

# Data 624\_Exercise 3.7\_HW2

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## 3.7 Exercises:

```
library(fpp3)

## Warning: package 'fpp3' was built under R version 4.4.2

## Registered S3 method overwritten by 'tsibble':
##   method           from
##   as_tibble.grouped_df dplyr

## -- Attaching packages ----- fpp3 1.0.1 --

## v tibble      3.2.1    v tsibble      1.1.6
## v dplyr       1.1.4    v tsibbledata  0.4.1
## v tidyr       1.3.1    v feasts        0.4.1
## v lubridate   1.9.4    v fable         0.4.1
## v ggplot2     3.5.1

## Warning: package 'dplyr' was built under R version 4.4.2

## Warning: package 'ggplot2' was built under R version 4.4.2

## Warning: package 'tsibbledata' was built under R version 4.4.2

## Warning: package 'feasts' was built under R version 4.4.2

## Warning: package 'fabletools' was built under R version 4.4.2

## Warning: package 'fable' was built under R version 4.4.2

## -- Conflicts ----- fpp3_conflicts --
## x lubridate::date()    masks base::date()
## x dplyr::filter()      masks stats::filter()
## x tsibble::intersect() masks base::intersect()
## x tsibble::interval()  masks lubridate::interval()
## x dplyr::lag()         masks stats::lag()
## x tsibble::setdiff()   masks base::setdiff()
## x tsibble::union()     masks base::union()
```

```

library(seasonal)

## Warning: package 'seasonal' was built under R version 4.4.2

##
## Attaching package: 'seasonal'

## The following object is masked from 'package:tibble':
##
##     view

```

1. Consider the GDP information in global\_economy. Plot the GDP per capita for each country over time. Which country has the highest GDP per capita? How has this changed over time?

- Monaco is the highest GDP per capita country in 2014. Overall the country's GDP per Capita is increasing, except around the ear of 2000, it dropped.

```
?global_economy
```

```
## starting httpd help server ... done
```

```
head(global_economy)
```

```

## # A tsibble: 6 x 9 [1Y]
## # Key:      Country [1]
##   Country    Code Year      GDP Growth   CPI Imports Exports Population
##   <fct>     <fct> <dbl>    <dbl> <dbl> <dbl>  <dbl>    <dbl>
## 1 Afghanistan AFG  1960 537777811.    NA    NA  7.02    4.13    8996351
## 2 Afghanistan AFG  1961 548888896.    NA    NA  8.10    4.45    9166764
## 3 Afghanistan AFG  1962 546666678.    NA    NA  9.35    4.88    9345868
## 4 Afghanistan AFG  1963 751111191.   NA    NA 16.9     9.17    9533954
## 5 Afghanistan AFG  1964 800000044.   NA    NA 18.1     8.89    9731361
## 6 Afghanistan AFG  1965 1006666638.   NA    NA 21.4     11.3    9938414

```

```

global_economy <- global_economy %>%
  mutate(GDP_cap = GDP/Population)

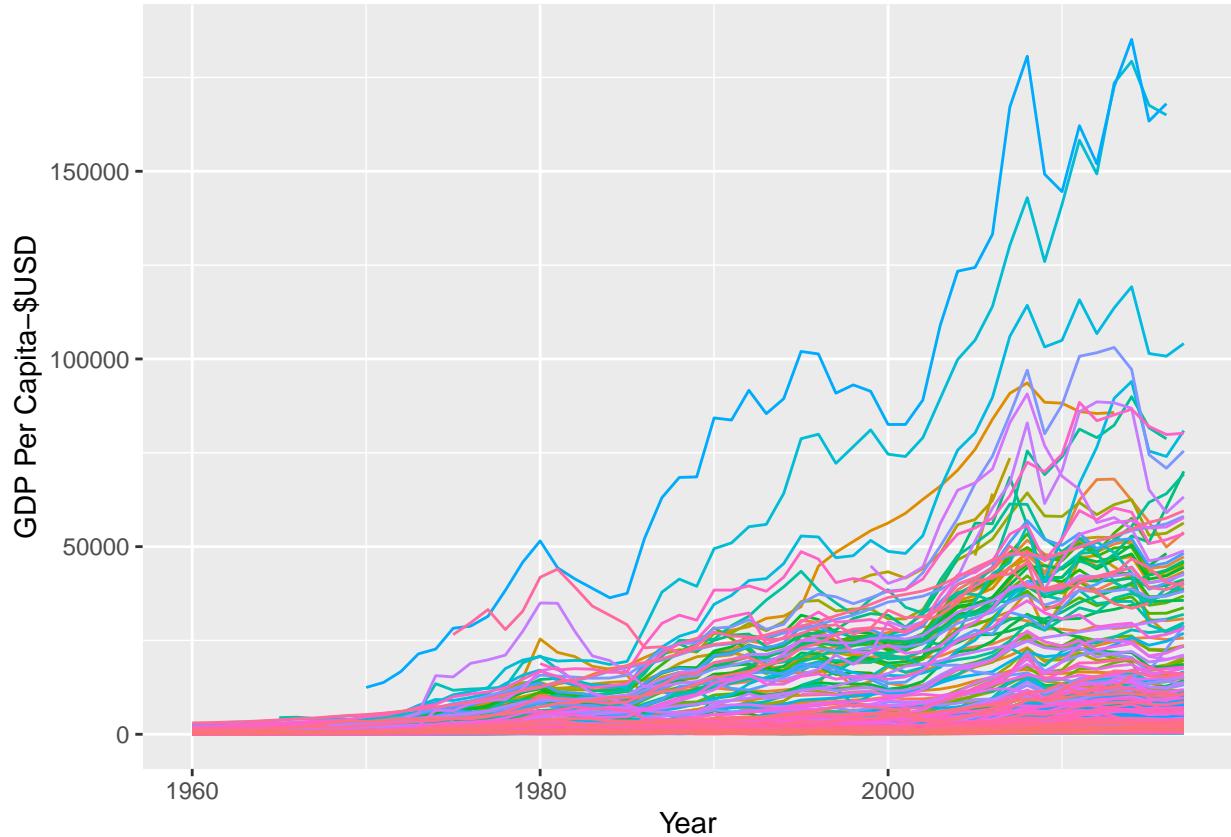
global_economy %>%
  autoplot(GDP_cap, show.legend = FALSE) +
  labs(x = "Year", y = "GDP Per Capita-$USD")

```

```

## Warning: Removed 3242 rows containing missing values or values outside the scale range
## ('geom_line()').

