

Time Series Decomposition

Introducing classical models (Additive, Multiplicative)

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Time Series Decomposition

What does 'decomposition' mean?

One approach to time series analysis is based on smoothing past data in order to separate the underlying pattern in the data series from randomness

can be projected into the future and used as the **forecast**

can be broken down into **sub patterns** to identify **the component factors**

Decomposition

Time Series Decomposition

Components

Systematic

Level Trend Seasonality

A combination of these components
= A series

$$y_t = f(S_t, T_t, R_t)$$

Non-Systematic

Noise

where,

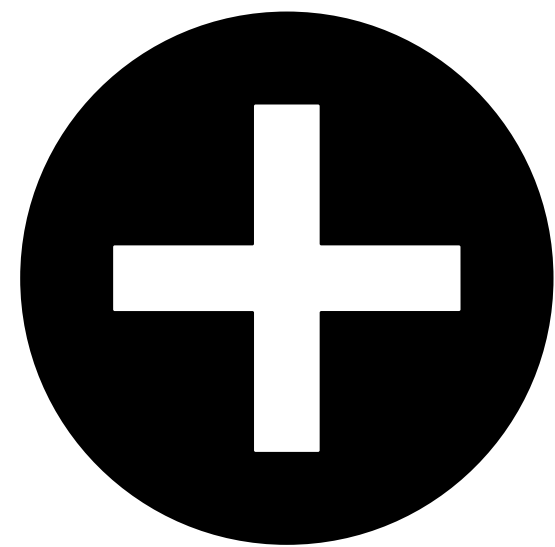
- y_t = data at period t
- T_t = trend-cycle components at period t
- S_t = seasonal component at period t
- R_t = remainder(Noise) components at period t

Time Series Decomposition

Classical Decomposition Models

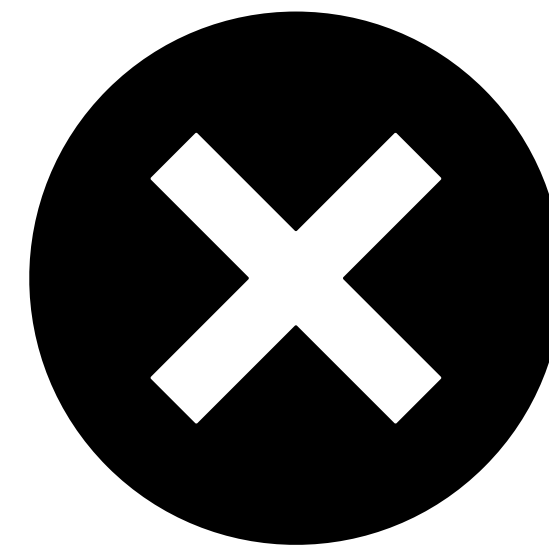
assume that the seasonal component is constant from year to year

How to combine these components?



