Wavelet-Based Bootstrapping for Non-Gaussian Time Series

Don Percival

Applied Physics Laboratory
Department of Statistics
University of Washington
Seattle, Washington, USA

overheads for talk available at

`http://faculty.washington.edu/dbp/talks.html`

Overview

- question of interest: how can we assess the sampling variability in statistics computed from a time series $X_0, X_1, \ldots, X_{N-1}$?
- start with some background on bootstrapping
- review parametric and block bootstrapping (two approaching for handling correlated time series)
- review previously proposed wavelet-based approach to bootstrapping (Percival, Sardy and Davison, 2001)
- describe a new wavelet-based approach that uses ‘trees’ for resampling and is potentially useful for non-Gaussian time series
- demonstrate methodology on time series related to BMW stock
- conclude with some remarks

Motivating Question

- let $\mathbf{X} = [X_0, \ldots, X_{N-1}]^T$ be a portion of a stationary process with autocorrelation sequence (ACS)

$$\rho_\tau = \frac{s_\tau}{s_0}, \text{ where } s_\tau = \text{cov}\{X_t, X_{t+\tau}\} \text{ and } s_0 = \text{var}\{X_t\}$$

- given a time series, we can estimate its ACS at $\tau = 1$ using

$$\hat{\rho}_1 = \frac{\sum_{t=0}^{N-2}(X_t - \overline{X})(X_{t+1} - \overline{X})}{\sum_{t=0}^{N-1}(X_t - \overline{X})^2}, \text{ where } \overline{X} = \frac{1}{N}\sum_{t=0}^{N-1} X_t$$

- Q: given the amount of data N we have, how close can we expect $\hat{\rho}_1$ to be to the true unknown ρ_1?
- i.e., how can we assess the sampling variability in $\hat{\rho}_1$?

Classic Approach – Large Sample Theory

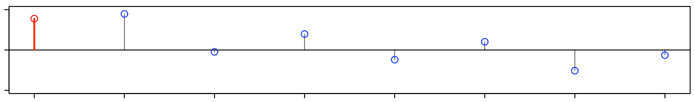
- let $\mathcal{N}(\mu, \sigma^2)$ denote a Gaussian (normal) random variable (RV) with mean μ and variance σ^2
- under suitable conditions (see, e.g., Fuller, 1996), $\hat{\rho}_1$ has a distribution close to that of $\mathcal{N}(\rho_1, \sigma_N^2)$ as $N \to \infty$, where

$$\sigma_N^2 = \frac{1}{N}\sum_{\tau=-\infty}^{\infty}\left\{\rho_\tau^2(1 + 2\rho_1^2) + \rho_{\tau+1}\rho_{\tau-1} - 4\rho_1\rho_\tau\rho_{\tau-1}\right\}$$

- in practice, this result is unappealing because it requires
  - knowledge of theoretical ACS (including the unknown ρ_1!)
  - ACS to damp down fast, ruling out some processes of interest
- while large sample theory has been worked out for $\hat{\rho}_1$ under certain conditions, similar theory for other statistics can be hard to come by

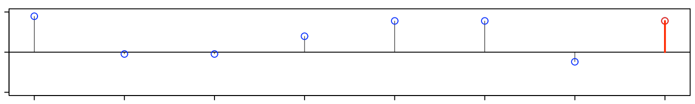
Alternative Approach – Bootstrapping: I

- if X_t's were IID, we could apply 'bootstrapping' to assess the variability in $\hat{\rho}_1$, as follows
- consider a time series of length $N = 8$ that is a realization of a Gaussian white noise process ($\rho_1 = 0$):



$\hat{\rho}_1 \doteq 0.18$

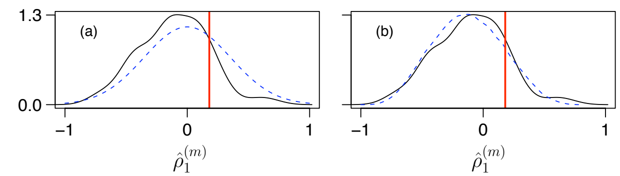
- generate new series by randomly sampling with replacement:



$\hat{\rho}_1^{(1)} \doteq -0.24$

Alternative Approach – Bootstrapping: II

- repeat a large number of times M to get $\hat{\rho}_1^{(1)}, \hat{\rho}_1^{(2)}, \ldots, \hat{\rho}_1^{(M)}$
- plots shows estimated probability density function (PDF) for $\hat{\rho}_1^{(1)}, \hat{\rho}_1^{(2)}, \ldots, \hat{\rho}_1^{(100)}$, along with (a) PDF for $\mathcal{N}(0, \frac{1}{8})$ and (b) approximation to the true PDF for $\hat{\rho}_1$