```



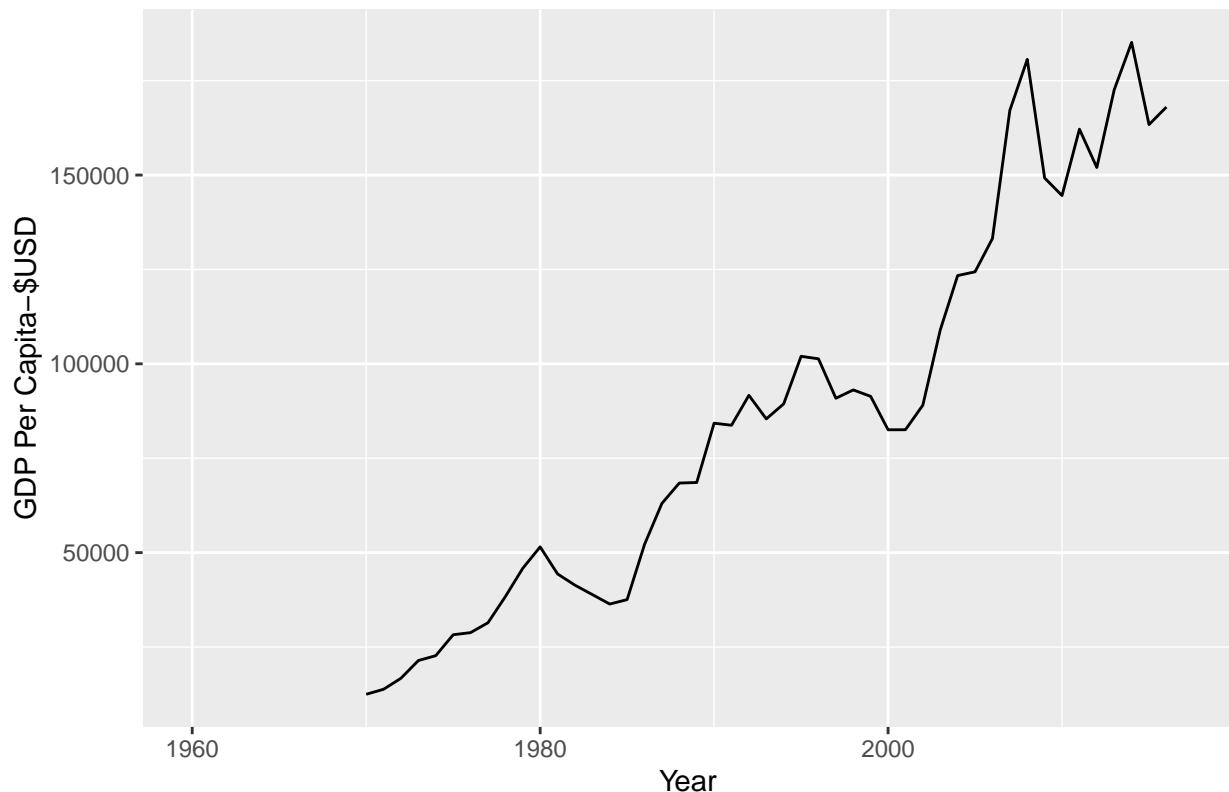
```
global_economy %>%
  filter(GDP_cap == max(GDP_cap, na.rm=T))
```

```
## # A tsibble: 1 x 10 [1Y]
## # Key:      Country [1]
##   Country Code Year     GDP Growth   CPI Imports Exports Population GDP_cap
##   <fct>    <fct> <dbl>    <dbl> <dbl> <dbl> <dbl> <dbl>    <dbl>    <dbl>
## 1 Monaco   MCO   2014 7.06e9  7.18    NA     NA     NA     NA 38132 185153.
```

```
global_economy %>%
  filter(Country == "Monaco") %>%
  autoplot(GDP_cap) +
  labs(x = "Year", y = "GDP Per Capita-$USD", title = "GDP per Capita for Monaco")
```

```
## Warning: Removed 11 rows containing missing values or values outside the scale range
## ('geom_line()').
```

## GDP per Capita for Monaco



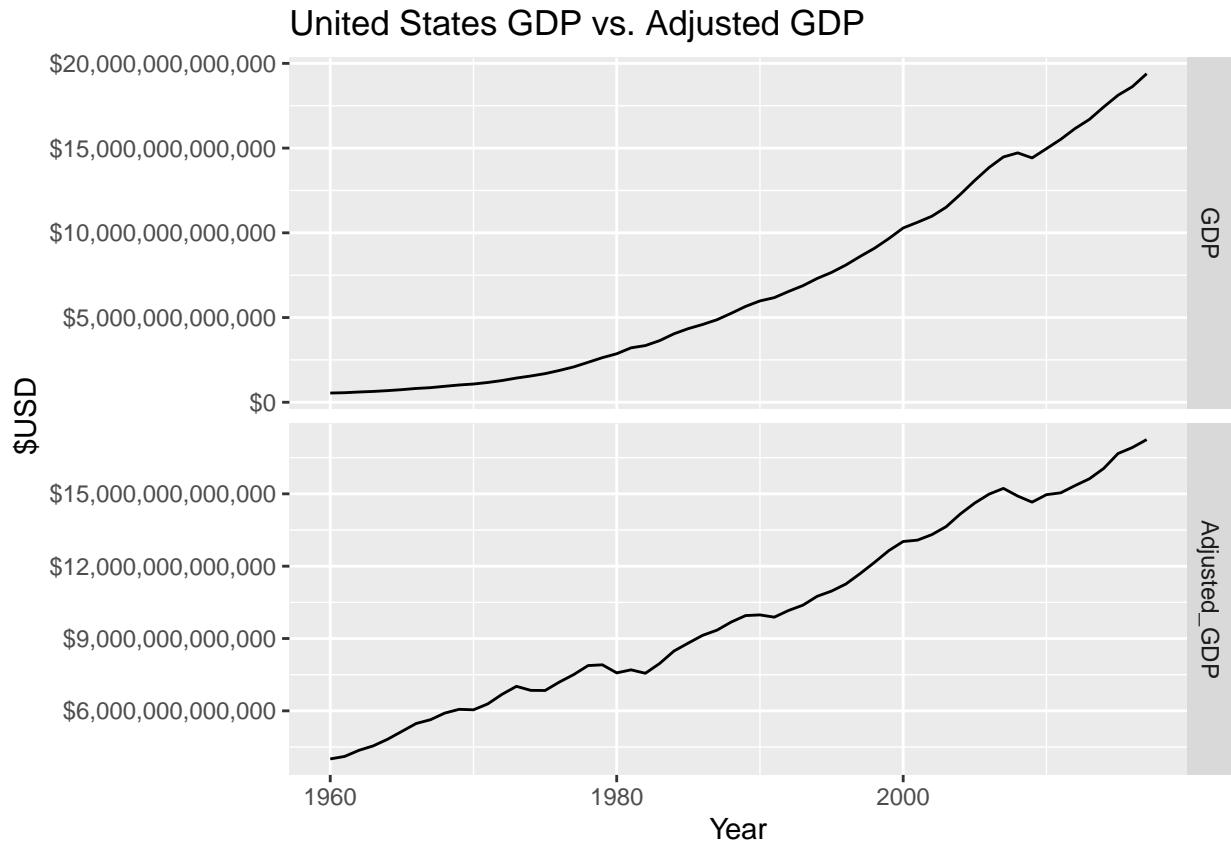
2. For each of the following series, make a graph of the data. If transforming seems appropriate, do so and describe the effect.

- a. United States GDP from global\_economy.
- a Answer: There is not much change between the United States GDP vs. Adjusted GDP. The trends are going upward.

```
us_economy <- global_economy %>%
  filter(Country == "United States") %>%
  index_by(Year)

us_economy <- us_economy %>%
  mutate(Adjusted_GDP = GDP / CPI * 100) %>%
  pivot_longer(c(GDP, Adjusted_GDP), names_to = "GDP_Type", values_to = "GDP_Value") %>%
  mutate(GDP_Type = factor(GDP_Type, levels = c("GDP", "Adjusted_GDP")))

ggplot(us_economy, aes(x = Year, y = GDP_Value)) +
  geom_line() +
  facet_grid(GDP_Type ~ ., scales = "free_y") +
  labs(title = "United States GDP vs. Adjusted GDP",
       y = "$USD",
       x = "Year") +
  scale_y_continuous(labels = scales::dollar)
```



- b.Slaughter of Victorian “Bulls, bullocks and steers” in aus\_livestock.
- b Answer: The data for “Bulls, bullocks and steers” in aus\_livestock for State Victoria doesn’t appear any upward trend, but it shows seasonal cyclicity. The lambda guerrero is a negative number, I don’t think the transformation is useful.

