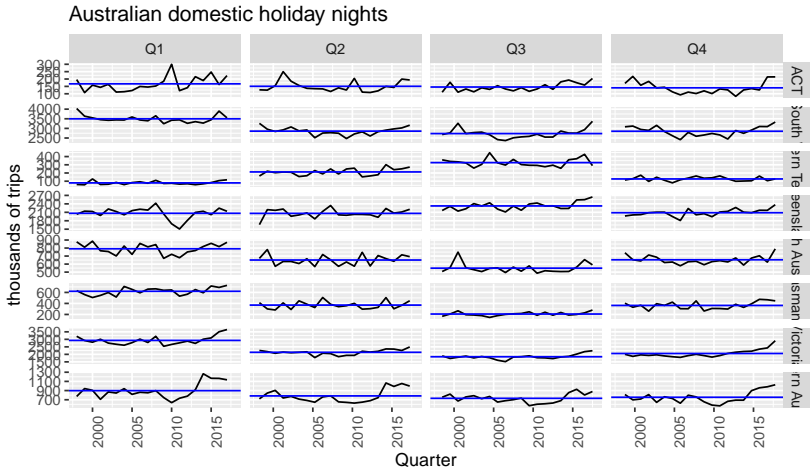
```
holidays %>% gg_season(Trips) +  
  ylab("thousands of trips") +  
  ggtitle("Australian domestic holiday nights")
```



Seasonal subseries plots

holidays %>%

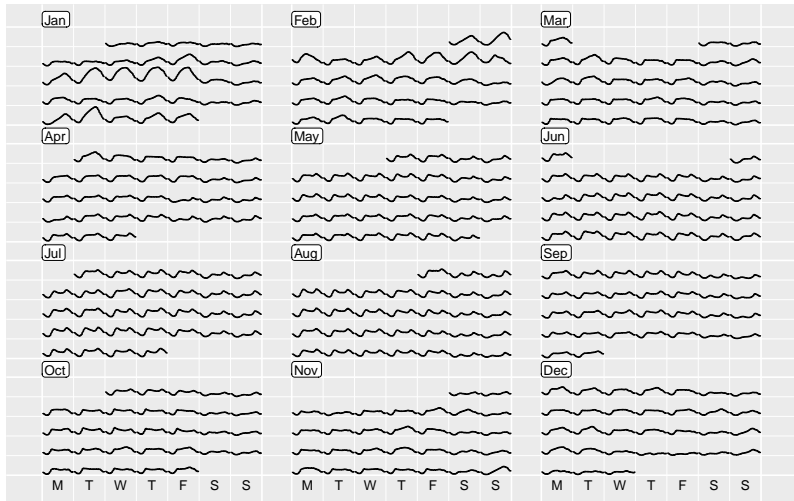
```
gg_subseries(Trips) + ylab("thousands of trips") +  
ggtitle("Australian domestic holiday nights")
```



Calendar plots

```
library(sugrrants)
vic_elec %>%
  filter(year(Date) == 2014) %>%
  mutate(Hour = hour(Time)) %>%
  frame_calendar(x = Hour, y = Demand, date = Date,
    nrow = 4) %>%
  ggplot(aes(x = .Hour, y = .Demand, group = Date)) +
  geom_line() -> p1
prettify(p1, size = 3,
  label.padding = unit(0.15, "lines"))
```

Calendar plots



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Lab Session 3

- 1 Look at the quarterly tourism data for the Snowy Mountains

```
snowy <- filter(tourism, Region == "Snowy")
```

- ▶ Use `autoplot()`, `gg_season()` and `gg_subseries()` to explore the data.
- ▶ What do you learn?

- 2 Produce a calendar plot for the pedestrian data from one location and one year.

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Time series patterns

Trend pattern exists when there is a long-term increase or decrease in the data.

Seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

Cyclic pattern exists when data exhibit rises and falls that are *not of fixed period* (duration usually of at least 2 years).

