

# AST 4320 - Assignment 2

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## EXERCISE 1.

We will now consider the top-hat smoothing function in 1D, also known as the window function  $W(x)$ . The top-hat smoothing function is expressed as

$$W(x) = \begin{cases} 1, & \text{if } |x| < R \\ 0, & \text{otherwise} \end{cases}, \quad (1)$$

where  $R$  is the smoothing scale. We are interested in computing the Fourier conjugate  $\tilde{W}$  of the smoothing function. The Fourier transformation of a function  $f(x)$  is given as

$$\tilde{f}(k) = \int_{-\infty}^{\infty} f(x) e^{-ikx} dx. \quad (2)$$

Applying this transformation to  $W(x)$  gives us the following expression to solve

$$\tilde{W}(k) = \int_{-\infty}^{\infty} W(x) e^{-ikx} dx.$$

If we insert for the definition of  $W(x)$ , we see that only the non-zero contributions occur in the limits  $R$  to  $-R$ . This reduces our expression to

$$\tilde{W}(k) = \int_{-R}^R e^{-ikx} dx.$$

This is a trivial integral to compute. Doing so results in

$$\tilde{W}(k) = -\frac{1}{ik} \left[ e^{-ikx} \right]_{-R}^R = \frac{1}{ik} \left[ e^{ikR} - e^{-ikR} \right].$$

From Euler's formula, we know that

$$\sin(kx) = \frac{e^{ikx} - e^{-ikx}}{2i}.$$

We see that this can be substituted into the bracket on the right hand side, which leaves us with the final expression

$$\tilde{W}(k) = \frac{2}{k} \sin(kR). \quad (3)$$

We can now study this quantity. We start by plotting equation (3) for wavenumbers  $k \in [-4\pi, 4\pi]$ . The results are seen in figure 1. We are also interested in knowing what the full width at half the maximum is (FWHM). This quantity is given as  $\text{FWHM} = 2\sqrt{2\ln 2}\sigma$ , where  $\sigma$  is the standard deviation in the distribution. However, since we have a non-gaussian distribution with multiple amplitudes, we will have to find the value numerically. We do so by writing a short script in python which finds the value of  $k$  at half the maximum.

We find that the FWHM of the Fourier conjugate of  $W(x)$  with smoothing scale  $R = 2$  is  $\text{FWHM} = 1.899$ .

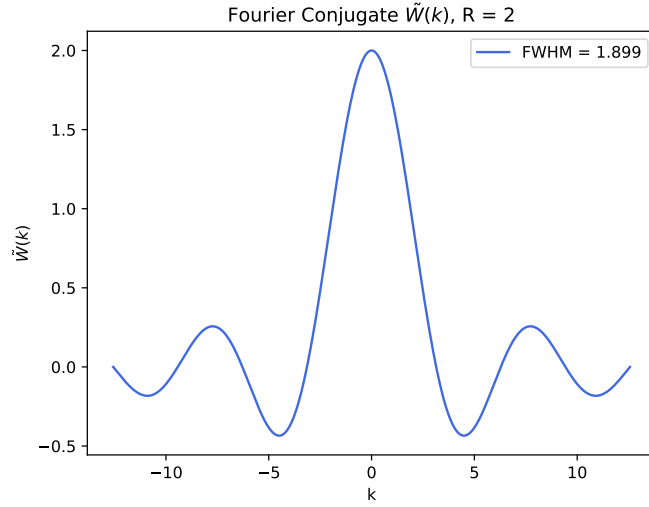


Figure 1: Top-hat smoothing function in 1D with a smoothing scale  $R = 2$ .

## EXERCISE 2.

We will now look into the random walk process. We will consider a power spectrum on the form  $P(k) = k$  and extract random numbers from Gaussian random distributions. We define the variance as a function of scale as

$$\sigma^2(S_c) = \frac{\pi}{S_c^4}, \quad (4)$$

where  $S_c$ , the smoothing scale is given as

$$S_c = \frac{2\pi}{k}. \quad (5)$$

The initial condition of  $k$  is found by requiring that we start at a radius so that  $\sigma^2(S_c) = \sigma^2(S_1) < 10^{-4}$ . We can find an expression for  $k$  which only depends on  $\sigma$  by solving equations for  $k$ . Doing so leaves us with

$$k = 2\pi \left( \frac{\pi}{\sigma^2} \right)^{-1/4}. \quad (6)$$

This can then be inserted back into equation (5), which leaves us with our initial scale

$$S_1 = \left( \frac{\pi}{\sigma^2} \right)^{1/4}. \quad (7)$$

By then inserting for a initial sigma  $\sigma < 10^{-4}$ , for instance  $0.9 \times 10^{-4}$ , we get our initial  $S_1 = 13.66$ .

