

Day 3 - Decomposition of time series

Introduction

The purpose of today's lecture is to understand how to decompose a time series into its constituent components in R. To guide our exploration, we will return to the Vermont temperatures and Pan Am data sets.

```
# packages
library(tidyverse)

# load data and rename
## Pan Am
data(AirPassengers)
ap <- AirPassengers

## vt temps
vt_temps <- readr::read_csv("vt_temps.csv")
```

Review: creating `ts` objects

Create a `ts` object, called `vt_ts`, for the monthly temperatures in Vermont that spans from 1970/06/01 to 2013/04/01. Plot the time series.

```
# alternative using window()
vt_ts_long <- ts(
  vt_temps$AverageTemperature,
  start = c(1850, 1),
  end = c(2013, 9),
  freq = 12
)

vt_ts <- window(
  vt_ts_long,
  start = c(1970, 6),
  end = c(2013, 4)
)
```

Introducing definitions and notation

i Random variables

A _____, usually written X , is a variable whose possible values are the numerical outcomes of _____ phenomenon. There are two types of random variables, _____ and _____.

Formally, a random variable is a mapping from a sample space S to the real numbers.

Discrete random variables:

Continuous random variables:

i Time series notation

A _____ of length n is a sequence of _____, which we denote $\{X_t : t = 1, \dots, n\} = \{X_1, X_2, \dots, X_n\}$. When referring to an observed time series, we use lowercase letters, $\{x_t : t = 1, \dots, n\} = \{x_1, x_2, \dots, x_n\}$. If the length of the series n does not need to be specified, we will often use the abbreviated notation $\{x_t\}$.

- $\bar{x} = \frac{\sum x_i}{n}$

- \hat{x}

- $\hat{x}_{t+k|t}$

Our first time series model

i Decomposition models

An _____ is a simple model for a time series that estimates the _____, _____, and _____.

$$x_t = m_t + s_t + z_t$$

A _____ allows for the seasonal effect to increase as the trend increase.

$$x_t = m_t \cdot s_t \cdot z_t$$

If the time series is strictly positive, it may be easier to fit an additive model on the log scale than a multiplicative model on the original scale.

$$\log(x_t) = m_t + s_t + z_t$$

Estimating m_t , s_t , and z_t

How can we obtain an estimate of the trend effect?

i Centered moving average

For time series with a period of 12 (i.e. monthly data), the _____ at time t is given by

$$\hat{m}_t = \frac{\frac{1}{2}x_{t-6} + x_{t-5} + \cdots + x_{t-1} + x_t + x_{t+1} + \cdots + x_{t+5} + \frac{1}{2}x_{t+6}}{12}$$

where $t = 7, \dots, n - 6$

How can we obtain an estimate of the seasonal effect at each time t ? How can we obtain an estimate of the overall seasonal effect associated with each month?

i Seasonal effects

For an additive time series with a monthly frequency, the seasonal effect at time t is estimated by

$$\hat{s}_t = x_t - \hat{m}_t$$

We can obtain a single estimate of the monthly effect by averaging the effect of each month.

$$\bar{s}_t = \frac{\sum s_t}{T - 1}$$

where T denotes the number of years. Often times, the estimated seasonal effect is **centered** after calculation - more on this on Wednesday. If a time series is multiplicative, the seasonal effect is instead estimated by

$$\hat{s}_t = \frac{x_t}{\hat{m}_t}$$

How can we obtain an estimate of z_t ?