Additive

$$y_t = S_t + T_t + R_t$$

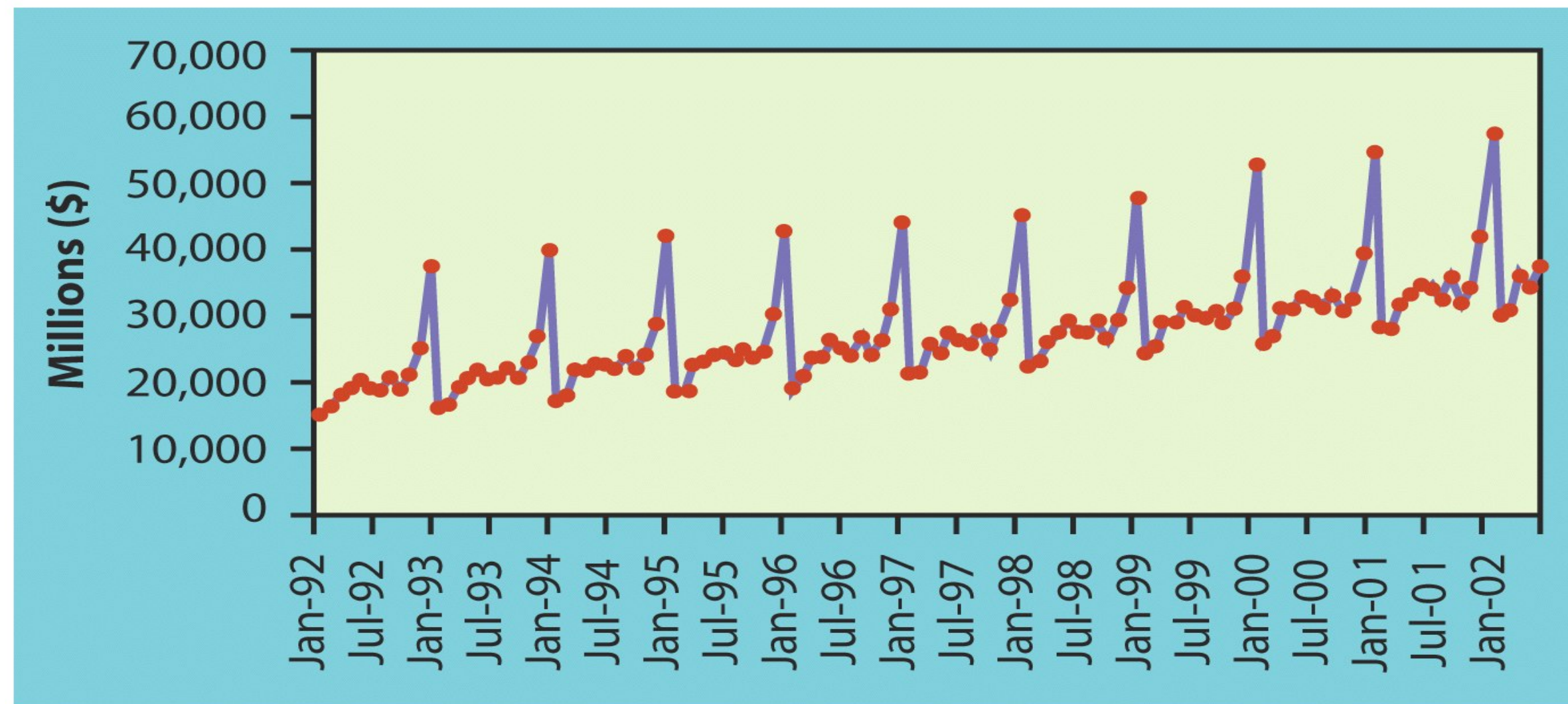


Multiplicative

$$y_t = S_t * T_t * R_t$$

Additive Decomposition

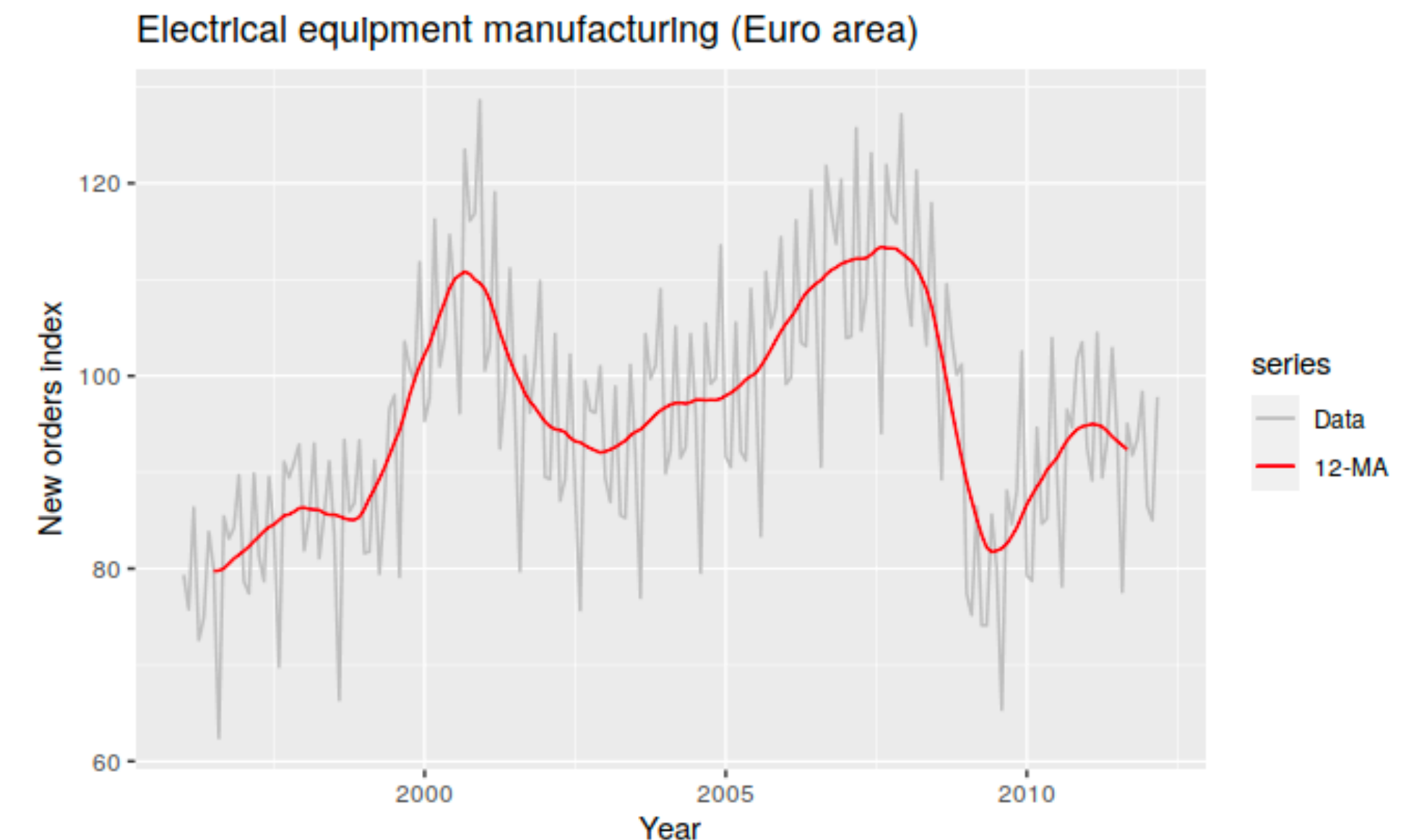
Time series data is a function of the **sum** of its components



Appropriate if the magnitude of the seasonal fluctuation **does not vary** with the level of the series