We start by creating an algorithm which first calculates the variance,  $\sigma^2$  in equation (4) using the initial scale  $S_1$ . It then subtracts a small value  $\epsilon$  from the scale  $S_c$ . It proceeds by computing a new variance using the new  $S_c$  value. It then finds the difference in variance between these two variances  $\sigma_{12}^2 = \sigma^2(S_2) - \sigma^2(s_1)$ . It then uses numpy's *random.normal* function which extracts a random normal distributed number  $\delta$  with the above variance  $\sigma_{12}^2$ . This is then continued until the scale  $S_c$  drops to  $S_c = 1$  at which point we extract the final  $\delta$  value corresponding to  $S_c = 1$ .

This whole sequence is computed  $10^5$  times. The distribution of the extracted  $\delta$  are then plotted in a histogram which is seen in figure 2.

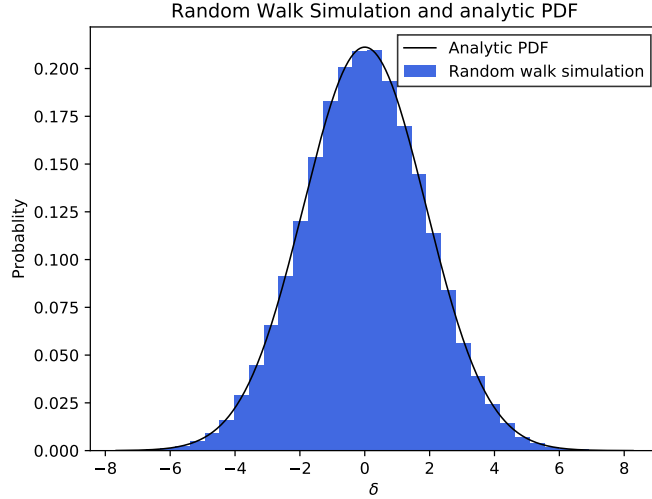


Figure 2: Distribution of  $10^5$  random walk realizations in addition to the Gaussian Probability distribution function (PDF).

We have also overplotted the analytic probability distribution for a Gaussian random field with overdensity  $\delta$ , smoothed by  $S_c$  with a variance  $\sigma^2$ , which is given as

$$P(\delta | M) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left[ -\frac{\delta^2}{2\sigma^2} \right]. \quad (8)$$

We see that the analytic probability distribution perfectly represents the random walk simulation.

We can further choose to only study the chains which never crosses the threshold  $\delta_{\text{crit}} = 1$ . Analytically, the probability of this is given by

$$P_{\text{nc}}(\delta | M) \frac{1}{\sqrt{2\pi}\sigma} \left( \exp \left[ -\frac{\delta^2}{2\sigma^2} \right] - \exp \left[ -\frac{[2\delta_{\text{crit}} - \delta]^2}{2\sigma^2} \right] \right). \quad (9)$$

By editing our program to extract only  $\delta \leq 1$  We get the following distribution, with the analytic expression overplotted seen in figure 3.

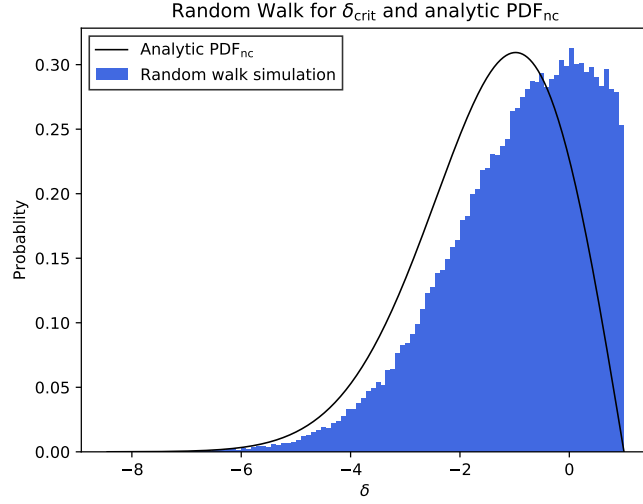


Figure 3: Distribution of  $10^5$  random walk realizations where only the chains up to  $\delta \leq 1$  have been included. This is then compared to the analytic probability distribution  $\text{PDF}_{\text{nc}}$ .