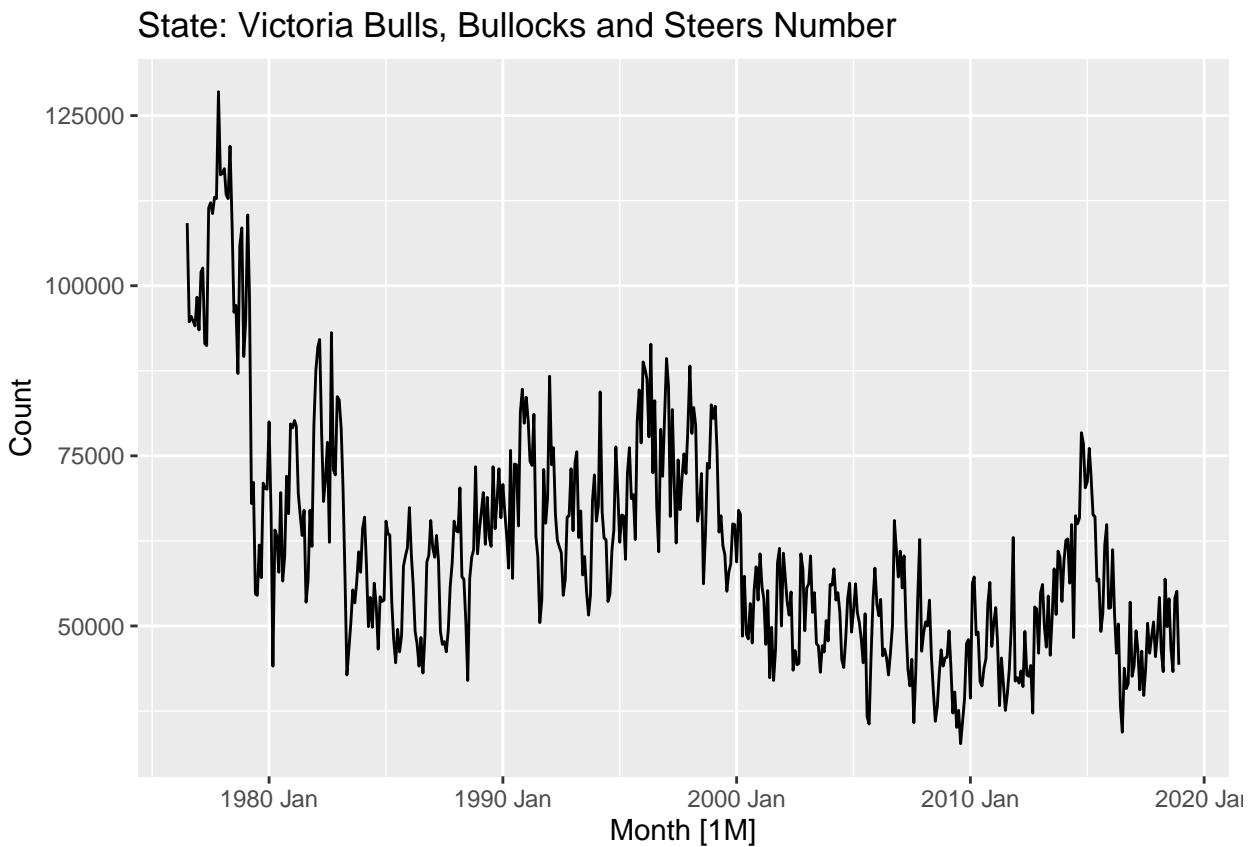
```
?aus_livestock
```

```
head(aus_livestock)
```

```
## # A tsibble: 6 x 4 [1M]
## # Key:      Animal, State [1]
##       Month Animal           State     Count
##       <mth> <fct>           <fct>    <dbl>
## 1 1976 Jul  Bulls, bullocks and steers Australian Capital Territory 2300
## 2 1976 Aug  Bulls, bullocks and steers Australian Capital Territory 2100
## 3 1976 Sep  Bulls, bullocks and steers Australian Capital Territory 2100
## 4 1976 Oct  Bulls, bullocks and steers Australian Capital Territory 1900
## 5 1976 Nov  Bulls, bullocks and steers Australian Capital Territory 2100
## 6 1976 Dec  Bulls, bullocks and steers Australian Capital Territory 1800
```

```
aus_livestock %>%
  filter(Animal == "Bulls, bullocks and steers", State == "Victoria") %>%
  autoplot() +
  labs(title = "State: Victoria Bulls, Bullocks and Steers Number")
```

```
## Plot variable not specified, automatically selected '.vars = Count'
```



```
lambda <- aus_livestock %>%
  filter(Animal == "Bulls, bullocks and steers", State == "Victoria") %>%
  features(Count, features = guerrero)
```

```
lambda
```

```
## # A tibble: 1 x 3
##   Animal           State    lambda_guerrero
##   <fct>            <fct>      <dbl>
## 1 Bulls, bullocks and steers Victoria -0.0446
```

- c.Victorian Electricity Demand from vic\_elec.
- c Answer: I don't think the transformation is useful. Seems there is no upward or downward trend, but a seasonal pattern.

```
?vic_elec
```

```
head(vic_elec)
```

```
## # A tsibble: 6 x 5 [30m] <Australia/Melbourne>
##   Time           Demand Temperature Date       Holiday
##   <dttm>        <dbl>     <dbl> <date>     <lgl>
```

```

## 1 2012-01-01 00:00:00 4383.      21.4 2012-01-01 TRUE
## 2 2012-01-01 00:30:00 4263.      21.0 2012-01-01 TRUE
## 3 2012-01-01 01:00:00 4049.      20.7 2012-01-01 TRUE
## 4 2012-01-01 01:30:00 3878.      20.6 2012-01-01 TRUE
## 5 2012-01-01 02:00:00 4036.      20.4 2012-01-01 TRUE
## 6 2012-01-01 02:30:00 3866.      20.2 2012-01-01 TRUE

```

```

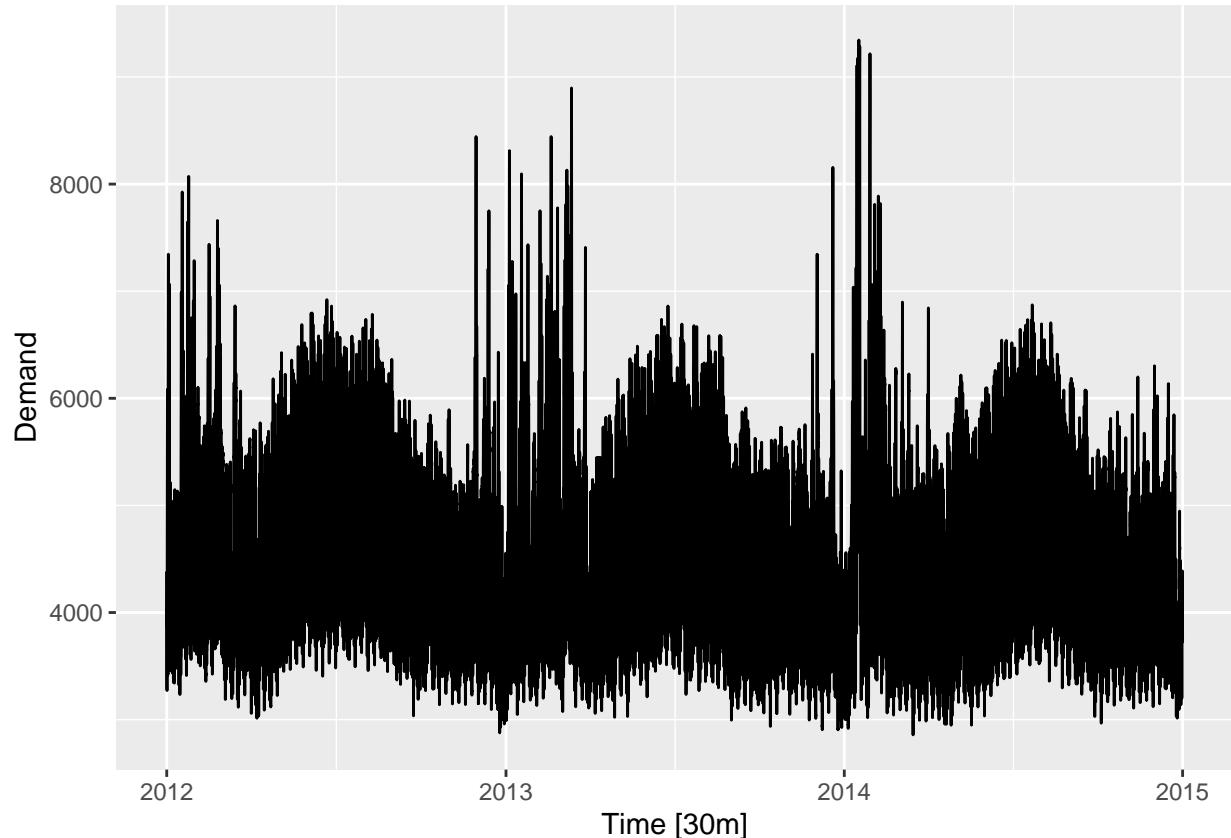
vic_elec %>%
  autoplot()

```

```

## Plot variable not specified, automatically selected '.vars = Demand'

```



- d.Gas production from aus\_production.
- d Answer: The data shows an upward trend so the transformation is useful. Compared to the original data plot, a Box-Cox transformation helps us to see the seasonal trend better.

```
?aus_production
```

```
head(aus_production)
```

```

## # A tsibble: 6 x 7 [1Q]
##   Quarter Beer Tobacco Bricks Cement Electricity   Gas
##       <qtr> <dbl>    <dbl>  <dbl>  <dbl>      <dbl> <dbl>