i Residual error series

The _____, also called _____, is the raw time series adjusted for the trend and seasonal effects. On average, this series should have a mean of _____. For an additive decomposition model, the residual error series is

$$\hat{z}_t = x_t - \hat{m}_t - \bar{s}_t$$

For a multiplicative decomposition model, the residual error series is

$$\hat{z}_t = \frac{x_t}{\hat{m}_t \cdot \bar{s}_t}$$

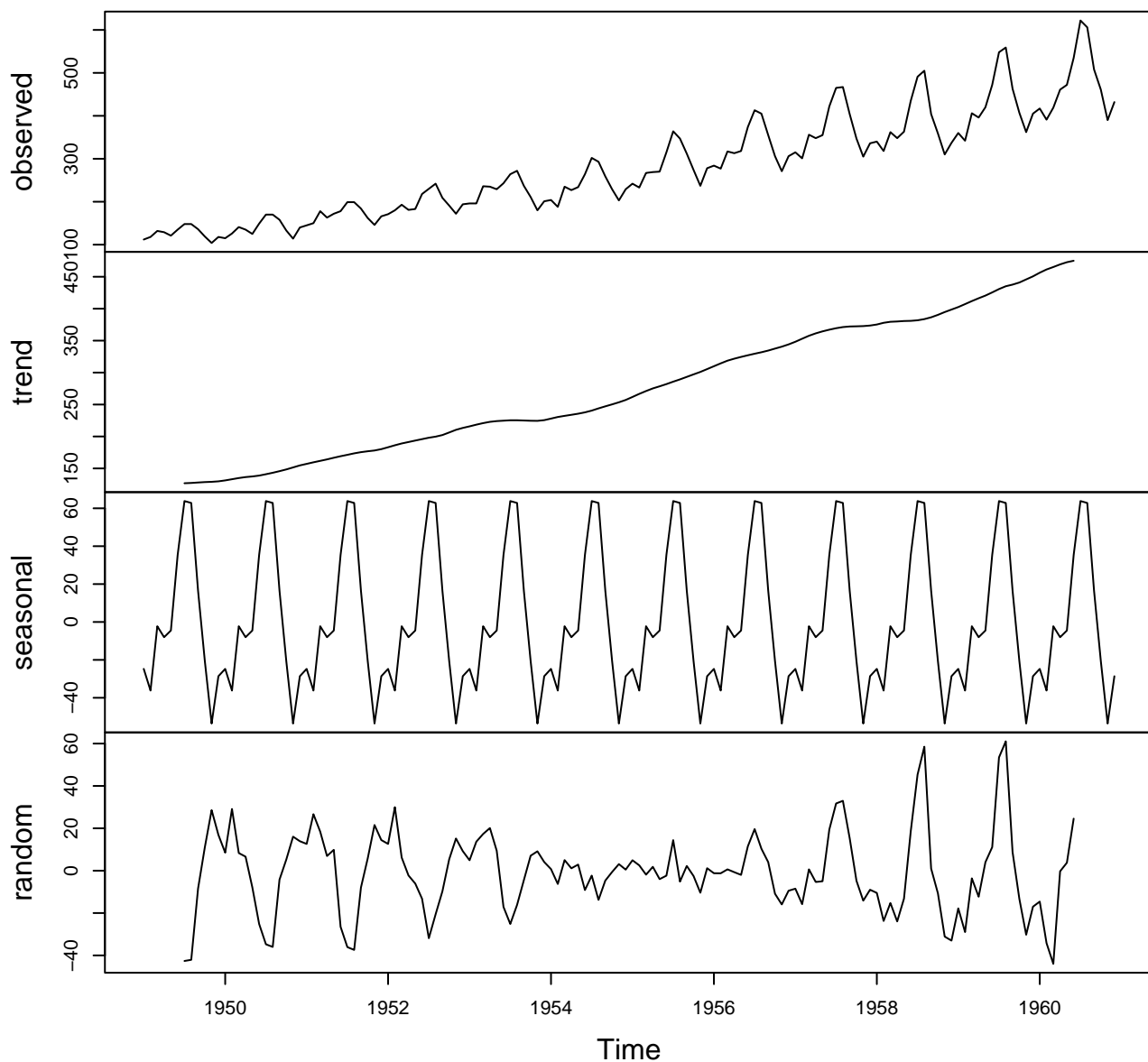
Decomposition in R

i Note

The `decompose` function may be used in R to obtain a decomposition of a time series object.

