

# Listening to the Sound of the Early Universe

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## Abstract

The accelerating expansion of the universe is one of the most intriguing discovery made in cosmology. To further investigate the properties of the drive of this expansion – dark energy, efforts have been made both observationally and simulationally, in order to constrain the cosmological parameters to test the cosmological models. Amongst which baryonic acoustic oscillations (BAO) is with the least systematics, complementary to the most probed technique – supernovae Ia. In this project, we aim to observe the BAO signal from a large N-body simulation, using the GADGET-2 code (Springel, 2005). Two runs were carried out, one with wiggles in the initial power spectrum and the other without (for comparison). We have observed the oscillatory feature of the BAO signal, and have also estimated the sound horizon to be  $\sim 136$  Mpc, with an error of  $\sim 9\%$ .

## 1 Introduction

In cosmology, baryon acoustic oscillations (BAO) are fluctuations in the density field of the baryonic matter in the early universe. During the radiation epoch, photons and baryons are coupled to each other, leading to acoustic oscillations in the primordial photon-baryon plasma. This tight coupling between electrons, baryons and photons due to Compton scattering then causes baryons to oscillate in phase with radiation. Thus, the whole plasma oscillates due to the sound waves. More importantly, just as supernovae provide "standard candles" for astronomical observations, BAO also provides a "standard ruler" in cosmology. BAO measurements is a powerful tool helping cosmologists understand the nature of dark energy by constraining cosmological parameters.

## 2 The BAO Signal and Power Spectrum

Prior to redshifts around 1000, the universe is a hot dense plasma of ionised gas. The cross section of the free electrons is sufficient for the CMB photons to Thomson scatter, resulting in a mean free time less than the Hubble time. The net result is a close coupling between the electrons baryons and photons. The radiation pressure of the photons is larger than the gravitational forces between the baryons and dark matter, resulting in perturbations in the primordial photon-baryon fluid to oscillate like sound waves. Diffusion of photons relative to baryons damps these oscillations, a phenomenon known as "Silk damping". After recombination, the mean free time of the photons became longer than the Hubble time. Photons decouple from the baryons, and the perturbations in the baryons soon became smoothly distributed, just like the perturbations in cold dark matter.

### 2.1 Density field and correlation function

Since the BAO signal is imprint of the density perturbations in the primordial plasma, our story begins with the density field. Let us focus on a continuous density field over a finite cube volume  $V = L^3$  with periodic boundary conditions applied to all three directions. A dimensionless overdensity  $\delta(\mathbf{x})$  can be written in terms of matter density  $\rho(\mathbf{x})$

$$\delta(\mathbf{x}) = \frac{\rho(\mathbf{x})}{\bar{\rho}} - 1 \quad (1)$$

where  $\bar{\rho}$  is the mean density in the volume  $V$ . In Fourier space this becomes

$$\delta(\mathbf{k}) = \int_V \frac{d^3x}{(2\pi)^3} e^{-i\mathbf{k}\cdot\mathbf{x}} \delta(\mathbf{x}) \quad (2)$$

And the power spectrum is related to the density by

$$P(k) \equiv \langle |\delta(\mathbf{k})|^2 \rangle \quad (3)$$

where  $\langle \dots \rangle$  represents the ensemble average

$$\langle \delta(\mathbf{k}_1) \delta(\mathbf{k}_2) \rangle = \frac{\delta_{\mathbf{k}_{12}}^K}{k_f^3} P(k_1) \quad (4)$$

with  $\mathbf{k}_{i_1, \dots, i_n} \equiv \mathbf{k}_{i_1} + \dots + \mathbf{k}_{i_n}$  and  $\delta_{\mathbf{k}}^K$  being a Kronecker delta. For  $V \rightarrow \infty$ ,  $k_f \rightarrow 0$ , and  $\delta_{\mathbf{k}}^K/k_f^3 \rightarrow \delta_D(\mathbf{k})$  becomes a Dirac delta<sup>12</sup>. However, in practice we have an N-body simulation with finite particle numbers  $N_p$  with positions  $\{\mathbf{x}_i\}$  for  $i = 1, \dots, N_p$ . In this case the density becomes

$$\rho(\mathbf{x}) = \sum_i^{N_p} m \delta_D(\mathbf{x} - \mathbf{x}_i) \quad (5)$$

where  $m$  is the particle mass. It follows that

$$\delta(\mathbf{x}) = \frac{1}{\bar{n}} \sum_i^{N_p} \delta_D(\mathbf{x} - \mathbf{x}_i) - 1 \quad (6)$$

and its Fourier transform becomes

$$\delta(\mathbf{k}) = \frac{1}{(2\pi)^3} \frac{1}{\bar{n}} \sum_i^{N_p} e^{-i\mathbf{k} \cdot \mathbf{x}_i} - \frac{\delta_{\mathbf{k}}^K}{k_f^3} \quad (7)$$

and the estimator of the power spectrum is given by

$$\hat{P}(k) = k_f^3 |\delta(\mathbf{k})|^2 = \delta_f^3 \left[ |\delta(\mathbf{k})|^2 - \frac{1}{N_p} \right] \quad (8)$$

