



# ENV797 - TIME SERIES ANALYSIS FOR ENERGY AND ENVIRONMENT APPLICATIONS

## M3 - Trend and Seasonality | Stationarity Tests

Prof. Luana Medeiros Marangon Lima, Ph.D.

# Learning Goals



- Trend Component
  - ▣ Linear and Non-linear
  - ▣ How to Estimate Linear Trend
  - ▣ How to Model/Remove Linear Trend from a Series
- Seasonal Trend
  - ▣ How to Estimate Seasonal Trend
  - ▣ How to Model/Remove Seasonal Trend from a Series
- Stationarity Tests

# Time Series Components

- A time series may have the following components:

Trend  
Component

Seasonal  
Component

**Decomposing the Time Series means separating trend/cycle, seasonal and random components.**

Cyclical  
Component

Random  
Component

**TSA will find and exploit predictable patterns/components.**

# Causes of Variation in TS data

- **Calendar:** seasons, holidays, weekends
- **Example**

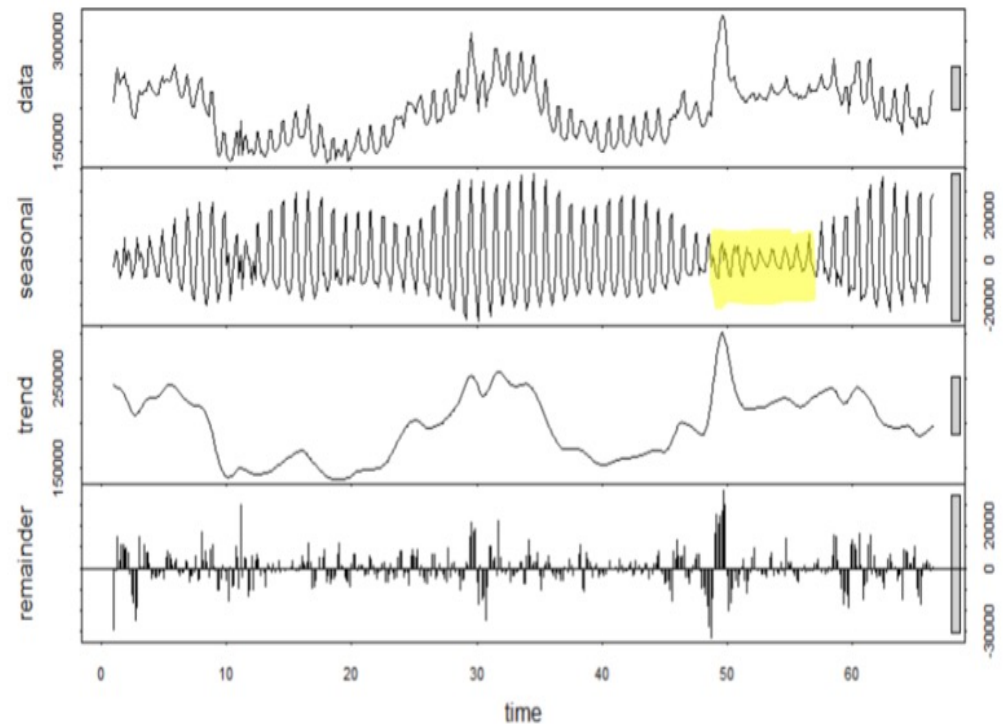
## Interest

- Trend of usage over time
- Popularity of games
- Weekly cycle of usage

## Knowledge

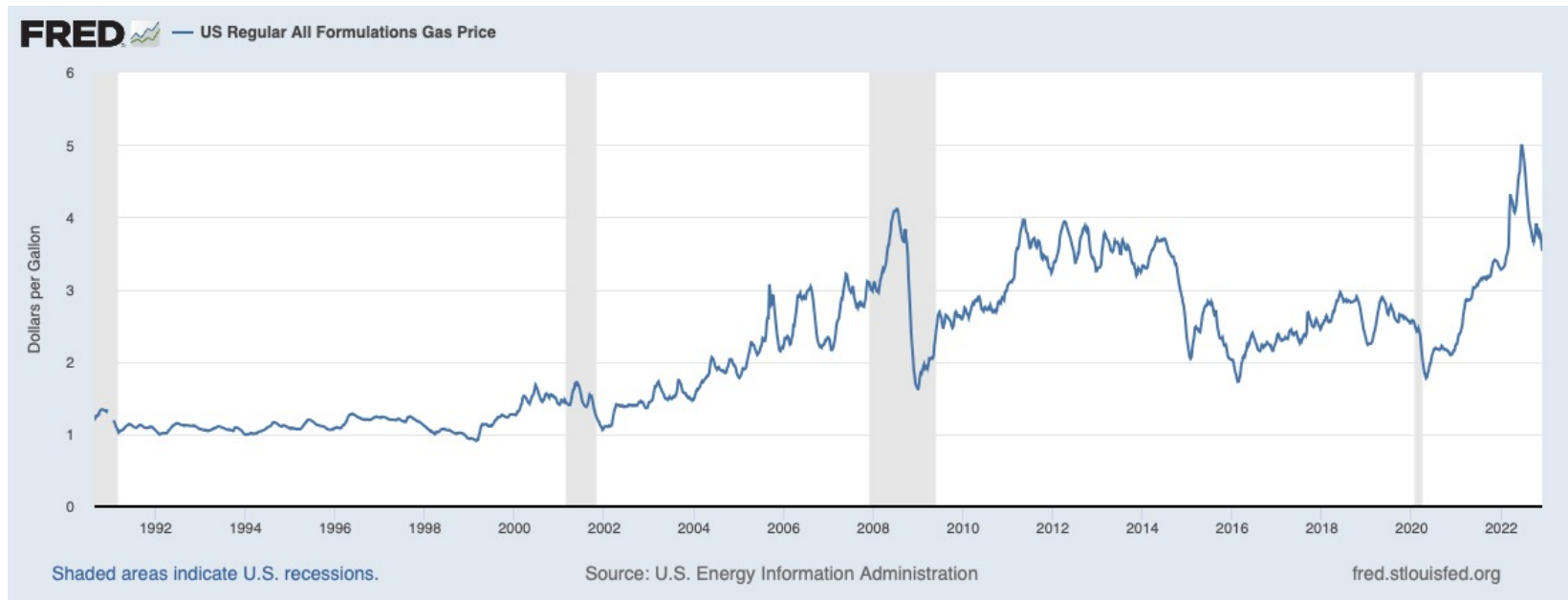
- Usage up on the weekend and down during the week
- Increased usage during holidays
- Summer time:  
weekdays/weekends blend together

**Video game usage over time – daily basis**



# Causes of Variation in TS data

- **Natural calamities:** earthquake, epidemic, flood, drought
- Political movements or changes, policies, war
- Example



Source: <https://fred.stlouisfed.org/series/GASREGW#>

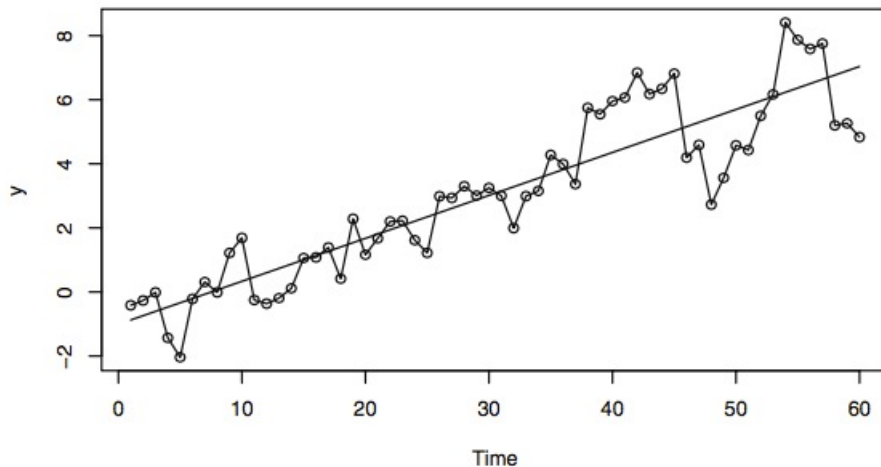


# Trend Component

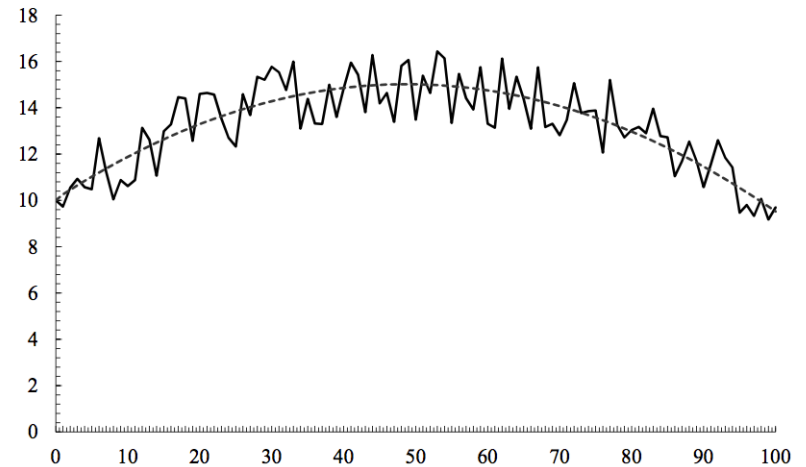
# Trend Component

- Long-term tendency
  - ▣ Increase (upward movement) or
  - ▣ Decrease (downward movement)
- Trend can be linear or non-linear