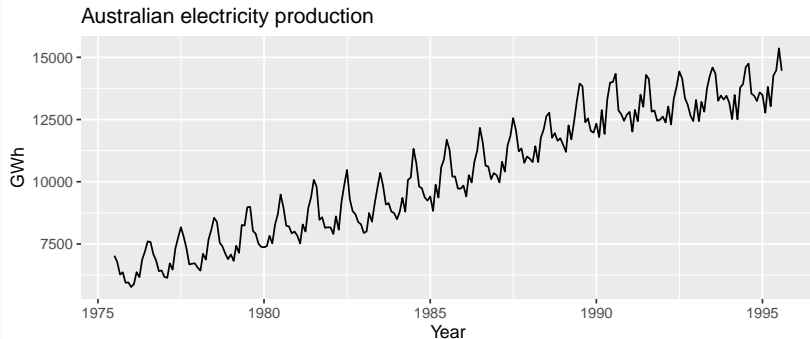
Time series components

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

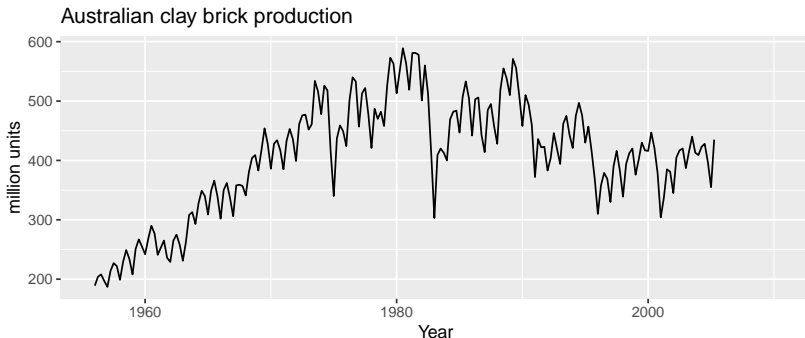
Time series patterns

```
as_tsibble(fma::elec) %>%  
  filter(index >= 1980) %>%  
  autoplot(value) + xlab("Year") + ylab("GWh") +  
  ggtitle("Australian electricity production")
```



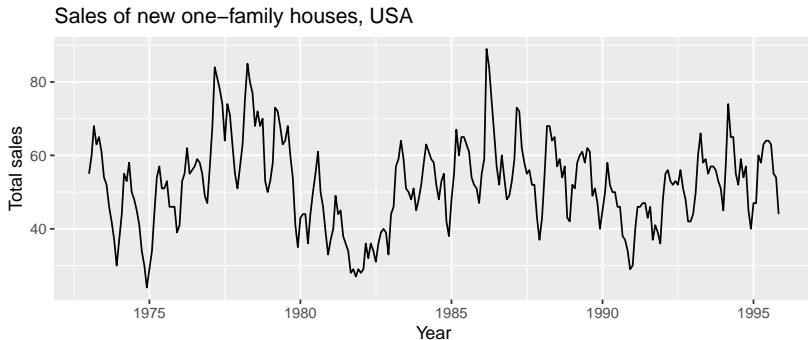
Time series patterns

```
aus_production %>%  
  autoplot(Bricks) +  
  ggtitle("Australian clay brick production") +  
  xlab("Year") + ylab("million units")
```



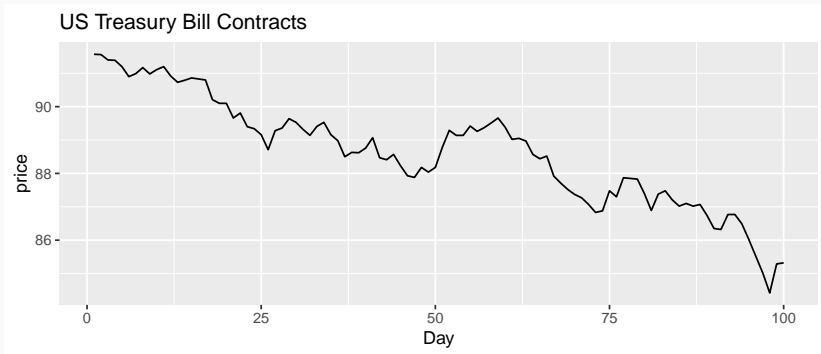
Time series patterns

```
as_tsibble(fma::hsales) %>%  
  autoplot(value) +  
  ggtitle("Sales of new one-family houses, USA") +  
  xlab("Year") + ylab("Total sales")
```



