

# *Applied Time Series Analysis*

FISH 507

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# Introductions

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- Who are we?
- Who & why you're here?
- What are you looking to get from this class?

# Days and Times

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- Lectures  
When: Tues & Thurs from 1:30-2:50  
Where: FSH 203
- Computer lab  
When: Thurs from 3:00-3:50  
Where: FSH 207

# Grading

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- **Weekly homework (30% of total)**
  - Assigned Thurs at the end of computer lab
  - Due by 5:00 PM the following Tues
  - Based on material from lecture & computer lab
- **Research project & paper (40% of total)**
  - Must involve some form of time series model(s)
  - Due by 11:59 PM PST on March 10
- **Two anonymous peer-reviews (20% of total)**
  - One review each for 2 colleague's papers
  - Due by 11:59 PM PST on March 16

# Expectations for final project

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- Research paper or thesis chapter that you can turn into a peer-reviewed publication
- Ideally a solo effort, but you can work in pairs
- Focus on applied time series analysis
  - Univariate or multivariate
- Short format similar to “Report” in *Ecology* or “Rapid Communication” in *CJFAS*
  - Max of 20 pages, inclusive of refs, tables, figs, etc
  - 12-pt font, double-spaced throughout

# Don't have any time series data?

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- RAM Legacy  
<http://ramlegacy.marinebiodiversity.ca/>
- RAM's Stock-Recruitment Database  
<http://www.mscs.dal.ca/~myers/welcome.html>
- Global Population Dynamics Database  
<http://www3.imperial.ac.uk/cpb/databases/gpdd>
- NOAA NWFSC Salmon Population Summary  
<https://www.webapps.nwfsc.noaa.gov/apex/f?p=261:home:0>
- SAFS
  - Alaska Salmon Program
  - Lake Washington plankton

# Course topics

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Week 1: Decomposition, covariance, autocorrelation

Week 2: Autoregressive & moving-average models, model estimation

Week 3: Univariate & multivariate state-space models

Week 4: Covariates & seasonal effects; model selection

Week 5: Dynamic linear models

Week 6: Forecasting & dynamic factor analysis

Week 7: Multistage & non-Gaussian models

Week 8: Detection of outliers & perturbation analysis

Week 9: Spatial effects & hierarchical models

Week 10: Presentations of final projects

# An introduction to time series and their analysis

Mark Scheuerell

*FISH 507 – Applied Time Series Analysis*

3 January 2017



# Topics for today (lecture)

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- Characteristics of time series (ts)
  - What is a ts?
  - Classifying ts
  - Trends
  - Seasonality (periodicity)
- Classical decomposition

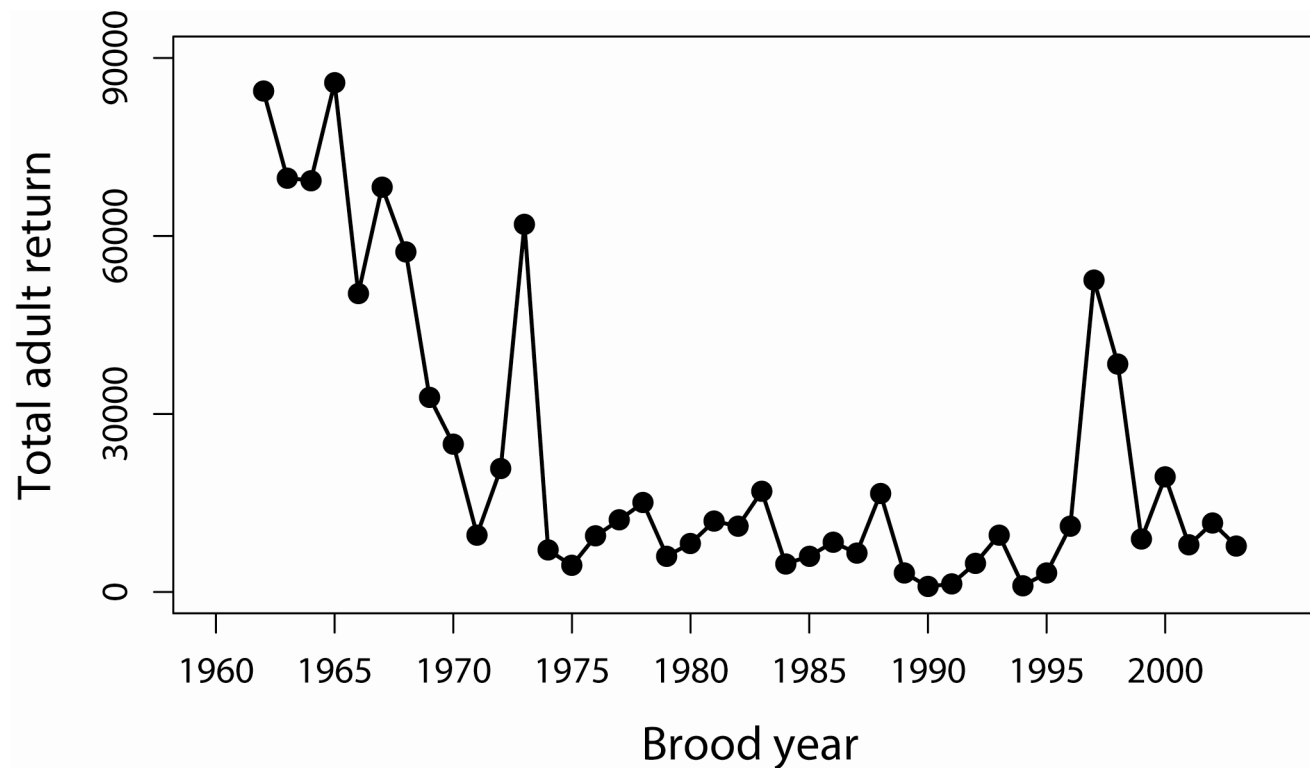
# What is a time series?

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- A *time series* (ts) is a set of observations taken sequentially in time
- A ts can be represented as a set  
 $\{x_t : t = 1, 2, 3, \dots, n\} = \{x_1, x_2, x_3, \dots, x_n\}$
- For example,  
 $\{10, 31, 27, 42, 53, 15\}$

# Example of a time series

*Number of wild spr/sum Chinook salmon returning to the Snake R*



# Classification of time series (I)

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## I. By some index set

A. Interval across real time  $x(t); t \in [1, 2.5]$

B. Discrete time  $x_t$

1. Equally spaced;  $t = \{1, 2, 3, 4, 5\}$

2. Equally spaced w/ missing values;  $t = \{1, 2, 4, 5, 6\}$

3. Unequally spaced;  $t = \{2, 3, 4, 6, 9\}$

# Classification of time series (II)

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## II. By underlying process

- A. Discrete (eg, total # of fish caught per trawl)
- B. Continuous (eg, salinity, temperature)

# Classification of time series (III)

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## III. By number of values recorded

