

Note (??) gives us a non-linear equation for the Whittle estimator  $\hat{H}$ :

$$\int_{-\pi}^{\pi} \frac{n^{2\hat{H}_n} |Z_n(\omega)|^2}{\sigma^2 f_{\hat{H}_n}(\omega)} d\omega = 2\pi$$

in terms of  $\sigma$ . Substitute expression for  $\sigma^2$ .

## Asymptotic behaviour of estimators for $H$ and $\sigma$ as $n \rightarrow \infty$

(updated 05/08 03.16am). Let  $X$  be a real-valued **stationary** Gaussian process  $(X_t)_{t=0}^{\infty}$  (i.e.  $X_t$  has the same (Normal) distribution for all  $t \in \mathbb{N}$ ) with a summable **autocovariance function**  $r(k) := \mathbb{E}(X_t X_{t+k})$ , i.e.  $\sum_{k=1}^{\infty} |r(k)| < \infty$  (our interest will be **fractional Gaussian noise** (fGN)  $X_n = B_n^H - B_{n-1}^H$ , where  $B^H$  is fBM so  $X_t \sim N(0, 1)$  for all  $t$ ). The **spectral density** of a stationary process  $X$  is the function  $f_{\theta}(\omega)$  whose **Fourier series** coefficients are equal to  $(r(k))_{k=0}^{\infty}$ , i.e.

$$r(k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{i\omega k} f_{\theta}(\omega) d\omega$$

so  $f_{\theta}(\omega) = \sum_{k=-\infty}^{\infty} r(k) e^{i\omega k}$  when the infinite series here converges (which is the case when  $r(k)$  is summable). For fGN there is an explicit formula for  $f_{\theta} = f_H$  in Proposition 7.2.9 in [Taq02] (note the [Taq02] form for the spectral density is divided by  $2\pi$ , and Eq 5.40 in [Ber94] has a spurious factor of  $1/(2\pi)$ ).

The covariance matrix of a stationary process is clearly **Toeplitz** (which makes it fast to compute). The **Whittle approximation** for the determinant and the Inverse of the Covariance matrix  $\Sigma$  of  $X$  is

$$\log(\det \Sigma) \sim \frac{n}{4\pi} \int_{-\pi}^{\pi} \log f_{\theta}(\omega) d\omega, \quad \Sigma_{ij}^{-1} \sim \int_{-\pi}^{\pi} \frac{1}{f_{\theta}(\omega)} e^{i(j-k)\omega} d\omega \quad (1)$$

as  $n \rightarrow \infty$  (this is the so-called **Szegö** limit (or Grenander–Szegö theorem) for Toeplitz matrices).

Define the normalized **discrete Fourier transform** (DFT) at frequency  $\omega_j = \frac{2\pi j}{n}$  as:

$$Z_n(\omega_j) := \frac{1}{\sqrt{n}} \sum_{k=1}^n X_k e^{-i\omega_j k}.$$

Then can re-write the covariance part of the log likelihood (LL) of  $X$  in terms of  $Z_n(\omega_j)$  as

$$\begin{aligned} \frac{1}{\pi} \sum_{j=0}^{n-1} \sum_{k=0}^{n-1} X_j \left( \int_{-\pi}^{\pi} \frac{1}{f_{\theta}(\omega)} e^{i(j-k)\omega} d\omega \right) X_k &= \frac{1}{\pi} \int_{-\pi}^{\pi} \frac{1}{f_{\theta}(\omega)} \sum_{j,k} e^{i(j-k)\omega} X_j X_k d\omega \\ &= \frac{1}{\pi} \int_{-\pi}^{\pi} \frac{1}{f_{\theta}(\omega)} \sum_{j,k} e^{ij\omega} X_j e^{-ik\omega} X_k d\omega \\ &= \frac{1}{\pi} \int_{-\pi}^{\pi} \frac{1}{f_{\theta}(\omega)} |Z_n(\omega)|^2 d\omega \end{aligned} \quad (2)$$

where  $|Z_n(\omega)|^2 = I_n(\omega, y) = (\sum_{j=0}^{n-1} e^{ij\omega} X_j) (\sum_{j=0}^{n-1} e^{-ij\omega} X_j) = |\sum_{j=0}^{n-1} e^{ij\omega} X_j|^2$  is the **periodogram** of the random vector  $X$  (see plot below for fGN), and we can trivially verify that  $I_n(\omega, y)$  is symmetric in  $\omega$ .