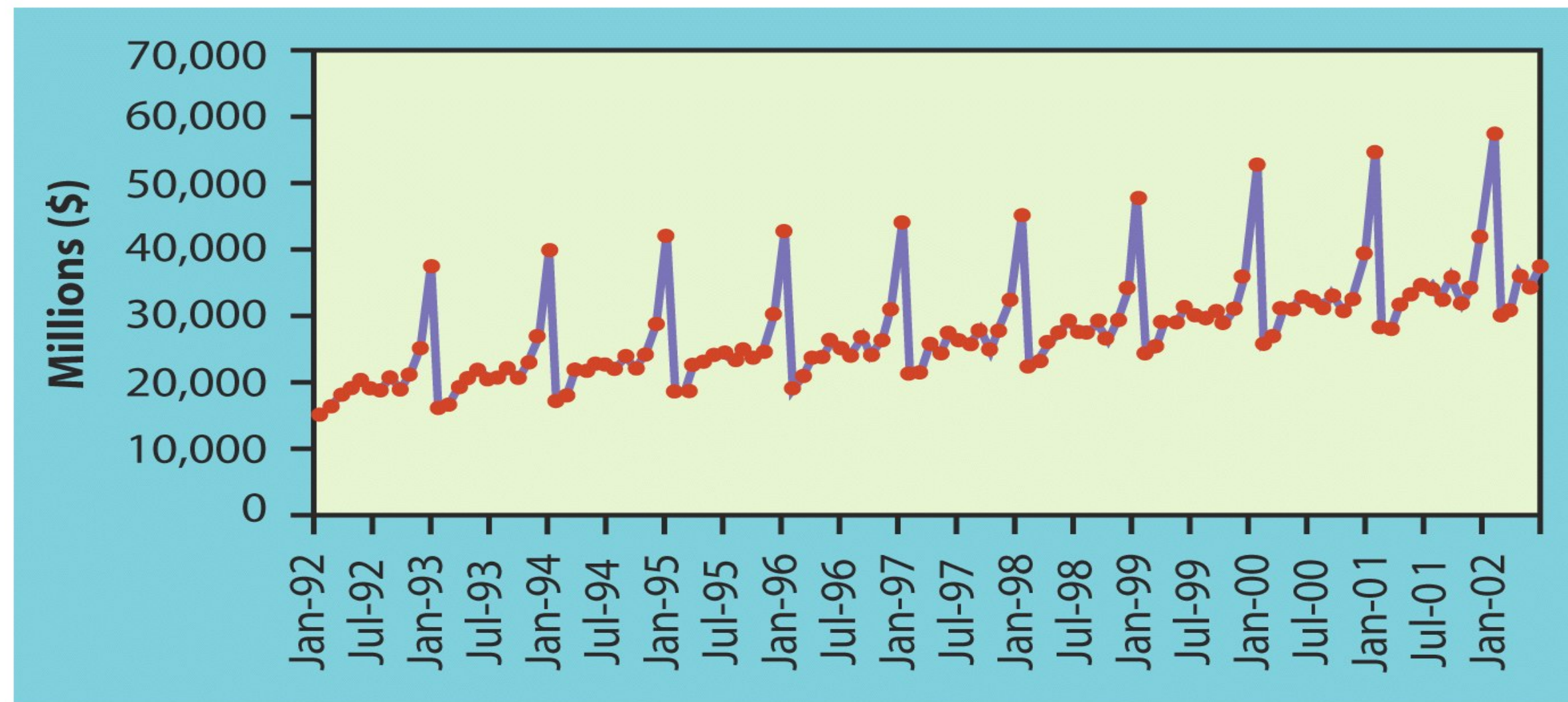
Step 1.

Compute trend-cycle(T_t) using MA(Moving Average)



Additive Decomposition

Time series data is a function of the **sum** of its components



Appropriate if the magnitude of the seasonal fluctuation **does not vary** with the level of the series

Step 1.

Compute trend-cycle(T_t) using MA(Moving Average)

If period(m) is an **odd** num: $m - MA$

If period(m) is an **even** num: $2 * m - MA$

Step 2.

Calculate the detrended series ($y_t - T_t$)

Step 3.