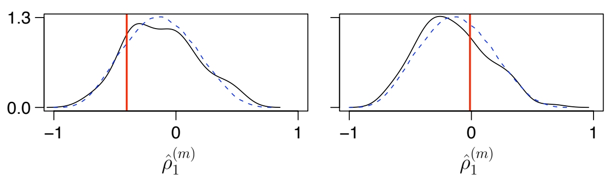


vertical line indicates $\hat{\rho}_1$

- can regard sample distribution of $\{\hat{\rho}_1^{(m)}\}$ as an approximation to the unknown distribution of $\hat{\rho}_1$

Alternative Approach – Bootstrapping: III

- quality of approximation depends upon particular time series
- here are bootstrap approximations to PDF of $\hat{\rho}_1$ based upon two other time series of length $N = 8$, along with true PDF



vertical line indicates $\hat{\rho}_1$

- repeating the above for 50 time series yields 50 bootstrap PDFs
- summarize via sample means and standard deviations (SDs):

average of 50 sample means $\doteq -0.127$ (truth $\doteq -0.124$)

average of 50 sample SDs $\doteq 0.280$ (truth $\doteq 0.284$)

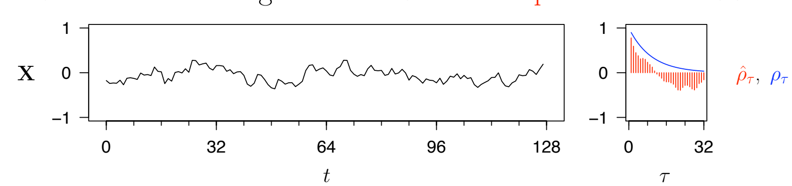
Bootstrapping Correlated Time Series: I

- key assumption: $\mathbf{X}$ contains IID RVs
- if not true (as for most time series!), sample distribution of $\{\hat{\rho}_1^{(m)}\}$ can be a poor approximation to distribution of $\hat{\rho}_1$
- as an example, consider first order autoregressive (AR) process:

$$X_t = \phi X_{t-1} + \epsilon_t,$$

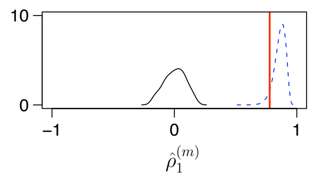
where $\phi = 0.9$ and $\{\epsilon_t\}$ is zero mean Gaussian white noise

- AR time series of length $N = 128$ with sample and true ACSs:



Bootstrapping Correlated Time Series: II

- use same procedure as before to get $\hat{\rho}_1^{(1)}, \hat{\rho}_1^{(2)}, \ldots, \hat{\rho}_1^{(100)}$
- bootstrap approximation to PDF of $\hat{\rho}_1$ along with true PDF:



vertical line indicates $\hat{\rho}_1$

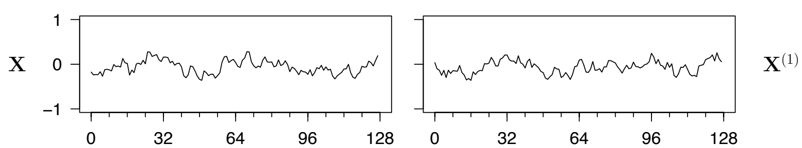
- bootstrap approximation gets even worse as N increases
- to correct the problem caused by correlation in time series, can use specialized time- or frequency-domain bootstrapping (assuming true ACS damps downs sufficiently fast)

Parametric Bootstrapping: I

- one well-known time-domain bootstrapping scheme is the parametric (or residual) bootstrap
- suppose $\mathbf{X}$ is a realization of AR process $X_t = \phi X_{t-1} + \epsilon_t$
- note that $\mathrm{var}\,\{X_t\} = \mathrm{var}\,\{\epsilon_t\}/(1-\phi^2)$ and $\rho_\tau = \phi^{|\tau|}$
- in particular, $\rho_1 = \phi$, so can estimate ϕ using $\hat{\phi} = \hat{\rho}_1$
- since $\epsilon_t = X_t - \phi X_{t-1}$, can form residuals
$$r_t = X_t - \hat{\phi} X_{t-1}, \quad t = 1, \ldots, N-1,$$
with the idea that r_t will be a good approximation to ϵ_t
- let $r_0^{(1)}, r_1^{(1)}, \ldots, r_{N-1}^{(1)}$ be a random sample from $r_1, r_2, \ldots, r_{N-1}$
- let $X_0^{(1)} = r_0^{(1)}/(1-\hat{\phi}^2)^{1/2}$ ('stationary initial condition')

Parametric Bootstrapping: II

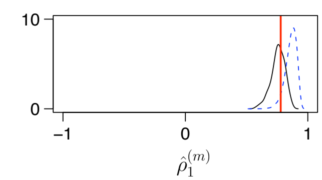
- form
$$X_t^{(1)} = \hat{\phi} X_{t-1}^{(1)} + r_t^{(1)}, \quad t = 1, \ldots, N-1,$$
yielding the bootstrapped time series $X_0^{(1)}, X_1^{(1)}, \ldots, X_{N-1}^{(1)}$
- AR time series (left-hand plot) and bootstrapped series (right):