Time series patterns

```
as_tsibble(fma::ustreas) %>%  
  autoplot(value) +  
  ggtitle("US Treasury Bill Contracts") +  
  xlab("Day") + ylab("price")
```



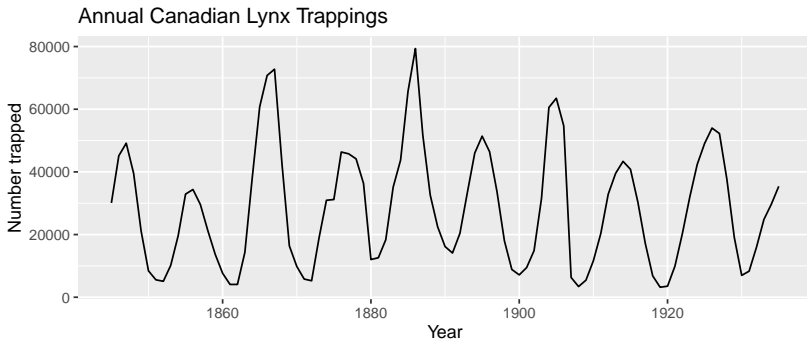
Time series patterns

```
pelt %>%
```

```
  autoplot(Lynx) +
```

```
  ggtitle("Annual Canadian Lynx Trappings") +
```

```
  xlab("Year") + ylab("Number trapped")
```



Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

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Example: Beer production

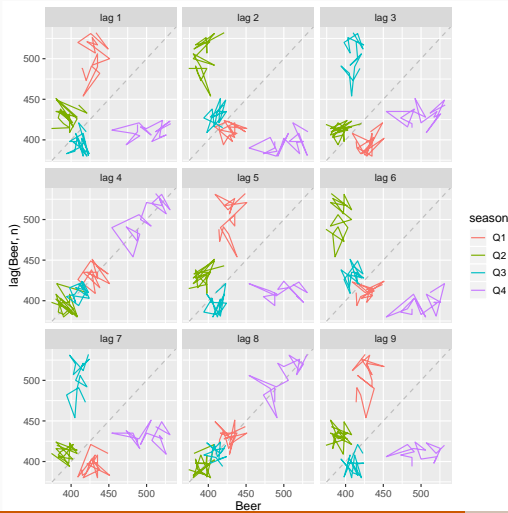
```
new_production <- aus_production %>%  
  filter(year(Quarter) >= 1992)  
new_production
```

```
## # A tsibble: 74 x 7 [1Q]
```

##		Quarter	Beer	Tobacco	Bricks	Cement	Electricity	Gas
##		<qtr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
##	1	1992 Q1	443	5777	383	1289	38332	117
##	2	1992 Q2	410	5853	404	1501	39774	151
##	3	1992 Q3	420	6416	446	1539	42246	175
##	4	1992 Q4	532	5825	420	1568	38498	129
##	5	1993 Q1	433	5724	394	1450	39460	116
##	6	1993 Q2	421	6036	462	1668	41356	149
##	7	1993 Q3	410	6570	475	1648	42949	163
##	8	1993 Q4	512	5675	443	1863	40974	138
##	9	1994 Q1	449	5311	421	1468	40162	127

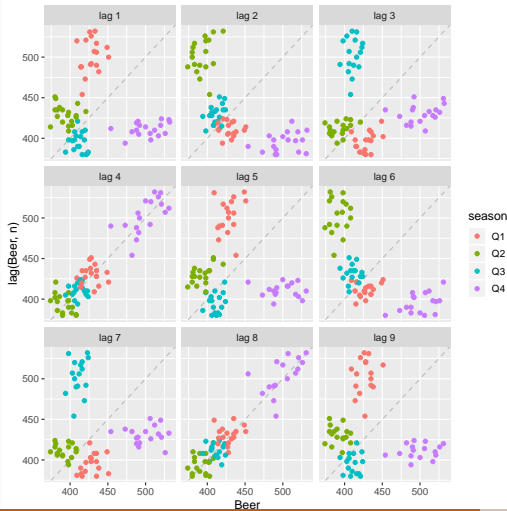
Example: Beer production

```
new_production %>% gg_lag(Beer)
```



