

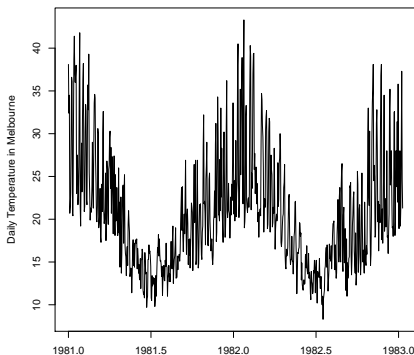
Automatic Detection of Seasonality Using Wavelets

Rebecca Killick
and Ben Norwood
ONS Workshop 2018/03

- Motivation
- Periodic Series
- Wavelet Approach
- Results

MOTIVATION

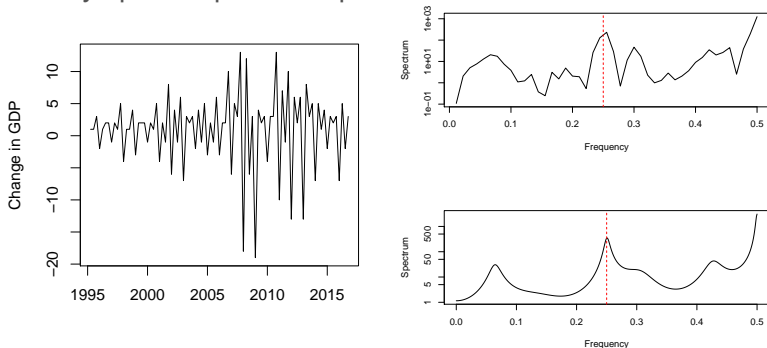
- As data collection is growing with the rise of big data, larger seasonal periods are expected.
- Data shows daily, monthly, yearly patterns.
- Automatic Detection of such periods would aid adjustment of them substantially.



EXISTING METHODS

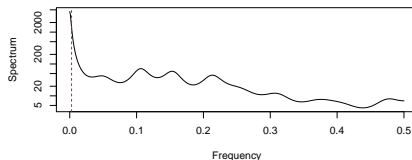
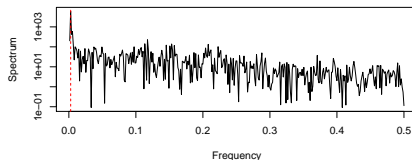
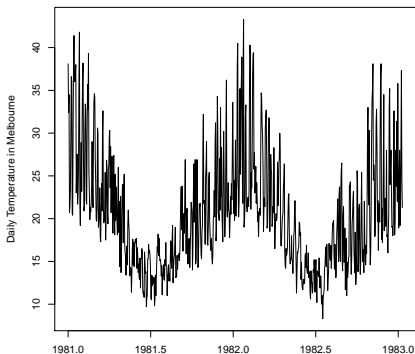


- Most common way to determine periodicity
- Compute the (smoothed) Fourier periodogram
- Identify spectral peaks as periodicities



- This requires human intervention or peak-detection systems.

- For longer periodicities the cycle is often too close to the origin to detect.



- Manually, i.e. by eye or guessing
- Seasonal F test (Friedman Test)
- Automatically with visual significance
(Soukup & Findley 1999, McElroy & Roy 2017)
- Automatically with findFrequency
(first peak of smoothed periodogram)

There are other ways to determine seasonality using autocorrelations at various lags.