```

```

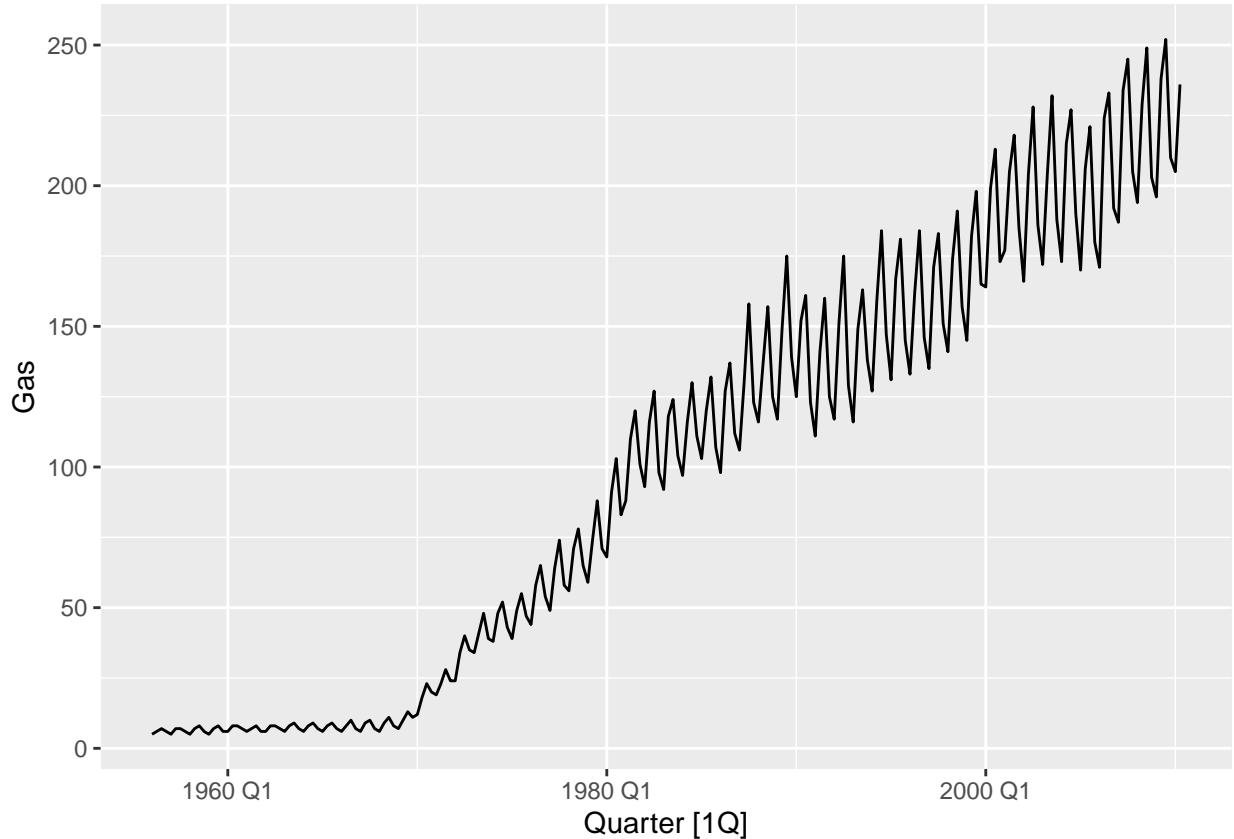
## 1 1956 Q1    284    5225    189    465    3923    5
## 2 1956 Q2    213    5178    204    532    4436    6
## 3 1956 Q3    227    5297    208    561    4806    7
## 4 1956 Q4    308    5681    197    570    4418    6
## 5 1957 Q1    262    5577    187    529    4339    5
## 6 1957 Q2    228    5651    214    604    4811    7

```

```

aus_production %>%
  autoplot(Gas)

```



```

lambda_2 <- aus_production %>%
  features(Gas, features = guerrero)

```

```

lambda_2

```

```

## # A tibble: 1 x 1
##   lambda_guerrero
##             <dbl>
## 1           0.110

```

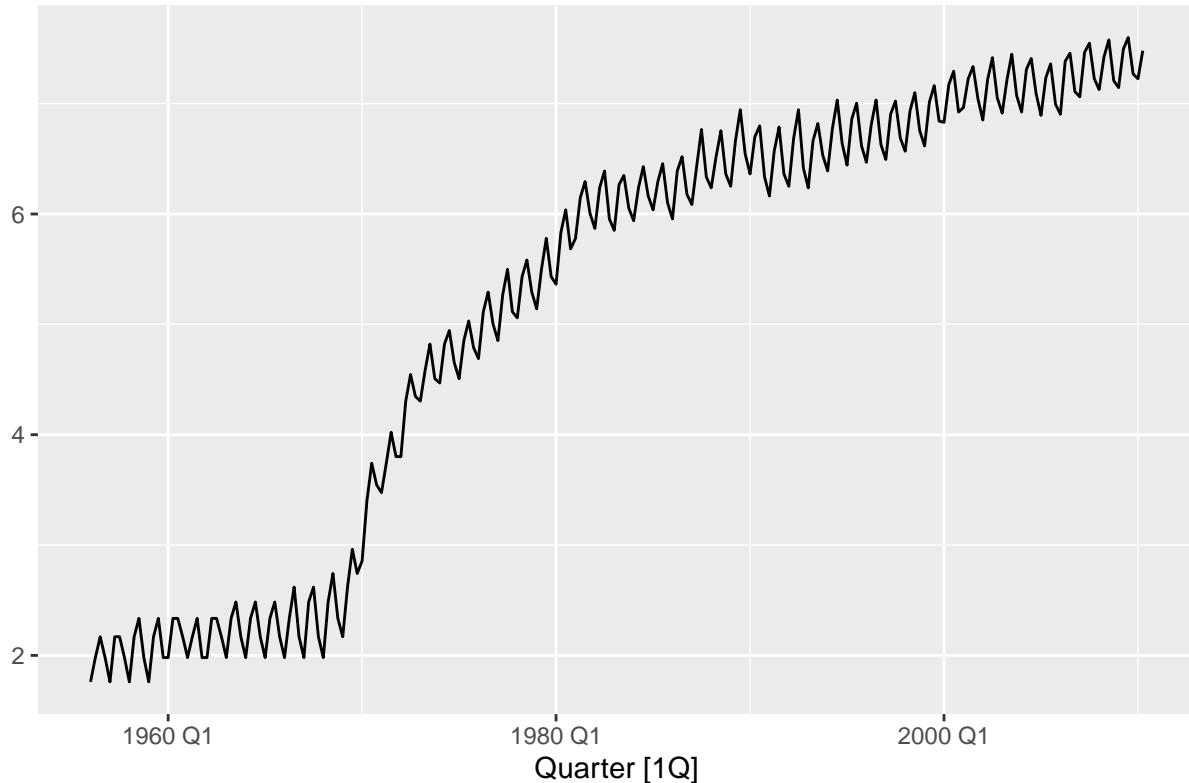
```

aus_production %>%
  autoplot(box_cox(Gas, lambda_2)) +
  labs(y = ""),
  title = latex2exp::TeX(paste0(

```

```
"Transformed gas production with $\\lambda$ = ",
round(lambda_2,2)))
```

