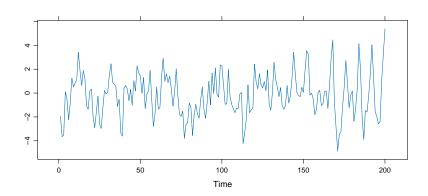
Monte Carlo SSA for extracting weak signals

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Is There a Signal?



Question: is it pure noise, or is there a signal?

Problem Statement

Let $X = (x_1, \dots, x_N)$, $x_i \in \mathbb{R}$ be a time series.

Given: X = T + H + R, where T is a trend, H is a periodic component, and R is a noise.

Problems:

- How to test for the presence of a signal S = T + H?
- 4 How to extract the signal S, if present?

Methods:

- Monte Carlo SSA (MC-SSA) [Allen and Smith, 1996] tests $H_0: \mathsf{S} = 0.$
- Singular spectrum analysis (SSA) [Golyandina, Nekrutkin and Zhigljavsky, 2001].

Goal: to implement an algorithm for automatic signal extraction based on MC-SSA

Notations & Known Results: Embedding and Hankelization

For $X = (x_1, ..., x_N)$, fix L (1 < L < N).

Embedding operator T_{SSA}:

$$\mathfrak{T}_{\mathsf{SSA}}(\mathsf{X}) = \mathbf{X} = \begin{pmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{pmatrix},$$

where K = N - L + 1.

Hankelization operator ${\mathfrak H}$ — averaging the matrix over its anti-diagonals.

Notations & Known Results: The SSA Algorithm

Input: time series $X = (x_1, \dots, x_N)$.

Parameters: window length L, index set $I \subset \{1, \ldots, d\}$.

Output: signal estimate.

Input: X — time series

1. Embedding

2. Decomposition

Sum of rank-one matrices $\mathbf{X} = \sum_{i=1}^{d} \mathbf{X}_{j}$

3. Grouping

Result: SSA decomposition $X = \widetilde{S} + \widetilde{R}$ $\widetilde{S} = \mathcal{T}_{SSA}^{-1} \circ \mathcal{H}(\mathbf{X}_I)$

4. Reconstruction

Grouping of matrices, corresponding to the signal $\mathbf{X} = \mathbf{X}_I + (\mathbf{X} - \mathbf{X}_I)$ $\mathbf{X}_I = \sum \mathbf{X}_i$

Example: Applying SSA

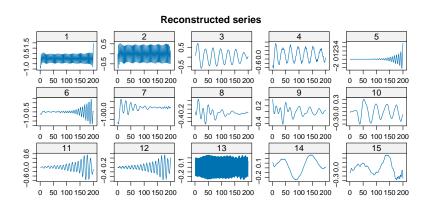


Figure: Elementary reconstructed components (L=100)

Components corresponding to the signal: 1, 2, 5, 6 and 13.

Notations & Known Results: Monte Carlo SSA

Input: X = S + R, where S is the signal and R is a realization of a zero-mean stationary process ξ with spectral density f_{θ} .

Parameters: window length L, normalized vectors corresponding to specific frequencies $W_1, \ldots, W_M \in \mathbb{R}^L$.

Test statistics:

$$\widehat{p}_k = \left\| \mathbf{X}^{\mathrm{T}} W_k \right\|^2.$$

Its distribution under H_0 is generally unknown and is estimated via Monte Carlo.

Multiple MC-SSA [Golyandina, 2023]: modification with multiple comparisons correction.

We chose sine waves with equidistant frequencies $\omega_k=k/(2L)$, $k=1,\ldots,L$ as projection vectors.

Notations & Known Results: Noise Parameters Estimation

Noise parameters θ are generally unknown and must be estimated.

Parameter estimates can be obtained by maximizing the Whittle's likelihood [Whittle, 1953]:

$$\ell_W(\boldsymbol{\theta}) = -\frac{1}{m} \sum_{j=1}^m \left(\ln f_{\boldsymbol{\theta}}(\omega_j) + \frac{I_N(\omega_j)}{f_{\boldsymbol{\theta}}(\omega_j)} \right),$$

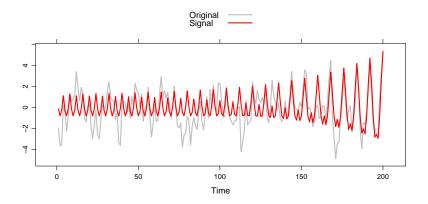
where $m = \lfloor (N-1)/2 \rfloor$, f_{θ} is the spectral density of ξ , I_N is the periodogram of the original series, and $\omega_j = j/N$.