## 2.2 Cloud-in-Cell mass assignment scheme

Getting the density field straight from the discrete particle distribution is slow. A more efficient way of obtaining the density field, is the so-called Cloud-in-Cell (CIC) mass assignment scheme. It takes advantage of the FFT algorithm, and requires first order interpolation of the density field on a regular grid in position space. The explicit form of the CIC window function reads

$$W_{CIC}(x) = \frac{1}{H} \begin{cases} 1 - |x|/H, & |x| < H \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

with  $N_G$  the linear size of the grid and  $H = L/N_G$  the grid spacing. The window function can be easily extended to three dimensions

$$W(\mathbf{x}) = W(x_1)W(x_2)W(x_3) \quad (10)$$

whose Fourier transform is [3]

$$W(\mathbf{k}) = \left[ \text{sinc} \left( \frac{\pi \mathbf{k}_1}{2k_N} \right) \left( \frac{\pi \mathbf{k}_2}{2k_N} \right) \left( \frac{\pi \mathbf{k}_3}{2k_N} \right) \right]^2 \quad (11)$$

where  $k_N = \pi/H$  is the Nyquist frequency. While this method provides a. reasonable and effective solution, it also introduces an alias in the power spectrum estimation. After the window function, the estimator of the power spectrum is now related to the correlation function  $\langle |\delta(\mathbf{k})|^2 \rangle$  by

$$\langle |\delta(\mathbf{k})|^2 \rangle = \sum_i^{N_p} |W(\mathbf{k} + 2k_N \mathbf{x}_i)|^2 P(k + 2k_N \mathbf{x}_i) + \frac{1}{N} \sum_i^{N_p} |W(\mathbf{k} + 2k_N \mathbf{x}_i)|^2 \quad (12)$$

---

<sup>1</sup>  $\delta_D(\mathbf{x}) = \frac{1}{V} \sum_{\mathbf{k}} e^{i\mathbf{k} \cdot \mathbf{x}}$   
<sup>2</sup>  $\delta_{\mathbf{k}}^K = \frac{1}{V} \int d^3x e^{-i\mathbf{k} \cdot \mathbf{x}}$

where the summation is over all 3D integer vectors  $\mathbf{x}_i$ . The density convolution introduces a factor  $W^2$  both to the power spectrum and the shot noise (the  $1/N$  term). The analytical form of the shot noise can be expressed as

$$D^2(\mathbf{k}) = \frac{1}{N} \sum_i^{N_p} |W(\mathbf{k} + 2k_N \mathbf{x}_i)|^2 = \frac{1}{N} C_1(\mathbf{k}) \quad (13)$$

with

$$C_1(\mathbf{k}) = \Pi_i \left[ 1 - \frac{2}{3} \sin^2 \left( \frac{\pi k_i}{2k_N} \right) \right] \quad (14)$$

where  $\Pi_i(\mathbf{k})$  is the Fourier transform of the sampling function  $\Pi(\mathbf{x})$

$$\Pi(\mathbf{x}) = \sum_i^{N_p} \delta_D(\mathbf{x} - \mathbf{x}_i) \quad (15)$$

Therefore after correcting the shot noise effect we can recover the true power spectrum from (12).

Finally, since the BAO signal is weak, to subtract it from the power spectrum, we divide it by a smoothed power spectrum in order to see the oscillations produced by the baryons

$$\mathcal{S}_{\text{BAO}} = \frac{P(k)}{P_{\text{smoothed}}(k)} - 1 \quad (16)$$

### 3 N-body Simulation

In this project, we ran a large N-body simulation with a box size of 500 Mpc/h and  $512^3$  dark matter particles. The particles were evolved from  $z_{\text{ini}} = 127$ , up to redshift zero, using the *Gadget-2* code[4]. Our simulation adopt cosmological parameters from WMAP9[5]:  $\Omega_M = 0.279$ ,  $\Omega_\Lambda = 0.721$ ,  $\Omega_b = 0.0463$ , and  $H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}$ . We have in total two runs, one whose initial power spectrum is with wiggles and the other without (used only for comparison in recovering the BAO signal). For each run we have stored 13 snapshots. Four snapshots of the cubic volume of particles projected onto the  $xy$ -plane is shown in Fig. 1. It can be seen, initially at high redshifts (panel 1 and 2), the projection of the density field is somewhat uniform. In lower redshifts (panel 3 and 4), large scale structures represented by the darker regions in the figures can be seen delineating voids which are the underdensities.