## Asymptotic independence and normality of the DFT

For fixed  $\omega_j \in (0, \pi)$ , as  $n \rightarrow \infty$   $Z_n(\omega_j) \xrightarrow{d} N(0, f(\omega_j))$  and for  $\omega_j \neq \omega_k$ , the coefficients  $Z_n(\omega_j)$  and  $Z_n(\omega_k)$  are asymptotically uncorrelated (we numerically test this in Python here:

<https://colab.research.google.com/drive/1ruxvZX8brSOKGTi5RFTznRNj0wpQ1VUC?usp=sharing>)

**Sketch proof:**

$$\text{Cov}(Z_n(\omega_j), Z_n(\omega_k)) = \mathbb{E}[Z_n(\omega_j) \overline{Z_n(\omega_k)}] = \frac{1}{n} \sum_{s=1}^n \sum_{t=1}^n \mathbb{E}[X_s X_t] e^{-i\omega_j s} e^{i\omega_k t} = \frac{1}{n} \sum_{s=1}^n \sum_{t=1}^n r(t-s) e^{-i\omega_j s} e^{i\omega_k t}.$$

Now let  $h = t - s$ , so  $t = s + h$ . Then we see that

$$\text{Cov}(Z_n(\omega_j), Z_n(\omega_k)) = \frac{1}{n} \sum_{s=1}^n \sum_{h=-(s-1)}^{n-s} r(h) e^{-i\omega_j s} e^{i\omega_k (s+h)} = \frac{1}{n} \sum_{s=1}^n e^{i(\omega_k - \omega_j)s} \sum_{h=-(s-1)}^{n-s} r(h) e^{i\omega_k h}.$$

As  $n \rightarrow \infty$ , and since  $r(h)$  is absolutely summable, we see that

$$\sum_{h=-(s-1)}^{n-s} r(h)e^{i\omega_k h} \rightarrow \sum_{h=-\infty}^{\infty} r(h)e^{i\omega_k h} = f_{\theta}(\omega_k).$$

Thus  $\text{Cov}(Z_n(\omega_j), Z_n(\omega_k)) \approx \frac{1}{n} \sum_{s=1}^n e^{i(\omega_k - \omega_j)s} f_{\theta}(\omega_k)$ . This is a geometric series with partial sum  $\frac{1}{n} \sum_{s=1}^n e^{i(\omega_k - \omega_j)s} = \frac{1}{n} \cdot \frac{e^{i(\omega_k - \omega_j)}(1 - e^{in(\omega_k - \omega_j)})}{1 - e^{i(\omega_k - \omega_j)}}$  which is clearly 1 if  $j = k$ , or tends to zero if  $j \neq k$ , as claimed.

## Using the Whittle approximation to derive the Local Asymptotic Normality (LAN) property

Using (1) and (2), the Whittle approximation for the LL of  $X$  is

$$\ell_n(\theta) = -\frac{n}{4\pi} \int_{-\pi}^{\pi} (\log f_{\theta}(\omega) + \frac{|Z_n(\omega)|^2}{f_{\theta}(\omega)}) d\omega + \text{const.}$$

where the log part approximates the determinant part, the  $Z_n$  part approximates the covariance part, and the constant is unimportant as it doesn't depend on  $\theta$ .

The **Whittle estimator** is then defined as argmax of the Whittle approximation for the LL, which we can re-write (using similar notation to [FTW21] and [Syz23] as  $\hat{\theta}_n = \arg \min_{\theta} U_n(\theta)$ , where

$$U_n(\theta) = \frac{1}{4\pi} \int_{-\pi}^{\pi} (\log f_{\theta}(\omega) + \frac{|Z_n(\omega)|^2}{f_{\theta}(\omega)}) d\omega \quad (3)$$

since the  $\frac{n}{4\pi}$  prefactor doesn't affect the maximizer(s), and removing the minus sign here just transforms this to a minimization problem.