Transformed gas production with  $\lambda = 0.11$



### 3. Why is a Box-Cox transformation unhelpful for the canadian\_gas data?

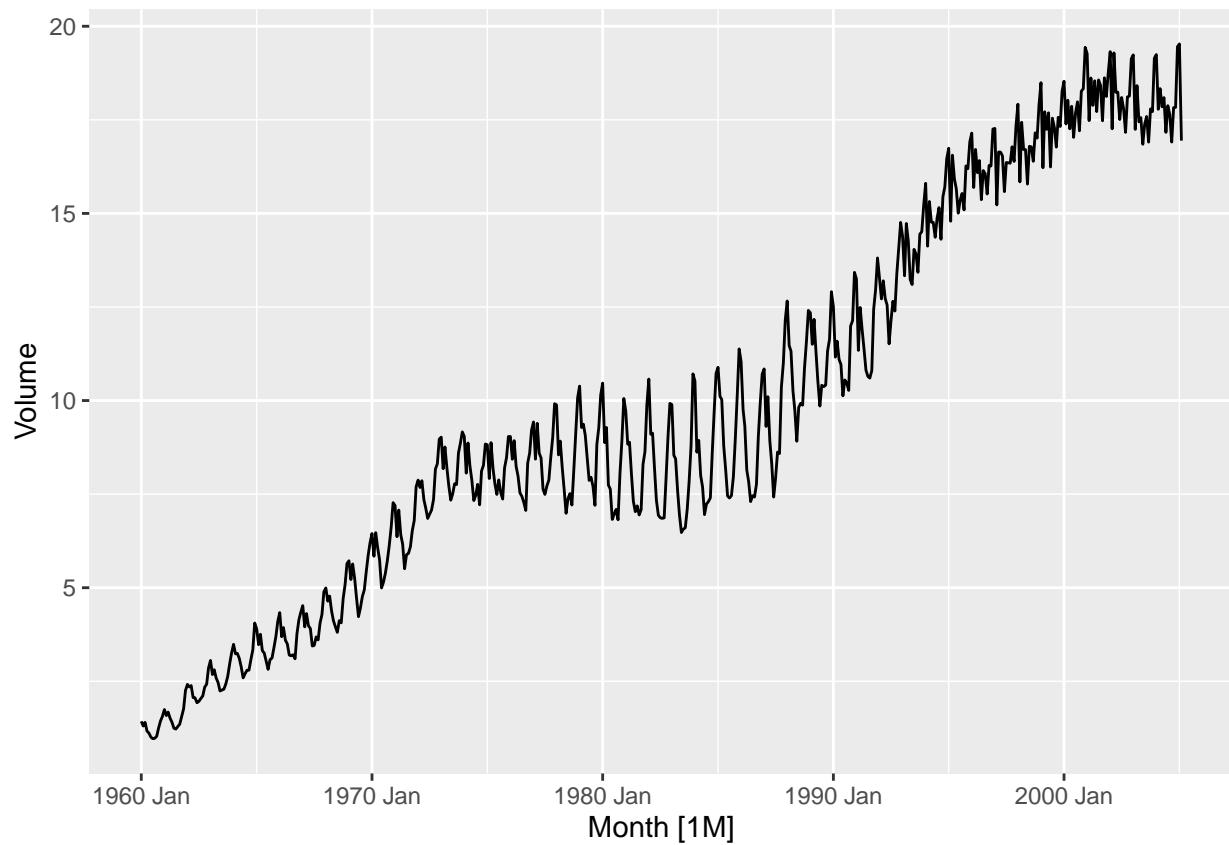
- Answer: It could be the data's trend is already spread well.

```
?canadian_gas
```

```
head(canadian_gas)
```

```
## # A tsibble: 6 x 2 [1M]
##   Month Volume
##   <mth>  <dbl>
## 1 1960 Jan    1.43
## 2 1960 Feb    1.31
## 3 1960 Mar    1.40
## 4 1960 Apr    1.17
## 5 1960 May    1.12
## 6 1960 Jun    1.01
```

```
canadian_gas %>%
  autoplot(Volume)
```



#### 4.What Box-Cox transformation would you select for your retail data (from Exercise 7 in Section 2.10)?

- Answer: The lambda is 0.08303631, the BOX-Cox transformation may be the best for this retail data?

```
head(aus_retail)
```

```
## # A tsibble: 6 x 5 [1M]
## # Key:      State, Industry [1]
##   State           Industry      'Series ID' Month Turnover
##   <chr>          <chr>        <chr>       <mth>    <dbl>
## 1 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 Apr     4.4
## 2 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 May     3.4
## 3 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 Jun     3.6
## 4 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 Jul     4
## 5 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 Aug     3.6
## 6 Australian Capital Territory Cafes, restaurants~ A3349849A 1982 Sep     4.2
```

```
set.seed(12345678)
myseries <- aus_retail %>%
```

```

filter(`Series ID` == sample(aus_retail$`Series ID`, 1)) %>%
  features(Turnover, features = guerero) %>%
  pull(lambda_guerero)

myseries

## [1] 0.08303631

```

5. For the following series, find an appropriate Box-Cox transformation in order to stabilise the variance. Tobacco from aus\_production, Economy class passengers between Melbourne and Sydney from ansett, and Pedestrian counts at Southern Cross Station from pedestrian.

- 5a Answer: Tobacco from aus\_production: lambda = 0.9264636

```

print(aus_production)

## # A tsibble: 218 x 7 [1Q]
##   Quarter Beer Tobacco Bricks Cement Electricity Gas
##   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 1956    Q1     284    5225    189    465    3923     5
## 2 1956    Q2     213    5178    204    532    4436     6
## 3 1956    Q3     227    5297    208    561    4806     7
## 4 1956    Q4     308    5681    197    570    4418     6
## 5 1957    Q1     262    5577    187    529    4339     5
## 6 1957    Q2     228    5651    214    604    4811     7
## 7 1957    Q3     236    5317    227    603    5259     7
## 8 1957    Q4     320    6152    222    582    4735     6
## 9 1958    Q1     272    5758    199    554    4608     5
## 10 1958   Q2     233    5641    229    620    5196     7
## # i 208 more rows

```

```

aus_production %>%
  features(Tobacco, features = guerero) %>%
  pull(lambda_guerero)

```

```
## [1] 0.9264636
```

- 5b Answer: Economy class passengers between Melbourne and Sydney from ansett: lambda = 1.999927

```

head(ansonett)

## # A tsibble: 6 x 4 [1W]
## # Key:      Airports, Class [1]
##   Week Airports Class Passengers
##   <dbl> <chr>   <chr>      <dbl>
## 1 1989 W28 ADL-PER Business     193
## 2 1989 W29 ADL-PER Business     254
## 3 1989 W30 ADL-PER Business     185
## 4 1989 W31 ADL-PER Business     254
## 5 1989 W32 ADL-PER Business     191
## 6 1989 W33 ADL-PER Business     136

```

```

ansett %>%
  filter(Class == "Economy", Airports == "MEL-SYD") %>%
  features(Passengers, features = guererro) %>%
  pull(lambda_guererro)

## [1] 1.999927

```

- 5c: Pedestrian counts at Southern Cross Station from pedestrian: lambda = -0.2501616

```
head(pedestrian)
```

```

## # A tsibble: 6 x 5 [1h] <Australia/Melbourne>
## # Key:      Sensor [1]
##   Sensor       Date_Time       Date     Time Count
##   <chr>        <dttm>       <date>    <int> <int>
## 1 Birrarung Marr 2015-01-01 00:00:00 2015-01-01     0 1630
## 2 Birrarung Marr 2015-01-01 01:00:00 2015-01-01     1  826
## 3 Birrarung Marr 2015-01-01 02:00:00 2015-01-01     2  567
## 4 Birrarung Marr 2015-01-01 03:00:00 2015-01-01     3  264
## 5 Birrarung Marr 2015-01-01 04:00:00 2015-01-01     4  139
## 6 Birrarung Marr 2015-01-01 05:00:00 2015-01-01     5    77

```

```

pedestrian %>%
  filter(Sensor == "Southern Cross Station") %>%
  features(Count, features = guererro) %>%
  pull(lambda_guererro)

```

```
## [1] -0.2501616
```

## 7. Consider the last five years of the Gas data from aus\_production.

- a. Plot the time series. Can you identify seasonal fluctuations and/or a trend-cycle?
- Answer: The overall trend is going upward, every 3rd quarter is the highest, and every 1st quarter is the lowest.

```
?aus_production
```

```

## # A tsibble: 6 x 7 [1Q]
##   Quarter Beer Tobacco Bricks Cement Electricity   Gas
##   <qtr> <dbl>   <dbl>   <dbl>   <dbl>       <dbl> <dbl>
## 1 1956 Q1  284    5225    189    465      3923     5
## 2 1956 Q2  213    5178    204    532      4436     6
## 3 1956 Q3  227    5297    208    561      4806     7
## 4 1956 Q4  308    5681    197    570      4418     6
## 5 1957 Q1  262    5577    187    529      4339     5
## 6 1957 Q2  228    5651    214    604      4811     7