- use bootstrapped series to compute $\hat{\rho}_1^{(1)}$
- repeat this procedure M times to get $\hat{\rho}_1^{(1)}, \hat{\rho}_1^{(2)}, \ldots, \hat{\rho}_1^{(M)}$

Parametric Bootstrapping: III

- bootstrap approximation to PDF of $\hat{\rho}_1$ along with true PDF:



vertical line indicates $\hat{\rho}_1$

- repeating the above for 50 AR time series yields:

average of 50 sample means $\doteq 0.83$ (truth $\doteq 0.86$)
average of 50 sample SDs $\doteq 0.053$ (truth $\doteq 0.048$)

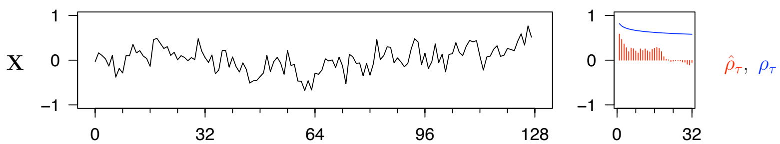
Parametric Bootstrapping: IV

- important assumption: $\mathbf{X}$ generated by AR process
- to see what happens if assumption fails, consider a fractionally differenced (FD) process

$$X_t = \sum_{k=0}^{\infty} \frac{\Gamma(1-\delta)}{\Gamma(k+1)\Gamma(1-\delta-k)} \epsilon_{t-k},$$

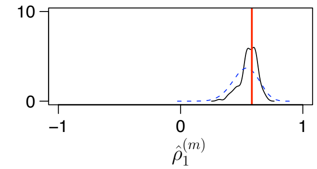
where $\delta = 0.45$ and $\{\epsilon_t\}$ is zero mean Gaussian white noise

- FD time series of length $N = 128$ with sample and true ACSs:



Parametric Bootstrapping: V

- AR process has 'short-range' dependence, whereas FD process exhibits 'long-range' (or 'long-memory') dependence
- bootstrap approximation to PDF of $\hat{\rho}_1$ along with true PDF:



vertical line indicates $\hat{\rho}_1$

- repeating the above for 50 FD time series yields:

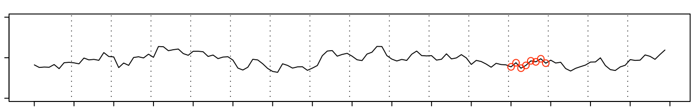
average of 50 sample means $\doteq 0.49$ (truth $\doteq 0.53$)

average of 50 sample SDs $\doteq 0.078$ (truth $\doteq 0.107$)

note: $\rho_1 \doteq 0.82$ for this FD process; agreement in SD gets worse (better) as N increases (decreases)

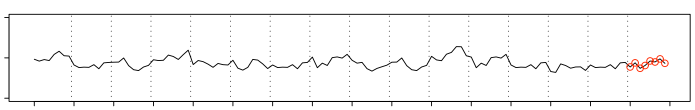
Block Bootstrapping: I

- another time-domain approach is block bootstrapping, which has many variations, of which the following is the simplest
- break time series up into B blocks (subseries) of equal length:



$\hat{\rho}_1 \doteq 0.78$

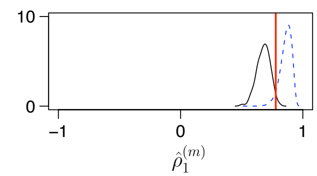
- generate bootstrapped AR series by randomly sampling blocks:



$\hat{\rho}_1^{(1)} \doteq 0.63$

Block Bootstrapping: II

- bootstrap approximation to PDF of $\hat{\rho}_1$ along with true PDF:



vertical line indicates $\hat{\rho}_1$

- repeating the above for 50 AR time series yields:

average of 50 sample means $\doteq 0.75$ (truth $\doteq 0.86$)

average of 50 sample SDs $\doteq 0.049$ (truth $\doteq 0.048$)

- repeating the above for 50 FD time series yields:

average of 50 sample means $\doteq 0.46$ (truth $\doteq 0.53$)

average of 50 sample SDs $\doteq 0.082$ (truth $\doteq 0.107$)

Frequency-Domain Bootstrapping

- again, many variations, including the following three
- 'phase scramble' discrete Fourier transform (DFT)

$$\mathcal{X}_k = \sum_{t=0}^{N-1} X_t e^{-i2\pi kt/N} = A_k e^{i\theta_k}$$

  of $\mathbf{X}$ and apply inverse DFT to create new series
- periodogram-based bootstrapping: in addition to phase scrambling, evoke large sample result that $|A_k|$'s are approximately uncorrelated with distribution related to a chi-square RV with 2 degrees of freedom
- circulant embedding bootstrapping: form nonparametric estimate of spectral density function and generate realizations using circulant embedding (Percival and Constantine, 2006)