After mass assignment using the CIC scheme, the density field can be seen as in Fig. 2.

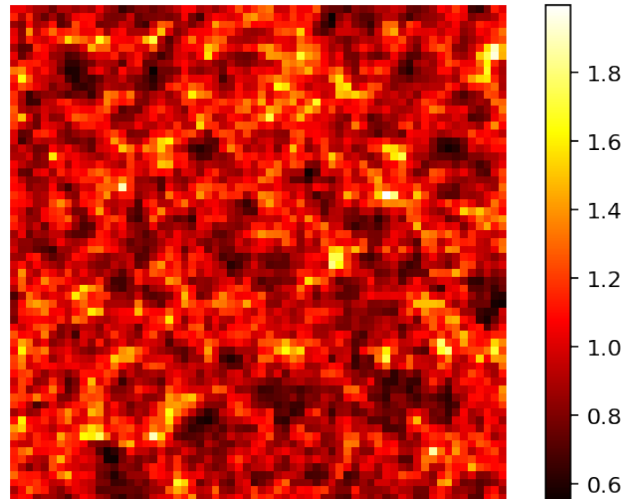


Figure 2: The projected image of the density field at redshift zero, after the mass assignment scheme. The grid number used here is  $64^3$ , colour bar represents the density, where hotter regions have higher values in colour.

Afterwards we can recover the power spectrum from the Fourier transform of the correlation function, which can be seen in Fig. 3

