

Bootstrap for testing the equality of selfsimilarity exponents across multivariate time series

EUSIPCO 2021

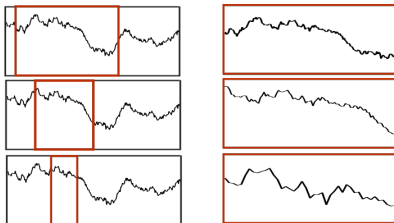
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Univariate self-similarity

Scale-free dynamics



$$\{X(t)\}_{t \in \mathbb{R}} \stackrel{fdd}{=} \{a^H X(t/a)\}_{t \in \mathbb{R}, \forall a > 0}$$

$$0 < H < 1$$

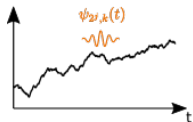
Goal: estimation of H

Univariate estimation of H (Flandrin et al., 1992)

Univariate wavelet transform:

- $D_X(2^j, k) = \langle 2^{-j/2} \psi_0(2^{-j}t - k) | X(t) \rangle$
- ψ_0 : mother wavelet

Univariate signal



Wavelet coefficients



X self-similar

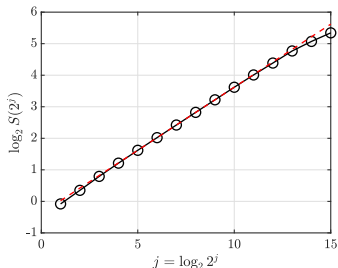
\Rightarrow power law: $S(2^j) \propto 2^{j(2H+1)}$

Linear regression in a log-log diagram

Wavelet spectrum

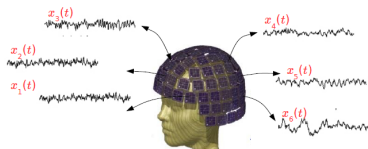
$$S(2^j) = \frac{1}{N_j} \sum_{k=1}^{N_j} D_X(2^j, k)^2 \in \mathbb{R}$$

$$N_j = \frac{N}{2^j}, N: \text{sample size}$$



Multivariate self-similarity

Collection of signals



Multivariate setting

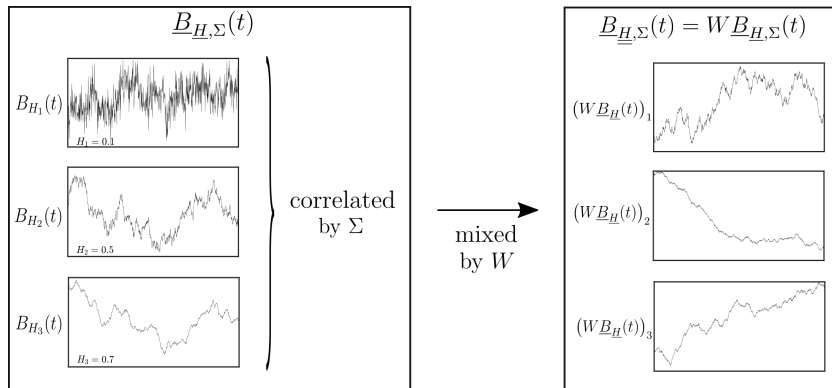
Multivariate self-similarity exponent

$$\underline{H} = (H_1, \dots, H_M)$$

where $0 < H_1 \leq \dots \leq H_M < 1$

Goal: testing $H_1 = \dots = H_M$

Multivariate self-similarity (Didier et al., 2011)



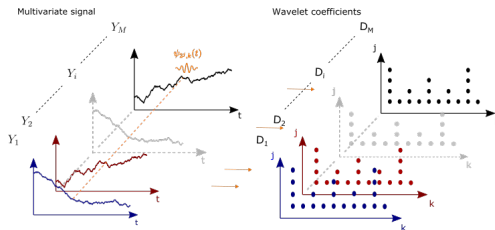
$$\{\underline{B}_{\underline{H},\Sigma}(t)\}_{t \in \mathbb{R}} \stackrel{fdd}{=} \{a^{\underline{H}} \underline{B}_{\underline{H},\Sigma}(t/a)\}_{t \in \mathbb{R}}, \forall a > 0$$

$$\underline{H} = W \text{diag}(\underline{H}) W^{-1}$$

Goal: estimation of \underline{H}

Multivariate estimation

Multivariate wavelet transform of $Y = W\underline{B}_{H,\Sigma}$: $D(2^j, k) = (D_1(2^j, k), \dots, D_M(2^j, k))$