Critique of Time/Frequency-Domain Bootstrapping

- time- and frequency-domain approaches are mainly designed for series with short-range dependence (e.g., AR) and are problematic for those exhibiting long-range dependence (e.g., FD)
- parametric and frequency-domain bootstraps work best for series that obey a Gaussian distribution, but can be problematic for non-Gaussian series
- non-Gaussian series better handled by block bootstrapping, but quality of this approach depends critically on chosen size for blocks (*ad hoc rule* is to set size close to $\sqrt{N}$)
- room for improvement: will consider wavelet-based approaches

Overview of Discrete Wavelet Transform (DWT): I

- DWT is an orthonormal transform $\mathcal{W}$ that reexpresses a time series $\mathbf{X}$ of length N as a vector of DWT coefficients $\mathbf{W}$:

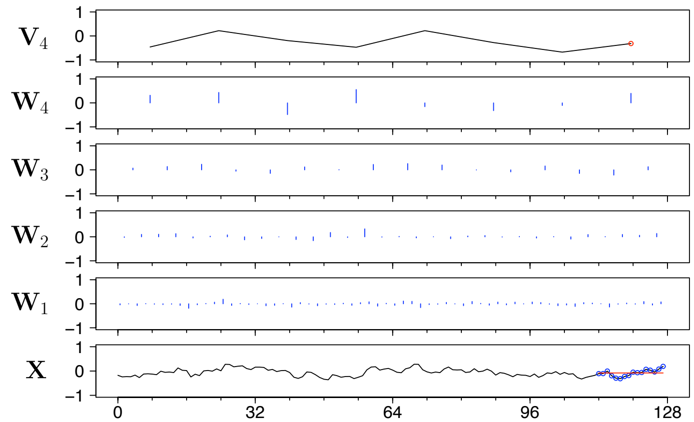
$$\mathbf{W} = \mathcal{W}\mathbf{X},$$

  where $\mathcal{W}$ is an $N \times N$ matrix such that $\mathbf{X} = \mathcal{W}^T\mathbf{W}$
- particular $\mathcal{W}$ depends on the choice of
  - wavelet filter, the most basic of which is the Haar filter (fancier filters include the Daubechies family of 'least asymmetric' filters of width L – denoted by LA(L), with $L = 8$ being a popular choice)
  - level J_0, which determines the number of dyadic scales $\tau_j = 2^{j-1}$, $j = 1, 2, \ldots, J_0$, involved in the transform

Overview of Discrete Wavelet Transform (DWT): II

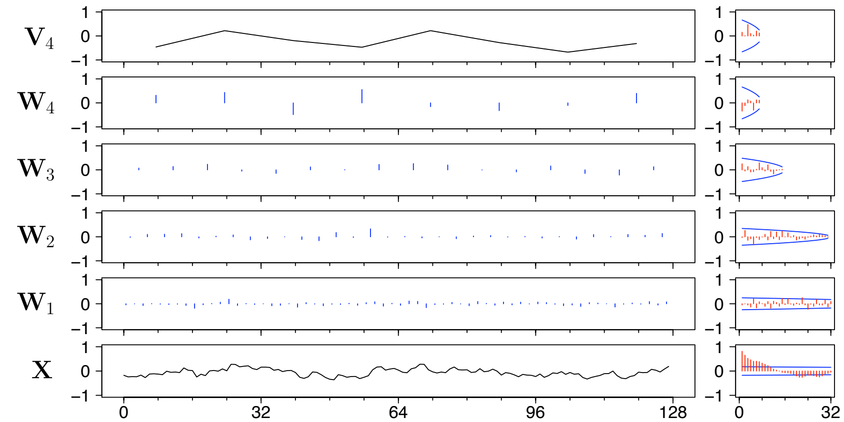
- DWT coefficient vector $\mathbf{W}$ can be partitioned into J_0 sub-vectors of wavelet coefficients $\mathbf{W}_j$, $j = 1, 2, \ldots, J_0$, along with one sub-vector of scaling coefficients $\mathbf{V}_{J_0}$
- wavelet coefficients in $\mathbf{W}_j$ are associated with changes in averages over a scale of τ_j, whereas the scaling coefficients in $\mathbf{V}_{J_0}$ are associated with averages over a scale of $2\tau_{J_0}$
- as a concrete example, let's look at a level $J_0 = 4$ Haar DWT of the AR time series