A NEW APPROACH

Discrete Non-Decimated Approach

- The discrete transform can be seen as a filtering operation over different bands.
- Given a time series Y_t we calculate the wavelet coefficients as

$$d_{j,k} = \frac{1}{\sqrt{2^j}} \left[\left\{ \sum_{i=0}^{2^j-1} Y_{k+i} \right\} - \left\{ \sum_{i=2^{j-1}+1}^{2^j-1} Y_{k+i} \right\} \right],$$

for

$$t = 1, 2, \dots, n = 2^J,$$

$$j = 1, 2, \dots, J-1,$$

$$k = 1, \dots, 2^j - 2^{j-1} + 1.$$

Periodic Series

Length of period

- Throughout we now assume the series we are dealing with can be expressed as a sinusoid with noise:

$$Y_t \sim \sin\left(\frac{2\pi t}{p}\right) + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_\epsilon^2), \quad p \in \mathbb{R}$$

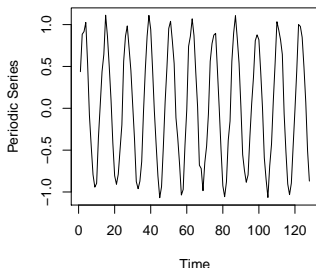


Figure: $p = 12, \sigma_\epsilon = 0.1$

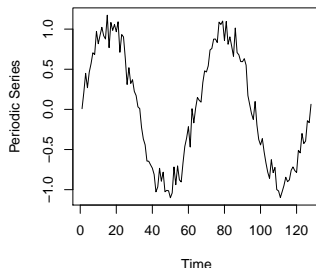
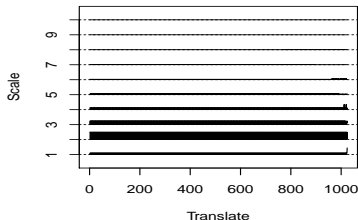


Figure: $p = 64, \sigma_\epsilon = 0.1$

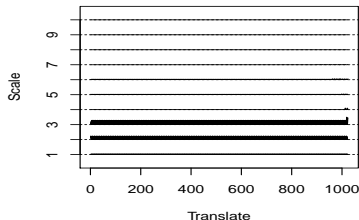
Wavelet Representation

Square of the $d_{j,k}$ coefficients

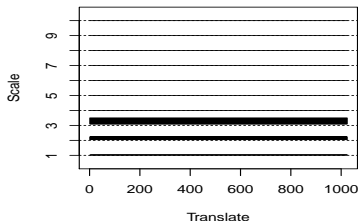
p = 6, sd = 0



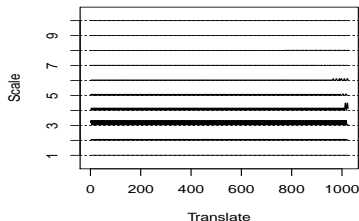
p = 7, sd = 0



p = 8, sd = 0



p = 12, sd = 0



Definition

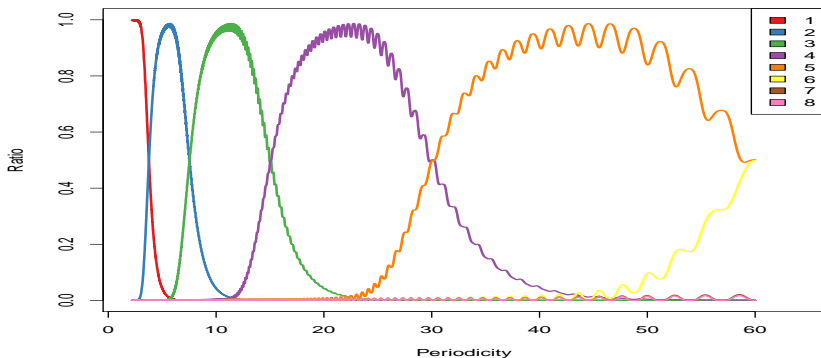
- To monitor the variance of each scale, we analyse the squares of the coefficients.
- This is such that we are monitoring the ‘energy’ of each scale.
- We can normalize this energy at each scale to give Relative Wavelet Energy:

$$RWE_j = \frac{\sum_{k=1}^n d_{j,k}^2}{\sum_{j=1}^J \sum_{k=1}^n d_{j,k}^2}.$$

Wavelet Energy

A Beautiful Relationship

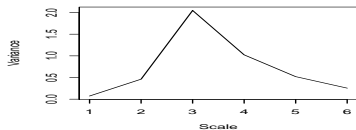
If we look at how the variance for each periodicity across the scales we get an interesting relationship.