**Remark 0.1**  $U_n(\theta) \rightarrow U_{\infty}(\theta) := \frac{1}{4\pi} \int_{-\pi}^{\pi} (\log(\sigma^2 f_H(\omega)) + \frac{\sigma^2 f_H(\theta_0)}{\sigma^2 f_H(\omega)}) d\omega$  under  $\mathbb{P}_{\theta_0}$ , and this expression is minimized at  $\theta = \theta_0$  and if  $\arg \min U_n(\theta) \rightarrow \arg \min U_{\infty}(\theta) = \theta_0$ , the Whittle estimator  $\hat{\theta}_n$  is **consistent**, i.e.  $\hat{\theta}_n \rightarrow \theta$  in probability.

Then the **score** is

$$\ell'_n(\theta) = -\frac{n}{2\pi} \int_{-\pi}^{\pi} \frac{f_{\theta}(\omega) - Z_n(\omega)^2}{f_{\theta}(\omega)^2} \nabla_{\theta} f_{\theta}(\omega) d\omega.$$

$Z_n(\omega)$  is symmetric in  $\omega$  (see above), and approximating this integral as a sum over each  $\omega_j = \frac{2\pi j}{n}$  we get

$$\ell'_n(\theta) \approx -\frac{2n\pi}{4n\pi} \sum_{j=1}^n \frac{f_{\theta}(\omega_j) - Z_n(\omega_j)^2}{f_{\theta}(\omega_j)^2} \nabla_{\theta} f_{\theta}(\omega_n).$$

From the result in previous section,  $Z_n(\omega)$  is a sequence of asymptotically independent Normal random variables and hence  $f_{\theta}(\omega_j) - Z_n(\omega_j)^2$  is a sequence of approximately independent shifted  $\chi^2(df = 1)$  random variables with zero expectation and variance  $2f_{\theta}(\omega_j)^2$  (using that  $\text{Var}(Z^2) = 2$  when  $Z \sim N(0, 1)$ );

Hence using a Lyapunov-type CLT, this sum has expectation zero, and variance equal to

$$\left(\frac{2}{4}\right)^2 \sum_{j=1}^n \frac{2f_{\theta}(\omega_j)^2}{f_{\theta}(\omega_j)^4} \nabla f_{\theta}(\omega_j)^{\top} \nabla f_{\theta}(\omega_j) \approx \frac{1}{2} \cdot \frac{n}{\pi} \int_0^{\pi} (...) d\omega = \frac{n}{4\pi} \int_{-\pi}^{\pi} \frac{\nabla_{\theta} f_{\theta}(\omega)^{\top} \nabla_{\theta} f_{\theta}(\omega)}{f_{\theta}(\omega)^2} d\omega = nI(\theta)$$

where  $I(\cdot)$  is the **Fisher information matrix**.  $n$  term here then cancels with  $(\frac{n}{\sqrt{n}})^2$  when we make perturbation to get the LAN property, as claimed in Cohen et. al.

## Asymptotic normality of MLEs

Using the Taylor remainder theorem and setting the answer to zero, we see that

$$\nabla \ell_n(\hat{\theta}_n) = \nabla \ell_n(\theta_0) + \nabla^2 \ell_n(\tilde{\theta}_n)(\hat{\theta}_n - \theta_0) = 0$$

for some  $\tilde{\theta}_n \in [\theta, \theta_n]$ , which we can re-arrange as

$$\sqrt{n}(\hat{\theta}_n - \theta_0) = -(\frac{1}{n} \nabla^2 \ell_n(\tilde{\theta}_n))^{-1} \frac{1}{\sqrt{n}} \nabla \ell_n(\theta_0).$$

## Asymptotic normality of the score

The (approximate) score function under the Whittle likelihood is:

$$\nabla \ell_n(\theta_0) = \int_{-\pi}^{\pi} \left[ \frac{\partial \log f_{\theta_0}(\omega)}{\partial \theta} \left( \frac{I_n(\omega)}{f_{\theta_0}(\omega)} - 1 \right) \right] d\omega \quad (4)$$

where  $I_n = |Z_n(\omega)|^2$  as before. Recall from above that  $\frac{1}{\sqrt{n}} \nabla \ell_n(\theta_0) \xrightarrow{d} N(0, I(\theta_0))$ , where the Whittle likelihood approximation for  $I(\theta_0)$  is  $I(\theta_0) = \frac{1}{4\pi} \int_{-\pi}^{\pi} \left( \frac{\partial \log f_{\theta_0}(\omega)}{\partial \theta} \right) \left( \frac{\partial \log f_{\theta_0}(\omega)}{\partial \theta} \right)^\top d\omega$