DWT of Autoregressive Process: I



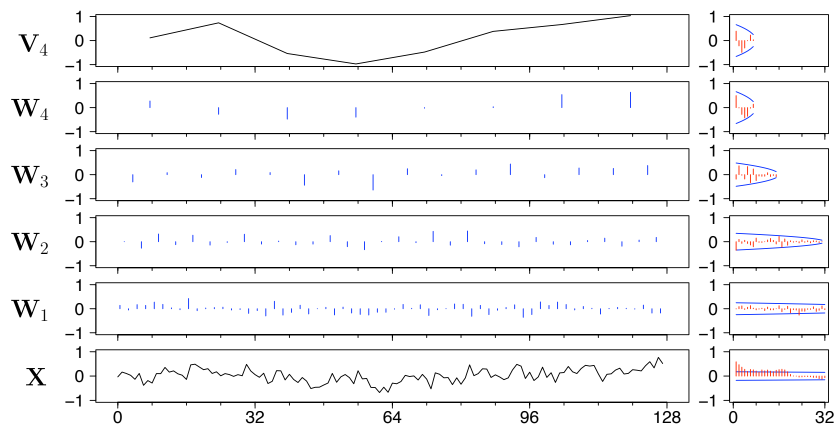
- level $J_0 = 4$ Haar DWT of AR series $\mathbf{X}$, with scale $2 * \tau_4 = 16$ scaling coefficient highlighted

DWT of Autoregressive Process: II



- Haar DWT of AR series $\mathbf{X}$ and sample ACSs for each $\mathbf{W}_j$ & $\mathbf{V}_4$, along with 95% confidence intervals for white noise

DWT of Fractionally Differenced Process



- Haar DWT of FD series $\mathbf{X}$ and sample ACSs for each $\mathbf{W}_j$ & $\mathbf{V}_4$, along with 95% confidence intervals for white noise

DWT as a Decorrelating Transform

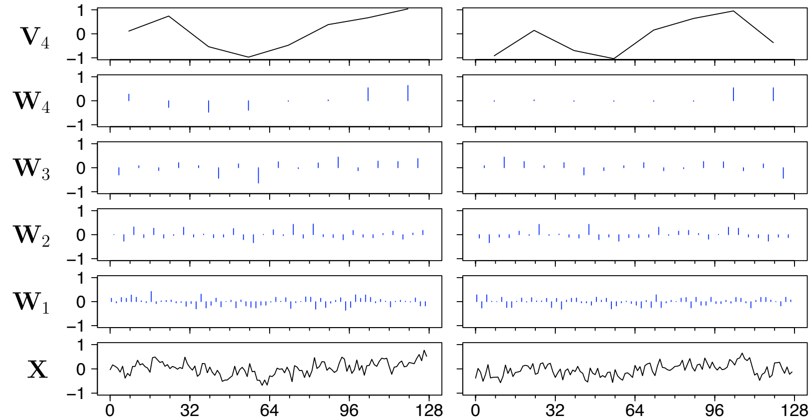
- for many (but not all!) time series, DWT acts as a decorrelating transform: to a good approximation, each $\mathbf{W}_j$ is a sample of a white noise process, and coefficients from different sub-vectors $\mathbf{W}_j$ and $\mathbf{W}_{j'}$ are also pairwise uncorrelated
- variance of coefficients in $\mathbf{W}_j$ depends on j
- scaling coefficients $\mathbf{V}_{J_0}$ are still autocorrelated, but there will be just a few of them if J_0 is selected to be large
- decorrelating property holds particularly well for FD and other processes with long-range dependence
- above suggests the following recipe for wavelet-domain bootstrapping

Recipe for Wavelet-Domain Bootstrapping

1. given $\mathbf{X}$ of length $N = 2^J$, compute level J_0 DWT (the choice $J_0 = J - 3$ yields 8 coefficients in $\mathbf{W}_{J_0}$ and $\mathbf{V}_{J_0}$)
2. randomly sample with replacement from $\mathbf{W}_j$ to create bootstrapped vector $\mathbf{W}_j^{(b)}$, $j = 1, \ldots, J_0$
3. create $\mathbf{V}_{J_0}^{(b)}$ using a parametric bootstrap
4. apply $\mathcal{W}^T$ to $\mathbf{W}_1^{(b)}, \ldots, \mathbf{W}_{J_0}^{(b)}$ and $\mathbf{V}_{J_0}^{(b)}$ to obtain bootstrapped time series $\mathbf{X}^{(b)}$ and then form corresponding $\hat{\rho}_1^{(b)}$

- repeat above many times to build up sample distribution of bootstrapped autocorrelations

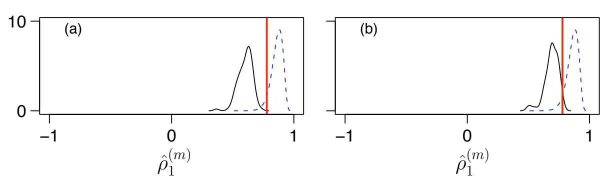
Illustration of Wavelet-Domain Bootstrapping