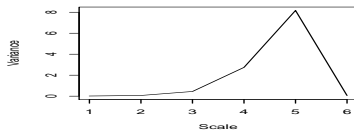
Variance Profiles

A Representation of a Series

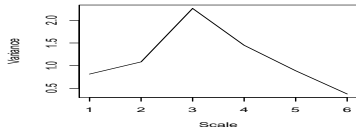
For each series we can now take a wavelet transform, and monitor the variance of the coefficients on each scale:



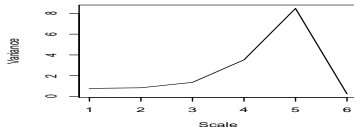
(a) $p = 12, \sigma_{\epsilon} = 0.1$



(b) $p = 36, \sigma_{\epsilon} = 0.1$



(a) $p = 12, \sigma_{\epsilon} = 1$



(b) $p = 36, \sigma_{\epsilon} = 1$

Theorem

Using the variance profile, on a sample of size T , we have proved that:

$$\begin{aligned}\mathbb{E} \left(\hat{d}_{j,k}^2 - d_{j,k}^2 \right)^2 &\rightarrow 0 && \text{as } T \rightarrow \infty \\ \hat{p} &\rightarrow p && \text{as } T \rightarrow \infty.\end{aligned}$$

SIMULATIONS

- Compare to the *findFrequency* function in *forecast* R package.
- We measure how close the predicted periodicity is to the truth.
- Also record computing time taken.

Simulation Constants:

$N = 1000$ Amount of realisations

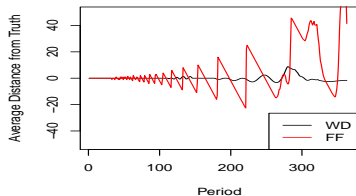
$T = 1024$ Length of each series

$p \in [3, 365]$ periodicity simulated

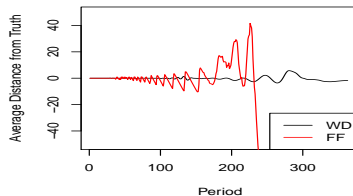
Weighted by number of coefficients in scale.