- A. Univariate/scalar (eg, total # of fish caught)
- B. Multivariate/vector (eg, # of each spp of fish caught)

# Classification of time series (IV)

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## IV. By type of values recorded

- A. Integer (eg, # of fish in 5 min trawl = 2413)
- B. Rational (eg, fraction of unclipped fish =  $47/951$ )
- C. Real (eg, fish mass = 10.2 g)
- D. Complex (eg,  $\cos[2\pi*2.43] + i \sin[2\pi*2.43]$ )

# Statistical analyses of time series

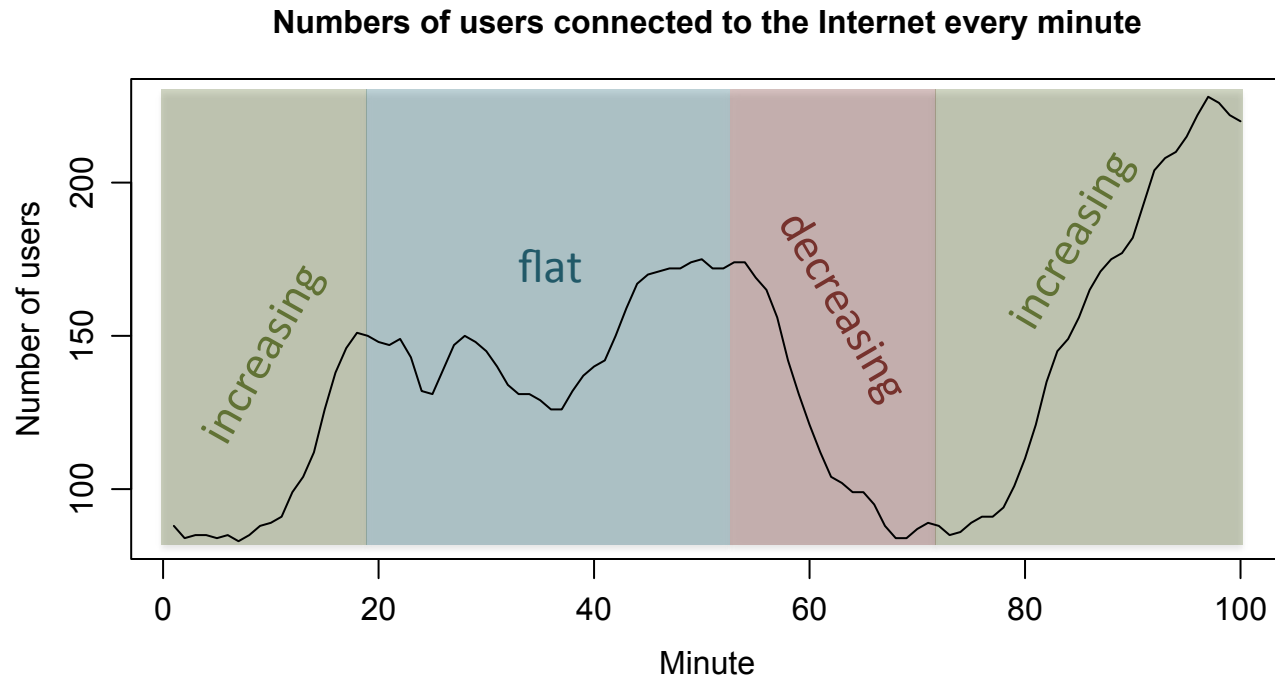
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- Most statistical analyses are concerned with estimating properties of a population from a sample
- Time series analysis, however, presents a different situation
- Although we could vary the length of an observed sample, it is often impossible to make multiple observations at a given time
- For example, one can't observe today's closing price of Microsoft stock more than once
- This makes conventional statistical procedures, based on large sample estimates, inappropriate



# Examples of time series

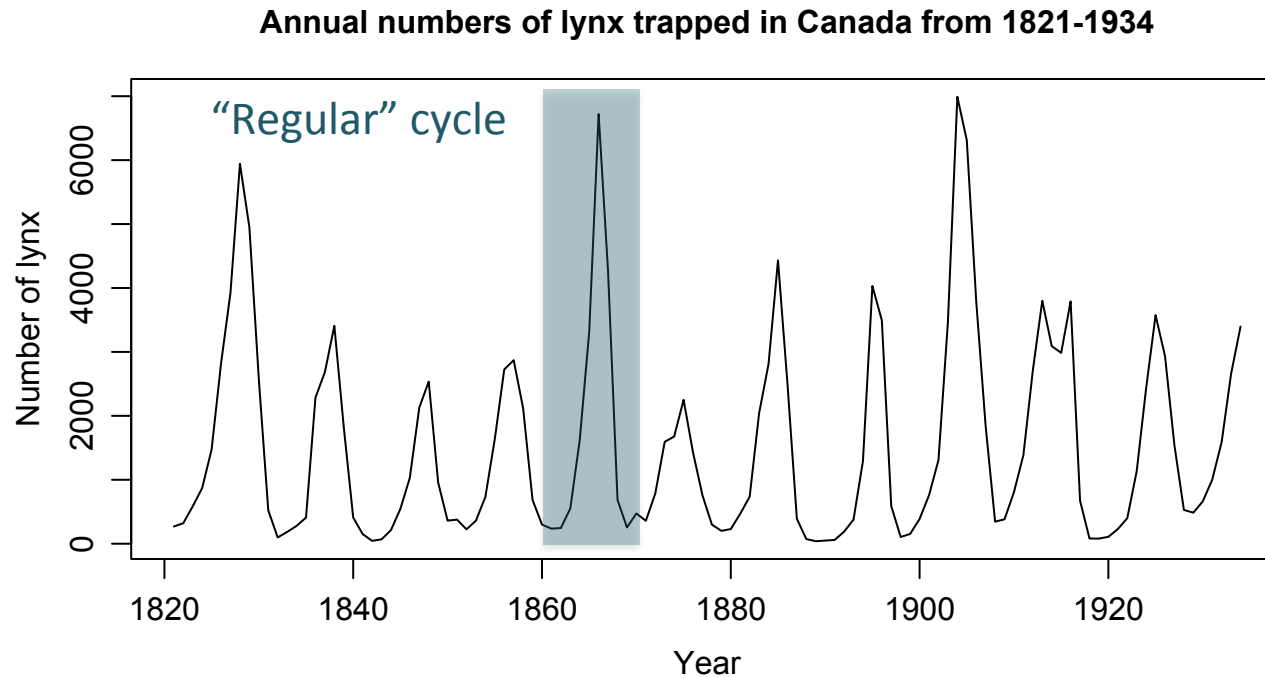
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How would we describe this ts?

# Examples of time series

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How would we describe this ts?