- Haar DWT of FD(0.45) series $\mathbf{X}$ (left-hand column) and wavelet-domain bootstrap thereof (right-hand)

Wavelet-Domain Bootstrapping of AR Series

- approximations to true PDF using (a) Haar & (b) LA(8) wavelets



vertical line indicates $\hat{\rho}_1$

- using 50 AR time series and the Haar DWT yields:

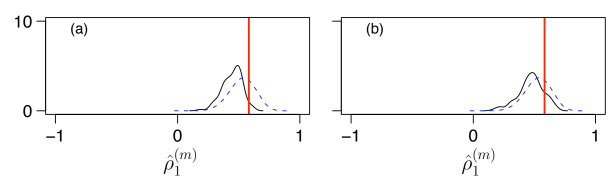
  average of 50 sample means $\doteq 0.67$ (truth $\doteq 0.86$)
  average of 50 sample SDs $\doteq 0.071$ (truth $\doteq 0.048$)

- using 50 AR time series and the LA(8) DWT yields:

  average of 50 sample means $\doteq 0.80$ (truth $\doteq 0.86$)
  average of 50 sample SDs $\doteq 0.055$ (truth $\doteq 0.048$)

Wavelet-Domain Bootstrapping of FD Series

- approximations to true PDF using (a) Haar & (b) LA(8) wavelets



vertical line indicates $\hat{\rho}_1$

- using 50 FD time series and the Haar DWT yields:

  average of 50 sample means $\doteq 0.35$ (truth $\doteq 0.53$)
  average of 50 sample SDs $\doteq 0.096$ (truth $\doteq 0.107$)

- using 50 FD time series and the LA(8) DWT yields:

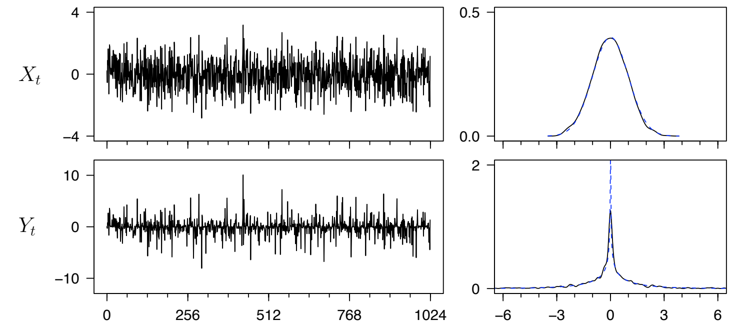
  average of 50 sample means $\doteq 0.43$ (truth $\doteq 0.53$)
  average of 50 sample SDs $\doteq 0.098$ (truth $\doteq 0.107$)

Effect of Non-Gaussianity: I

- wavelet-domain bootstrapping works well if we can assume Gaussianity, but can be problematic if this assumption fails
- for non-Gaussian series, wavelet-domain bootstraps are typically closer to Gaussianity than original series, which poses a problem for assessing variability in certain statistics

Effect of Non-Gaussianity: II

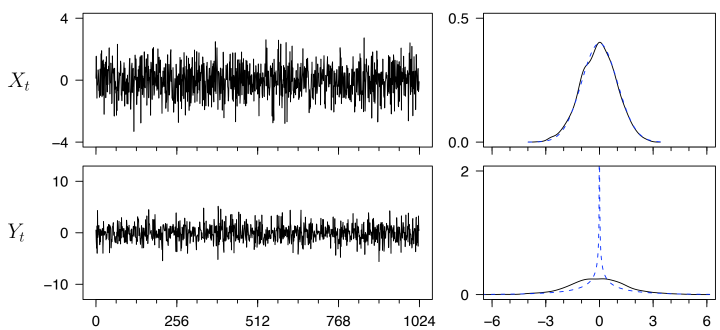
- consider Gaussian white noise X_t and $Y_t = \text{sign}\{X_t\} \times X_t^2$:



- right-hand plots show estimated PDFs and true PDFs

Effect of Non-Gaussianity: III

- wavelet-domain bootstraps of X_t and $Y_t = \text{sign}\{X_t\} \times X_t^2$:

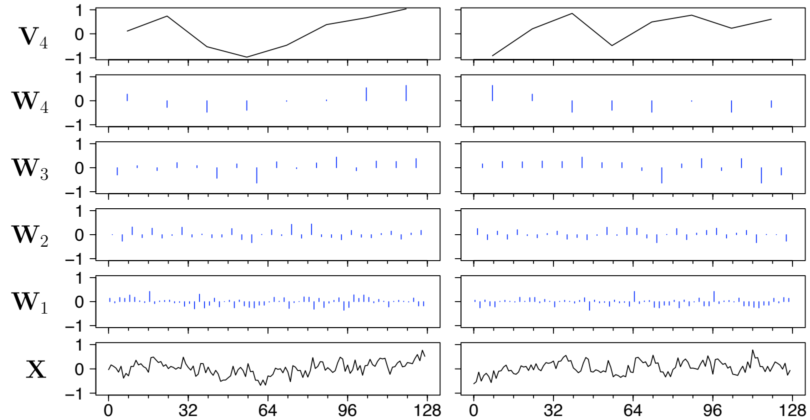


- right-hand plots show estimated PDFs and true original PDFs

Tree-Based Bootstrapping

- to preserve non-Gaussianity, consider using groups ('trees') of wavelet coefficients co-located across small scales as basic sampling unit for bootstrapping at those scales
- wavelet coefficients at large scales treated in same way as in usual wavelet-domain bootstrap
- scaling coefficients handled using parametric bootstrap
- certain wavelet-based signal denoising schemes for non-Gaussian noise treat small scales in a special way and large scales in the same way as in the Gaussian case (see, e.g., Gao, 1997)
- tree-based structuring of wavelet coefficients is key idea behind denoising using Markov models (Crouse *et al.*, 1998) and notion of wavelet 'footprints' (Dragotti and Vetterli, 2003)

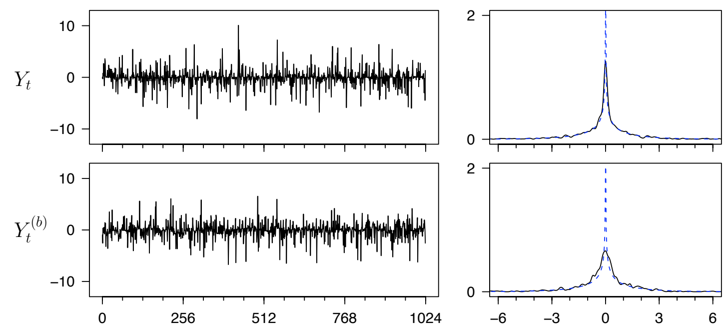
Illustration of Tree-Based Bootstrapping



- Haar DWT of FD(0.45) series $\mathbf{X}$ (left-hand column) and level $j = 3$ tree-based bootstrap thereof (right-hand)

Tree-Based Bootstraps of Non-Gaussian White Noise

- Y_t (top row) and $j = 5$ Haar tree-based bootstrap (bottom)



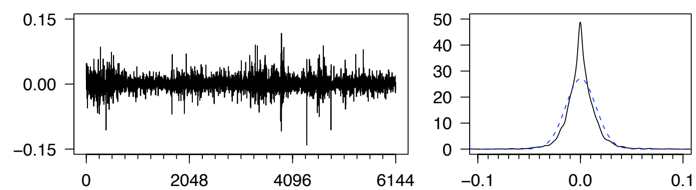
- right-hand plots show estimated PDFs and true original PDF

Summary of Computer Experiments

Statistic	Process	Parm	Block	LA(8) DWT	$j = 2$ Tree	$j = 4$ Tree	True
mean	AR	0.86	0.83	0.83	0.84	0.85	0.86
	FD	0.58	0.57	0.54	0.55	0.57	0.59
SD	AR	0.016	0.021	0.025	0.025	0.024	0.021
	FD	0.025	0.042	0.054	0.051	0.055	0.059

- 50 time series of length $N = 1024$ for each $Y_t = \text{sign}\{X_t\} \times X_t^2$
- 100 bootstrap samples from each series, yielding 100 unit lag sample autocorrelations $\hat{\rho}_1^{(m)}$
- mean and SD of 100 sample autocorrelations recorded
- table reports averages of these two statistics over 50 time series
- true values based on 100, 000 generated series for each process

Application to BMW Stock Prices - I



- right-hand plot: log of daily returns on BMW share prices
- left-hand: nonparametric and Gaussian PDF estimates
- series has small unit lag sample autocorrelation: $\hat{\rho}_1 \doteq 0.081$.
- large sample theory appropriate for Gaussian white noise gives standard deviation of $1/\sqrt{N} \doteq 0.013$

Application to BMW Stock Prices - II

- bootstrap estimates of standard deviations:

	Parm	Block	LA(8) DWT	$j = 2$ Tree	$j = 4$ Tree	Gaussian
SD est.	0.012	0.016	0.021	0.019	0.019	0.013

- since $\hat{\rho}_1 \doteq 0.081$, bootstrap methods all confirm presence of autocorrelation (small, but presumably exploitable by traders)

Concluding Remarks

- wavelet-domain & tree-based bootstraps competitive with parametric & block bootstraps for series with short-range dependence and offer improvement in case of long-range dependence
- results to date for tree-based bootstrapping encouraging, but many questions need to be answered, including:
  - are there statistics & non-Gaussian series for which tree-based approach offers more than just a marginal improvement over wavelet-domain approach?
  - what are asymptotic properties of tree-based approach?
  - how can the tree-based approach be adjusted to handle stationary processes that are not well decorrelated by the DWT?