### EXERCISE 3.

(1) From the analysis in exercise 2, we know that the probability distribution function for  $\delta \leq \delta_{\text{crit}}$  at some scale  $M' > M$  is given by equation (9). We know that the probability of finding mass larger than zero is given as

$$P(> 0) = P(> M) + P(< M) = 1.$$

We can rewrite this to

$$P(> M) = 1 - P(< M). \quad (10)$$

Mass smaller than  $M$  corresponds to the density being smaller than critical overdensity  $\delta_{\text{crit}}$ . From the randomwalk analysis, we know that this has the probability of not crossing  $P_{\text{nc}}$  seen in equation (9). By inserting this into the equation (11) we get the following expression

$$P(> M) = 1 - \int_{-\infty}^{\delta_{\text{crit}}} P_{\text{nc}}(\delta | M) d\delta, \quad (11)$$

where we have integrated  $P_{\text{nc}}$  from  $-\infty$  to  $\delta_{\text{crit}}$ .

(2) We will now show how the factor 2 in the Press-Schechter formalism naturally occurs. We do so by first combining equations (9) and (11). This leaves us with

$$P(> M) = 1 - \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\delta_{\text{crit}}} \left( \exp\left[-\frac{\delta^2}{2\sigma^2}\right] - \exp\left[-\frac{[2\delta_{\text{crit}} - \delta]^2}{2\sigma^2}\right] \right) d\delta \quad (12)$$

We split the integral into two integrals, I and II

$$\begin{aligned} \text{I : } & \int_{-\infty}^{\delta_{\text{crit}}} e^{-\delta^2/2\sigma^2} d\delta, \\ \text{II : } & \int_{-\infty}^{\delta_{\text{crit}}} e^{-(2\delta_{\text{crit}} - \delta)^2/2\sigma^2} d\delta. \end{aligned}$$

We start with computing I

$$\text{I : } \int_{-\infty}^{\delta_{\text{crit}}} e^{-\delta^2/2\sigma^2} d\delta = \frac{1}{2}\sqrt{2\pi}\sigma \left[ \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) + 1 \right],$$

where we have substituted  $\nu = \delta_{\text{crit}}/\sigma$ , and erf is the error function given as

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt.$$

Similarly, we compute II

$$\text{II : } \int_{-\infty}^{\delta_{\text{crit}}} e^{-(2\delta_{\text{crit}} - \delta)^2/2\sigma^2} d\delta = \frac{1}{2}\sqrt{2\pi}\sigma \text{erfc}\left(\frac{\nu}{\sqrt{2}}\right),$$

where erfc is given as

$$\text{erfc}(x) = 1 - \text{erf}(x).$$

We now solve the integral expression in equation (12) by computing I - II

$$\begin{aligned} \text{I} - \text{II} &= \frac{1}{2}\sqrt{2\pi}\sigma \left[ \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) + 1 \right] - \frac{1}{2}\sqrt{2\pi}\sigma \text{erfc}\left(\frac{\nu}{\sqrt{2}}\right) \\ &= \frac{1}{2}\sqrt{2\pi}\sigma \left[ \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) + 1 - \text{erfc}\left(\frac{\nu}{\sqrt{2}}\right) \right] \\ &= \frac{1}{2}\sqrt{2\pi}\sigma \left[ \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) + 1 - 1 + \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) \right] \\ &= \sqrt{2\pi}\sigma \text{erf}\left(\frac{\nu}{\sqrt{2}}\right) \end{aligned}$$

We can then insert this expression into the integral in equation (12), which leaves us with

$$P(> M) = 1 - \frac{1}{\sqrt{2\pi}\sigma} \sqrt{2\pi}\sigma \operatorname{erf}\left(\frac{\nu}{\sqrt{2}}\right).$$

We see that the factor  $\sqrt{2\pi}\sigma$  disappears, and we are left with the Press-Schelter expression

$$P(> M) = 1 - \operatorname{erf}\left(\frac{\nu}{\sqrt{2}}\right), \tag{13}$$

where the factor 2 now naturally comes in.