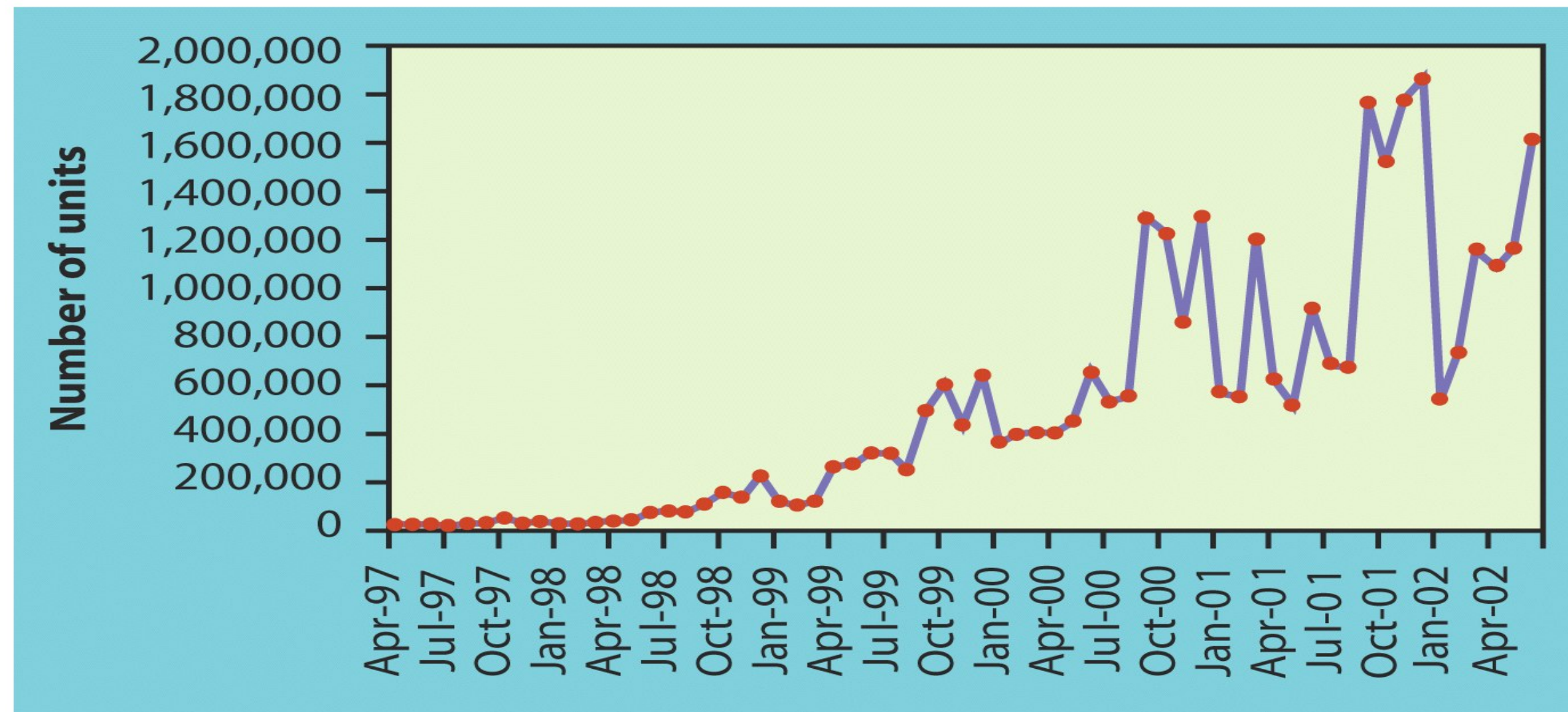
To estimate the seasonal component(S_t), **simply average the detrended values** for that season
+) adjust values so that they add to zero

Step 4.

Calculate the remainder(R_t) by subtracting S_t , T_t

Multiplicative Decomposition

Time series data is a function of the **product** of its components



Frequently used if the amplitude of the seasonality is **proportional** (increase or decrease) to level of series
e.g. economic series

Step 1.

Compute trend-cycle(T_t) using MA(Moving Average)

If period(m) is an **odd** num: $m - MA$

If period(m) is an **even** num: $2 * m - MA$

Step 2.

Calculate the detrended series (y_t / T_t)

Step 3.