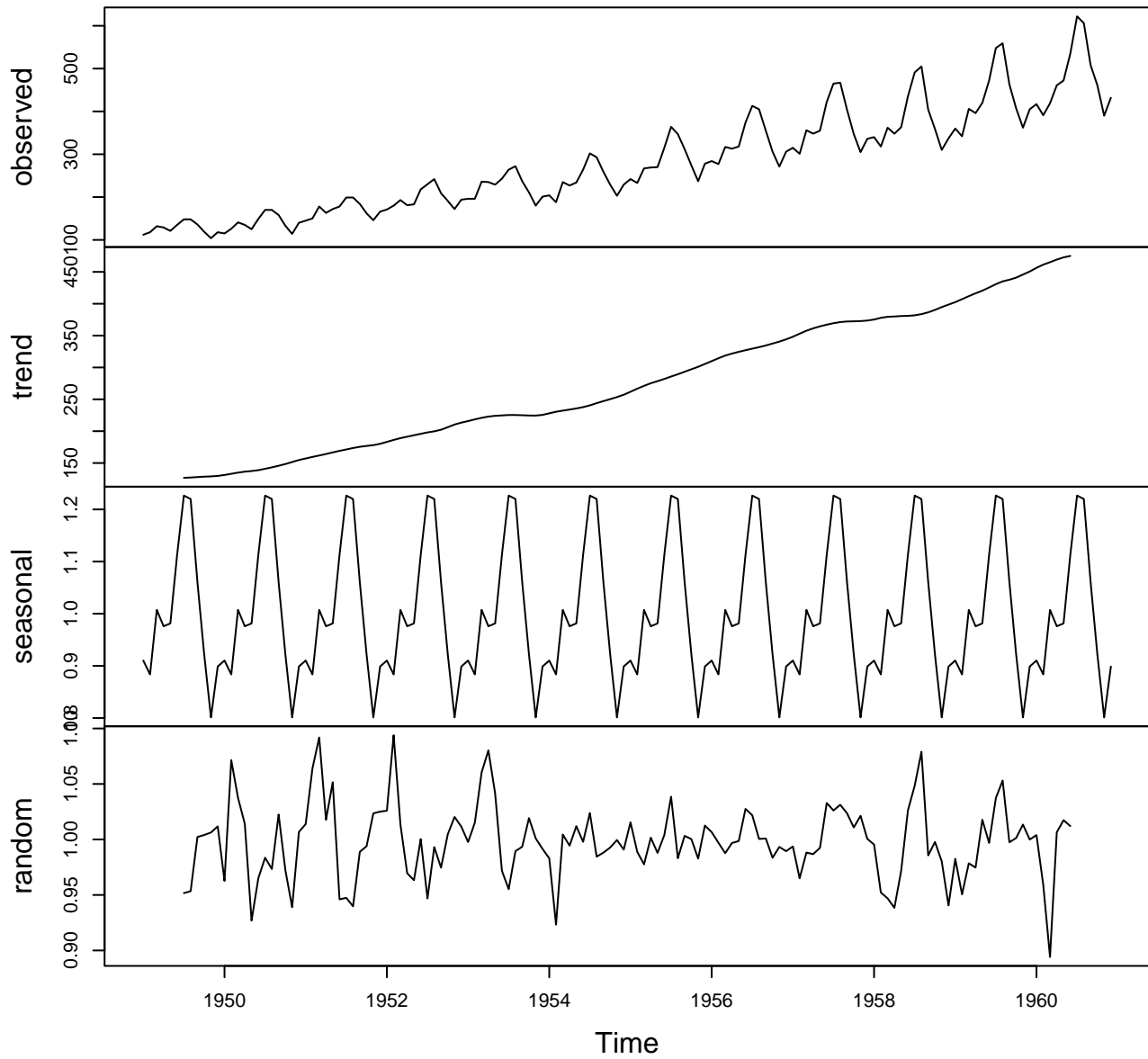
```
plot(decompose(ap))
```

Decomposition of additive time series



```
plot(decompose(ap, type = "multiplicative"))
```

Decomposition of multiplicative time series




```
plot(decompose(log(ap)))
```

Decomposition of additive time series