# What is a time series model?

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- A *time series model* for  $\{x_t\}$  is a specification of the joint distributions of a sequence of random variables  $\{X_t\}$  of which  $\{x_t\}$  is thought to be a realization

- For example,

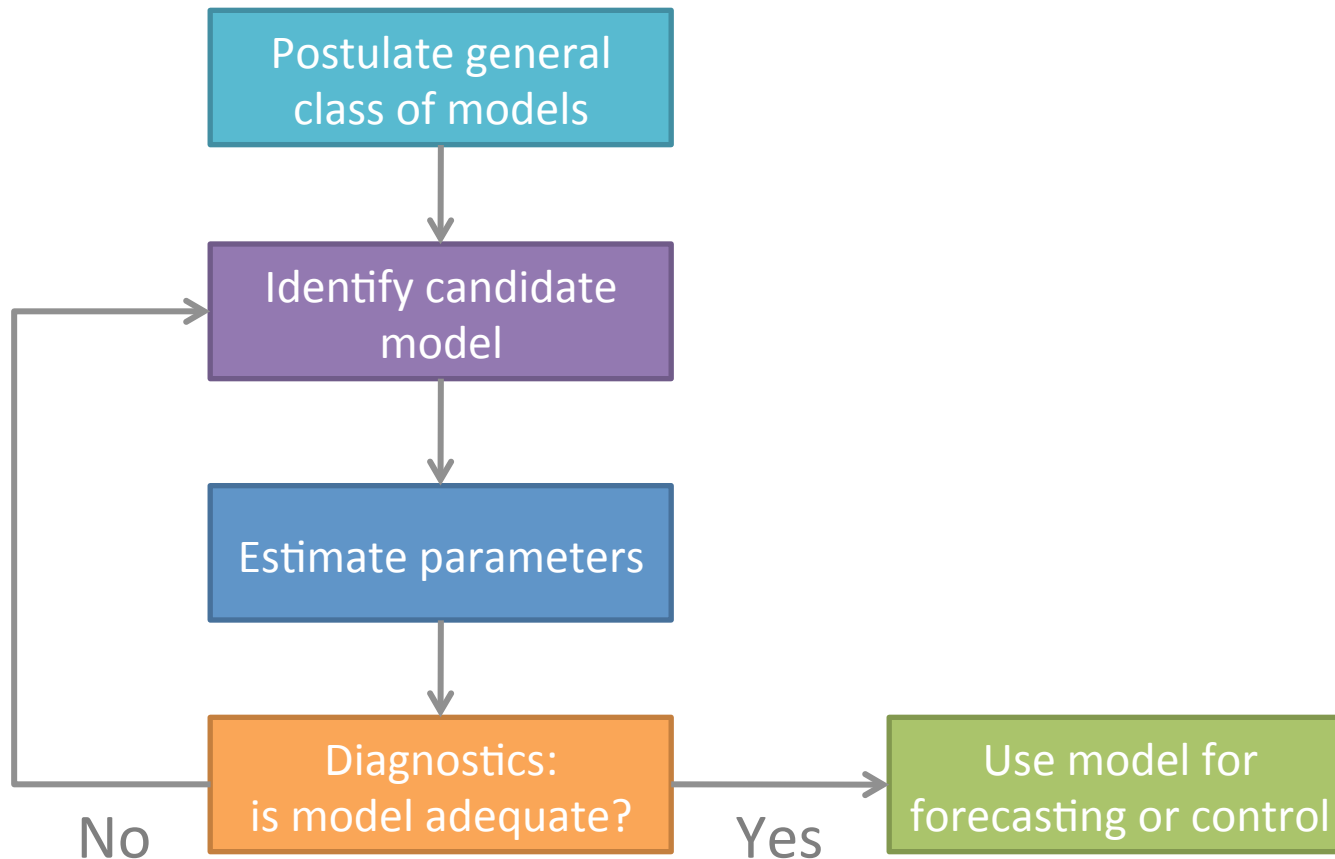
“white” noise:  $x_t = w_t$  and  $w_t \sim N(0,1)$

autoregressive:  $x_t = x_{t-1} + w_t$  and  $w_t \sim N(0,1)$

# Iterative approach to model building

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*Also known as the “Box-Jenkins Approach”*



# Classical decomposition of time series

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- *Classical decomposition* of an observed time series is a fundamental approach in time series analysis
- The idea is to decompose a time series  $\{x_t\}$  into a trend ( $m_t$ ), a seasonal component ( $s_t$ ), and a remainder ( $e_t$ )

$$x_t = m_t + s_t + e_t$$

# Linear filtering of time series

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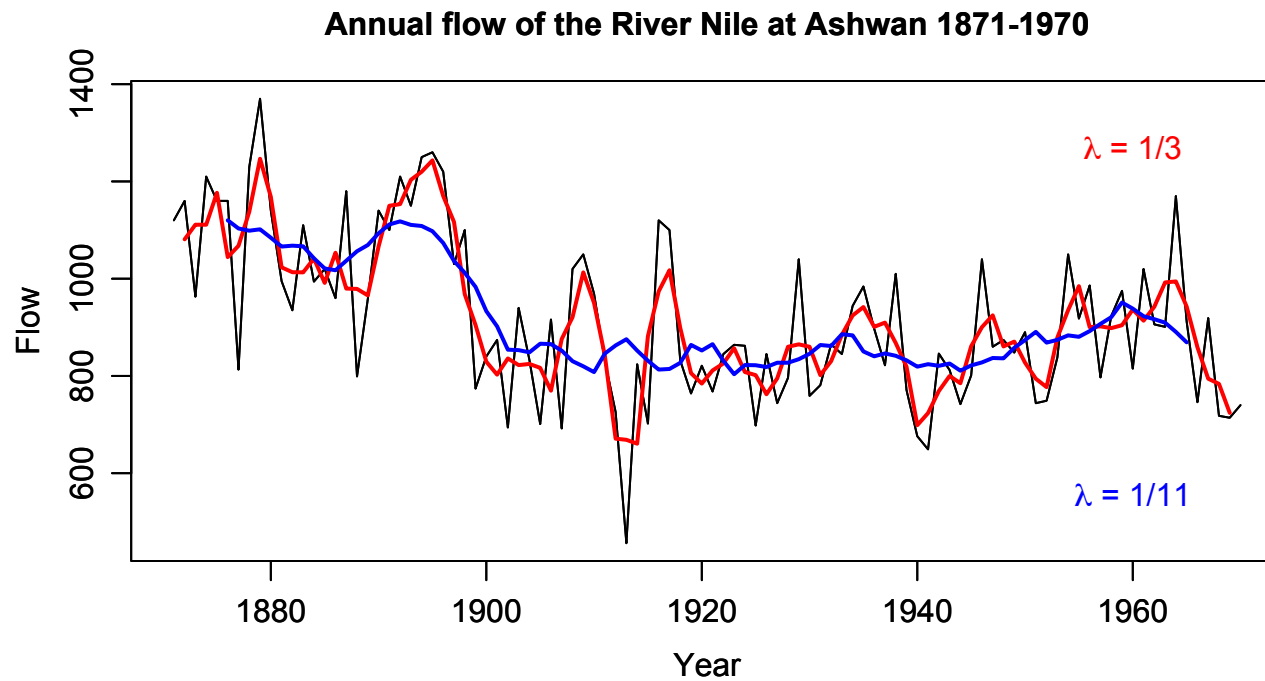
- Beginning with the trend ( $m_t$ ), we need a means for extracting a “signal”
- A common method is to use linear filters

$$m_t = \sum_{i=-\infty}^{\infty} \lambda_i x_{t+i}$$

- For example, moving averages with equal weights

$$m_t = \sum_{i=-a}^a \frac{1}{2a+1} x_{t+i} \quad (\text{FYI, this is what Excel does})$$