## Hessian convergence to a constant

The Hessian of the Whittle log-likelihood is

$$\nabla^2 \ell_n(\theta_0) = - \int_{-\pi}^{\pi} \left[ \frac{\partial^2 \log f_{\theta_0}(\omega)}{\partial \theta \partial \theta^\top} \left( 1 - \frac{I_n(\omega)}{f_{\theta_0}(\omega)} \right) + \left( \frac{\partial}{\partial \theta} \log f_{\theta_0}(\omega) \right)^\top \left( \frac{\partial}{\partial \theta} \log f_{\theta_0}(\omega) \right) \frac{I_n(\omega)}{f_{\theta_0}(\omega)} \right] d\omega.$$

Using that  $\mathbb{E}_{\theta_0}(I_n(\omega)) = f_{\theta_0}(\omega)$ , the expectation of this expression is just  $-I(\theta_0)$ , and (under ergodicity and mixing condition) we have the convergence  $\frac{1}{n} \nabla^2 \ell_n(\tilde{\theta}_n) \xrightarrow{p} -I(\theta_0)$  where  $\tilde{\theta}_n$  lies between  $\hat{\theta}_n$  and  $\theta_0$ , and the Fisher information  $I(\theta_0)$  is as defined above. By Slutsky's theorem, we conclude that  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} N(0, I^{-1}(\theta_0))$ .

## Estimating $(H, \sigma)$ under high-frequency observations

The high-frequency (HF) regime corresponds to observations of the process  $X = (\sigma B_{T/n}^H, \sigma B_{2T/n}^H, \dots, \sigma B_T^H)$  (with  $\theta = (H, \sigma)$  unknown (as in Part 2, where  $\nu$  plays the role of  $\sigma$ ), and W.L.O.G. we set  $T = 1$ . Note that  $Y_j = \sigma n^H (B_{j/n}^H - B_{(j-1)/n}^H)$  is a standard fGN, but the issue now is that the true  $H$  is unknown, so the  $Y$  process here is unobserved.

Without any add-on noise, we can easily verify that the true MLE is **scale-independent** (since there is an explicit expression for the MLE for  $\hat{\sigma}$ , see FM14 2023 chapter2, and the **Whittle estimator** for  $H$  (defined above, which we will henceforth denote by  $\hat{H}_n$ ) is also scale-independent (assuming  $\sigma$  is unknown)<sup>1</sup>.

To see this, for fGN we can re-write  $U_n(\theta)$  in (3) in the form

$$U_n(\theta) = \frac{1}{4\pi} \int_{-\pi}^{\pi} (\log(\sigma^2 f_H(\omega)) + \frac{|Z_n(\omega)|^2}{\sigma^2 f_H(\omega)}) d\omega.$$

Minimizing the integrand in  $\sigma$  we find that  $\hat{\sigma}_n^2 = \int_{-\pi}^{\pi} \frac{|Z_n(\omega_1)|^2}{f_H(\omega_1)} d\omega_1$ , and evaluating the integrand at  $\hat{\sigma}_n$ , we see that

$$U_n(H, \hat{\sigma}_n^2) = \frac{1}{4\pi} \int_{-\pi}^{\pi} d\omega \cdot \log \left( \int_{-\pi}^{\pi} \frac{|Z_n(\omega_1)|^2}{f_H(\omega_1)} d\omega_1 \right) + \frac{1}{4\pi} \int_{-\pi}^{\pi} \left( \log f_H(\omega) + \frac{|Z_n(\omega)|^2}{\int_{-\pi}^{\pi} \frac{|Z_n(\omega_1)|^2}{f_H(\omega_1)} d\omega_1 \cdot f_H(\omega)} \right) d\omega$$

which only changes by constant (which doesn't depend on  $H$ ) if we multiply  $Z_n$  by a constant; thus we still obtain the same  $\hat{H}_n$  when we minimize this expression over  $H$ , so  $\hat{H}_n$  is scale-independent as claimed.