Ex: Upward Linear Trend



Ex: Quadratic Trend



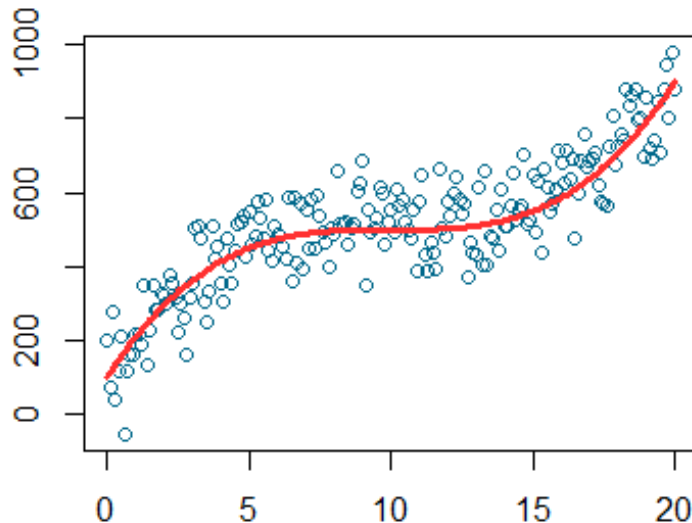
# Non-linear Trend

## Polynomial trend

- Example: quadratic trend

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 T_i^2 + \varepsilon_i$$

- Or any other order

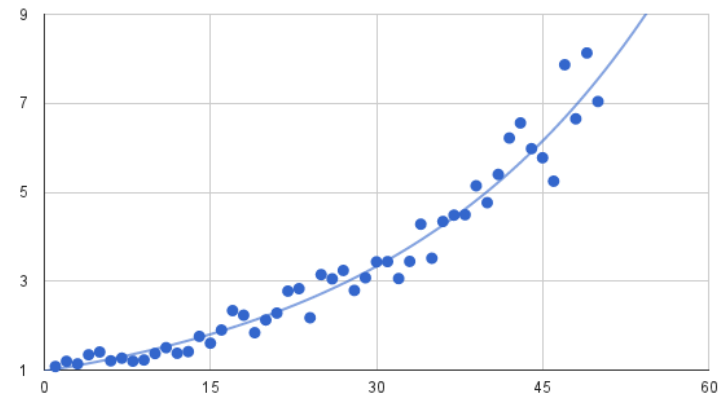


## Exponential trend

$$Y_i = (e^{\beta_0 + \beta_1 T_i}) \varepsilon_i$$

- Can be transformed into linear trend

$$\ln Y_i = \beta_0 + \beta_1 T_i + \ln \varepsilon_i$$



Most of the time we assume a linear trend to simplify the analysis

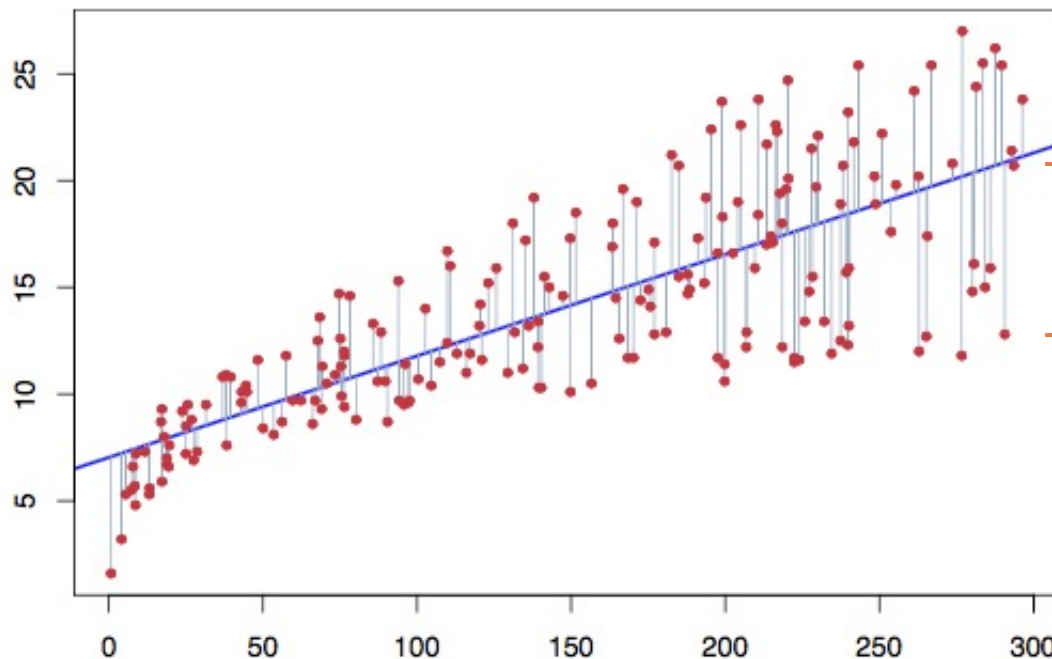


# Linear Trend Component

- For a linear trend we can write

$$Y_i = \beta_0 + \beta_1 t_i + \varepsilon_i$$

- **Slope** ( $\beta_1$ ) and the **intercept** ( $\beta_0$ ) are the unknown parameters, and  $\varepsilon_i$  is the **error term**



$$\hat{Y}_i = \beta_0 + \beta_1 t_i$$

The error term or residual  
is the distance from point  
 $Y_i$  to the estimate  $\hat{Y}_i$

$$\varepsilon_i = Y_i - \hat{Y}_i$$

# Linear Trend Estimation

- How do we estimate  $\beta_0$  and  $\beta_1$ ?
- One approach: **Least Squares Method**

- We want to minimize

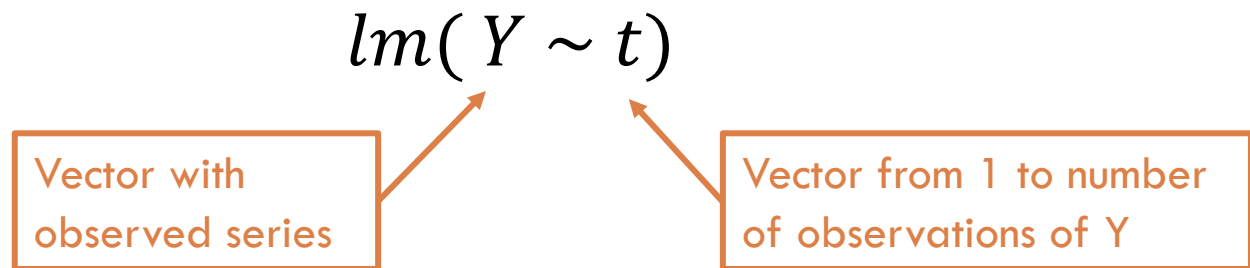
$$Q(\beta_0, \beta_1) = \sum_{t=1}^T [Y_t - (\beta_0 + \beta_1 t)]^2$$

- How do we minimize this function?
  - By taking the partial derivatives of  $Q(\beta_0, \beta_1)$  with respect to the coefficients  $\beta_0$  e  $\beta_1$
  - QR decomposition

**We will use R to solve it!**

# Estimating Linear Trend in R

- The function for simple linear regression in R is the *lm()* from package "stats", where *lm* stands for "linear model"
- The arguments you will need to provide are



Note: vectors  $Y$  and  $t$  should be in **data frame format**

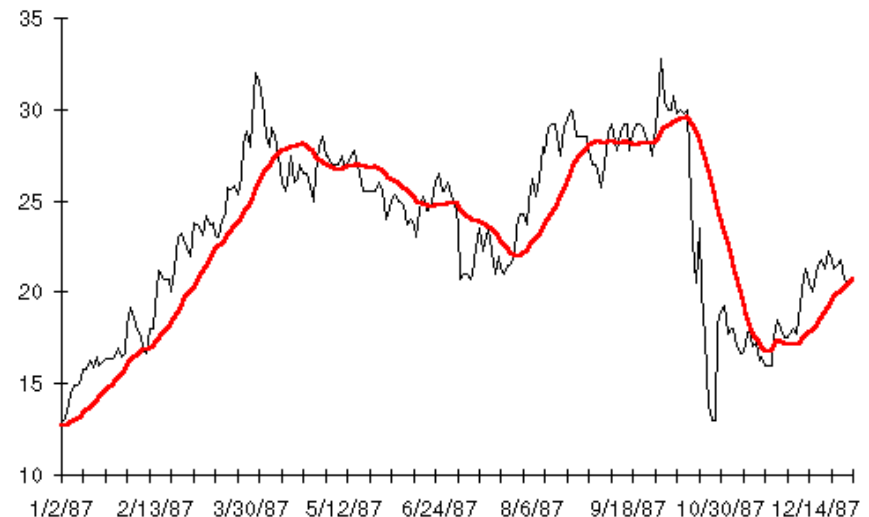
# Linear Trend Estimation and Removal

1. Model the trend: find  $\beta_0$  and  $\beta_1$
2. For each observation  $t$  remove trend

$$Y_{detrend_t} = Y_t - (\beta_0 + \beta_1 t)$$

# Moving Average for Non-Linear Trend Estimation

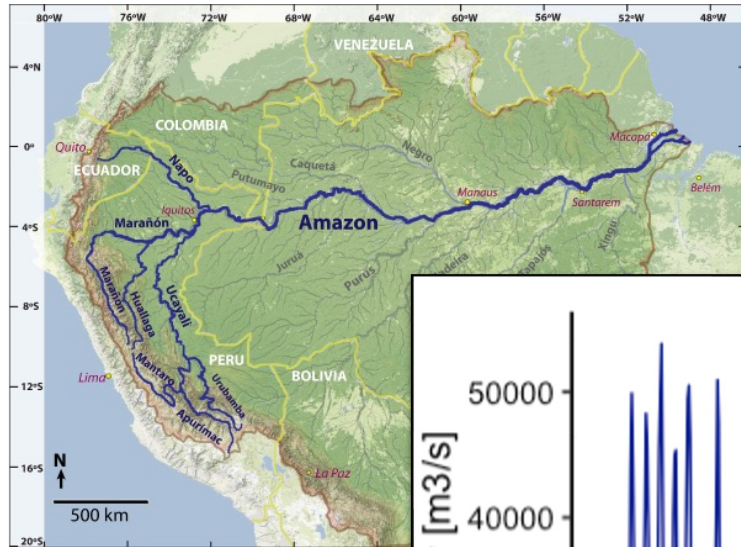
- Smooth out the trend with something like a rolling average
  - ▣ A moving average trendline smooth out fluctuations in data to show a pattern or trend more clearly
  - ▣ Which order to use for the moving average?
- Looking at the rolling average makes it easier to tell how the trend is moving underneath the noise