# Example of linear filtering



# Linear filtering of time series

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- Consider case where season is based on 12 months & ts begins in January ( $t=1$ )
- Monthly averages over year will result in  $t = 6.5$  for  $m_t$  (which is not good)
- One trick is to average (1) the average of Jan-Dec & (2) the average of Feb-Jan

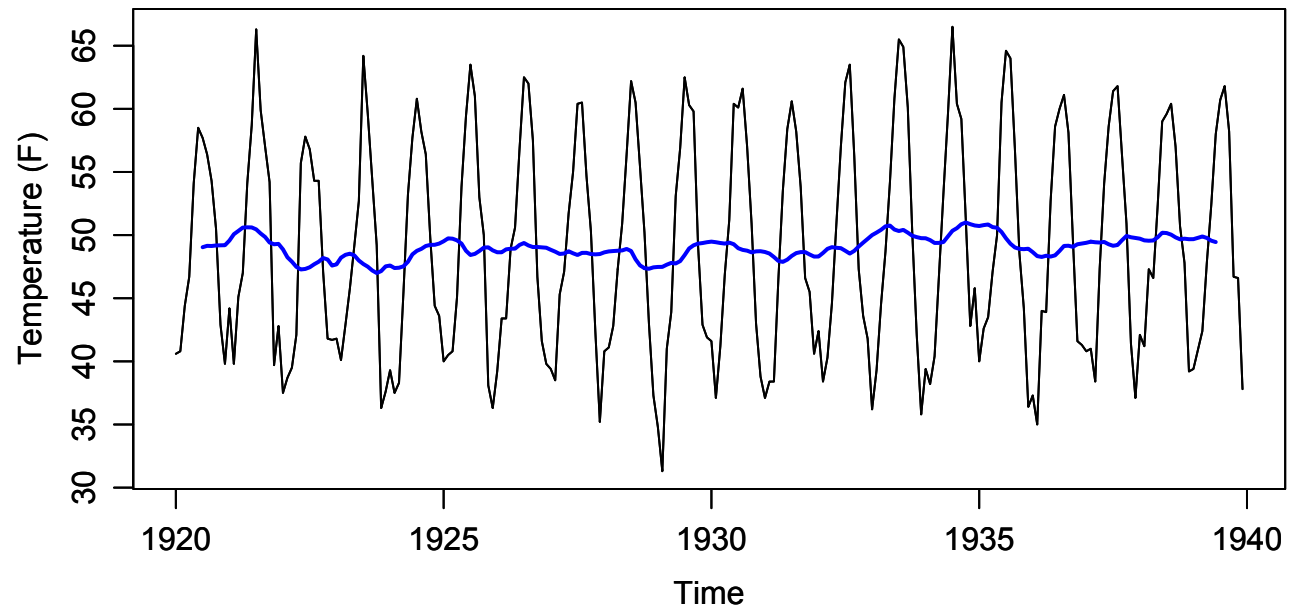
$$m_t = \frac{\frac{1}{2} x_{t-6} + x_{t-5} + \cdots + x_{t-1} + x_t + x_{t+1} + \cdots + x_{t+5} + \frac{1}{2} x_{t+6}}{12}$$



# Example of linear filtering

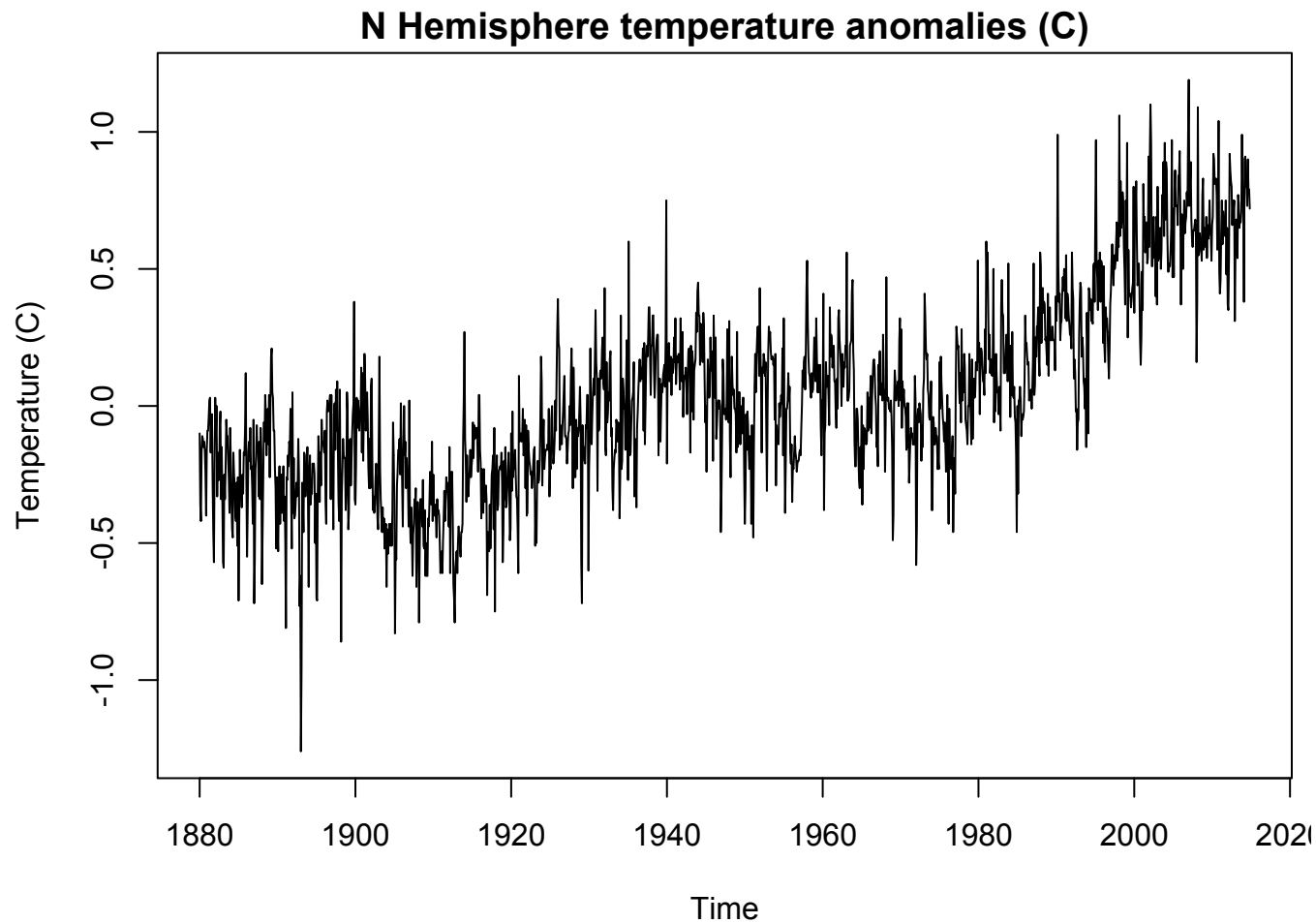
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**Average monthly temperature at Nottingham, UK (1920-1939)**