Thus for the high-frequency regime,  $\hat{H}_n$  has same behaviour as for original regime, and in particular  $\hat{H}_n$  tends asymptotically to a Normal RV with variance equal to the  $(1, 1)$  component of the inverse of the Fischer information matrix:

$$I(H, \sigma) = \frac{1}{4\pi} \begin{bmatrix} \int_{-\pi}^{\pi} \left( \frac{\partial}{\partial H} \log f_{\theta}(\omega) \right)^2 d\omega & \int_{-\pi}^{\pi} \frac{\partial}{\partial H} \log f_H(\omega) \frac{\partial}{\partial \sigma} \log f_{\theta}(\omega) d\omega \\ \int_{-\pi}^{\pi} \frac{\partial}{\partial H} \log f_H(\omega) \frac{\partial}{\partial \sigma} \log f_{\theta}(\omega) d\omega & \int_{-\pi}^{\pi} \left( \frac{\partial}{\partial \sigma} \log f_H(\omega) \right)^2 d\omega \end{bmatrix}.$$

Then using that  $f_{\theta}(\omega) = f_{\theta}((H, \sigma)) = \sigma^2 f_H(\omega)$ , this simplifies to

$$I(H, \sigma) = \frac{1}{4\pi} \begin{bmatrix} \int_{-\pi}^{\pi} \left( \frac{\partial}{\partial H} f_H(\omega) \right)^2 d\omega & \frac{1}{2\sigma} \int_{-\pi}^{\pi} \frac{\partial}{\partial H} f_H(\omega) d\omega \\ \frac{1}{2\sigma} \int_{-\pi}^{\pi} \frac{\partial}{\partial H} f_H(\omega) d\omega & \frac{2}{\sigma^2} \end{bmatrix}.$$

and we recommend computing these integrals in Mathematica with the `NIntegrate` command. Using that the inverse of a symmetric  $2 \times 2$  matrix  $A = \begin{bmatrix} a & b \\ b & d \end{bmatrix}$ , is  $A^{-1} = \frac{1}{ad-b^2} \begin{bmatrix} d & -b \\ -b & a \end{bmatrix}$  we see in particular that

$$(I(H, \sigma)^{-1})_{1,1} = \frac{1}{a - \frac{b^2}{d}} = \left( \frac{1}{4\pi} \int_{-\pi}^{\pi} \left( \frac{\partial}{\partial H} f_H(\omega) \right)^2 d\omega - \frac{1}{8\pi^2} \left( \int_{-\pi}^{\pi} \frac{\partial}{\partial H} f_H(\omega) d\omega \right)^2 \right)^{-1} \quad (5)$$

which agrees with Theorem 1 in [Syz23]. Note  $(I(H, \sigma)^{-1})_{1,1} > \frac{1}{I(H, \sigma)_{1,1}} = \frac{1}{\frac{1}{4\pi} \int_{-\pi}^{\pi} \left( \frac{\partial}{\partial H} f_H(\omega) \right)^2 d\omega}$  which is the

asymptotic variance we would get for  $\hat{H}$  if  $\sigma$  were known, so  $\sigma$  being unknown adds to the variance of  $\hat{H}_n$  as we would intuitively expect.

<sup>1</sup>As an aside we remark the Han-Schied [HS21] estimator for  $H$  is not scale-independent but has the advantage of being model agnostic

## The Syzmanski Whittle estimator for $(H, \sigma)$

We can define a re-scaled estimator  $\hat{\nu}_n$  as

$$\hat{\sigma}_n = n^{\hat{H}_n} \hat{\nu}_n$$

and set  $\tilde{\sigma}_n = n^H \hat{\nu}_n$ , where  $\hat{H}_n$  is the (scale-independent) Whittle estimator for  $H$  for  $X$  and  $\hat{\nu}_n$  is the Whittle estimator of the multiplicative constant for the observed “time-stretched” process  $\tilde{Y}_j = X_{j/n} = \sigma(B_{j/n}^H - B_{(j-1)/n}^H)$  (note  $\tilde{Y} = \nu \tilde{X}$  where  $\tilde{X}$  is an fGN with  $\nu \ll 1$  for  $n$  large), and we note that  $\hat{\sigma}_n$  is computable from observations of  $X$ . Moreover, we can re-write  $\hat{\sigma}_n$  as  $\hat{\sigma}_n = n^{\hat{H}_n - H} \tilde{\sigma}_n$  and we know that