Thanks to . . .

- Ann Maharaj and Giovanni Forchini for opportunity to speak
- CSIRO Mathematics, Informatics and Statistics (CMIS) for visiting scientist position allowing for extended Australian visit
- Crime Scene for 2nd place finish in Melbourne Cup (got $13 in $2 sweep – first winnings ever from a horse race!!!)

References: I

- C. Angelini, D. Cava, G. Katul and B. Vidakovic (2005), 'Resampling Hierarchical Processes in the Wavelet Domain: A Case Study Using Atmospheric Turbulence,' *Physica D*, **207**, pp. 24-40
- M. Breakspear, M. J. Brammer, E. T. Bullmore, P. Das and L. M. Williams (2004), 'Spatiotemporal Wavelet Resampling for Functional Neuroimaging Data,' *Human Brain Mapping*, **23**, pp. 1–25
- M. Breakspear, M. Brammer and P. A. Robinson (2003), 'Construction of Multivariate Surrogate Sets from Nonlinear Data Using the Wavelet Transform,' *Physica D*, **182**, pp. 1–22
- E. Bullmore, J. Fadili, V. Maxim, L. Şendur, B. Whitcher, J. Suckling, M. Brammer and M. Breakspear (2004), 'Wavelets and Functional Magnetic Resonance Imaging of the Human Brain,' *NeuroImage*, **23**, pp. S234-S249
- E. Bullmore, C. Long, J. Suckling, J. Fadili, G. Calvert, F. Zelaya, T. A. Carpenter and M. Brammer (2001), 'Colored Noise and Computational Inference in Neurophysiological (fMRI) Time Series Analysis: Resampling Methods in Time and Wavelet Domains,' *Human Brain Mapping*, **12**, pp. 61–78

References: II

- M.S. Crouse, R. D. Nowak and R. G. Baraniuk (1998), 'Wavelet-Based Statistical Signal Processing using Hidden Markov Models,' *IEEE Transactions on Signal Processing*, **46**(4), pp. 886–902
- A. C. Davison and D. V. Hinkley (1997), *Bootstrap Methods and their Applications*, Cambridge, England: Cambridge University Press
- P. L. Dragotti and M. Vetterli (2003), 'Wavelet Footprints: Theory, Algorithms, and Applications,' *IEEE Transactions on Signal Processing*, **51**(5), pp. 1306–23
- H. Feng, T. R. Willemain and N. Shang (2005), 'Wavelet-Based Bootstrap for Time Series Analysis,' *Communications in Statistics: Simulation and Computation*, **34**(2), pp. 393–413
- W. A. Fuller (1996), *Introduction to Statistical Time Series* (2nd Edition), New York: John Wiley & Sons.
- H.-Ye. Gao (1997), 'Choice of Thresholds for Wavelet Shrinkage estimate of the Spectrum,' *Journal of Time Series Analysis*, **18**(3), pp. 231–51
- S. Golia (2002), 'Evaluating the GPH Estimator via Bootstrap Technique,' in *Proceedings in Computational Statistics COMPSTAT2002*, edited by W. Härdle and B. Ronz. Heidelberg: Physica–Verlag, pp. 343–8

References: III

- L. Lin, Y. Fan and L. Tan (2008), 'Blockwise Bootstrap Wavelet in Nonparametric Regression Model with Weakly Dependent Processes.' *Metrika*, **67**(1), pp. 31–48
- D. B. Percival and W. L. B. Constantine (2006), 'Exact Simulation of Gaussian Time Series from Nonparametric Spectral Estimates with Application to Bootstrapping,' *Statistics and Computing*, **16**(1), pp. 25–35
- D. B. Percival, S. Sardy and A. C. Davison (2001), 'Wavestrapping Time Series: Adaptive Wavelet-Based Bootstrapping,' in *Nonlinear and Nonstationary Signal Processing*, edited by W. J. Fitzgerald, R. L. Smith, A. T. Walden and P. C. Young. Cambridge, England: Cambridge University Press, pp. 442–70
- D. B. Percival and A. T. Walden (2000), *Wavelet Methods for Time Series Analysis*, Cambridge, England: Cambridge University Press
- A. M. Sabatini (1999), 'Wavelet-Based Estimation of $1/f$-Type Signal Parameters: Confidence Intervals Using the Bootstrap,' *IEEE Transactions on Signal Processing*, **47**(12), pp. 3406–9
- A. M. Sabatini (2006), 'A Wavelet-Based Bootstrap Method Applied to Inertial Sensor Stochastic Error Modelling Using the Allan Variance,' *Measurement Science and Technology*, **17**, pp. 2980–2988

References: IV

- B. J Whitcher (2006), 'Wavelet-Based Bootstrapping of Spatial Patterns on a Finite Lattice,' *Computational Statistics & Data Analysis*, **50**(9), pp. 2399–421