# Example of linear filtering

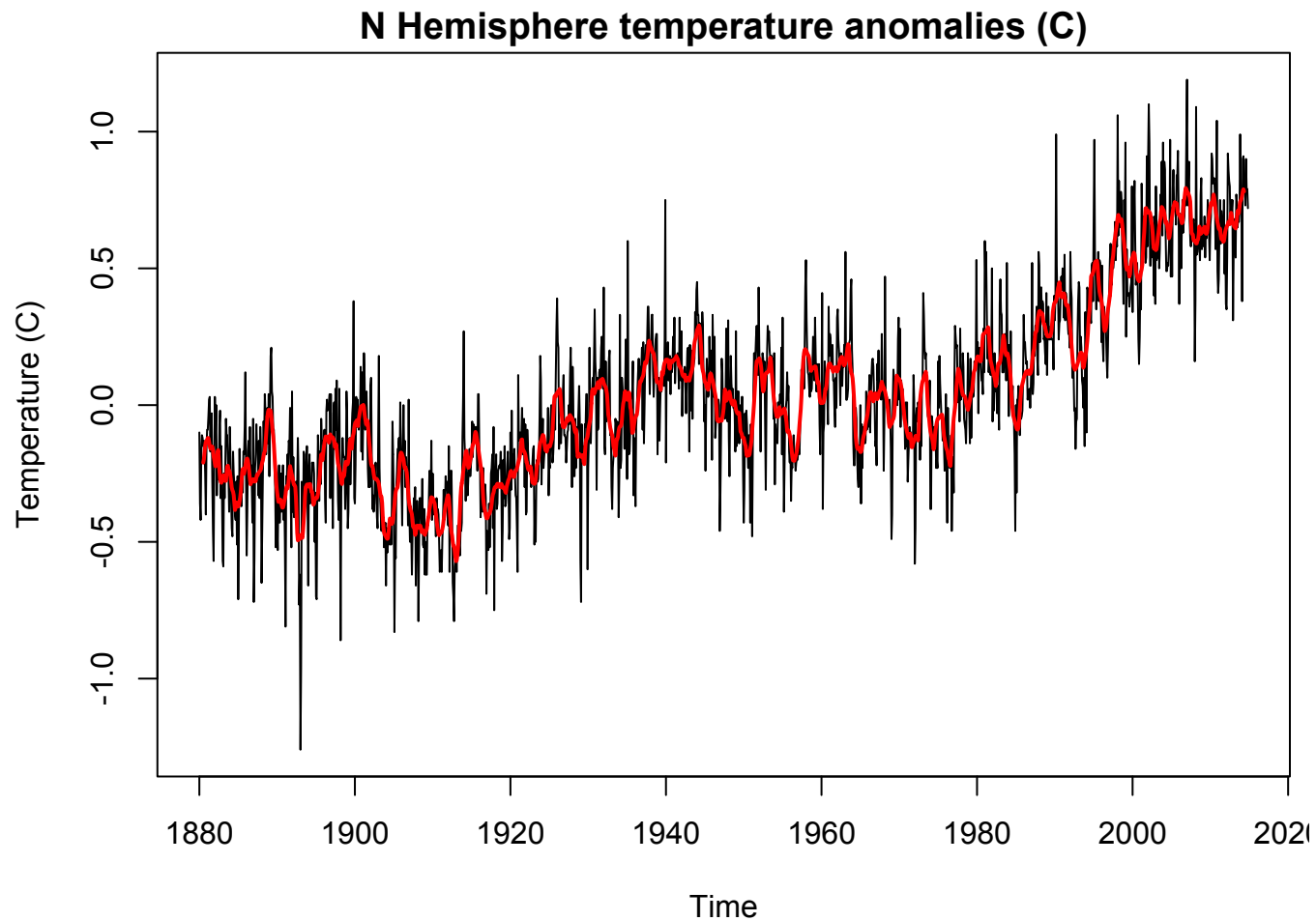
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Data from <http://www.ncdc.noaa.gov/>

# Example of linear filtering

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# Decomposition of time series

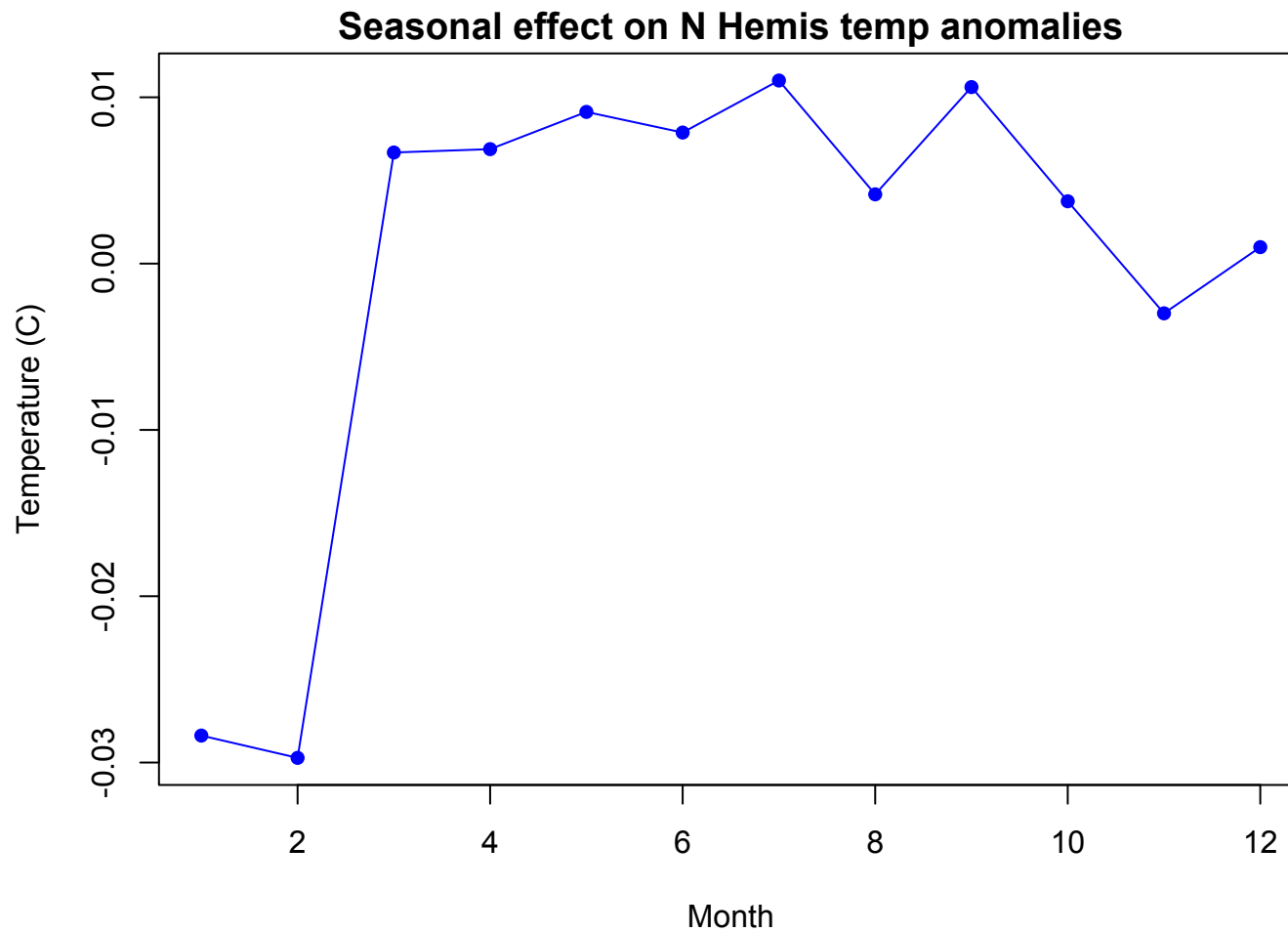
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Now that we have an estimate of  $m_t$ , we can get estimate of  $s_t$  simply by subtraction:

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

# Example of linear filtering

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# Decomposition of time series

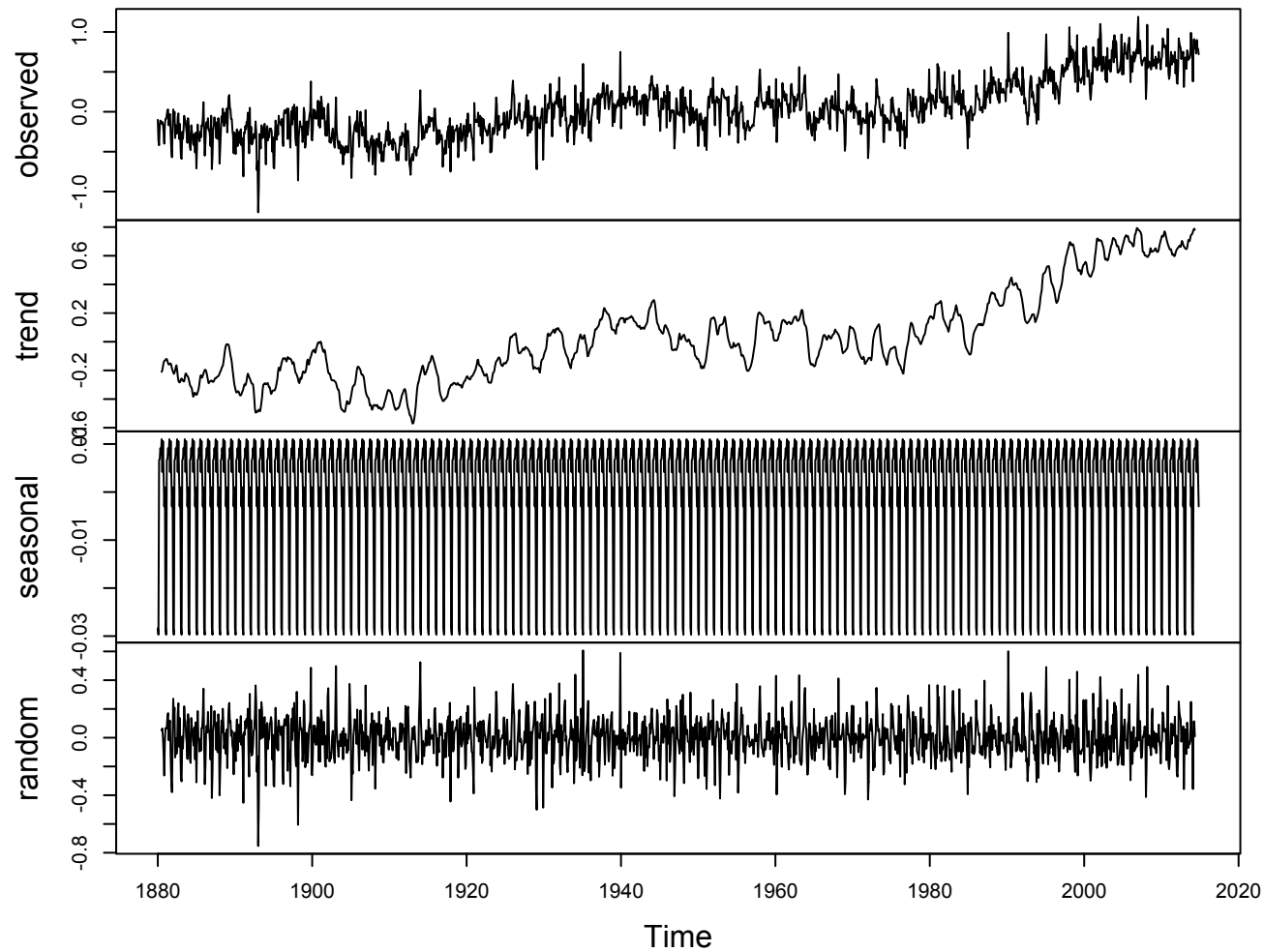
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Now that we have an estimate of  $s_t$ , we can get estimate of  $e_t$  simply by subtraction:

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

# Example of linear filtering

Decomposition of additive time series



# Notes on decomposition

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- Obtaining a “model” for a ts via decomposition is easy, but...
- You don't get a formula with which to obtain forecasts
- Let's look at an alternative