Results

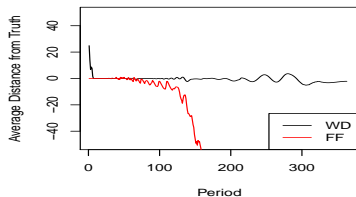
Average Distance



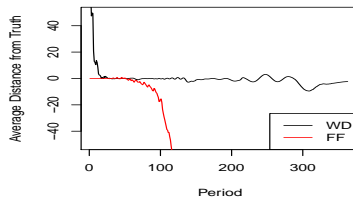
(a) $\sigma_{\epsilon} = 0.1$



(b) $\sigma_{\epsilon} = 0.4$



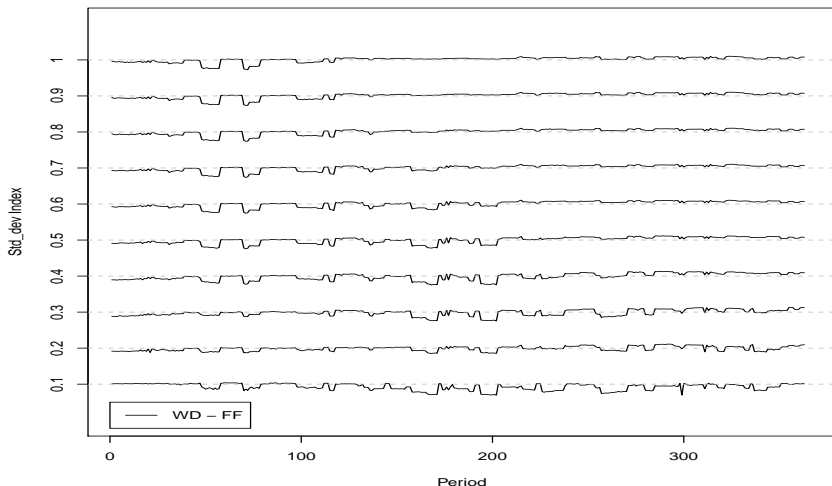
(a) $\sigma_{\epsilon} = 0.7$



(b) $\sigma_{\epsilon} = 1$

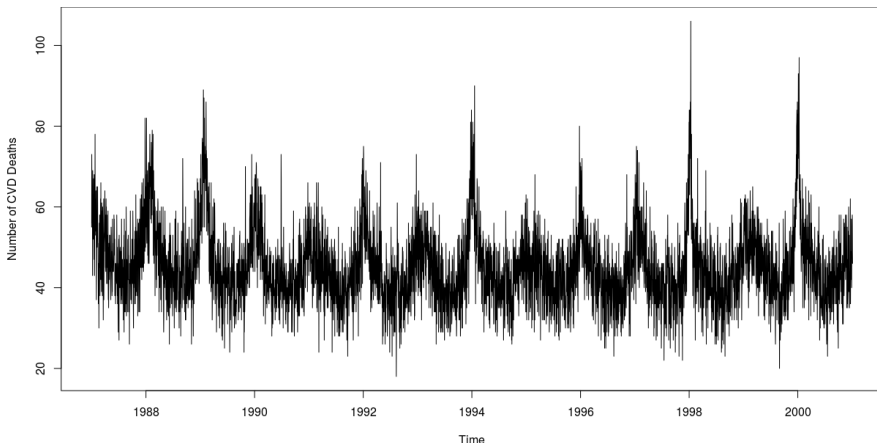
Results

Computing Time

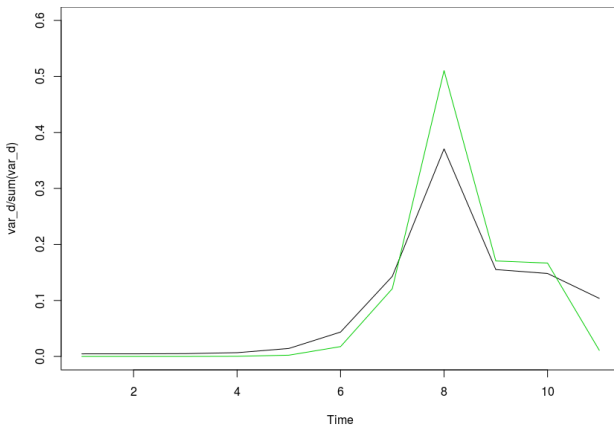


APPLICATION

- Daily cardiovascular deaths from 1987-2000 (seasonal R)
- findFrequency function returns 1 = no seasonality
- wavelet method returns 373