```

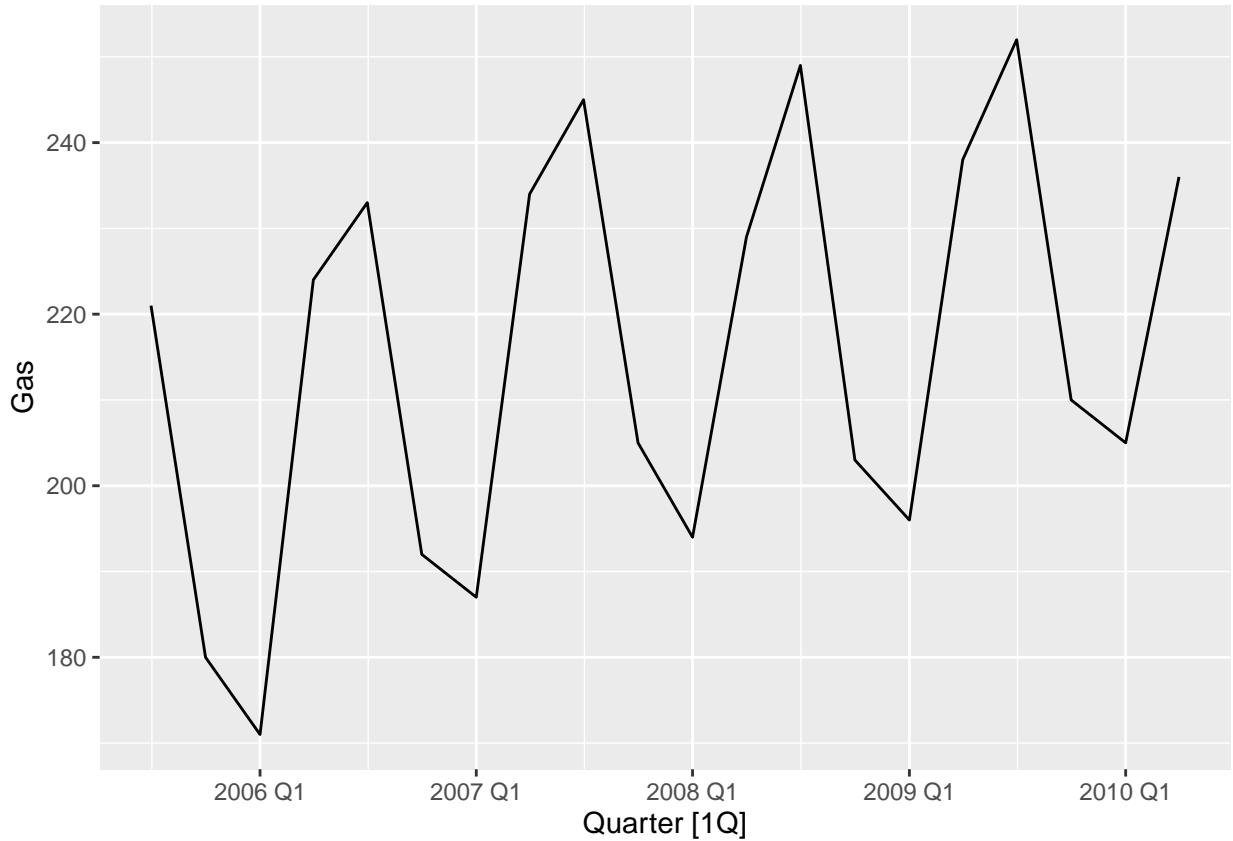
```

gas <- tail(aus_production, 5*4) |> select(Gas)

gas %>%
  autoplot()

## Plot variable not specified, automatically selected '.vars = Gas'

```



- b. Use classical\_decomposition with type=multiplicative to calculate the trend-cycle and seasonal indices.

```

gas %>%
  model(classical_decomposition(Gas, type = "multiplicative")) %>%
  components() %>%
  autoplot()

```

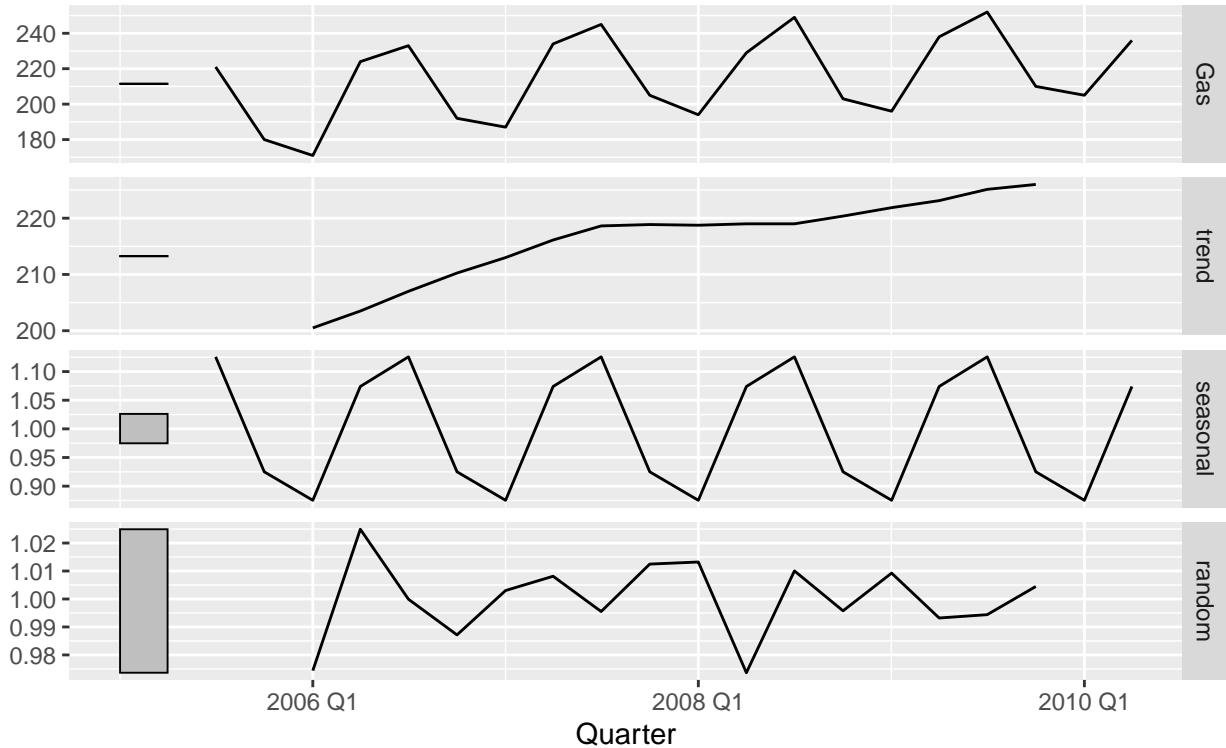
```

## Warning: Removed 2 rows containing missing values or values outside the scale range
## ('geom_line()').