# Example of linear trend fitting

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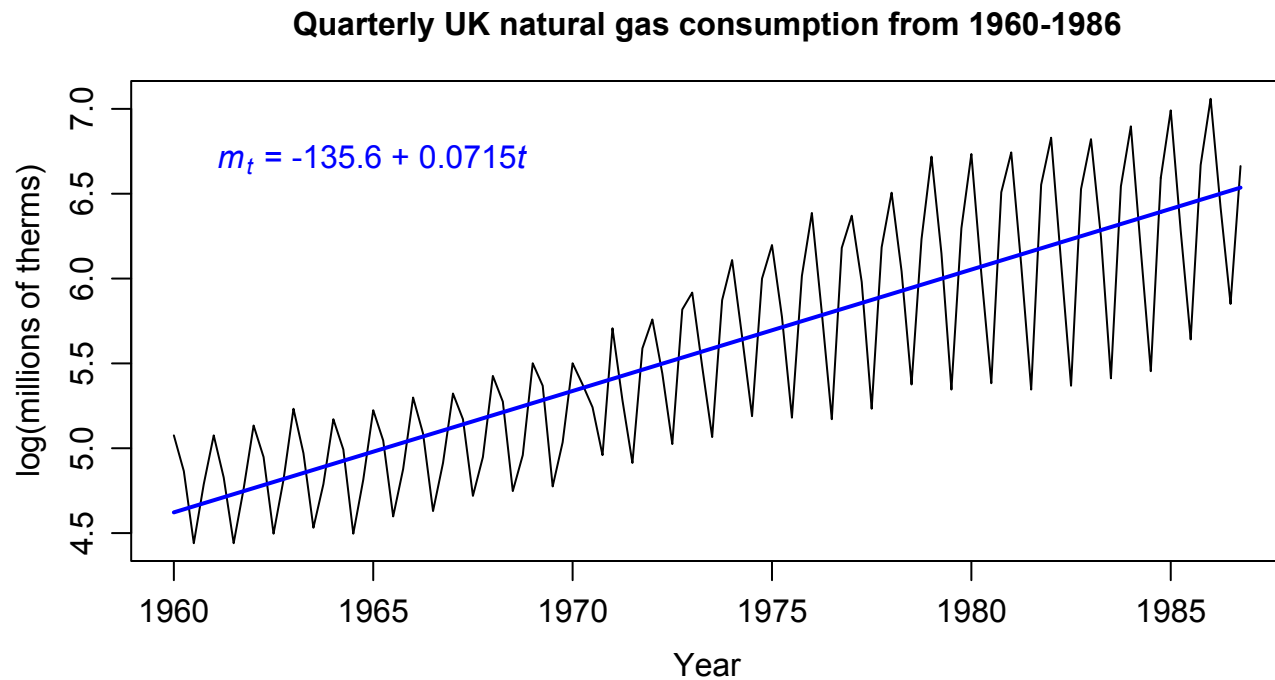
- A simple method for trend extraction is to use linear regression

$$m_t = \alpha + \beta t + e_t$$

- Note: the  $t$  index here could be a non-integer in cases with seasonal data

# Example of linear trend fitting

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# Decomposition of time series

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- Another means for extracting a trend is via nonparametric regression models (eg, LOESS)
- see R pkg `stl`

# Moving on with decomposition

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- We have decomposed our time series into a trend plus remainder ( $s_t + e_t$ )

$$x_t = (-135.6 + 0.0715t) + s_t + e_t$$

- Now let's consider the seasonal part

# Example of linear trend fitting

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- One method is to use fixed effects (eg, ANOVA)

$$x_t = m_t + s_t + e_t$$

$$x_t = (\alpha + \beta t) + s_t + e_t$$

# Example of linear trend fitting

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- Adding in a model for season (ie, quarters)

$$x_t = -137 + 0.072 \cdot t + s(q(t)) + e_t$$

$$q(t) = 4(t - \lfloor t \rfloor + 1) - 3$$

- So, for example, if  $q = 10.25$ :  
This is the "floor" function

$$q(10.25) = 4(10.25 - \lfloor 10.25 \rfloor + 1) - 3$$

$$q(10.25) = 4(10.25 - 10 + 1) - 3$$

$$q(10.25) = 4(1.25) - 3$$

$$q(10.25) = 5 - 3 = 2$$

# Example of linear trend fitting

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- Our final decomposition model

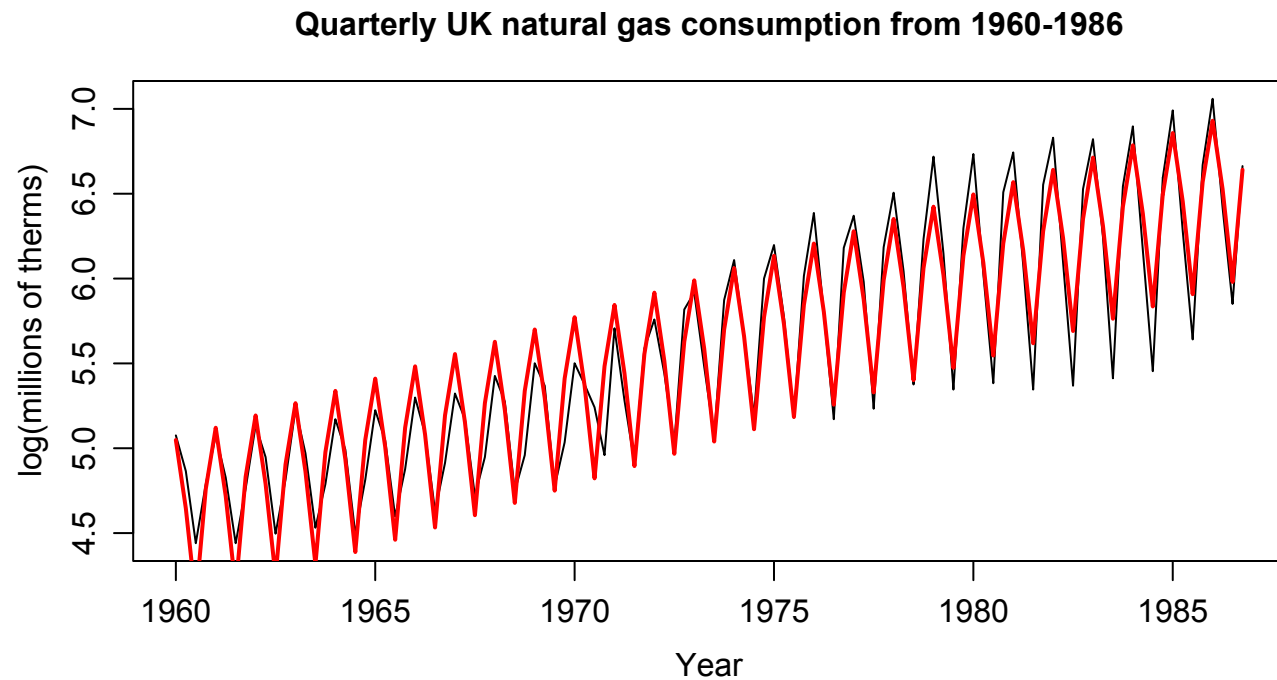
$$x_t = -137 + 0.072 \cdot t + \theta(q(t)) + e_t$$

$$q(t) = 4(t - [t] + 1) - 3$$

$$s(q(t)) = \begin{cases} 0 & \text{if } q = 1 \\ -0.42 & \text{if } q = 2 \\ -0.99 & \text{if } q = 3 \\ -0.34 & \text{if } q = 4 \end{cases}$$