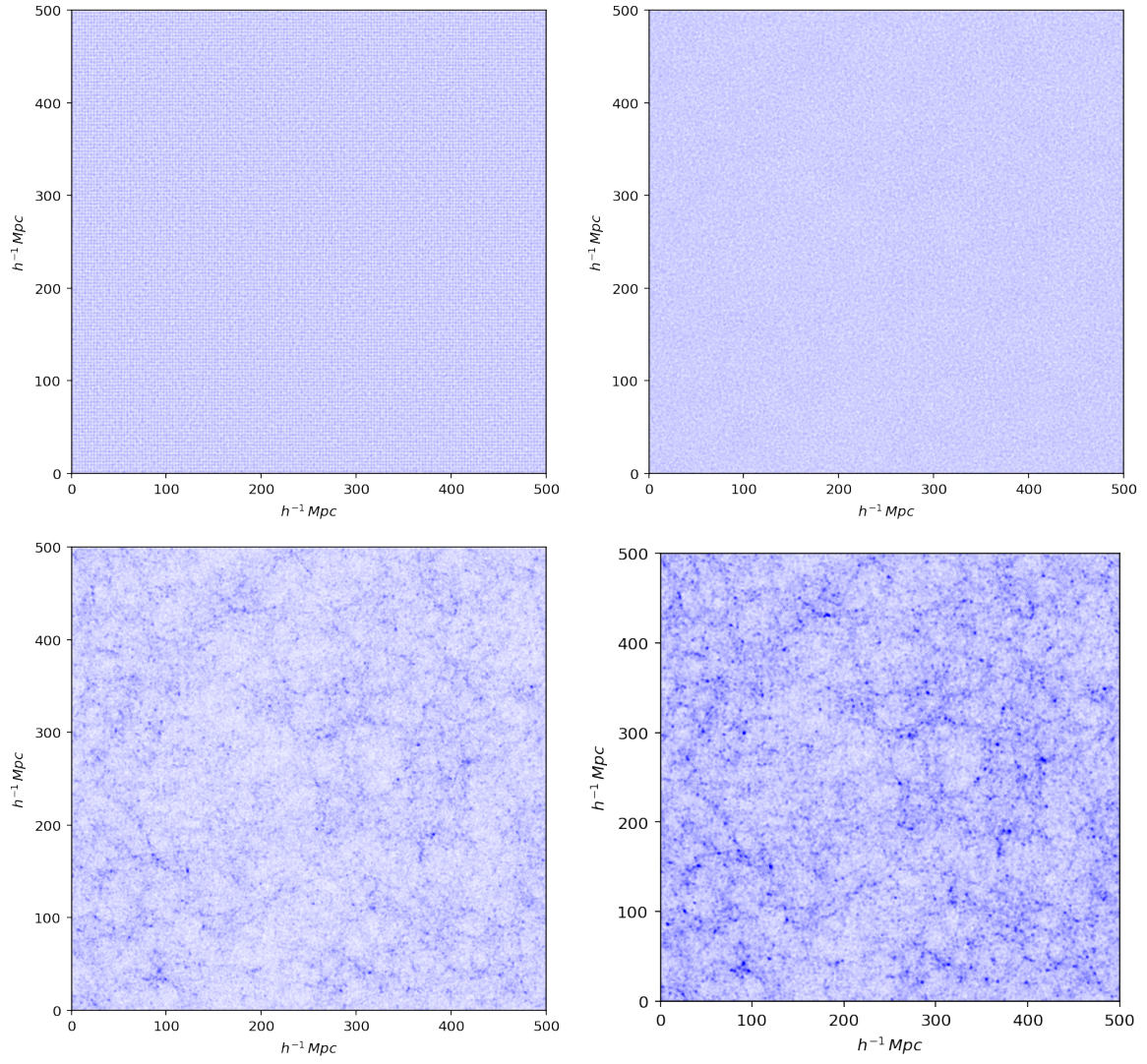


Figure 1: The projected image of the density field at various redshifts ( $z=127, 10, 0.4, 0$ ), for  $512^3$  dark matter particles in a cubic volume of  $(500 h^{-1} \text{ Mpc})^3$ . Filament-like structures can be seen delineating voids at redshift zero.

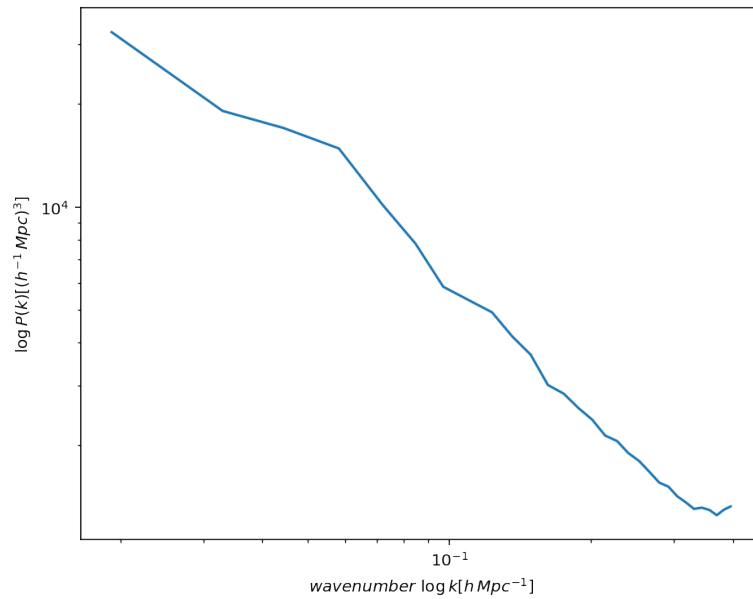


Figure 3: The power spectrum at redshift zero, recovered using the CIC scheme with a grid number of 64.

In order to see at what resolution of grid size the power spectrum can be deemed converged, we generate multiple spectra using different grid number. Fig. 4 shows the resultant power spectra.

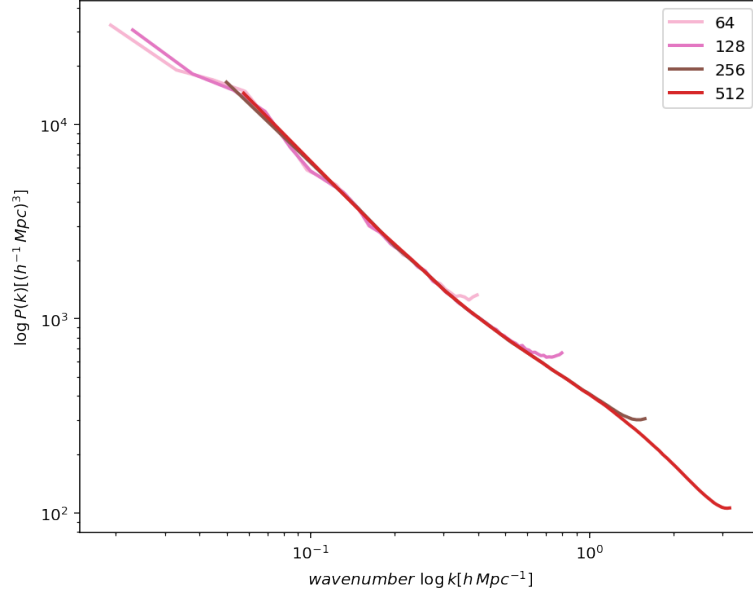


Figure 4: The power spectra at redshift zero, with varying grid sizes. The grid number used are  $64^3$ ,  $128^3$ ,  $256^3$ , and  $512^3$ .