$$\sqrt{n}(\hat{H}_n - H) \rightarrow N(0, (I^{-1})_{1,1})$$

from the standard theory for the non high-frequency regime above since (as discussed in previous section)  $\hat{H}$  is unaffected by switching between the HF and the original regime. Hence (following the top of page 13 in [Syz23], after correcting some typos there) we see that

$$\begin{aligned} \frac{\sqrt{n}}{\log n}(\hat{\sigma}_n - \sigma) &= \frac{\sqrt{n}}{\log n}(\tilde{\sigma}_n - \sigma) + \frac{\sqrt{n}}{\log n}(\hat{\sigma}_n - \tilde{\sigma}_n) \\ &= \frac{\sqrt{n}}{\log n}(\tilde{\sigma}_n - \sigma) + \frac{\sqrt{n}}{\log n} \tilde{\sigma}_n (n^{\hat{H}_n - H} - 1) \\ &= \frac{\sqrt{n}}{\log n}(\tilde{\sigma}_n - \sigma) + \frac{\sqrt{n}}{\log n} \tilde{\sigma}_n \log n (\hat{H}_n - H) + O((\hat{H}_n - H)^2) \\ &= \frac{\sqrt{n}}{\log n}(\tilde{\sigma}_n - \sigma) + \tilde{\sigma}_n \sqrt{n} (\hat{H}_n - H) + O((\hat{H}_n - H)^2) \end{aligned}$$

where we have used the Taylor expansion  $n^x - 1 = x \log n + O(x^2)$  in the penultimate line, with  $x = \hat{H}_n - H$  here. Then we see that the first term here is a higher order (i.e. smaller) term than the second term because  $\sqrt{n}(\tilde{\sigma}_n - \sigma)$  is asymptotically Normal from the standard theory above for the non high-frequency regime because  $\tilde{\sigma}_n$  behaves the same as the usual Whittle estimator  $\hat{\sigma}_n$  in the non-HF regime. Moreover, since  $\tilde{\sigma}_n$  is a **consistent estimator**,  $\tilde{\sigma}_n = \sigma(1 + o(1))$ , so (at leading order) we find that

$$\frac{\sqrt{n}}{\log n}(\hat{\sigma}_n - \sigma) = \sigma \sqrt{n} (\hat{H}_n - H) \rightarrow N(0, \sigma^2 (I^{-1})_{1,1})$$

where  $(I^{-1})_{1,1} = (I(H, \sigma)^{-1})_{1,1}$  was computed in (5), which also agrees with Theorem 1 in [Syz23] (note for us the  $\gamma(H)$  function in [Syz23] is just  $\gamma(H) = H$ , see Remark just above Section 1.2 in [Syz23]).

**Remark 0.2** Note that  $\hat{\sigma}_n - \sigma$  now has a larger standard deviation i.e.  $O(\frac{\log n}{\sqrt{n}})$  as opposed to just  $O(\frac{1}{\sqrt{n}})$  due to the HF regime.

## Singular Fisher information for the high-frequency regime

If we naively try to use the Whittle estimator in the HF regime, we get

$$U_n(H, \sigma) = \frac{1}{4\pi} \int_{-\pi}^{\pi} \left( \log \left( \frac{\sigma^2 f_H(\omega)}{n^{2H}} + \frac{|Z_n(\omega)|^2}{\sigma^2 f_\theta(\omega)/n^{2H}} \right) d\omega \right).$$

Then

$$\frac{\partial}{\partial H} U_n(H, \sigma) = \frac{1}{2\pi} \int_0^\pi \left( \frac{n^{2H} |Z_n(\omega)|^2}{\sigma^2 f_H(\omega)} - 1 \right) d\omega \cdot 2 \log n (1 + o(1)) \quad (6)$$

as  $n \rightarrow \infty$ , which (using the same argument as in ...) has asymptotic variance

$$\frac{1}{4\pi} \int_{-\pi}^{\pi} \frac{2\sigma^4 f_H(\omega)^2}{\sigma^4 f_H(\omega)^2} d\omega \cdot 2(\log n)^2 (1 + o(1)) \sim 2(\log n)^2.$$