# Example of trend + season fitting

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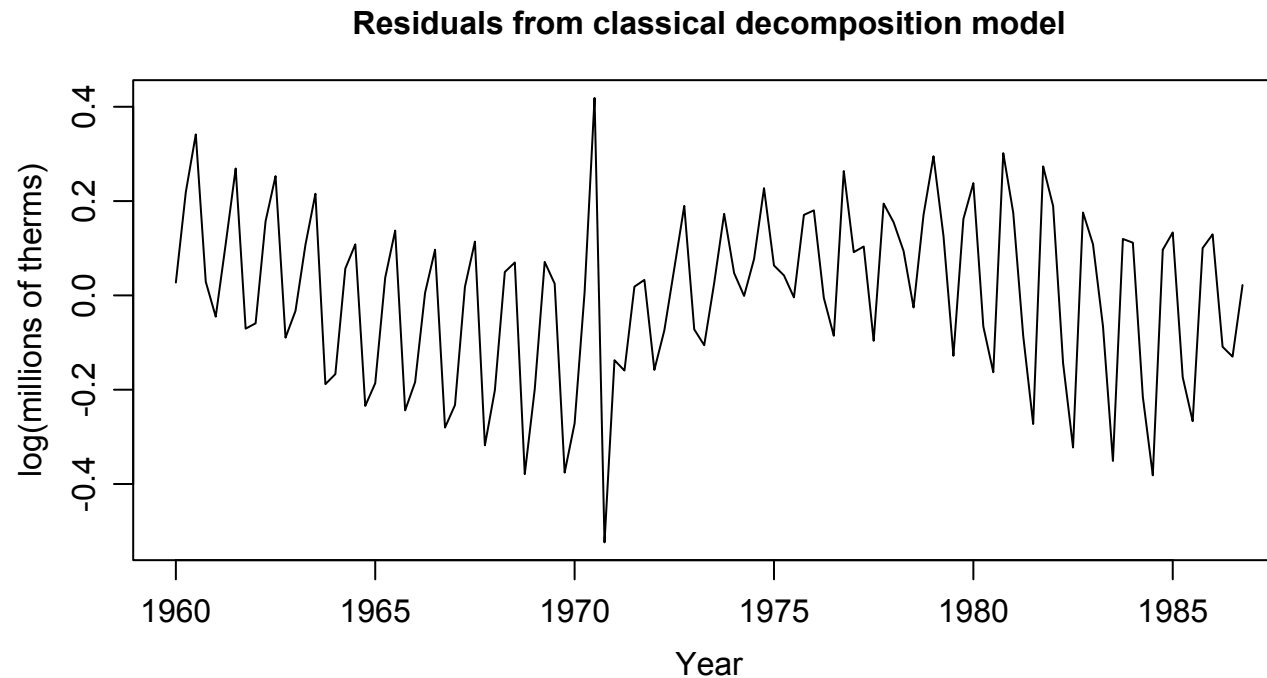




# Are the residuals stationary?

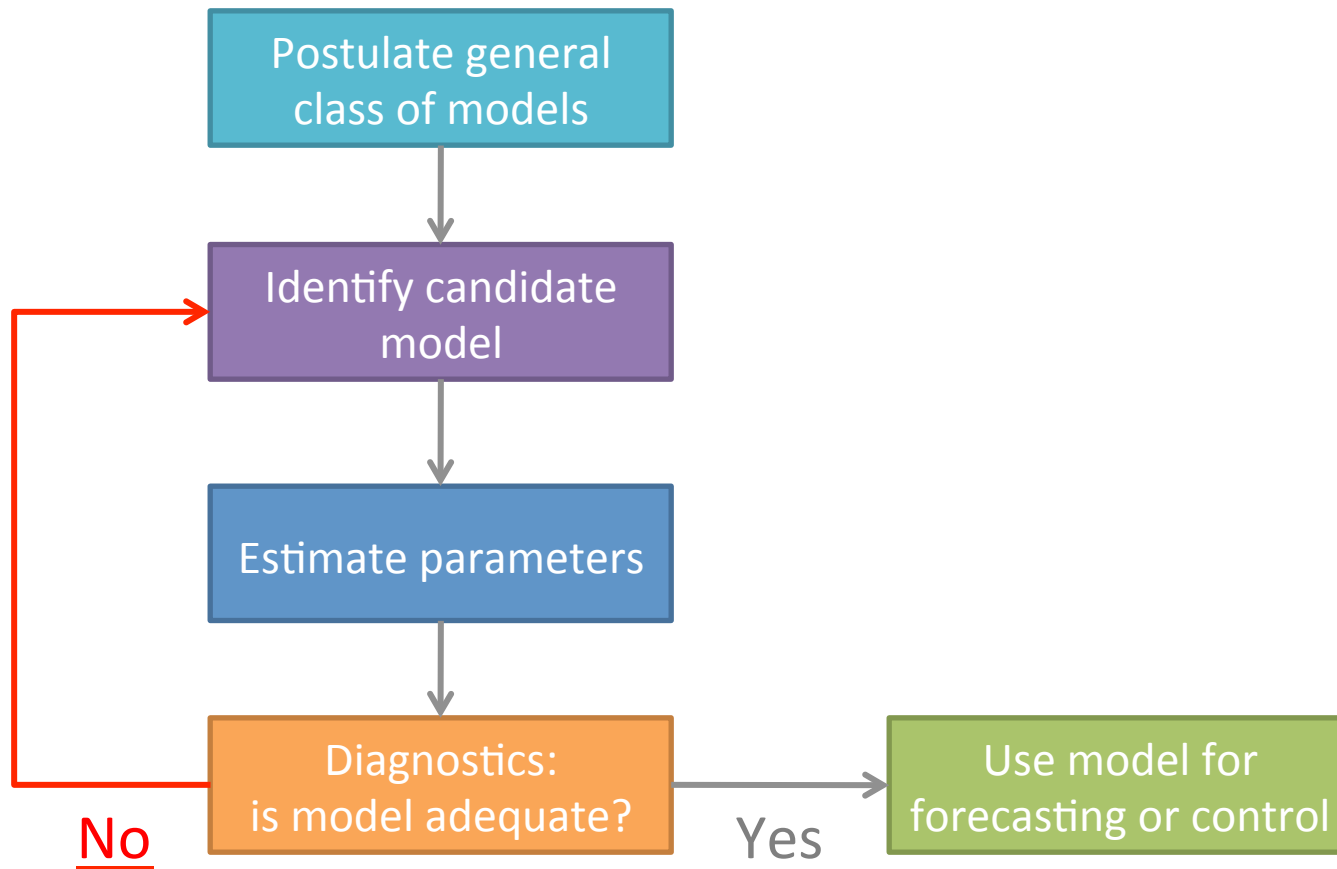
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- The goal with decomposition is to reduce the time series to a trend, season & stationary residuals



# Iterative approach to model building

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# Summary

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- This was a *brief* overview—there is *lots* of stuff we didn't cover
- Please ask for help/guidance if you're looking for more details, other R code, etc