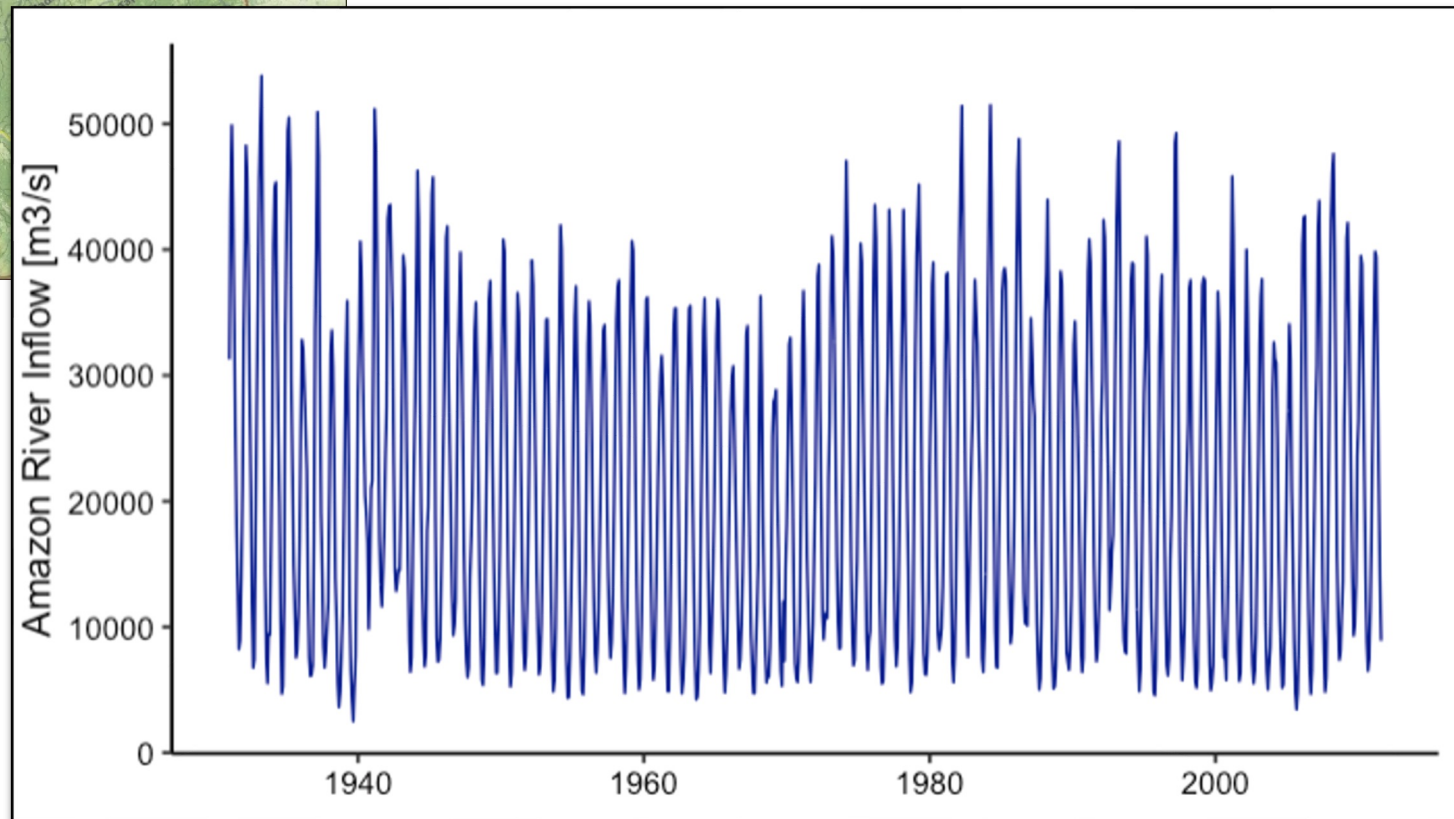


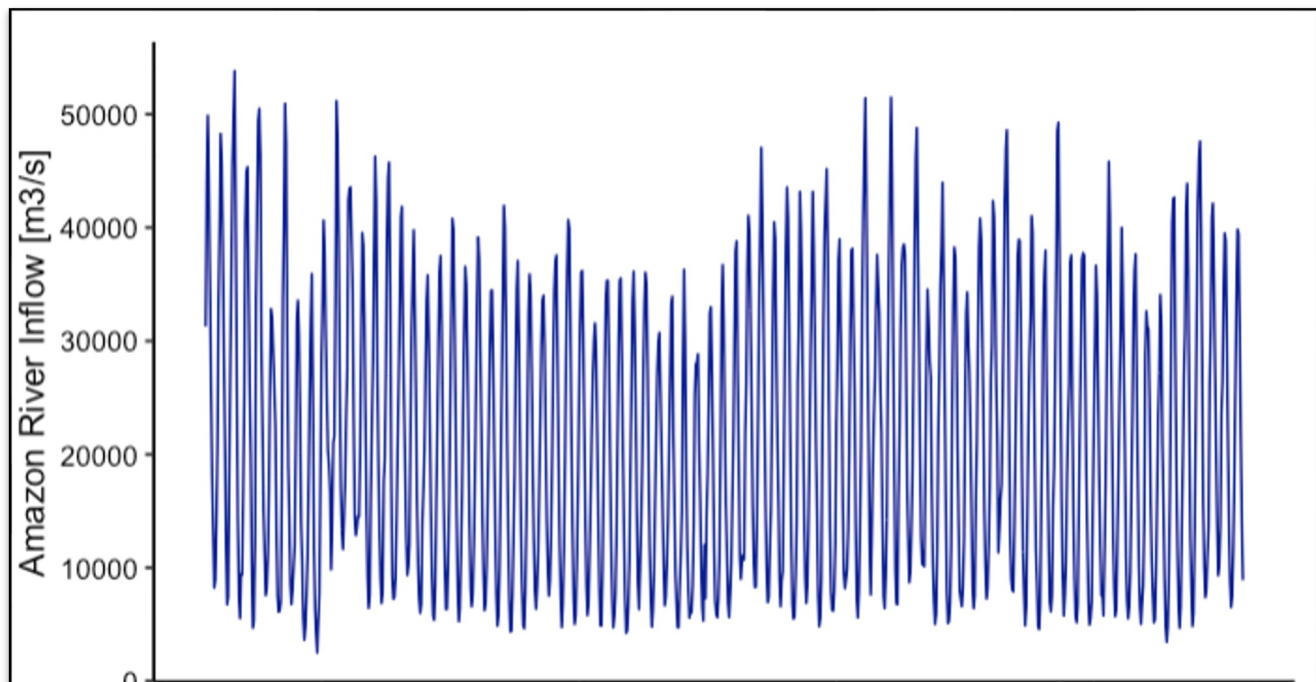
# Example: Inflow Data

# Amazon River Inflow in $\text{m}^3/\text{s}$



Which components/patterns can you see in this series?

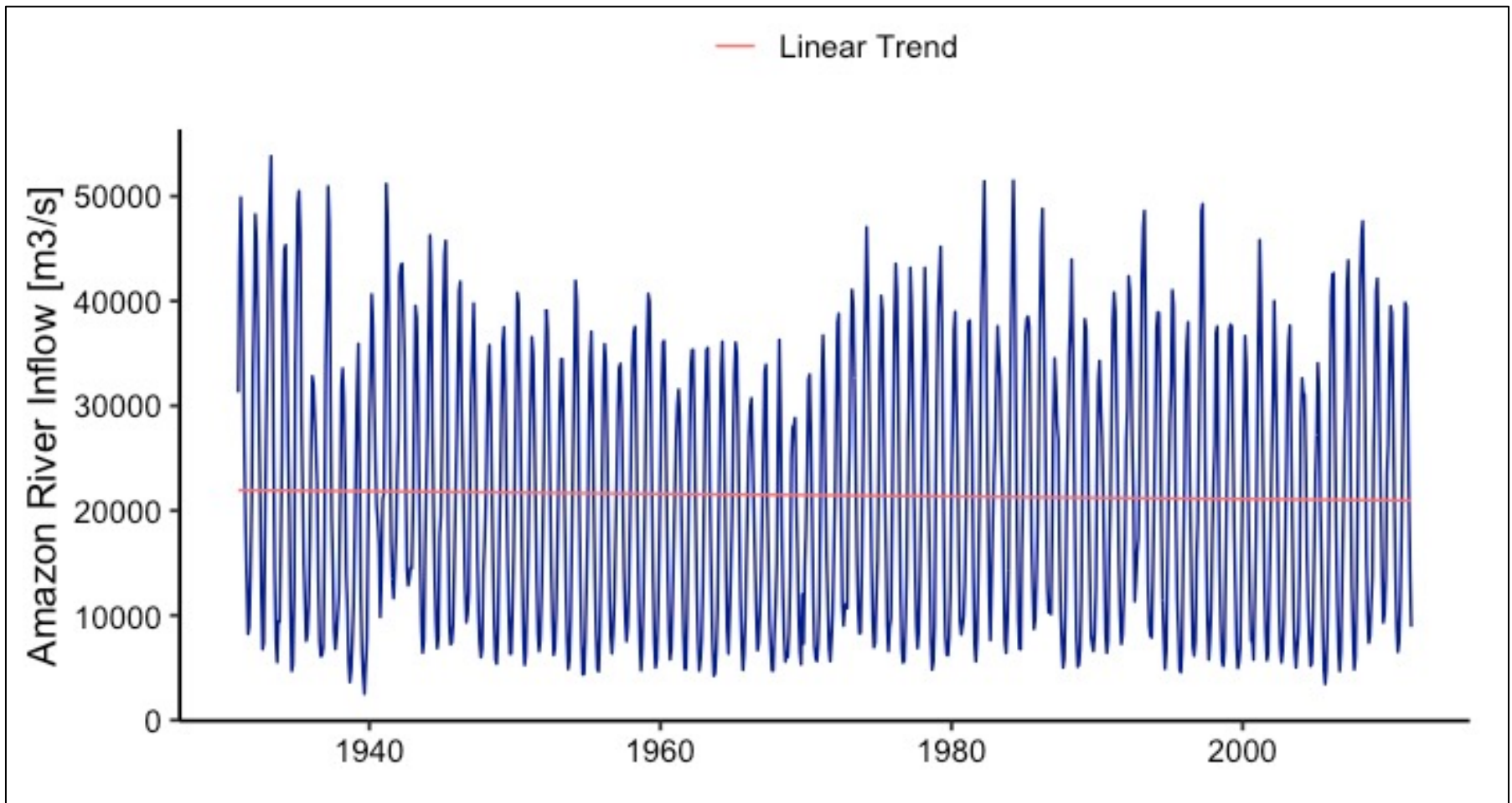






# Trend visualization

$$Y_{trend_t} = \beta_0 + \beta_1 t$$



# Trend visualization

$$Y_{trend_t} = \beta_0 + \beta_1 t$$

Call:

```
lm(formula = inflow ~ t, data = data)
```

Residuals:

Min	1Q	Median	3Q	Max
-19337	-11555	-1483	10061	31900

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	21949.403	797.962	27.507	<2e-16 ***
t	-1.024	1.427	-0.718	0.473