Example: Beer production

```
new_production %>% gg_lag(Beer, geom='point')
```



Lagged scatterplots

- Each graph shows y_t plotted against y_{t-k} for different values of k .
- The autocorrelations are the correlations associated with these scatterplots.
- ACF (autocorrelation function):
 - ▶ $r_1 = \text{Correlation}(y_t, y_{t-1})$
 - ▶ $r_2 = \text{Correlation}(y_t, y_{t-2})$
 - ▶ $r_3 = \text{Correlation}(y_t, y_{t-3})$
 - ▶ etc.
- If there is **seasonality**, the ACF at the seasonal lag (e.g., 12 for monthly data) will be **large and positive**.

Autocorrelation

Results for first 9 lags for beer data:

```
new_production %>% ACF(Beer, lag_max = 9)
```

```
## # A tsibble: 9 x 2 [1Q]
```

```
##   lag    acf
```

```
##   <lag>  <dbl>
```

```
## 1    1Q -0.102
```

```
## 2    2Q -0.657
```

```
## 3    3Q -0.0603
```

```
## 4    4Q  0.869
```

```
## 5    5Q -0.0892
```

```
## 6    6Q -0.635
```

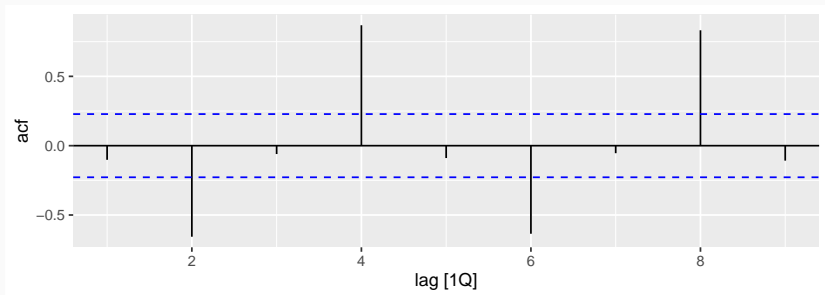
```
## 7    7Q -0.0542
```

```
## 8    8Q  0.832
```

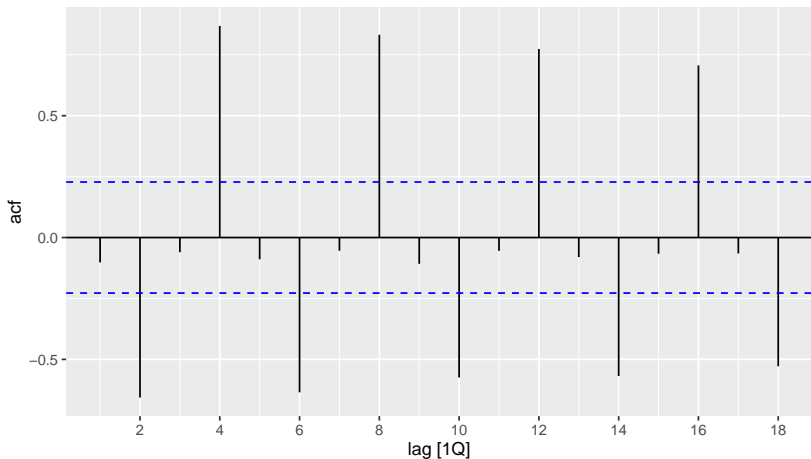
Autocorrelation

Results for first 9 lags for beer data:

```
new_production %>% ACF(Beer, lag_max = 9) %>% autoplot()
```



```
new_production %>% ACF(Beer) %>% autoplot()
```