```

## Classical decomposition

Gas = trend \* seasonal \* random

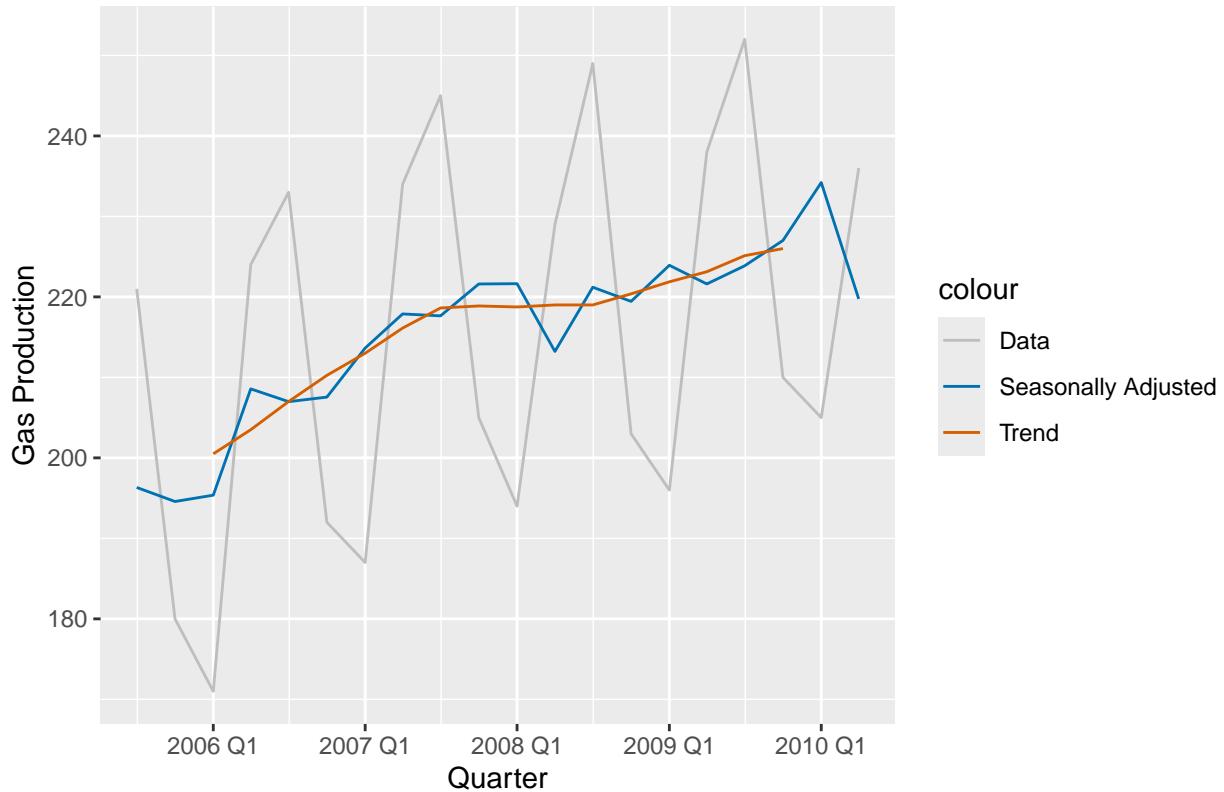


- c. Do the results support the graphical interpretation from part a?
- Answer: Yes, it seems every year's pattern are the same.
- d. Compute and plot the seasonally adjusted data.

```
gas %>%
  model(classical_decomposition(Gas, type = "multiplicative")) %>%
  components() %>%
  ggplot(aes(x = Quarter)) +
  geom_line(aes(y = Gas, colour = "Data")) +
  geom_line(aes(y = season_adjust,
                colour = "Seasonally Adjusted")) +
  geom_line(aes(y = trend, colour = "Trend")) +
  labs(y = "Gas Production",
       title = "Quarterly production of selected commodities in Australia (Gas)") +
  scale_colour_manual(
    values = c("gray", "#0072B2", "#D55E00"),
    breaks = c("Data", "Seasonally Adjusted", "Trend")
  )
```

```
## Warning: Removed 4 rows containing missing values or values outside the scale range
## ('geom_line()').
```

## Quarterly production of selected commodities in Australia (Gas)



- e. Change one observation to be an outlier (e.g., add 300 to one observation), and recompute the seasonally adjusted data. What is the effect of the outlier?
- Answer: When I add 300 to the outlier, it changed the shape of the data plot, it create a outlier during 1st quarter of 2006.

```
gas2 <- gas
gas2$Gas[3] <- gas2$Gas[3] + 300
```

```
gas2
```

```
## # A tsibble: 20 x 2 [1Q]
##   Gas Quarter
##   <dbl> <qtr>
## 1 221 2005 Q3
## 2 180 2005 Q4
## 3 471 2006 Q1
## 4 224 2006 Q2
## 5 233 2006 Q3
## 6 192 2006 Q4
## 7 187 2007 Q1
## 8 234 2007 Q2
## 9 245 2007 Q3
## 10 205 2007 Q4
## 11 194 2008 Q1
## 12 229 2008 Q2
```

```

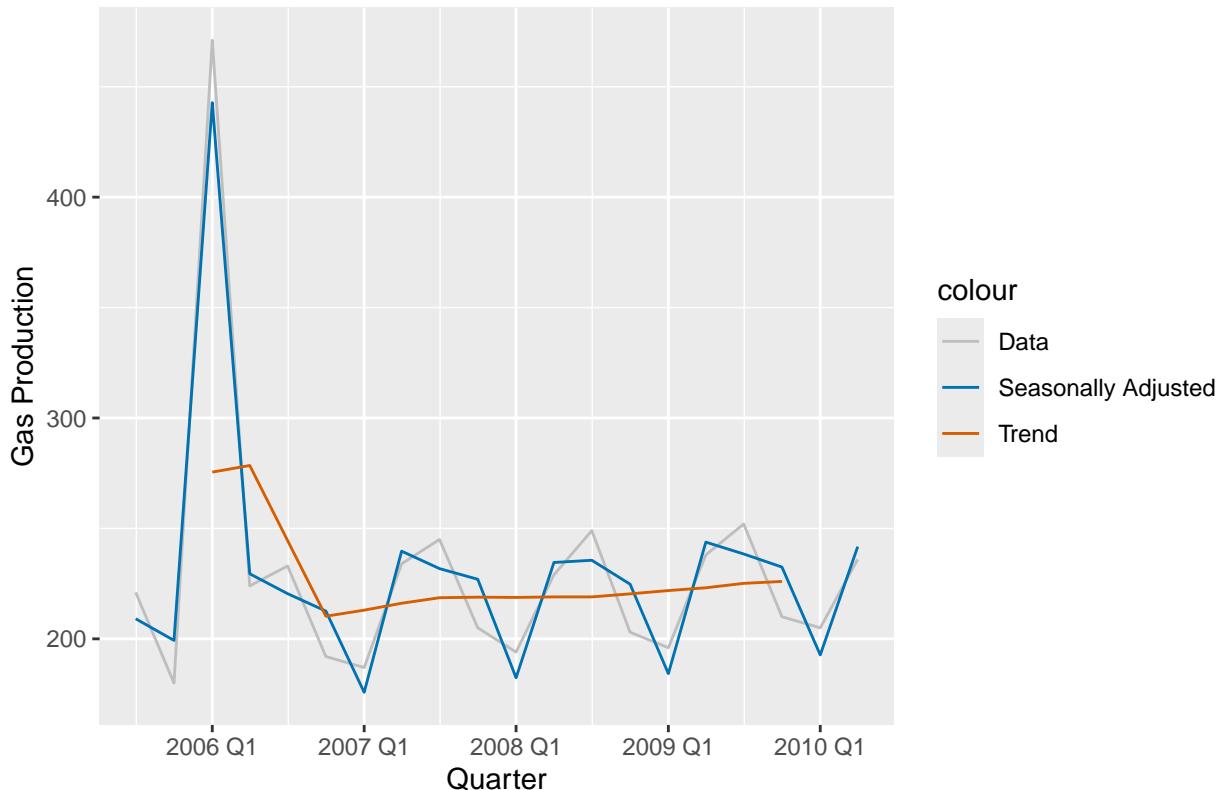
## 13 249 2008 Q3
## 14 203 2008 Q4
## 15 196 2009 Q1
## 16 238 2009 Q2
## 17 252 2009 Q3
## 18 210 2009 Q4
## 19 205 2010 Q1
## 20 236 2010 Q2

gas2 %>%
  model(classical_decomposition(Gas, type = "multiplicative")) %>%
  components() %>%
  ggplot(aes(x = Quarter)) +
  geom_line(aes(y = Gas, colour = "Data")) +
  geom_line(aes(y = season_adjust,
                colour = "Seasonally Adjusted")) +
  geom_line(aes(y = trend, colour = "Trend")) +
  labs(y = "Gas Production",
       title = "Quarterly production of selected commodities in Australia (Gas)") +
  scale_colour_manual(
    values = c("gray", "#0072B2", "#D55E00"),
    breaks = c("Data", "Seasonally Adjusted", "Trend")
  )

```

## Warning: Removed 4 rows containing missing values or values outside the scale range  
## ('geom\_line()').

Quarterly production of selected commodities in Australia (Gas)