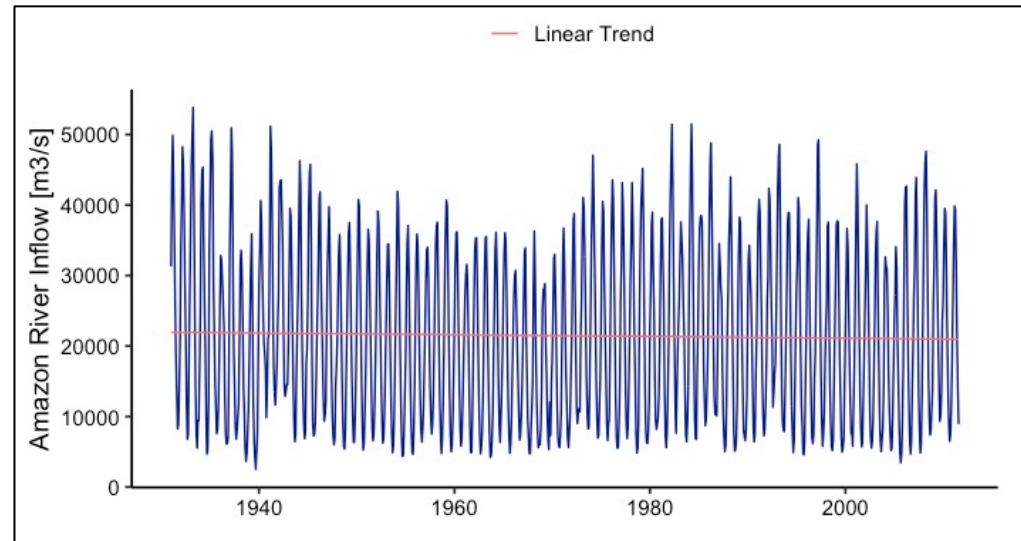
---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 12400 on 966 degrees of freedom

Multiple R-squared: 0.0005328, Adjusted R-squared: -0.0005018

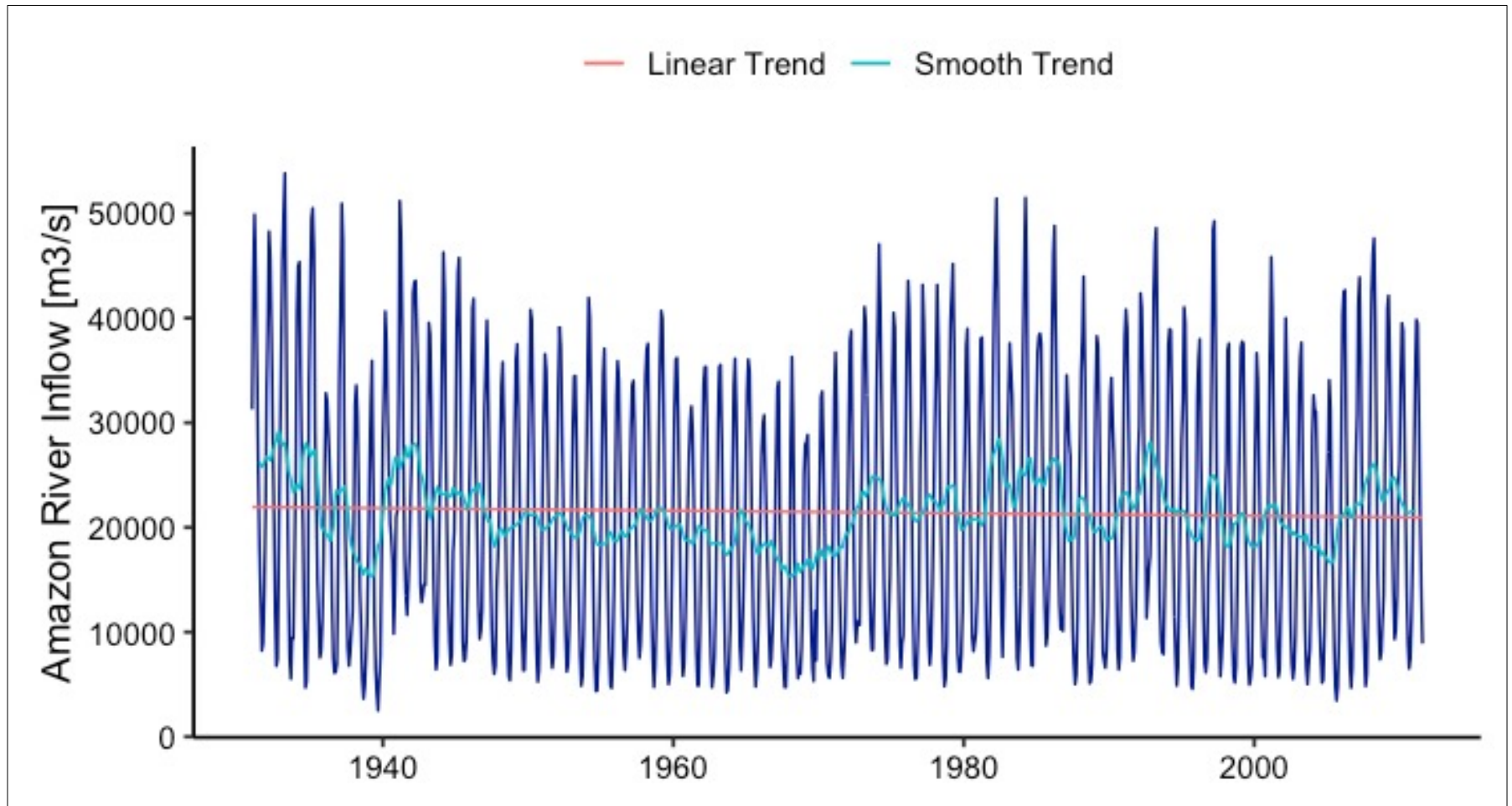
F-statistic: 0.515 on 1 and 966 DF, p-value: 0.4732



**p-value > 0.05**  
**Coefficient  $\beta_1$  not significant**

# Linear vs Smoothed Trend

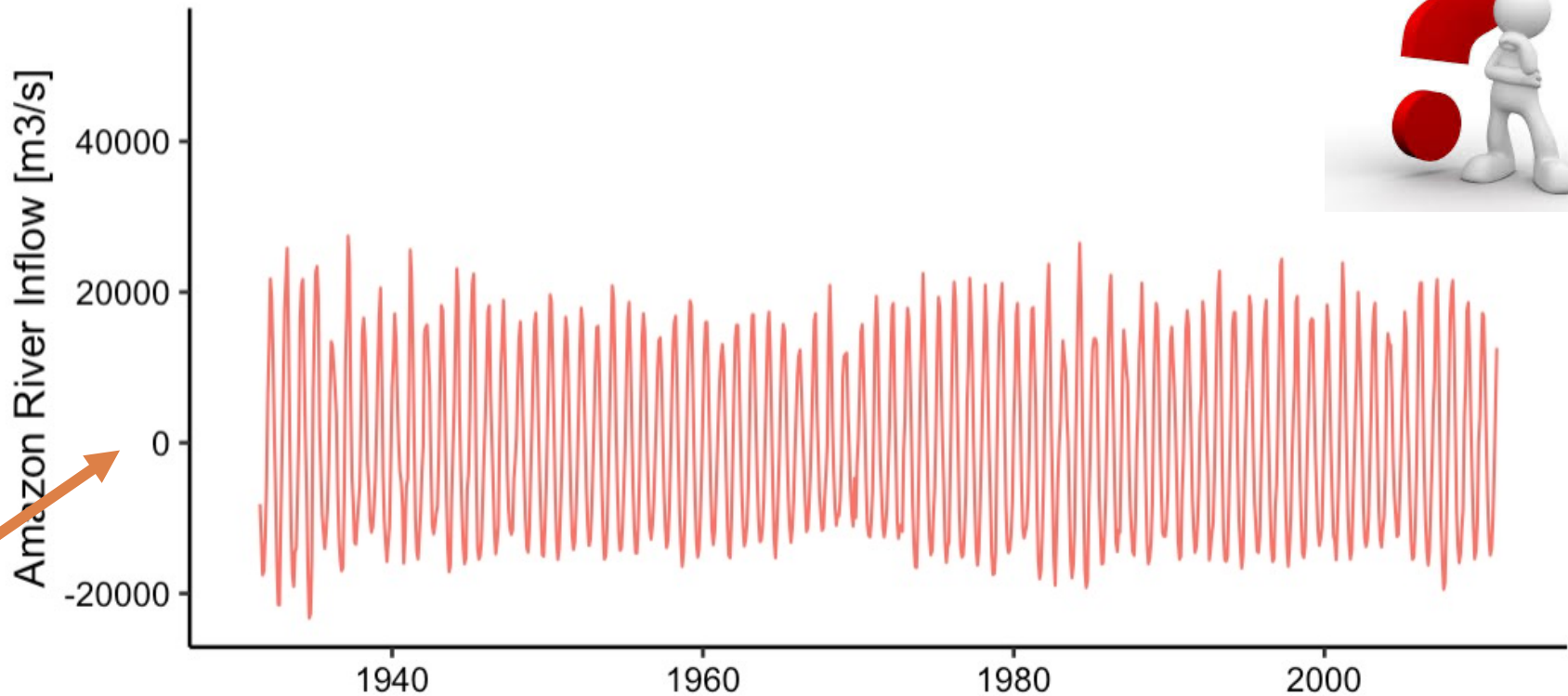
$$Y_{trend_t} = average(Y_{t-6} + Y_{t-5} + \dots + Y_t + \dots + Y_{t+5} + Y_{t+6})$$