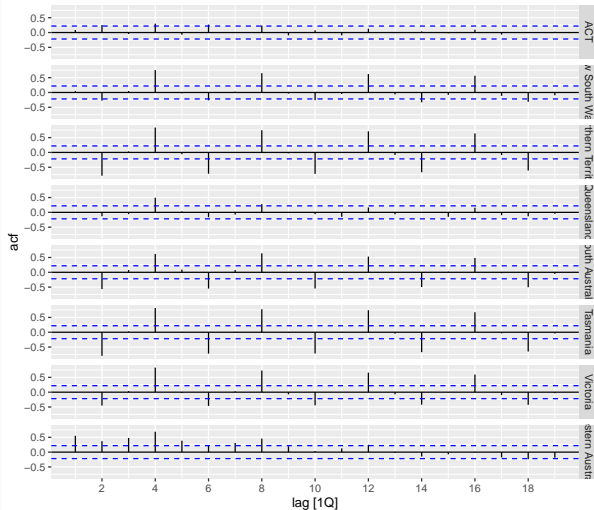
Australian holidays

```
holidays %>% ACF(Trips)
```

```
## # A tsibble: 152 x 3 [1Q]
## # Key:      State [8]
##   State lag      acf
##   <chr> <lag>    <dbl>
## 1 ACT    1Q    0.0877
## 2 ACT    2Q    0.252
## 3 ACT    3Q   -0.0496
## 4 ACT    4Q    0.300
## 5 ACT    5Q   -0.0741
## 6 ACT    6Q    0.269
## 7 ACT    7Q   -0.00504
## 8 ACT    8Q    0.236
## 9 ACT    9Q   -0.0953
## 10 ACT   10Q    0.0750
## # ... with 142 more rows
```

Australian holidays

```
holidays %>% ACF(Trips) %>% autoplot()
```

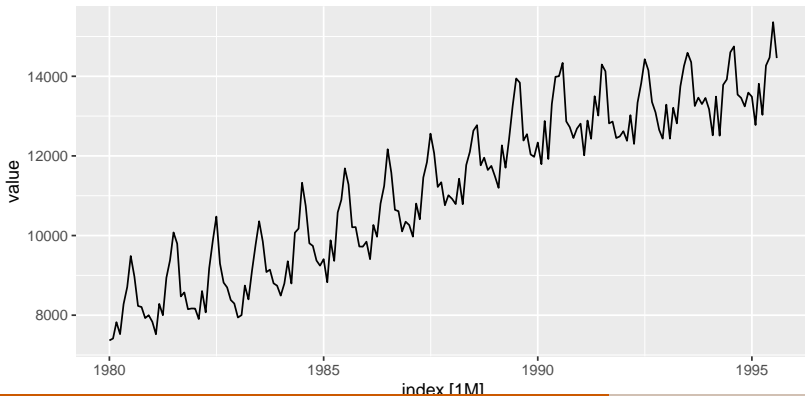


Trend and seasonality in ACF plots

- When data have a trend, the autocorrelations for small lags tend to be large and positive.
- When data are seasonal, the autocorrelations will be larger at the seasonal lags (i.e., at multiples of the seasonal frequency)
- When data are trended and seasonal, you see a combination of these effects.

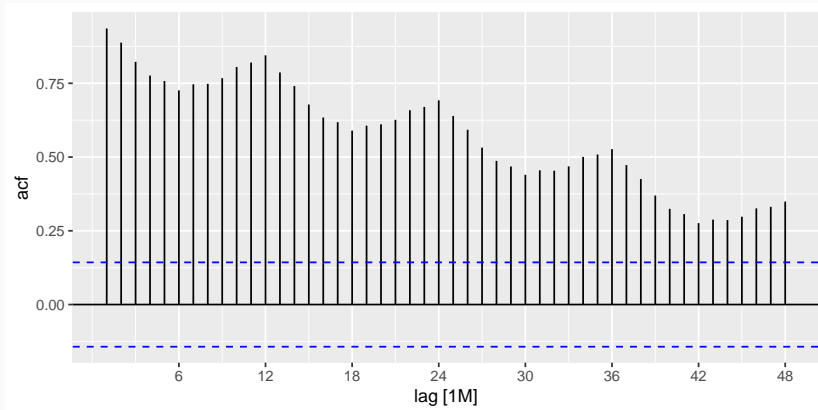
Aus monthly electricity production

```
elec2 <- as_tsibble(fma::elec) %>%  
  filter(year(index) >= 1980)  
elec2 %>% autoplot(value)
```