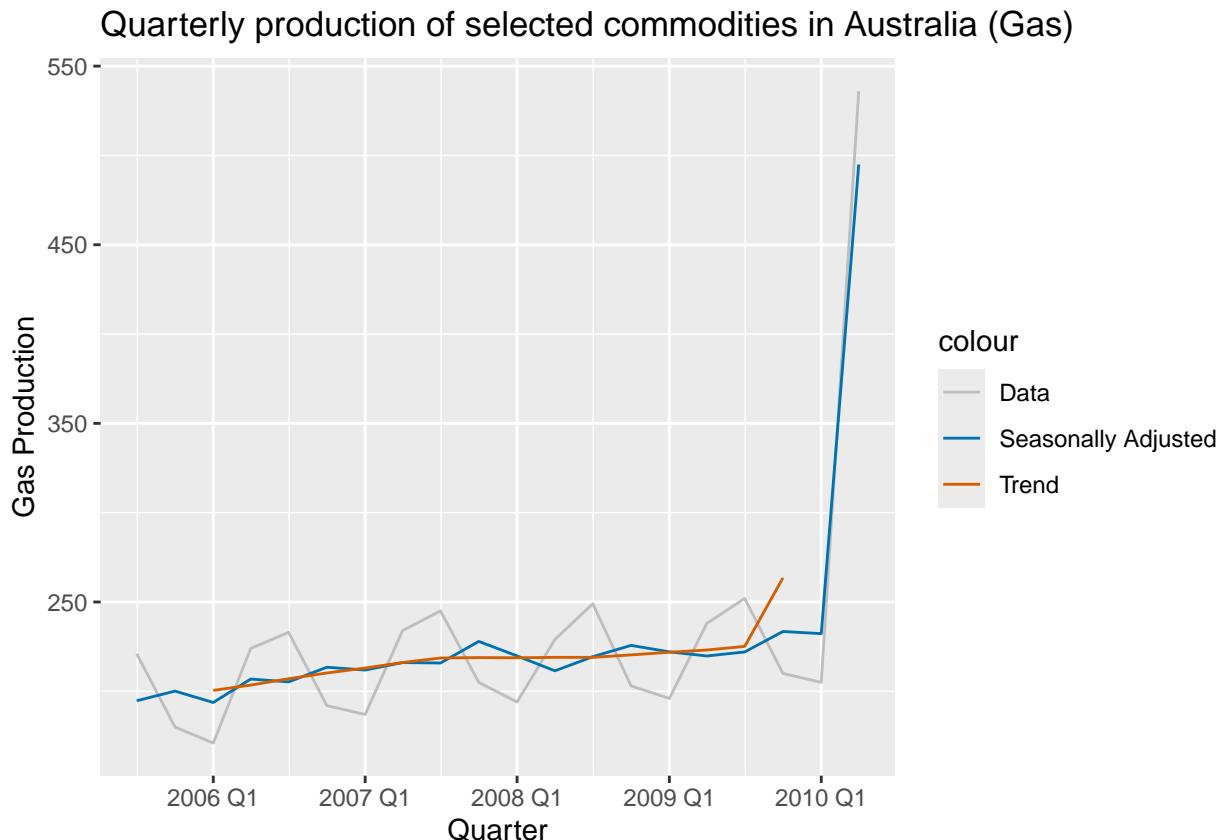


- f. Does it make any difference if the outlier is near the end rather than in the middle of the time series?
- Answer: It doesn't make any difference if the outlier is near the end rather than in the middle of the time series. If the outlier is present, it will change or adjust the whole plot.

```
gas3 <- gas
gas3$Gas[20] <- gas2$Gas[20] + 300
```

```
gas3 %>%
  model(classical_decomposition(Gas, type = "multiplicative")) %>%
  components() %>%
  ggplot(aes(x = Quarter)) +
  geom_line(aes(y = Gas, colour = "Data")) +
  geom_line(aes(y = season_adjust,
                colour = "Seasonally Adjusted")) +
  geom_line(aes(y = trend, colour = "Trend")) +
  labs(y = "Gas Production",
       title = "Quarterly production of selected commodities in Australia (Gas)") +
  scale_colour_manual(
    values = c("gray", "#0072B2", "#D55E00"),
    breaks = c("Data", "Seasonally Adjusted", "Trend")
  )
```

## Warning: Removed 4 rows containing missing values or values outside the scale range  
## ('geom\_line()'').

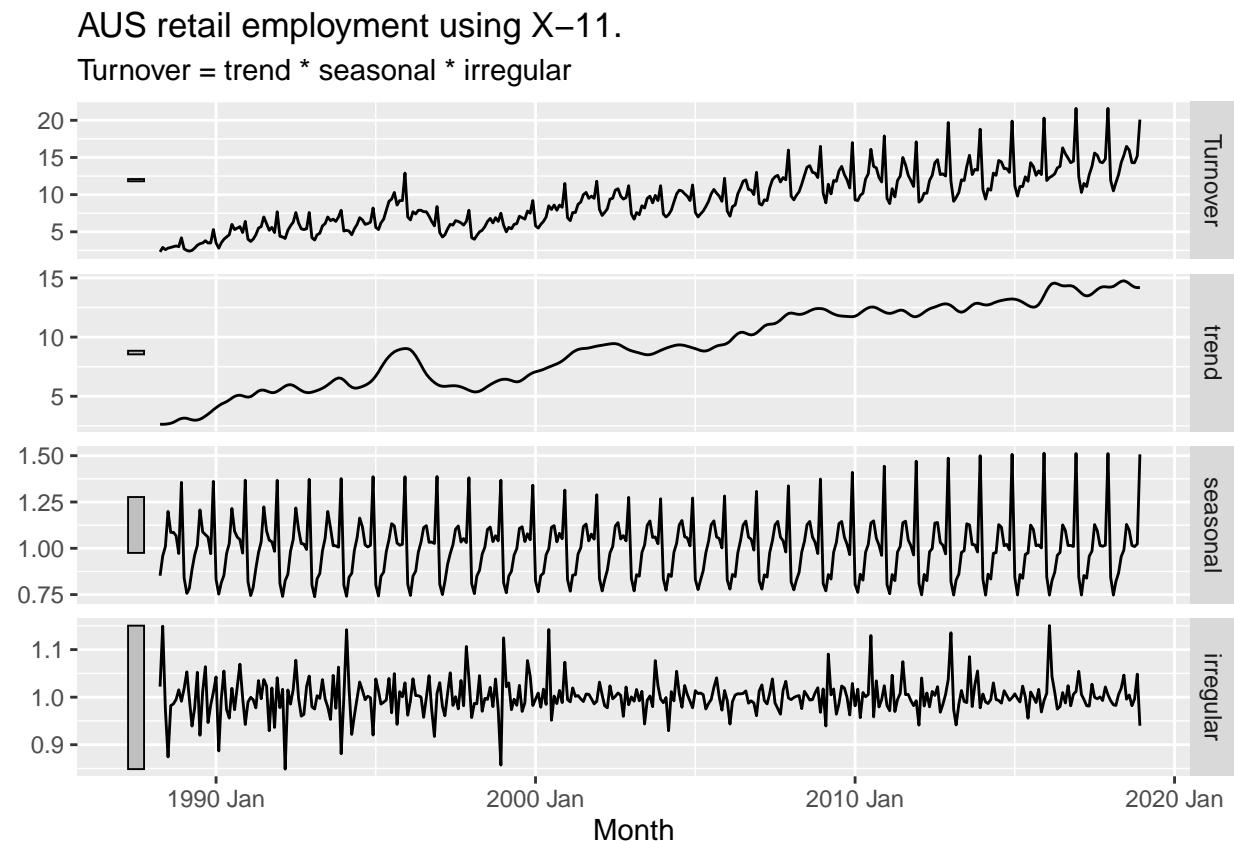


8. Recall your retail time series data (from Exercise 7 in Section 2.10). Decompose the series using X-11. Does it reveal any outliers, or unusual features that you had not noticed previously?

- Answer: Yes, in the plot, I see some peak trend, that may be the outliers. X-11 helps a lot to see the outliers in data.

```
set.seed(12345678)
myseries <- aus_retail %>%
  filter(`Series ID` == sample(aus_retail$`Series ID`, 1))

x11_dcmp <- myseries |>
  model(x11 = X_13ARIMA_SEATS(Turnover ~ x11())) |>
  components()
autoplot(x11_dcmp) +
  labs(title =
    "AUS retail employment using X-11.")
```



## 9. Figures 3.19 and 3.20 show the result of decomposing the number of persons in the civilian labour force in Australia each month from February 1978 to August 1995. - a. Write about 3–5 sentences describing the results of the decomposition. Pay particular attention to the scales of the graphs in making your interpretation. - a Answer: The overall trend is going upward. I observed there are many sharp upticks and sharp declines. This pattern is repeated seasonally. And there are a couple of outliers during 1992 and 1998, the trend decrease a lot. - b. Is the recession of 1991/1992 visible in the estimated components? - b Answer: Yes