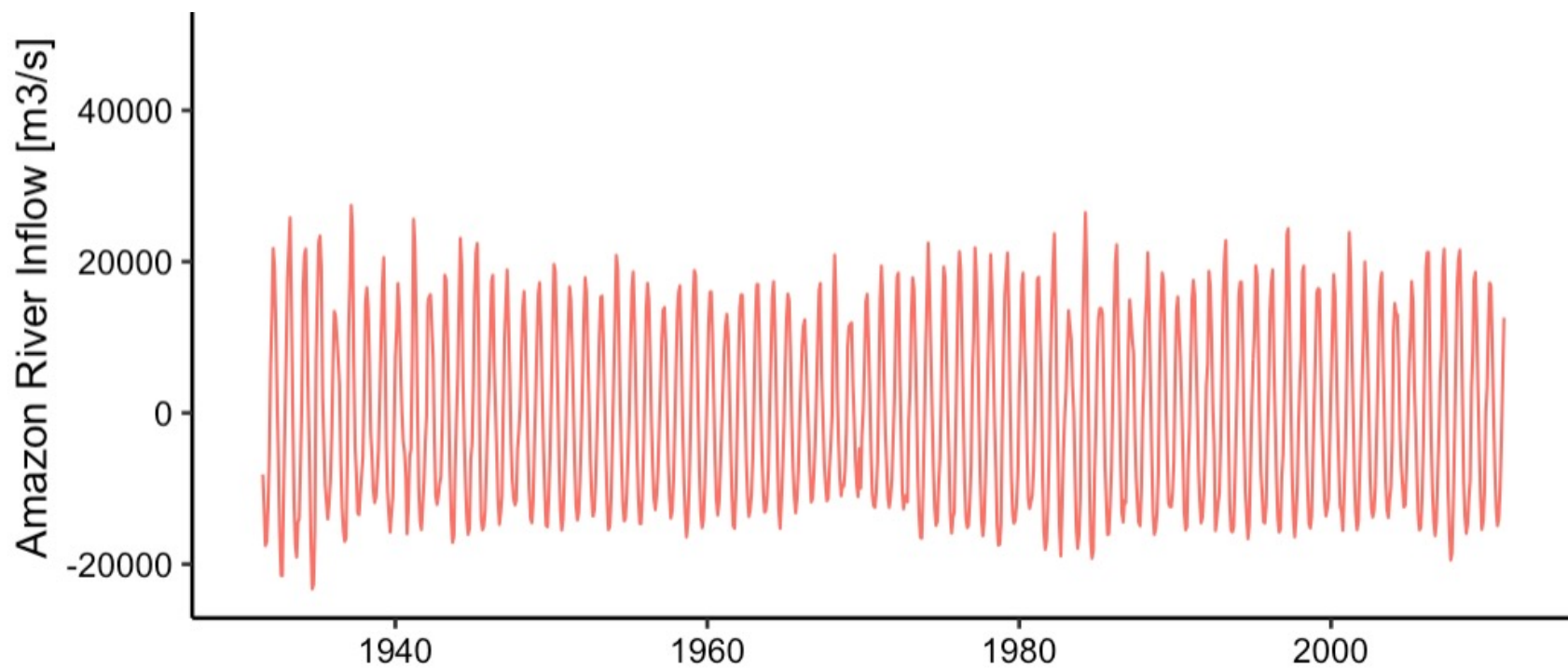


# Do you still see any patterns?

$$Y_{detrend_t} = Y_t - Y_{trend_t}$$

— Detrended Series





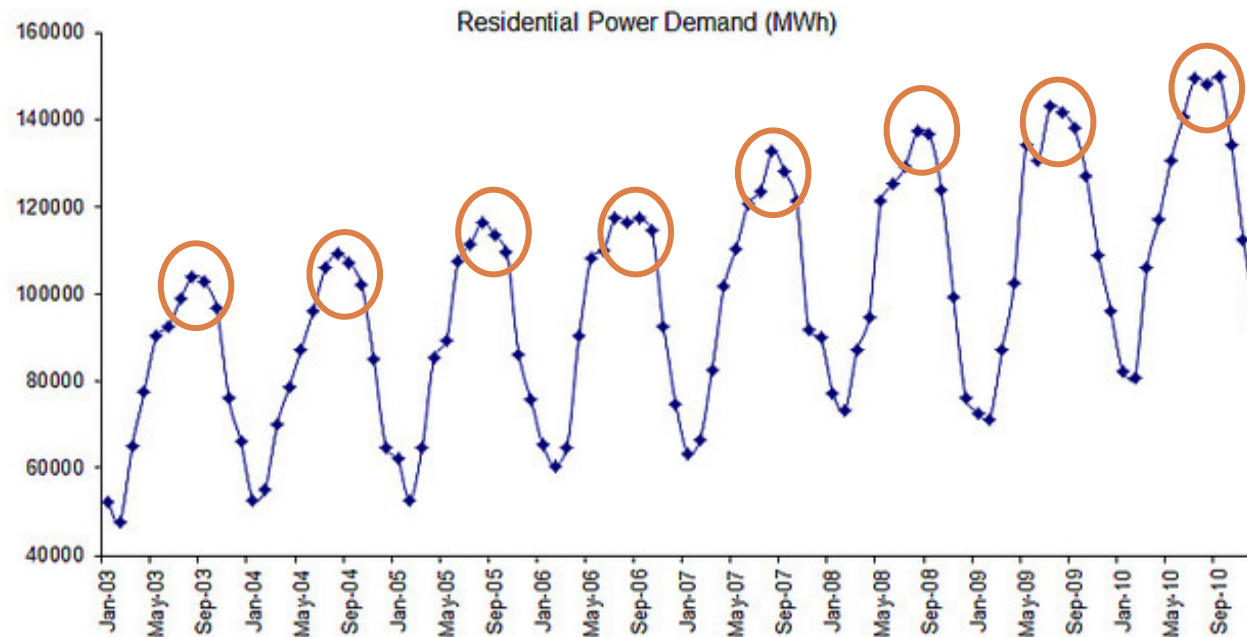


# Seasonal Component

# Seasonal Component

- Short-term regular wave-like patterns
  - ▣ Observed within 1 year - monthly or quarterly
  - ▣ Equally spaced peaks and troughs

**Calendar  
Related**



**Peaks in the  
Summer months  
Jun/Jul/Ago**

# Seasonal Component Estimation

1. **Smoothing the trend** with a moving average
2. **De-trend the series**

- ▣ Additive Model

- take original series and **subtract** the smoothed trend

$$Y_{seasonal} = Y - Y_{trend}$$

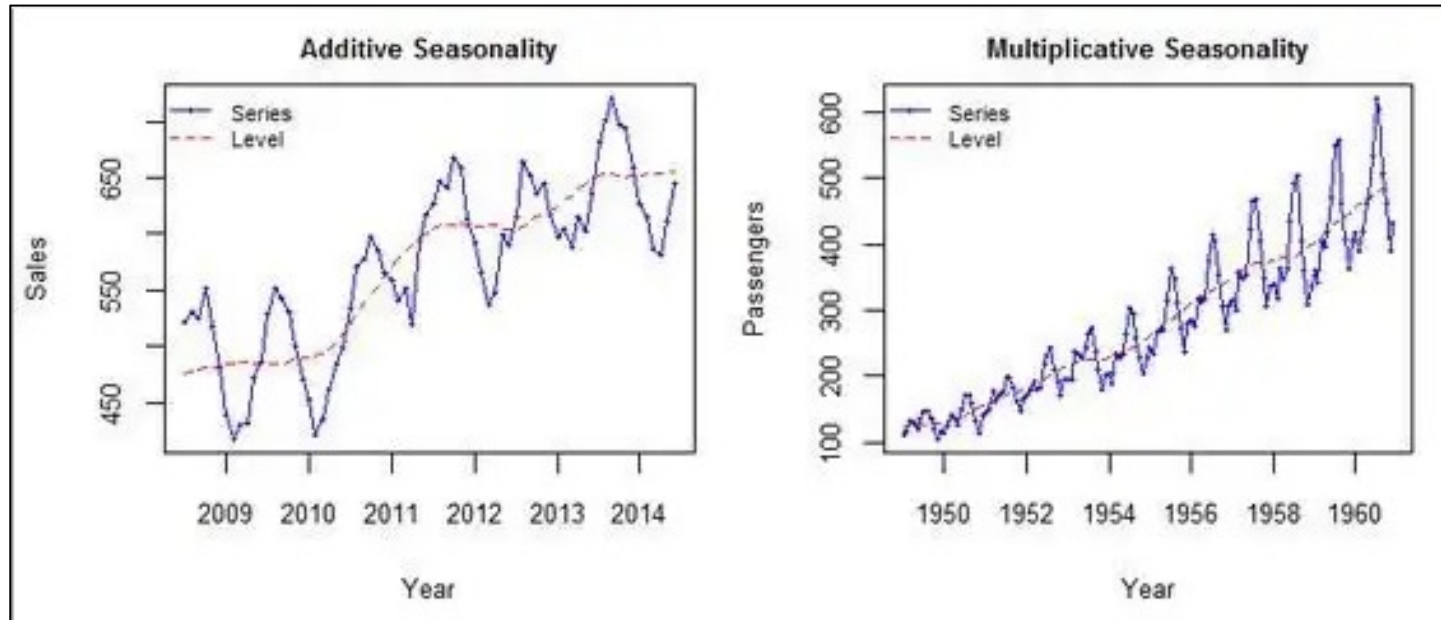
- ▣ Multiplicative model

- scales the size of the seasonal component as the trend rises or falls
- take original series and **divide** the original data by the trend

$$Y_{seasonal} = \frac{Y}{Y_{trend}}$$



# Additive vs Multiplicative Model



- In the **additive model** the magnitude of seasonality does not change in relation to time
- In the **multiplicative model** the magnitude of the seasonal pattern depends on the magnitude/level of the data.

# Seasonal Trend Estimation (cont'd)

3. Assume the observed detrended series can be represented as

$$Y_{seasonal_t} = \mu_t + X_t \quad \text{where } E[X_t] = 0$$

- ▣ Need to estimate  $\mu_t$
- ▣ For monthly seasonal data assume 12 parameters such as

$$\mu_t = \begin{cases} \beta_1 & \text{for } t = 1, 13, 25, \dots \\ \beta_2 & \text{for } t = 2, 14, 26, \dots \\ \vdots & \\ \beta_{12} & \text{for } t = 12, 24, 36, \dots \end{cases}$$

**Seasonal  
Means Model**

# Seasonal Trend Estimation (cont'd)

## 4. Estimate the parameters $\beta_1, \beta_2, \dots, \beta_{12}$

Create dummies (categorical variables with 2 levels)

$$D_{s,t} = \begin{cases} 1 & \text{if } t \text{ belongs to season } s \\ 0 & \text{o.w.} \end{cases} \quad \text{for } s = 1, 2, \dots, 12$$