Wavelet spectrum ($M \times M$ matrix):

$$S_{m_1, m_2}(2^j) = \frac{1}{N_j} \sum_{k=1}^{N_j} D_{m_1}(2^j, k) D_{m_2}(2^j, k)^*$$

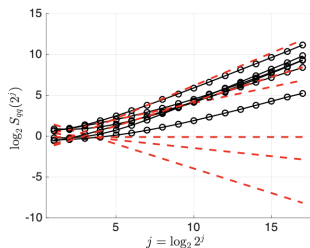
$$N_j = \frac{N}{2^j}, \quad N: \text{sample size}$$

$Y = W\underline{B}_{H,\Sigma}$ self-similar

\Rightarrow mixture of M^2 power laws when $W \neq I$:

$$S_{m_1, m_2}(2^j) = \sum_{k=1}^M \sum_{n=1}^M A_{k,n}^{(m_1, m_2)} 2^{j(H_k + H_n + 1)}$$

Linear regression in a log-log diagram



Estimation of H (Didier and Abry, 2018)

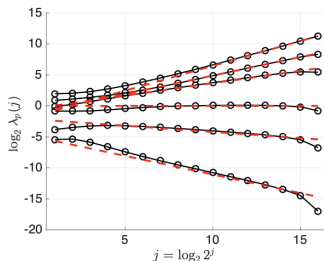
Eigenvalue decomposition:

$$S(2^j) = U(2^j) \begin{bmatrix} \lambda_1(2^j) & 0 & \cdots & \cdots & 0 \\ 0 & \lambda_2(2^j) & \cdots & \cdots & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \lambda_M(2^j) \end{bmatrix} U(2^j)^T$$

$Y = W \underline{B}_{H, \Sigma}$ self-similar
 \Rightarrow Asymptotical power law:
 $\lambda_m(2^j) \propto 2^{j(2H_m+1)}$

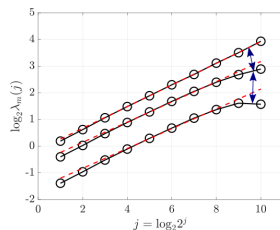
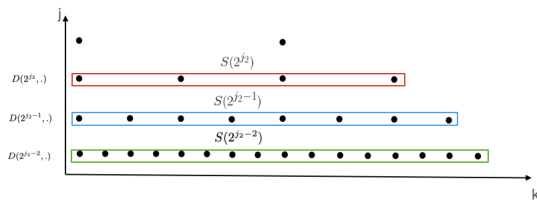
Linear regression on log-eigenvalues $\lambda_m(2^j)$:

$$\hat{H}_m = \frac{1}{2} \sum_{j=j_1}^{j_2} \omega_j \log_2 \lambda_m(2^j) - \frac{1}{2}$$



Repulsion effect

Gap between eigenvalues larger than expected at each scale



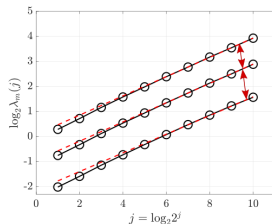
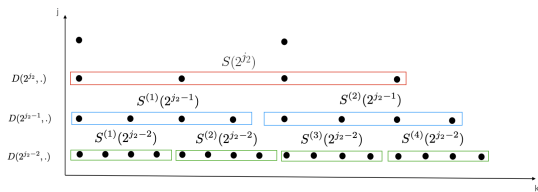
Few coefficients \Rightarrow repulsion effect: important bias when $H_1 = \dots = H_M$

Issue: repulsion effect increases with scale 2^j

Bias corrected estimation

$$s^{(w)}(2^j) \triangleq \frac{1}{n_{j2}} \sum_{k=1+(w-1)n_{j2}}^{wn_{j2}} D(2^j, k) D(2^j, k)^*, \quad w = 1, \dots, 2^j - j_2, \quad n_{j2} = \frac{N}{2^j}$$