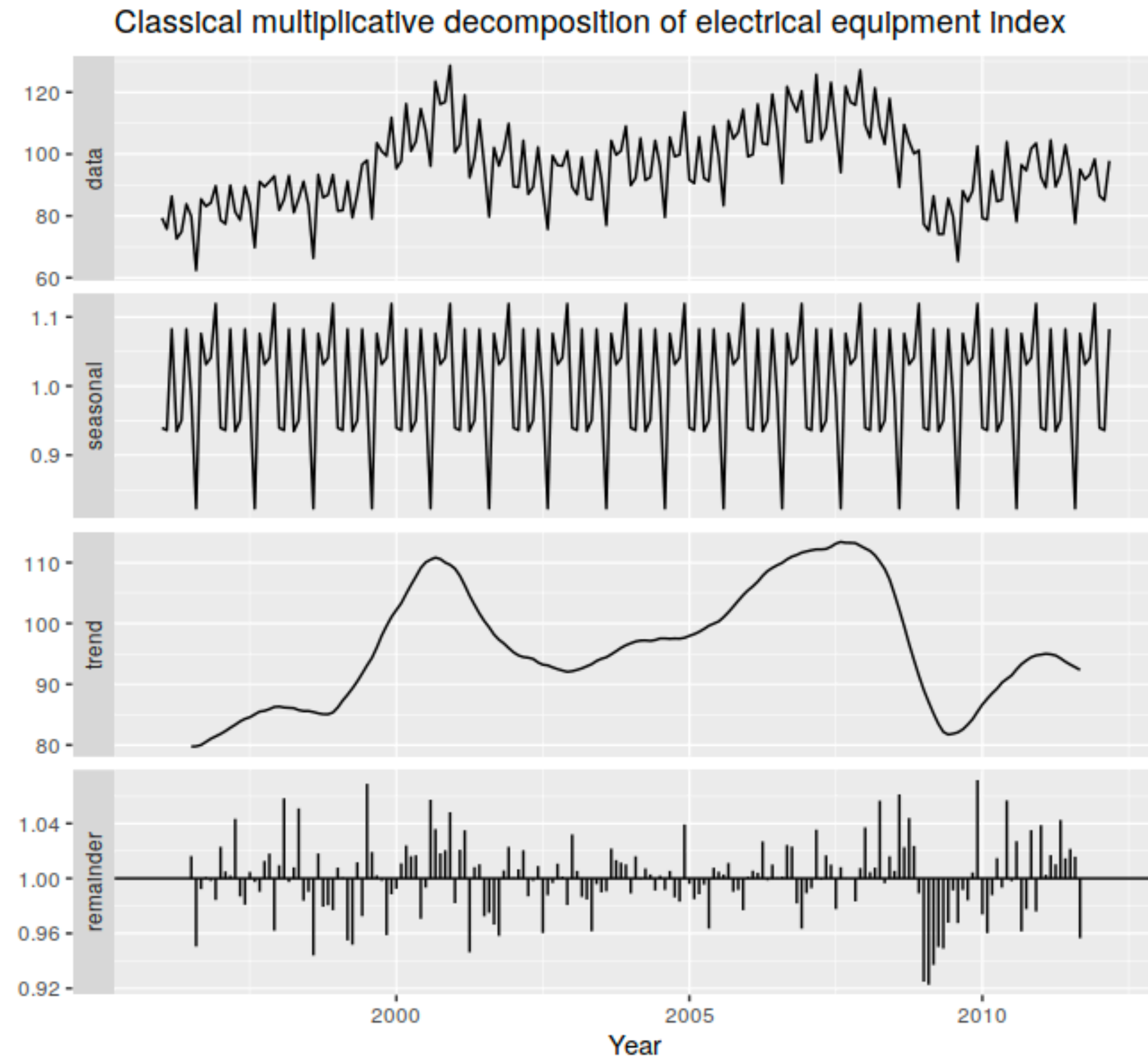
To estimate the seasonal component(S_t),
simply average the detrended values for that season
+) adjust values so that they add to m (average = 1)

Step 4.

Calculate the remainder(R_t) by dividing out S_t , T_t

Multiplicative Decomposition

Time series data is a function of the **product** of its components



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Compute trend-cycle(T_t) using MA(Moving Average)

If period(m) is an **odd** num: $m - MA$

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To estimate the seasonal component(S_t),
simply average the detrended values for that season
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Time Series Decomposition

Problems of classical models

The estimate of the trend-cycle is **unavailable for the first few & last few observations**
= no estimate of the remainder component for the same time period

The trend-cycle estimate tends to **over-smooth** rapid rises and falls in the data
= cause a large remainder component

The basic assumption (seasonal component is constant throughout the entire series)
might **not be suitable for longer periods**.

Uses alternative models like X11, STL

References

- https://yoongaemii.github.io/seasonal_decomposition/
- <https://math.unm.edu/~lil/Stat581/6-decomposition.pdf>
- <https://towardsdatascience.com/different-types-of-time-series-decomposition-396c09f92693>
- http://web.vu.lt/mif/a.buteikis/wp-content/uploads/2019/02/Lecture_03.pdf
- <https://otexts.com/fpp2/classical-decomposition.html>

Thank You 