At any time period  $t$ , one of the seasonal dummies

$D_{1,t}, D_{2,t}, \dots, D_{12,t}$  will equal 1, all the others will equal 0

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	HP1	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
Jan-31	4782	1	0	0	0	0	0	0	0	0	0	0	0
Feb-31	7323	0	1	0	0	0	0	0	0	0	0	0	0
Mar-31	8266	0	0	1	0	0	0	0	0	0	0	0	0
Apr-31	6247	0	0	0	1	0	0	0	0	0	0	0	0
May-31	3642	0	0	0	0	1	0	0	0	0	0	0	0
Jun-31	2425	0	0	0	0	0	1	0	0	0	0	0	0
Jul-31	2158	0	0	0	0	0	0	1	0	0	0	0	0
Aug-31	1854	0	0	0	0	0	0	0	1	0	0	0	0
Sep-31	1839	0	0	0	0	0	0	0	0	1	0	0	0
Oct-31	1896	0	0	0	0	0	0	0	0	0	1	0	0
Nov-31	2095	0	0	0	0	0	0	0	0	0	0	1	0
Dec-31	2725	0	0	0	0	0	0	0	0	0	0	0	1
Jan-32	4679	1	0	0	0	0	0	0	0	0	0	0	0
Feb-32	5535	0	1	0	0	0	0	0	0	0	0	0	0
Mar-32	4310	0	0	1	0	0	0	0	0	0	0	0	0
Apr-32	3026	0	0	0	1	0	0	0	0	0	0	0	0
May-32	2185	0	0	0	0	1	0	0	0	0	0	0	0
Jun-32	1919	0	0	0	0	0	1	0	0	0	0	0	0
Jul-32	1640	0	0	0	0	0	0	1	0	0	0	0	0
Aug-32	1302	0	0	0	0	0	0	0	1	0	0	0	0
Sep-32	1118	0	0	0	0	0	0	0	0	1	0	0	0
Oct-32	1688	0	0	0	0	0	0	0	0	0	1	0	0
Nov-32	2040	0	0	0	0	0	0	0	0	0	0	1	0
Dec-32	3790	0	0	0	0	0	0	0	0	0	0	0	1
Jan-33	6928	1	0	0	0	0	0	0	0	0	0	0	0
Feb-33	5793	0	1	0	0	0	0	0	0	0	0	0	0
Mar-33	4276	0	0	1	0	0	0	0	0	0	0	0	0
Apr-33	3863	0	0	0	1	0	0	0	0	0	0	0	0
May-33	2498	0	0	0	0	1	0	0	0	0	0	0	0
Jun-33	1940	0	0	0	0	0	1	0	0	0	0	0	0
Jul-33	1725	0	0	0	0	0	0	1	0	0	0	0	0
Aug-33	1375	0	0	0	0	0	0	0	1	0	0	0	0
Sep-33	1324	0	0	0	0	0	0	0	0	1	0	0	0
Oct-33	1551	0	0	0	0	0	0	0	0	0	1	0	0
Nov-33	1724	0	0	0	0	0	0	0	0	0	0	1	0
Dec-33	3352	0	0	0	0	0	0	0	0	0	0	0	1
Jan-34	4049	1	0	0	0	0	0	0	0	0	0	0	0
Feb-34	3166	0	1	0	0	0	0	0	0	0	0	0	0
Mar-34	3124	0	0	1	0	0	0	0	0	0	0	0	0
Apr-34	2507	0	0	0	1	0	0	0	0	0	0	0	0
May-34	1853	0	0	0	0	1	0	0	0	0	0	0	0
Jun-34	1131	0	0	0	0	0	1	0	0	0	0	0	0
Jul-34	978	0	0	0	0	0	0	1	0	0	0	0	0
Aug-34	826	0	0	0	0	0	0	0	1	0	0	0	0
Sep-34	1026	0	0	0	0	0	0	0	0	1	0	0	0
Oct-34	1203	0	0	0	0	0	0	0	0	0	1	0	0
Nov-34	1199	0	0	0	0	0	0	0	0	0	0	1	0
Dec-34	1621	0	0	0	0	0	0	0	0	0	0	0	1

$$Y_{seasonal_t} = \beta_1 D_{1,t} + \beta_2 D_{2,t} + \beta_3 D_{3,t} + \beta_4 D_{4,t} + \beta_5 D_{5,t} + \beta_6 D_{6,t} + \beta_7 D_{7,t} + \beta_8 D_{8,t} + \beta_9 D_{9,t} + \beta_{10} D_{10,t} + \beta_{11} D_{11,t} + \beta_{12} D_{12,t}$$

# Seasonal Trend Estimation (cont'd)

5. Write series  $Y_{seasonal}$  as a function of the dummies

$$Y_{seasonal_t} = \sum_{s=1}^{12} \beta_s D_{s,t}$$

6. Compute coefficients by linear regression

# Estimating Seasonal Trend in R

- First create seasonal dummies using `seasonaldummy()` from package "forecast"

*dummies = seasonaldummy(Y)*

- This will only work if Y is a time series object and if you specify frequency

*Y = ts(Y, frequency = 12)*

- Then just run a simple regression on the dummies

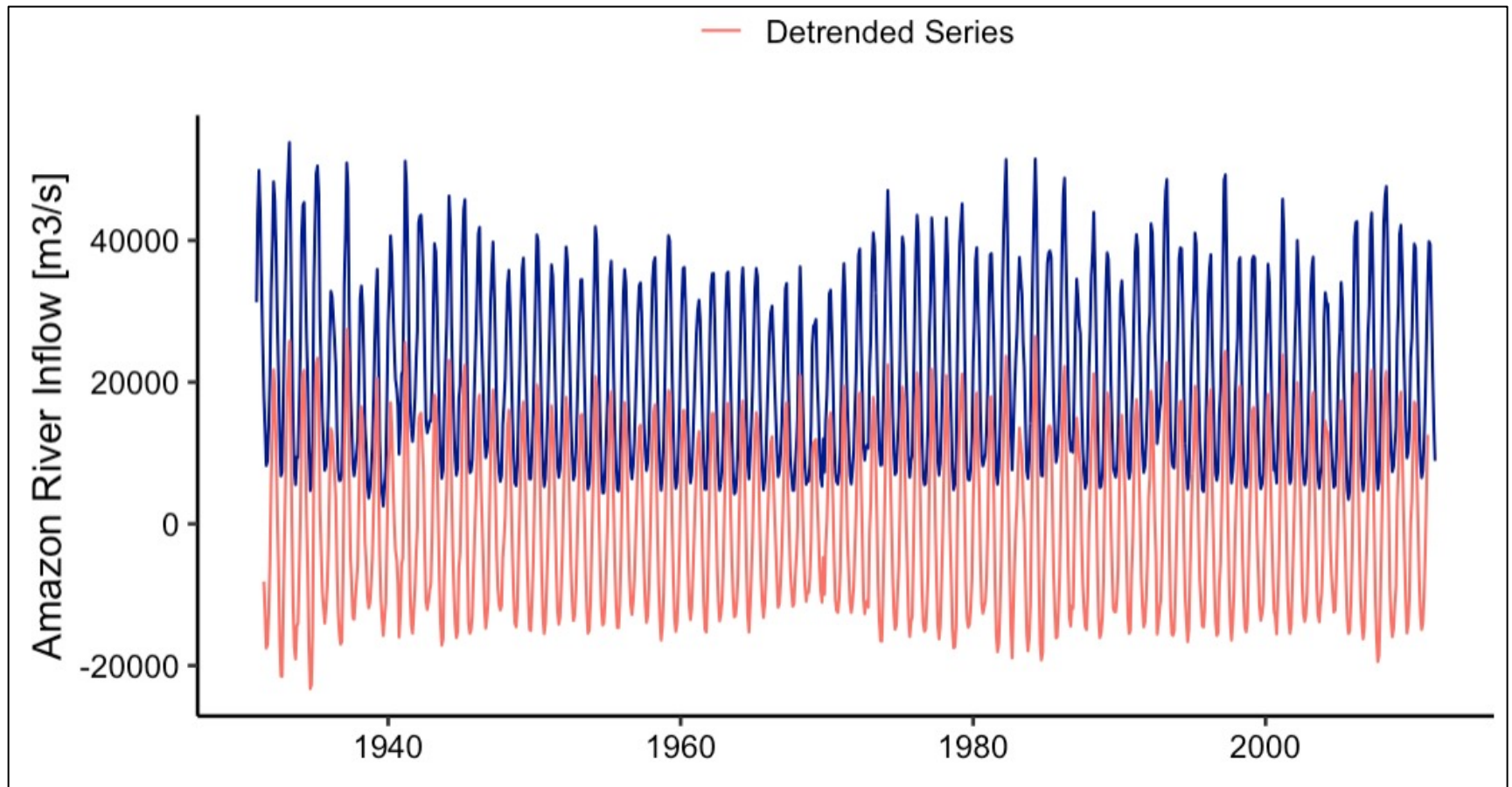
*lm(Y ~ dummies, data)*



Back to example: Inflow

# Detrended Series with Additive Model

$$Y_{detrend_t} = Y_t - Trend_t$$





# Seasonal Dummies Regression Results

```
Call:
lm(formula = detrend_smooth ~ dummies)
```

Residuals:

Min	1Q	Median	3Q	Max
-9430	-1552	-50	1654	10797

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-3545.7	307.4	-11.533	<2e-16 ***
dummiesJan	8131.5	434.8	18.702	<2e-16 ***
dummiesFeb	15948.6	434.8	36.682	<2e-16 ***
dummiesMar	21556.7	436.2	49.424	<2e-16 ***
dummiesApr	20984.3	436.2	48.112	<2e-16 ***
dummiesMay	12870.3	436.2	29.508	<2e-16 ***
dummiesJun	3959.1	436.2	9.077	<2e-16 ***
dummiesJul	-3731.7	434.8	-8.583	<2e-16 ***
dummiesAug	-8994.6	434.8	-20.688	<2e-16 ***
dummiesSep	-11306.9	434.8	-26.006	<2e-16 ***
dummiesOct	-10378.9	434.8	-23.872	<2e-16 ***
dummiesNov	-6515.4	434.8	-14.986	<2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2750 on 944 degrees of freedom

(12 observations deleted due to missingness)

Multiple R-squared: 0.9478, Adjusted R-squared: 0.9472

F-statistic: 1558 on 11 and 944 DF, p-value: < 2.2e-16



# Seasonal Dummies Regression Results

```
Call:
lm(formula = detrend_smooth ~ dummies)
```

Residuals:

Min	1Q	Median	3Q	Max
-9430	-1552	-50	1654	10797

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-3545.7	307.4	-11.533	<2e-16 ***
dummiesJan	8131.5	434.8	18.702	<2e-16 ***
dummiesFeb	15948.6	434.8	36.682	<2e-16 ***
dummiesMar	21556.7	436.2	49.424	<2e-16 ***
dummiesApr	20984.3	436.2	48.112	<2e-16 ***
dummiesMay	12870.3	436.2	29.508	<2e-16 ***
dummiesJun	3959.1	436.2	9.077	<2e-16 ***
dummiesJul	-3731.7	434.8	-8.583	<2e-16 ***
dummiesAug	-8994.6	434.8	-20.688	<2e-16 ***
dummiesSep	-11306.9	434.8	-26.006	<2e-16 ***
dummiesOct	-10378.9	434.8	-23.872	<2e-16 ***
dummiesNov	-6515.4	434.8	-14.986	<2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2750 on 944 degrees of freedom

(12 observations deleted due to missingness)