Wavelet spectra for same numbers of wavelet coefficients



Eigenvalues of $S^{(w)}(2^j)$: $\{\lambda_1^{(w)}(2^j), \dots, \lambda_M^{(w)}(2^j)\}$
 \rightarrow similar repulsion at all scales $j \in \{j_1, \dots, j_2\}$

Averaged log-eigenvalues: $\vartheta_m(2^j) \triangleq 2^{j_2-j} \sum_{w=1}^{2^j-j_2} \log_2(\lambda_m^{(w)}(2^j))$

Linear regression on averaged log-eigenvalues $\vartheta_m(2^j)$

Testing the equality of H_1, \dots, H_M

Single observation $\underline{H} = (H_1, \dots, H_M)$

Fluctuation of the estimator: maybe $H_i = H_j$ despite $\hat{H}_i \neq \hat{H}_j$

Testing $H_1 = \dots = H_M$

Asymptotic joint normality of $\underline{\hat{H}} = (\hat{H}_1, \dots, \hat{H}_M)$

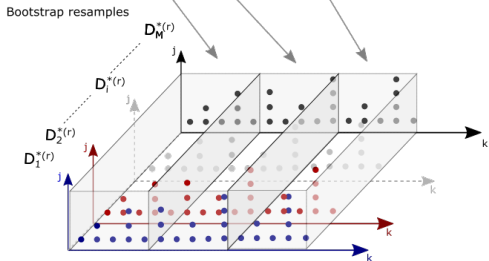
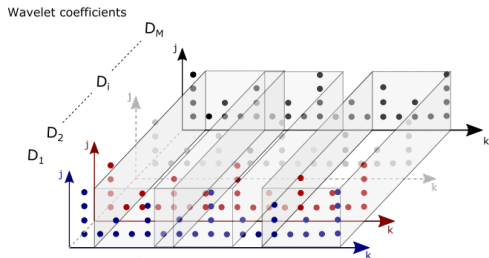
→ χ^2 statistic:

$$T = (\underline{\hat{H}} - \langle \hat{H}_m \rangle_m)^T \Sigma_{\underline{\hat{H}}}^{-1} (\underline{\hat{H}} - \langle \hat{H}_m \rangle_m).$$

Issue: single observation $\Rightarrow \Sigma_{\underline{\hat{H}}}$ unknown

→ estimation of $\Sigma_{\underline{\hat{H}}}$ by Bootstrap resampling

Multivariate wavelet block-bootstrap resamples



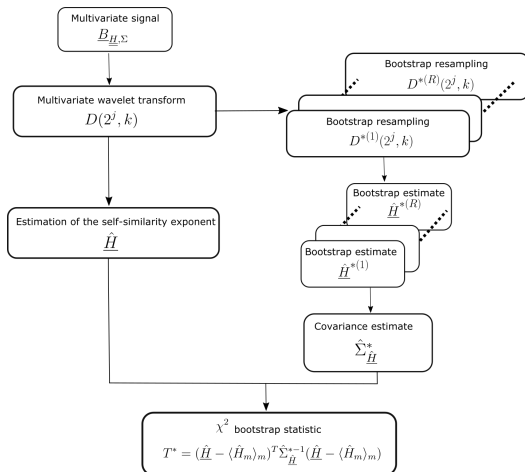
R Bootstrap estimates
 $\underline{\hat{H}}^{*(r)} = (\hat{H}_1^{*(r)}, \dots, \hat{H}_M^{*(r)})$
 computed from
 the R wavelet coefficient resamples
 $D^{*(r)} = (D_1^{*(r)}, \dots, D_M^{*(r)})$

$$\Rightarrow \hat{\Sigma}_{\underline{\hat{H}}}^* = \text{cov}(\underline{\hat{H}}^*)$$