Undoubtedly the spectrum with  $512^3$  grids has the least noise, albeit this is computationally demanding. The grid size is already equal to the particle number. Comparing it to the spectrum with  $256^3$  grids, we find the latter well converged within range  $[10^{-1}, 10^0] \log k$ . Hence for recovering the BAO signal, it is sufficient to use the spectrum with  $256^3$  grids.

Now using  $256^3$  grids we can obtain the power spectra at various redshifts ( $z=127, 10, 0.4, 0$ ) See Fig. 5. The lower the redshift, the higher the amplitude the power spectrum would be. This is due to the fact that at lower redshifts the clustering is stronger, which can be seen when compared to Fig. 1. With the decrease of redshifts, more structures would form. The gaps between the power spectra at larger scales (correspond to smaller value in wavenumber  $k$ ) evolves linearly according to perturbation theory, however this is not true for the evolution of the small scale structures. To see this more clearly we can subtract the linear effect.

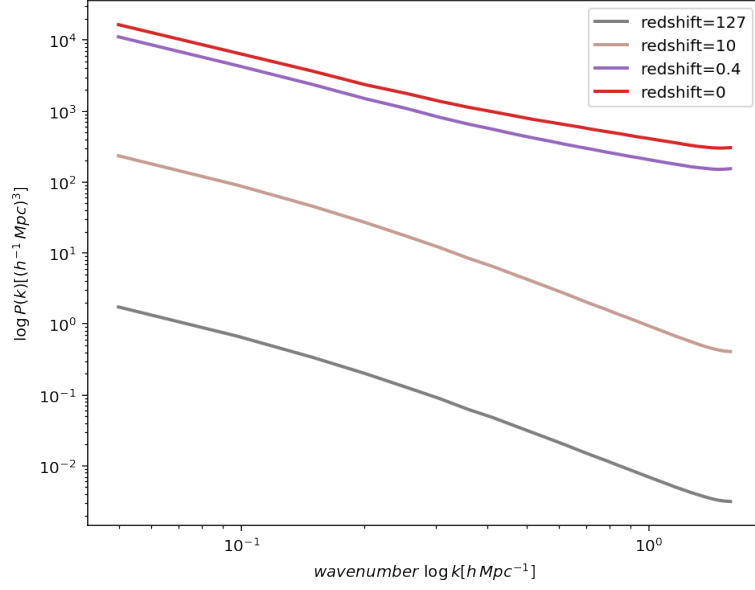


Figure 5: The power spectra at various redshifts ( $z=127, 10, 0.4, 0$ ).

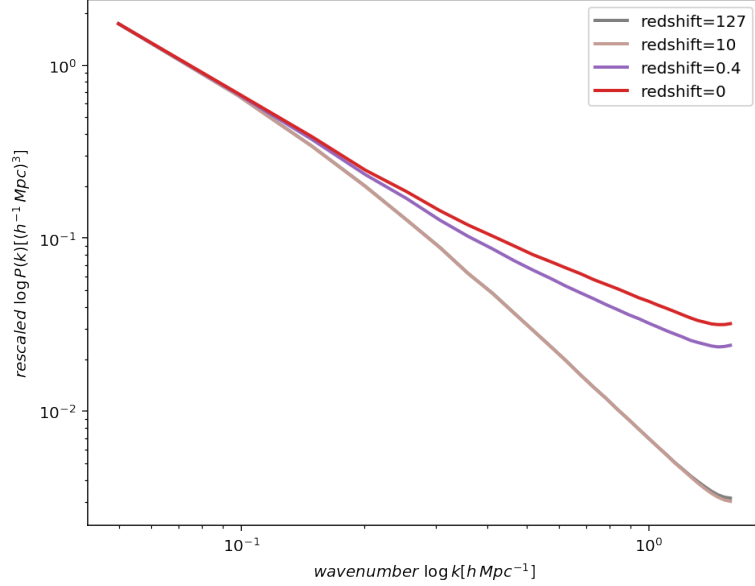


Figure 6: Same as 5, but now rescaled to the amplitude of the spectrum of  $z = 0$ .

If we rescale the power spectra so that they all begin with the same amplitude of the  $z = 0$ 's, we can see the effect of non-linear evolution in the small scale more clearly. From Fig. 6 it can be seen, the clustering at smaller scales is stronger at a later time epoch. This is because galaxy clusters form in a latter epoch in the evolution of the universe.

The BAO signal is finally recovered by dividing the power spectra by their smoothed counterparts. The evolution of the BAO signal can be seen in Fig. 8. To understand how the features form we first refer to Fig. 7[6]. In the beginning, the density field is smooth, the fluctuations are the same on all directions. As time goes by, this symmetry breaks down at smaller scales, particles originally located at the sound horizon gets "perturbed" around the ring, broadening the acoustic feature.