Multiple R-squared: 0.9478, Adjusted R-squared: 0.9472

F-statistic: 1558 on 11 and 944 DF, p-value: < 2.2e-16

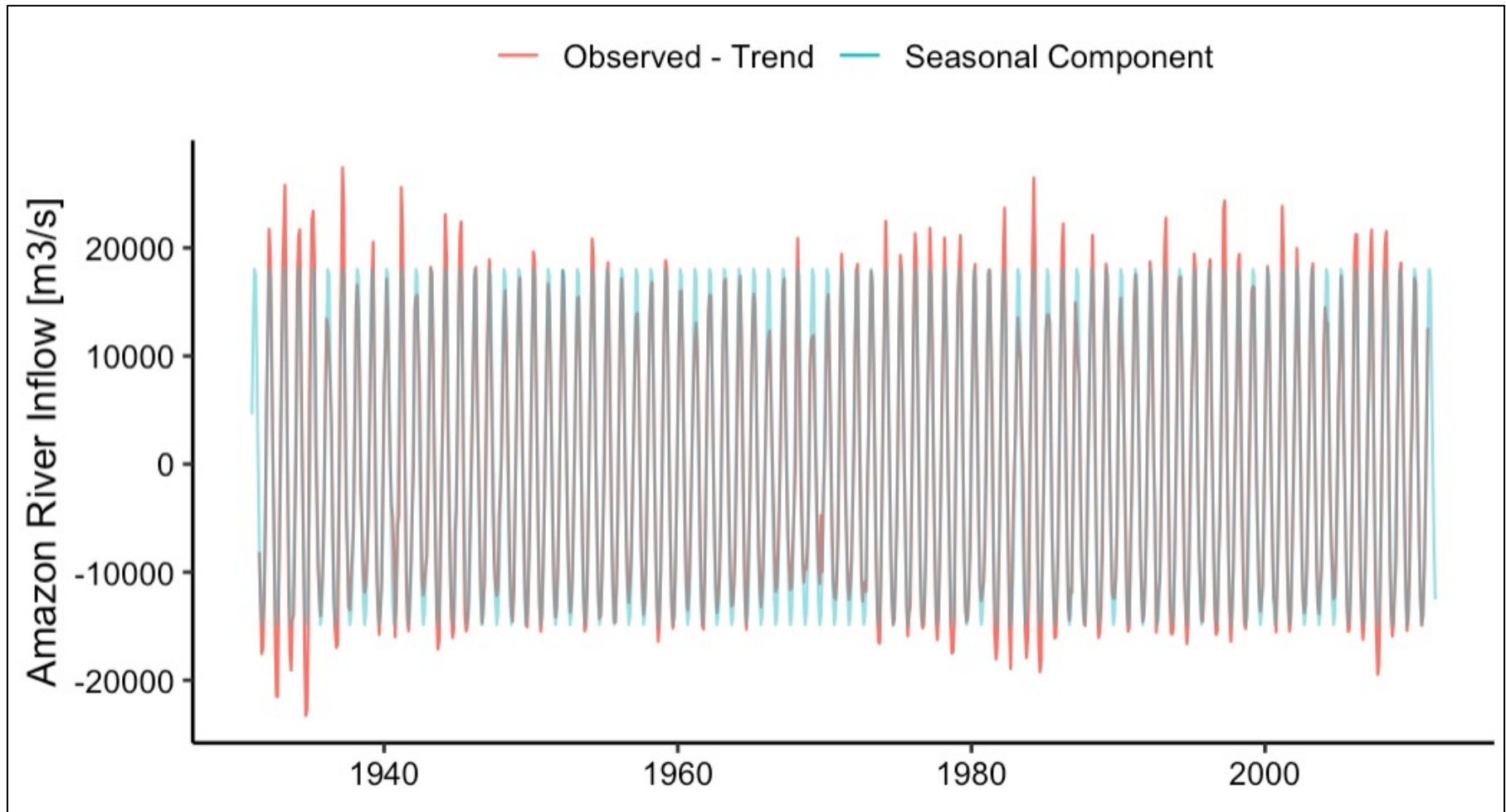
**Overall p-value < 0.05**

**R-squared: 0.9472**

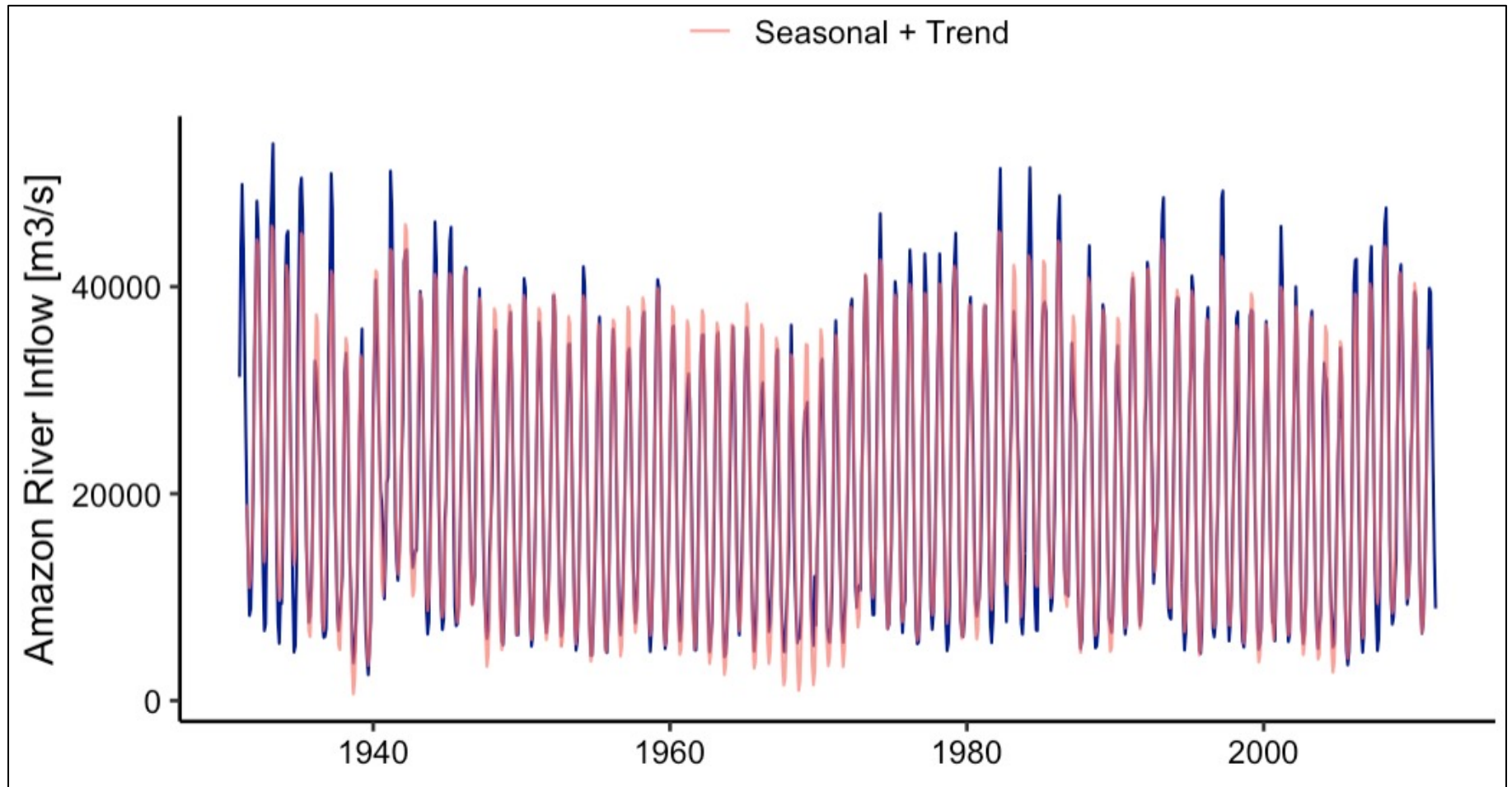
**All regression coefficients p-value < 0.05**

**Therefore, relationships in the model are statistically significant. In other word, the series has a seasonal component!**

# Seasonal Component Visualization



# Seasonal + Trend Decomposition





# Stochastic versus deterministic trend

# Series with Deterministic Trend

- Deterministic linear trend process

$$Y_i = \beta_0 + \beta_1 t_i + \varepsilon_i$$

- Or more generally, for a polynomial trend

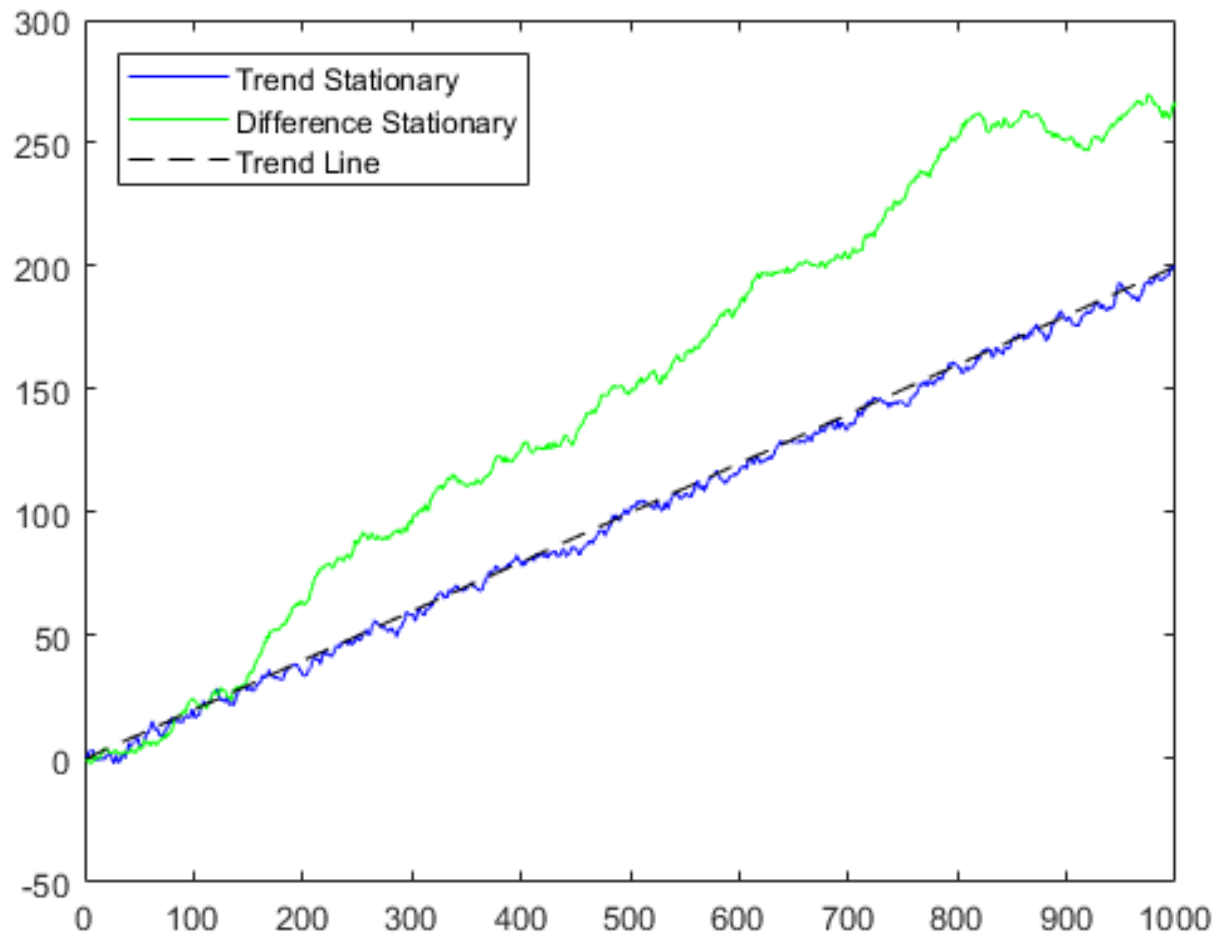
$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 T_i^2 + \cdots + \beta_n T_i^n + \varepsilon_i$$