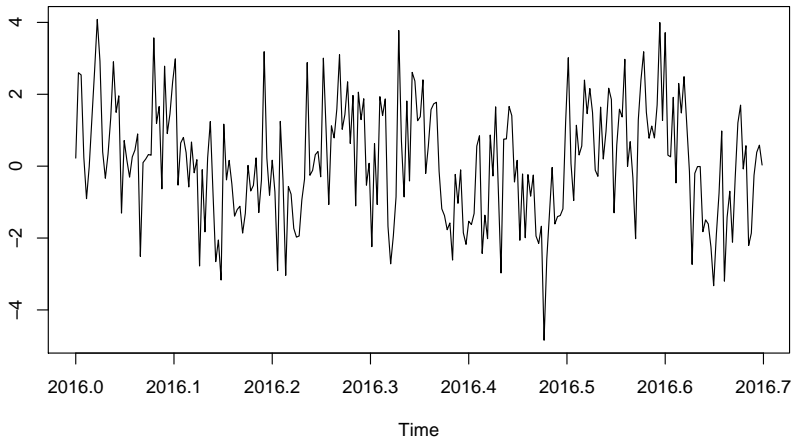


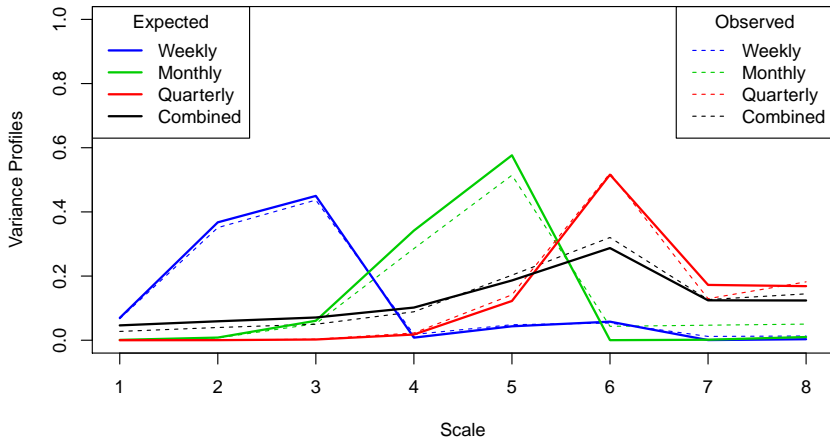
- findFrequency function returns 1 = no seasonality
- wavelet method returns 373





Quarterly + Monthly + Weekly + Noise





- Provided an alternative approach to detecting low frequency cycles.
- Resistant to noise.
- Computationally efficient.
- Seek to apply periodic boundary conditions to improve.
- Need to add confidence interval to estimate.
- Encouraging for further development.

Detecting Periodicity

Approaching an Algorithm

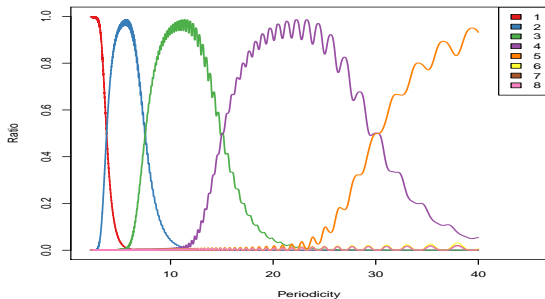
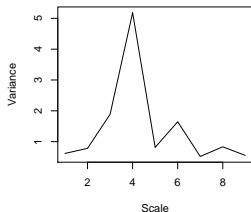
In detecting periodic behaviour we have to find the variance profile that fits correctly. This leads to a number of considerations:

- What region should we search?
- How should we weight the differences?
- How certain are we?

Detecting Periodicity

Search Regions

Suppose we are given the following variance profile for a series, how could we narrow down our search?

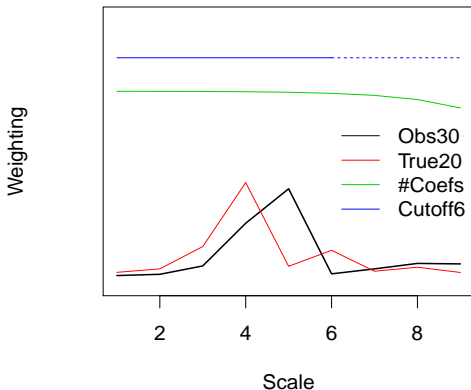


Detecting Periodicity

Weighting Functions

When considering any distance it is useful to consider a variety of weighting functions:

- According to the true variance profile.
- According to the observed profile.
- According to the amount of coefficients considered in each scale.
- Choose a cut-off scale.



Different Wavelets