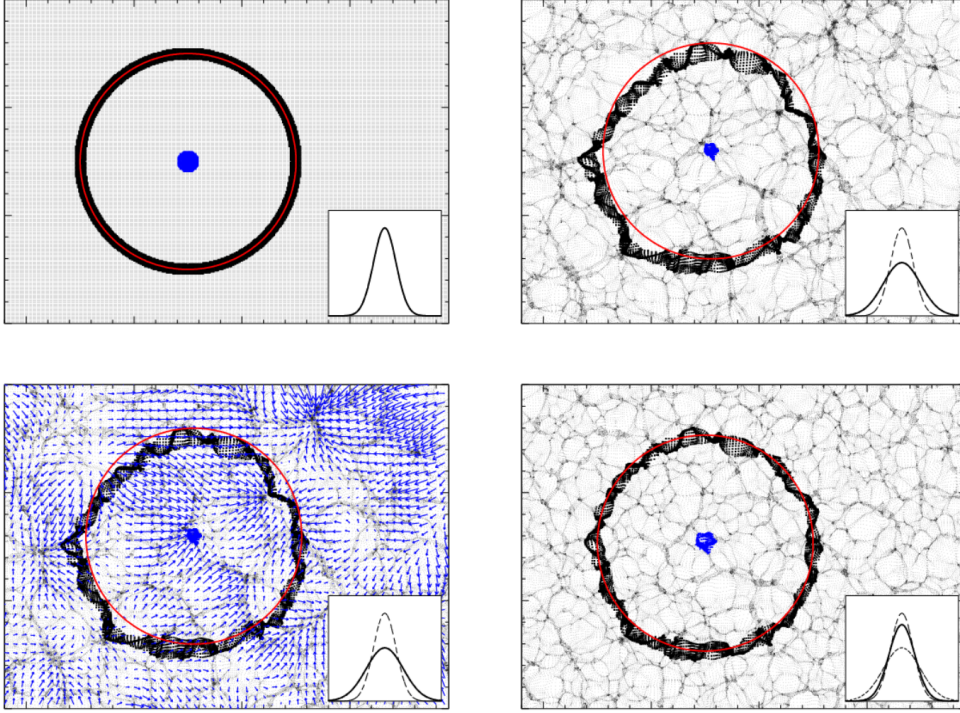


Figure 7: In each panel, we show a thin slice of a simulated cosmological density field. (top left) In the early universe, the initial densities are very smooth. We mark the acoustic feature with a ring of 150 Mpc radius from the central points. A Gaussian with the same rms width as the radial distribution of the black points from the centroid of the blue points is shown in the inset. (top right) We evolve the particles to the present day, here by the Zel'dovich approximation (Zel'dovich 1970). The red circle shows the initial radius of the ring, centered on the current centroid of the blue points. The large-scale velocity field has caused the black points to spread out; this causes the acoustic feature to be broader. The inset shows the current rms radius of the black points relative to the centroid of the blue points (solid line) compared to the initial rms (dashed line). (bottom left) As before, but overplotted with the Lagrangian displacement field, smoothed by a  $10h^{-1}$  Mpc Gaussian filter. The concept of reconstruction is to estimate this displacement field from the final density field and then move the particles back to their initial positions. (bottom right) We displace the present-day position of the particles by the opposite of the displacement field in the previous panel. Because of the smoothing of the displacement field, the result is not uniform. However, the acoustic ring has been moved substantially closer to the red circle. The inset shows that the new rms radius of the black points (solid), compared to the initial width (long-dashed) and the uncorrected present-day width (short-dashed). The narrower peak will make it easier to measure the acoustic scale[6].



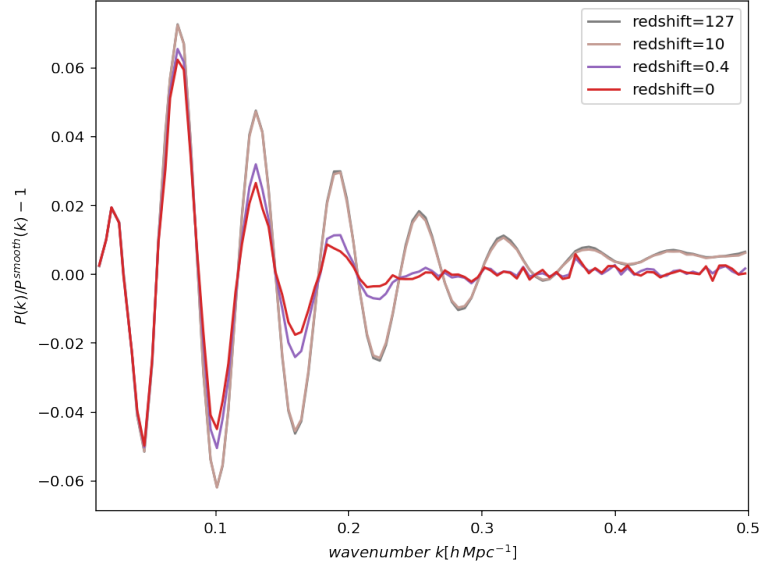


Figure 8: The BAO signal at various redshifts ( $z=127, 10, 0.4, 0$ ).