Aus monthly electricity production

```
elec2 %>% ACF(value, lag_max=48) %>%  
  autoplot()
```



Google stock price

```
google_2015 <- gafa_stock %>%  
  filter(Symbol == "GOOG", year(Date) == 2015) %>%  
  select(Date, Close)  
google_2015
```

```
## # A tsibble: 252 x 2 [!]
```

```
##   Date      Close
```

```
##   <date>    <dbl>
```

```
## 1 2015-01-02  522.
```

```
## 2 2015-01-05  511.
```

```
## 3 2015-01-06  499.
```

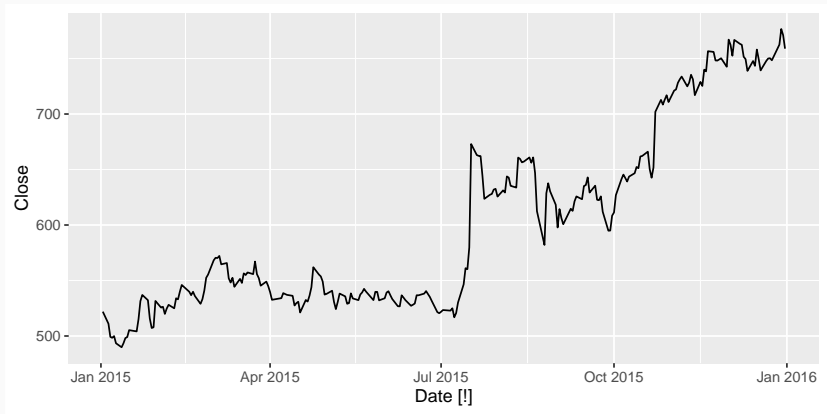
```
## 4 2015-01-07  498.
```

```
## 5 2015-01-08  500.
```

```
## 6 2015-01-09  493.
```

Google stock price

```
google_2015 %>% autoplot(Close)
```



Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100)  
# Error: Can't handle tsibble of irregular interval.
```

Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100)  
# Error: Can't handle tsibble of irregular interval.
```

```
google_2015
```

```
## # A tsibble: 252 x 2 [!]  
##   Date      Close  
##   <date>    <dbl>  
## 1 2015-01-02  522.  
## 2 2015-01-05  511.  
## 3 2015-01-06  499.
```

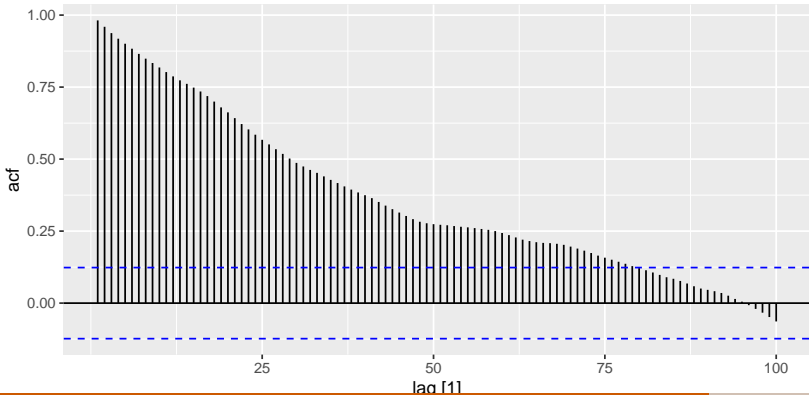
Google stock price

```
google_2015 <- google_2015 %>%  
  mutate(trading_day = row_number()) %>%  
  update_tsibble(index=trading_day, regular=TRUE)  
google_2015
```

```
## # A tsibble: 252 x 3 [1]  
##   Date          Close trading_day  
##   <date>        <dbl>      <int>  
## 1 2015-01-02    522.         1  
## 2 2015-01-05    511.         2  
## 3 2015-01-06    499.         3  
## 4 2015-01-07    498.         4  
## 5 2015-01-08    500.         5  
## 6 2015-01-09    493.         6
```


Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100) %>%  
  autoplot()
```



Outline

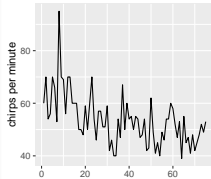
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Lab Session 4

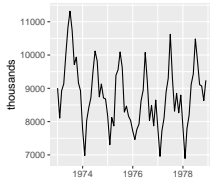
We have introduced the following functions: `gg_lag` and `ACF`. Use these functions to explore the four time series: Beer from `aus_production`, Lynx from `pelt`, Close from `gafa_stock`, Demand from `vic_elec`. Can you spot any seasonality, cyclicity and trend? What do you learn about the series?

Which is which?

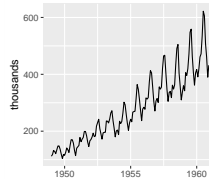
1. Daily temperature of cow



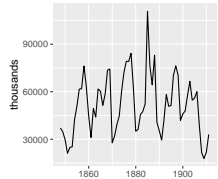
2. Monthly accidental deaths



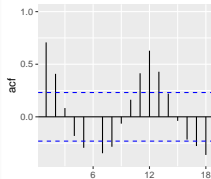
3. Monthly air passengers



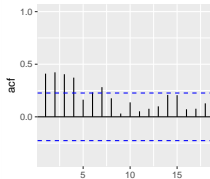
4. Annual mink trappings



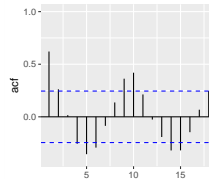
A



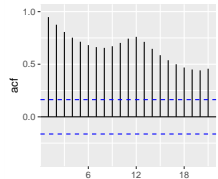
B



C



D

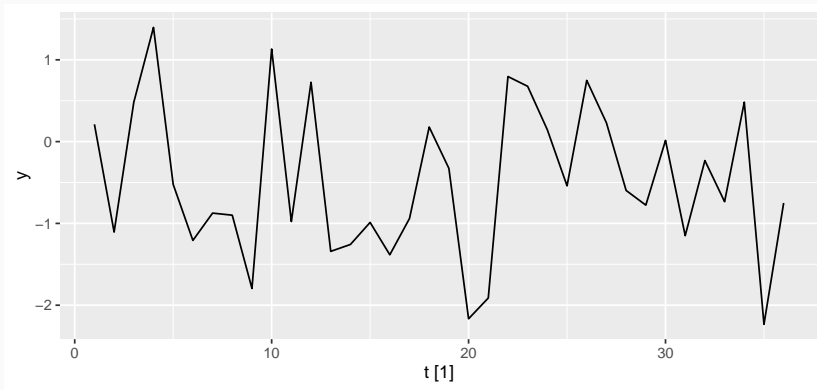


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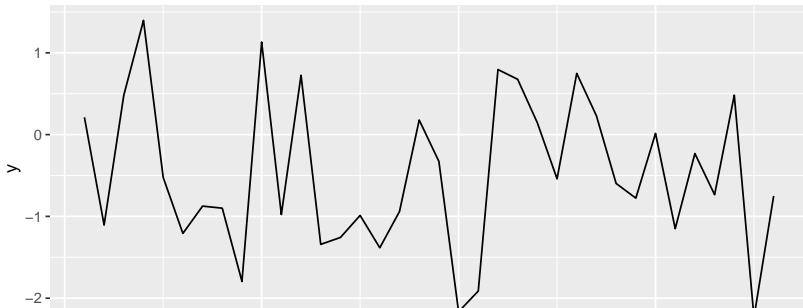
Example: White noise

```
wn <- tsibble(t=seq(36), y=rnorm(36), index=t)  
wn %>% autoplot(y)
```



Example: White noise