Bootstrap test statistic

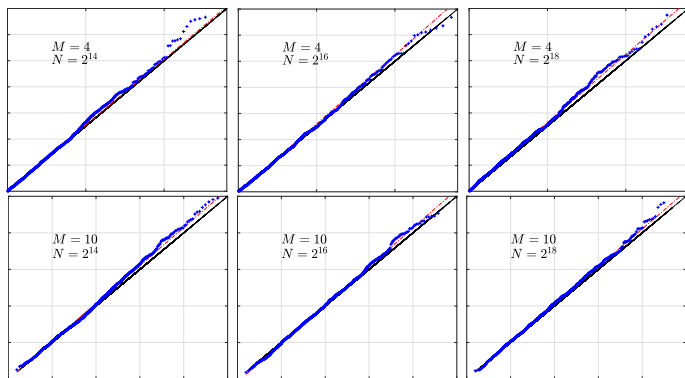
$$T^* = (\underline{\hat{H}} - \langle \hat{H}_m \rangle_m)^T \hat{\Sigma}_{\underline{\hat{H}}}^{*-1} (\underline{\hat{H}} - \langle \hat{H}_m \rangle_m)$$

Testing procedure

Algorithm for testing $H_1 = \dots = H_M$ 

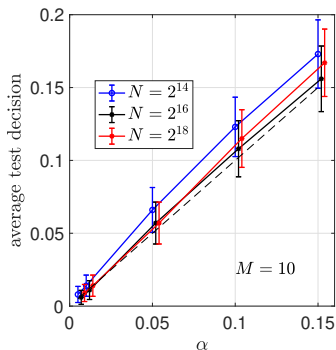
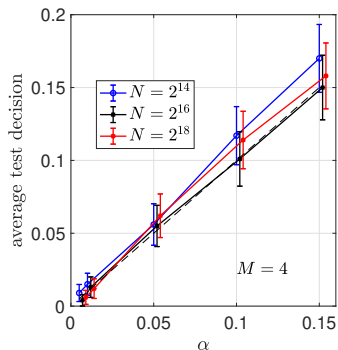
χ^2 statistic under null hypothesis $H_1 = \dots = H_M$

Monte Carlo simulations



Quantile-quantile plot under $H_1 = \dots = H_M$
 T^* against χ^2 distribution with $M - 1$ degrees of freedom
 N: sample size

Significance level under null hypothesis $H_1 = \dots = H_M$

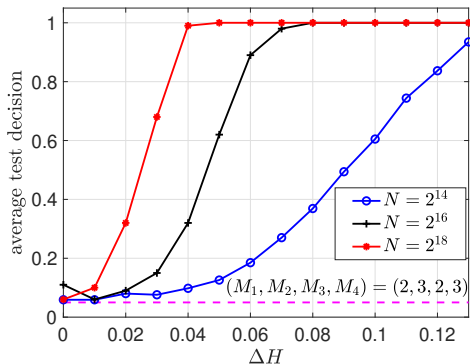
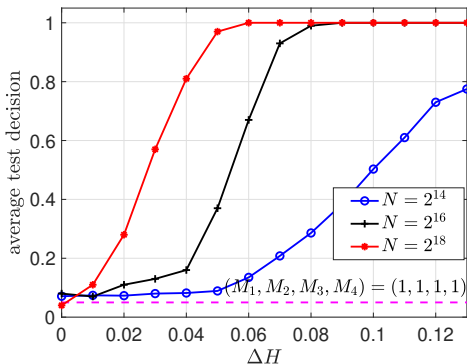


averaged test decisions $\hat{\alpha} \approx$ significance level α
 \Rightarrow Significance level well reproduced

Power of the test

$$\underline{H} = (\underbrace{H_1, \dots, H_1}_{M_1}, \underbrace{H_2, \dots, H_2}_{M_2}, \underbrace{H_3, \dots, H_3}_{M_3}, \underbrace{H_4, \dots, H_4}_{M_4})$$

$$\text{where } H_m = H_{m-1} + \Delta H$$



Conclusion

Achieved:

- bias corrected estimation of multivariate self-similarity exponents
- multivariate wavelet domain bootstrap procedure
- testing procedure for the equality exponents from a single observation

Perspectives:

- how many different values for \underline{H} ?
- large dimension: number of components $M \approx$ sample size N