Overall, oscillating wave structures can be seen in the BAO signal. As time goes by, the damping features in the tail are gradually smoothed. The BAO signal can be understood as a standing wave in Fourier space. In Fourier space, a single acoustic scale can result in a harmonic sequence of oscillations in the power spectrum, imprinting the response of the universe to a plane wave perturbation. Each wave crest in the initial wave produces a planar sound wave travelling a distance equal to the acoustic scale. If the sound wave is on the peak of the dark matter perturbation, then it gets constructive interference; otherwise it gets destructive interference. Hence there is a harmonic relation between the perturbation wavelength and the acoustic scale. The smearing-out of the features on the tail is due to the broadening in the acoustic waves, caused by the large-scale velocity field. Moreover, we can use the scale of the maximum peak to estimate the sound horizon. From Fig. 8, the scale of the maximum peak is at  $k = 0.0657 \text{ h Mpc}^{-1}$ , corresponds to a horizon size of  $\sim 136 \text{ Mpc}$ . However, due to the non-linear gravitational evolution of the acoustic wave, the scales are shifted and waves broadened, resulting in a 9.3% deviation from the value determined from other surveys. On the other hand, the density distribution is not uniform, pairs of overdensities fall toward each other, and pairs of underdensities fall away from each other, contributing to the systematics in the two point correlation, causing a partial cancellation.

## 4 Conclusions

In this project, we have carried out an N-body simulation in order to recover the power spectrum, and recover the initial BAO signal. We have observed the initial oscillating waves as a result of the density perturbations in the primordial plasma of coupled baryons and photons. An observed shift and broadening in the acoustic scale is noticed, caused by the non-linear structure formation in the low redshift universe. Using the scales of the acoustic peaks we can further constrain cosmological parameters from the inferred sound horizon. To further improve the precision, it is useful to apply a technique known as "reconstruction".

## References

- [1] Aubourg, E., Bailey, S., Bautista, J. E., et al. 2015, PRD, 92, 123516
- [2] Jing, Y. P. 2005, ApJ, 620, 559
- [3] Hockney, R.W. & Eastwood, J.W. 1981, Computer simulations using particles. Mc Graw-Hill
- [4] Springel V., 2005, MNRAS, 364, 1105
- [5] Hinshaw, G., Spergel, D. N., Verde, L., et al. 2003, ApJS, 148, 135
- [6] Padmanabhan, N., Xu, X., Eisenstein, D. J., et al. 2012, MNRAS, 427, 2132