```
wn <- tsibble(t=seq(36), y=rnorm(36), index=t)  
wn %>% autoplot(y)
```

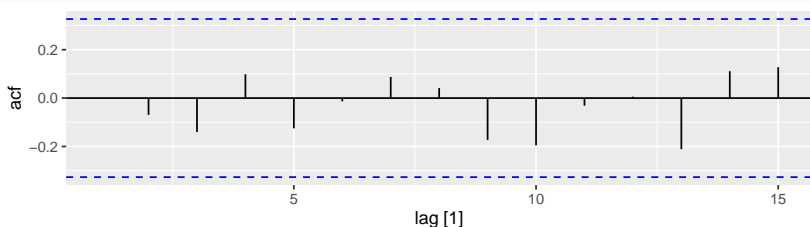


White noise data is uncorrelated across time with zero mean and constant variance.
(Technically, we require independence as well.)

Example: White noise

wn %>% ACF(y)

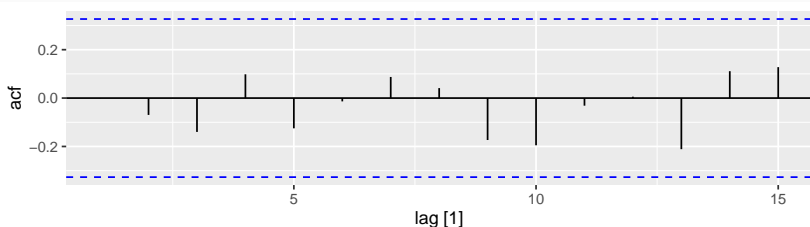
r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
-0.001	-0.070	-0.140	0.098	-0.125	-0.014	0.087	0.041	-0.173	-0.195



Example: White noise

wn %>% ACF(y)

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
-0.001	-0.070	-0.140	0.098	-0.125	-0.014	0.087	0.041	-0.173	-0.195



- Sample autocorrelations for white noise series.
- Expect each autocorrelation to be close to zero.
- Blue lines show 95% critical values.

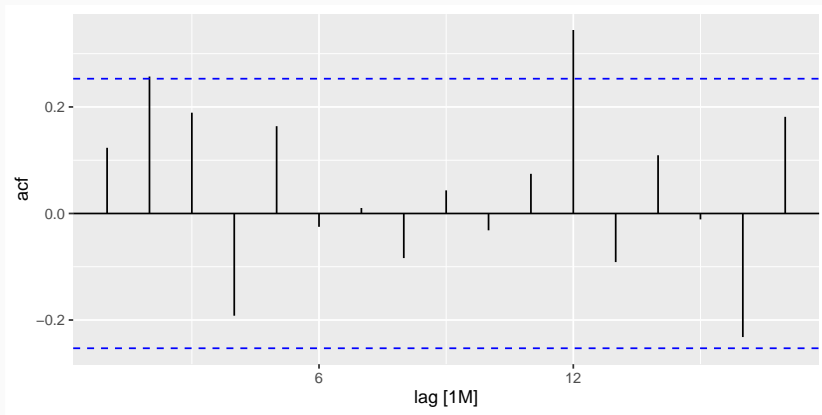
Example: Pigs slaughtered

```
pigs <- aus_livestock %>%  
  filter(State == "Victoria", Animal == "Pigs",  
         year(Month) >= 2014)  
pigs %>% autoplot(Count/1e3) +  
  xlab("Year") + ylab("Thousands") +  
  ggtitle("Number of pigs slaughtered in Victoria")
```



Example: Pigs slaughtered

```
pigs %>% ACF(Count) %>% autoplot()
```



Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

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These show the series is **not a white noise series**.

Outline

- 1 Seasonal plots
- 2 Lab Session 3
- 3 Seasonal or cyclic?
- 4 Lag plots and autocorrelation
- 5 Lab Session 4
- 6 White noise
- 7 Lab Session 5

Lab Session 5

You can compute the daily changes in the Google stock price in 2018 using

```
dgoog <- gafa_stock %>%  
  filter(Symbol == "GOOG", year(Date) >= 2018) %>%  
  mutate(trading_day = row_number()) %>%  
  update_tsibble(index=trading_day, regular=TRUE) %>%  
  mutate(diff = difference(Close))
```

Does `diff` look like white noise?