Similarly

$$\frac{\partial}{\partial \sigma} U_n(H, \sigma) = \frac{1}{\pi \sigma^3} \int_0^\pi \left( \sigma^2 - \frac{n^{2H} |Z_n(\omega_1)|^2}{f_H(\omega)} \right) d\omega_1.$$

Then  $\mathbb{E}(\frac{\partial}{\partial H} U_n(H, \sigma) \frac{\partial}{\partial \sigma} U_n(H, \sigma))$  tends to  $\frac{2}{\sigma} \log n$  and  $\mathbb{E}((\frac{\partial}{\partial \sigma} U_n(H, \sigma))^2)$  tends to  $\frac{2}{\sigma^2}$  (this agree with the matrix entries at the end of page 2 in [BF18] when we scale out the  $\log n$ ; see also Theorem 2.1 and the lower part of the matrix above it in [Kaw13], final (2,2) matrix of 2 is computed in ...). Hence the associated Fisher information here is singular, which is why we need the alternative Syzmanski approach with  $\hat{\nu}_n$  above.

## Adding additive noise

To incorporate the **microstructure noise** which arises from using realized variance to estimate  $B^H$  under high-frequency observations, we add  $\sqrt{\frac{2}{n}}$  times a standard Gaussian to the original observed  $\nu B^H$  (see CLT part of Brownian motion chapter in FM02 to see where the  $\frac{2}{n}$  comes from; this has nothing to do with fBM), or equivalently (if we work with increments instead as we do above) we add  $\sqrt{\frac{2}{n}}Y$  to fGN observed on  $[0, 1]$ , where  $Y_t = \varepsilon_t - \varepsilon_{t-1}$  and the  $\varepsilon'_t$ s are i.i.d. standard Normals (note  $Y$  is an MA(1) process of the form  $Y_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$  with  $\theta = -1$  here). Then

$$\mathbb{E}(Y_s Y_t) = \mathbb{E}((X_t - X_{t-1})(X_s - X_{s-1})) = 2r(t-s) - r(t-1-s) - r(t+1-s)$$

so  $Y$  is also a stationary Gaussian process.

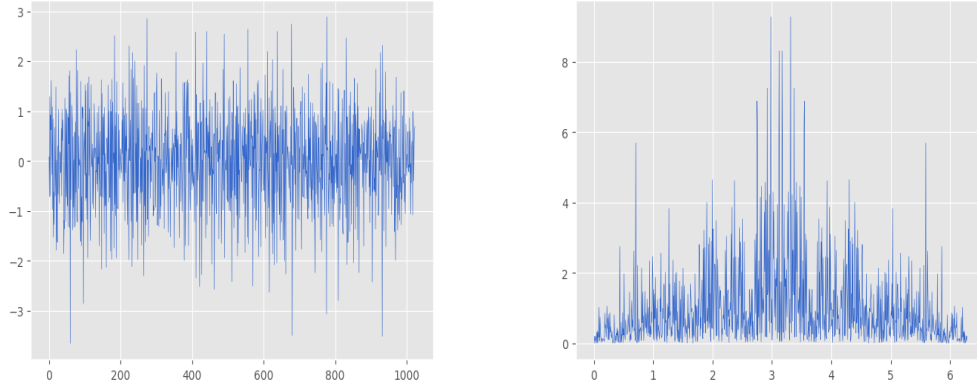


Figure 1: Simulation of fGN (left) and its periodogram (right) for  $H = .25$

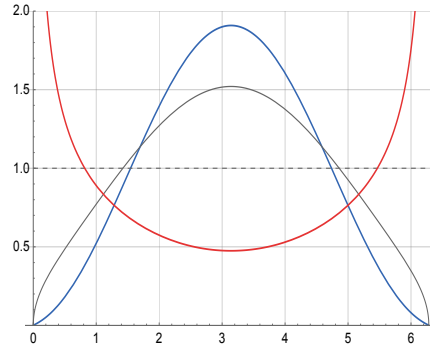


Figure 2: Spectral density  $f_H(\omega)$  of fGN for  $H = .1$  (blue),  $H = .25$  (grey),  $H = .5$  (grey dashed) and  $H = .75$  (red)

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