- Detrending is accomplished by running a regression and obtaining the series of residuals. The residuals will give you the detrended series
- That's what we call **trend-stationarity**

# Series with Stochastic Trend

- But some series have what we call **difference-stationarity**
- Although trend-stationary and difference-stationary series are both “trending” over time, the stationarity is achieved by a **distinct procedure**
- In the case of difference-stationarity, stationarity is achieved by differencing the series
- Sometimes we need to difference the series more than once

# Trend-stationarity vs difference-stationarity







# Stationarity Tests

# Stationarity Assessment

- Mann-Kendall Test
  - ▣ monotonic trend or deterministic trend or trend-stationary
- Spearman's Rank Correlation Test
  - ▣ monotonic trend or deterministic or trend-stationary
- Dickey-Fuller (ADF) Test – unit root tests
  - ▣ stochastic trend or difference-stationary

# Review: Hypothesis Testing

- Why do we use hypothesis testing?
  - ▣ To analyze evidence provided by data
  - ▣ To make decisions based on data
- What is a statistical hypothesis?
  - ▣ An assumption about a population parameter that may or may not be true
- In Hypothesis Testing we usually have

$$\begin{cases} H_0: & \text{the null hypothesis} \\ H_1: & \text{the alternative hypothesis} \end{cases}$$

# Review: Hypothesis Testing (cont'd)

## □ Procedure

1. State the hypotheses and identify the claim
2. Find the critical value(s) from the appropriate table
3. Compute the test value
4. Make the decision to reject or not reject the null hypothesis

If  $P\text{-value} \leq \alpha$ , **reject** the null hypothesis.  
If  $P\text{-value} > \alpha$ , **do not reject** the null hypothesis.



# Mann-Kendall Test

- Commonly employed to detect deterministic trends in series of environmental data, climate data or hydrological data
- **Cannot be applied to seasonal data**
- Hypothesis Test

$$\begin{cases} H_0: Y_t \text{ is i.i.d. (stationary)} \\ H_1: Y_t \text{ follow a trend} \end{cases}$$

# Mann-Kendall Test

- Mann-Kendall statistic is

$$S = \sum_{k=1}^{N-1} \sum_{j=k+1}^N \text{sgn}(Y_j - Y_k)$$

where

$$\text{sgn}(Y_j - Y_k) = \begin{cases} 1 & \text{if } Y_j - Y_k > 0 \\ 0 & \text{if } Y_j - Y_k = 0 \\ -1 & \text{if } Y_j - Y_k < 0 \end{cases}$$

- The test will check the magnitude of  $S$  and its significance based on the number of observations
- In other words, the bigger the number of observations the higher  $S$  will need to be

# Mann-Kendall Test

$$\begin{cases} H_0: Y_t \text{ is i.i.d. (stationary)} \\ H_1: Y_t \text{ follow a trend} \end{cases}$$

Mann-Kendall test statistic is

$$S = \sum_{k=1}^{N-1} \sum_{j=k+1}^N \text{sgn}(Y_j - Y_k) \quad \rightarrow \quad \text{sgn}(Y_j - Y_k) = \begin{cases} 1 & \text{if } Y_j - Y_k > 0 \\ 0 & \text{if } Y_j - Y_k = 0 \\ -1 & \text{if } Y_j - Y_k < 0 \end{cases}$$

$$E[S] = 0$$

$$\text{Var}[S] = \sigma_S^2 = \frac{1}{18} n(n-1)(2n+5)$$

$$\tau = \frac{2S}{N(N-1)}$$

Under  $H_0$ ,  $Z$  follow a standard normal distribution

$$Z = \begin{cases} \frac{(S-1)}{\sigma_S} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{(S+1)}{\sigma_S} & \text{if } S < 0 \end{cases}$$

Reject  $H_0$  when  $Z < Z_{\alpha/2}$

# Mann-Kendall test in R

- The Mann-Kendall test in R is done with the command `MannKendall()` from package “Kendall”

## Description

This is a test for monotonic trend in a time series  $z[t]$  based on the Kendall rank correlation of  $z[t]$  and  $t$ .

## Usage

```
MannKendall(x)
```

## Arguments

**x** a vector of data, often a time series

## Details

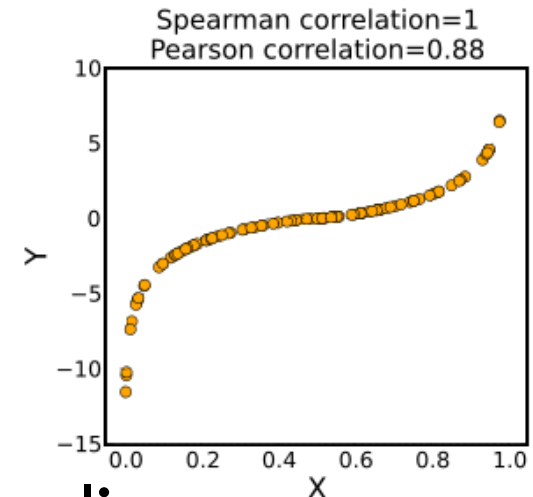
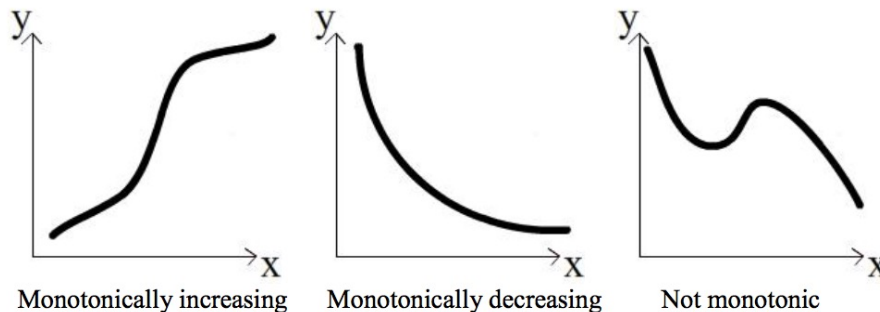
The test was suggested by Mann (1945) and has been extensively used with environmental time series (Hipel and McLeod, 2005). For autocorrelated time series, the block bootstrap may be used to obtain an improved significance test.

- For seasonal data you can use `SeasonalMannKendall()` from the same package



# Spearman's Rank Correlation Coefficient

- Spearman's correlation coefficient is a statistical measure of the strength of a monotonic relationship



- Unlike Pearson's correlation, the relationship does not need to be linear
- In other words, if one variable increases so does the other, it **does not matter the proportion of the increase**

# Spearman's Rank Correlation Coefficient

- To verify a monotonic trend in your data, compute the spearman correlation between your data and series  $T$

$Y_t$	$T$
$Y_1$	1
$Y_2$	2
$Y_3$	3
$\vdots$	$\vdots$
$Y_{N-2}$	$N - 2$
$Y_{N-1}$	$N - 1$
$Y_N$	$N$

- If the correlation is close to 0, then there is no trend
- The function to compute spearman correlation is `cor()` or the `cor.test()` from package "stats". The latter provides the significance of the coefficient

# Dickey-Fuller Test

- The first work on testing for a unit root in time series was done by Dickey and Fuller

- Consider the model

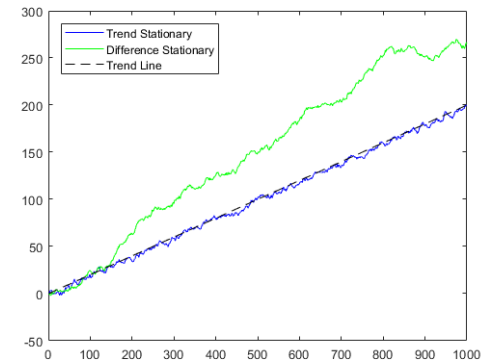
$$Y_t = a + \phi Y_{t-1} + \epsilon_t$$

- The objective is to test

$$\begin{cases} H_0: \phi = 1 \text{ (i.e. contain a unit root)} \\ H_1: |\phi| < 1 \text{ (i.e. is stationary)} \end{cases}$$

- More general case can include more lags, the so called Augmented Dickey-Fuller (ADF) test

White noise series



# Dickey-Fuller Test in R

- The ADF test in R is done with the command `adf.test()` from package “tseries”

## Description

Computes the Augmented Dickey-Fuller test for the null that `x` has a unit root.

## Usage

```
adf.test(x, alternative = c("stationary", "explosive"),  
        k = trunc((length(x)-1)^(1/3)))
```

## Arguments

- |                          |                                                                                                                                         |
|--------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| <code>x</code>           | a numeric vector or time series.                                                                                                        |
| <code>alternative</code> | indicates the alternative hypothesis and must be one of "stationary" (default) or "explosive". You can specify just the initial letter. |
| <code>k</code>           | the lag order to calculate the test statistic.                                                                                          |

# Summary of Stationary Tests

Mann Kendall	Spearman Correlation	Augmented Dickey-Fuller
Check for deterministic trend	Check for deterministic trend	Check for stochastic trend
Hypothesis test	Hypothesis test	Hypothesis test
$\begin{cases} H_0: Y_t \text{ is i.i.d. (stationary)} \\ H_1: Y_t \text{ follow a trend} \end{cases}$	$\begin{cases} H_0: Y_t \text{ is i.i.d. (stationary)} \\ H_1: Y_t \text{ follow a trend} \end{cases}$	$\begin{cases} H_0: \phi = 1 \text{ (i.e. contain a unit root)} \\ H_1: \phi < 1 \text{ (i.e. is stationary)} \end{cases}$
Test statistic	Test statistic	Test statistic
<p>Find</p> $S = \sum_{k=1}^{N-1} \sum_{j=k+1}^N \text{sgn}(Y_j - Y_k)$ $\text{sgn}(Y_j - Y_k) = \begin{cases} 1 & \text{if } Y_j - Y_k > 0 \\ 0 & \text{if } Y_j - Y_k = 0 \\ -1 & \text{if } Y_j - Y_k < 0 \end{cases}$	<p>Find the spearman correlation coefficient</p> $\rho = \text{Corr}(Y_t, T) \text{ where } T = 1, \dots, N$ <p>PS: spearman measure any type of monotonic relationship not only linear</p>	<p>Check if model</p> $Y_t = \phi Y_{t-1} + \epsilon_t$ <p>has a unit root i.e. <math>\phi=1</math></p>
Can't handle seasonality, if working with seasonal data use Seasonal Mann Kendall instead or group data	Can't handle seasonality, if working with seasonal data use group data	Can handle seasonality



# THANK YOU !

[luana.marangon.lima@duke.edu](mailto:luana.marangon.lima@duke.edu)