Estimation can be done on part of the spectrum: let $J=\{j_1,\ldots,j_p\}$ be frequency indices we want to exclude when estimating parameters. Then $\ell_W(\boldsymbol{\theta})$ is computed only over indices $j \notin J$.

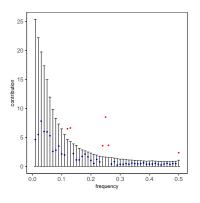
Example: Applying Monte Carlo SSA

 ${\rm X}={\rm S}+\pmb{\xi},$ where $\pmb{\xi}$ is red noise with parameters $\phi=0.7$ and $\sigma^2=1,~N=200,$

$$s_n = 0.075 e^{0.02n} \cos(2\pi n/8) + 2\cos(2\pi n/4) + 0.2 \cdot (-1)^n.$$



Example: Applying Monte Carlo SSA



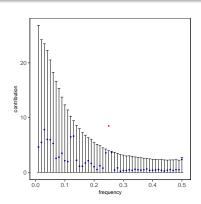


Figure: True noise model

Figure: Estimated noise model

Problem: not all frequencies are detected during parameter estimation.

Solution: apply the test iteratively, extracting one harmonic at a time until H_0 : $\mathsf{S}=0$ is no longer rejected.

Notations & Known Results: Automatic Grouping in SSA

For a series X of length N and $0 \leqslant \omega_1 \leqslant \omega_2 \leqslant 0.5$, define

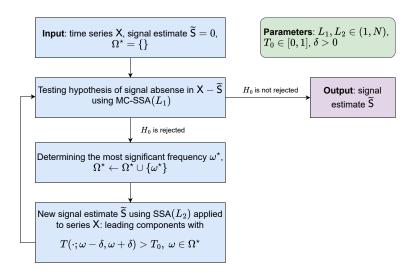
$$T(\mathsf{X};\omega_1,\omega_2) = \frac{1}{\|\mathsf{X}\|^2} \sum_{k:\omega_1 \leqslant k/N \leqslant \omega_2} I_N(k/N),$$

where I_N is the periodogram of X.

 $T(X; \omega_1, \omega_2)$ may be interpreted as the fraction of total contribution of frequencies within $[\omega_1, \omega_2]$.

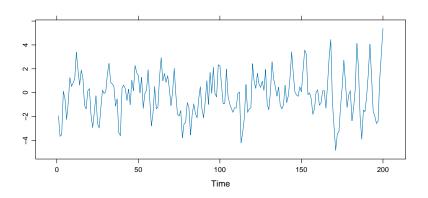
Let ω^{\star} be a significant frequency. Then we take $[\omega_1,\omega_2]=[\omega^{\star}-\delta,\omega^{\star}+\delta].$

The autoMCSSA Algorithm

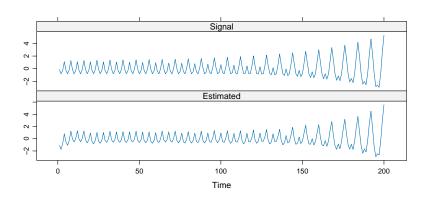


Example: Applying autoMCSSA

 ${\sf X} = {\sf S} + {\pmb \xi}$, where ${\pmb \xi}$ is red noise with $\phi = 0.7$ and $\sigma^2 = 1$, N = 200, $s_n = 0.075 \, e^{0.02n} \cos(2\pi n/8) + 2\cos(2\pi n/4) + 0.2 \cdot (-1)^n$.



Example: Applying autoMCSSA



Parameters: $L_1 = 50$, $L_2 = 100$, $\delta = 1/80$, $T_0 = 0.5$.

Result: autoMCSSA correctly identified significant components (1, 2, 5, 6 and 13).

Conclusions

To sum up, we:

- Implemented autoMCSSA, which automatically extracts a significant signal, plus a modification of the Whittle approach using part of the spectrum.
- Pound that autoMCSSA can extract signals whose SSA components are not necessarily dominant.

In the future, we plan to formulate a strategy for selecting autoMCSSA parameters.