## 5 Appendix

```
1 #!/usr/bin/env python
2 # coding: utf-8
3
4 import numpy as np
5 import os
6 import logging
7 import matplotlib.pyplot as plt
8 logging.basicConfig(level=logging.INFO)
9 import matplotlib as mpl
10
11
12 from cic import cic
13 from read_snapshot import ReadSnapshot
14 from ps import PowerSpectrum
15
16
17 OutBase = "/data/dell5/userdir/test/Qing"
18
19
20 Ng = 64
21 L = 500
22 binsnum = 30
23
24
25 snap = 12
26 Base =
27     '/data/dell5/userdir/BAO/par-dependence/SIMs/{_WMAP9/output/snapdir_{:03d}/snapshot_{:03d}',
28
29 Base.format('nw01', snap, snap)
30
31
32 rs = ReadSnapshot(Base.format('w01', snap, snap))
33
34
35
36 def func_readpos(name='nw01', snap=snap):
37     rs = ReadSnapshot(Base.format(name, snap, snap))
38     logging.info("redshift: %f"%rs.Info['redshift'][0])
39     Pos = []
40     for i in np.arange(rs.Info['Nsubfiles'][0]):
41         pos = rs.ReadPos(Filename=i)
42         Pos.append(pos['pos'])
43     Pos = np.vstack(Pos)
44     return Pos
45
46 def func_cic(Pos, Ng, L, name, snap=snap):
47     grid = cic(Pos, Ng=Ng, L=L)
48     logging.info('Check: {} should be {}'.format(
49         grid.astype(np.float64).sum(), rs.Info['npartall'][0, 1]))
50     grid /= grid.mean()
51     np.save(os.path.join(OutBase, '{}_cic_Ng{}_snap{}.npz'.format(name, Ng, snap)), grid)
52     return grid
53
54
55 def func_ps(grid, Ng, L, binsnum, name, snap=snap, BAO=False):
56     ps = PowerSpectrum(L=float(L), Ng=Ng)
57     ps.set_binsnum(binsnum)
58     if BAO:
59         ps.set_binskrange(1e-2, 0.5)
60     ps.set_binstyle('linear')
61     ps.AutoPS(grid)
62     k, pk, nbins = ps.get_bin1d()
63     if BAO:
64         path = '{}_BAO_Ng{}_snap{}.txt'.format(name, Ng, snap)
65     else:
66         path = '{}_ps_Ng{}_snap{}.txt'.format(name, Ng, snap)
67     np.savetxt(os.path.join(OutBase, path), np.c_[k, pk, nbins])
68     return k, pk, nbins
```

```

69
70
71
72 def pipeline(name, snap, Ng, L, binsnum, BAO=False):
73     pos = func_readpos(name, snap)
74     grid = func_cic(pos, Ng, L, name, snap)
75     ps = func_ps(grid, Ng, L, binsnum, name, snap, BAO=BAO)
76
77
78 Pos = func_readpos('w01', 12)
79
80
81
82 plt.figure(figsize=(5,5))
83 plt.plot(Pos[:,100, 0], Pos[:,100, 1], 'b.', alpha=0.1, ms=0.1)
84 plt.xlim([0,500])
85 plt.ylim([0,500])
86 plt.xlabel(r'$h^{-1}\backslash$,Mpc$')
87 plt.ylabel(r'$h^{-1}\backslash$,Mpc$')
88 plt.show()
89
90
91 grid = func_cic(Pos, Ng, L, name='w01')
92
93
94 plt.imshow(grid.mean(0), cmap='hot')
95 plt.axis('off')
96 plt.colorbar()
97 plt.show()
98
99
100
101 plt.imshow(grid.mean(1), cmap='hot')
102 plt.axis('off')
103 plt.colorbar()
104 plt.show()
105
106
107 k, pk, nbins = func_ps(grid, Ng, L, binsnum, 'w01')
108
109
110
111 plt.figure(figsize=(7.5,6))
112 plt.loglog(k, pk)
113 plt.xlabel(r'$\text{wavenumber} \backslash \backslash \log \backslash$, $k[h\backslash$,Mpc$^{-1}]$')
114 plt.ylabel(r'$\log \backslash$, $P(k)[(h^{-1}\backslash$,Mpc$)^3]$')
115 plt.show()
116
117 for i in [64,128,256,512]:
118     pipeline('w01', snap=12, Ng=i, L=L, binsnum=binsnum)
119
120 import matplotlib.pyplot as pl
121
122 def showps(Ng):
123     colors = pl.cm.tab20(np.linspace(0.3,0.7,512))[:, -1]
124     color = colors[Ng-1]
125     pk = np.loadtxt(os.path.join(OutBase, '{}_ps_Ng{}_snap{}.txt'.format('w01', Ng, 12)))
126     plt.plot(pk[:,0], pk[:,1], lw=2, color=color, label='{}'.format(Ng))
127
128
129
130 plt.figure(figsize=(7.5,6))
131 for i in [64, 128, 256, 512]:
132     showps(i)
133 plt.legend()
134 plt.xscale('log')
135 plt.yscale('log')
136 plt.xlabel(r'$\text{wavenumber} \backslash \backslash \log \backslash$, $k[h\backslash$,Mpc$^{-1}]$')
137 plt.ylabel(r'$\log \backslash$, $P(k)[(h^{-1}\backslash$,Mpc$)^3]$')
138 plt.show()
139
140

```

```

141
142 for i in [0, 4, 8, 12]:
143     pipeline('w01', snap=i, Ng=256, L=L, binsnum=30, BAO=False)
144
145
146 snap = 0
147 z = [127,10,0.4,0]
148 colors = pl.cm.tab20(np.linspace(0.3,0.7,13))[:-1]
149 plt.figure(figsize=(7.5,6))
150 for j,snap in enumerate([0, 4, 8, 12]):
151     color = colors[snap]
152     pkw = np.loadtxt(os.path.join(OutBase, '{}_ps_Ng{}_{}_snap{}.txt'.format('w01', 256, snap)))
153     plt.plot(pkw[:,0], pkw[:,1], lw=2, color=color, label='redshift={}'.format(z[j]))
154 plt.legend()
155 plt.xscale('log')
156 plt.yscale('log')
157 plt.xlabel(r'$wavenumber \ \log \ k[h\,Mpc^{-1}]$')
158 plt.ylabel(r'$\log \ ,P(k) [(h^{-1}\,Mpc)^3]$')
159 plt.show()
160
161
162
163
164 for i in [0, 4, 8, 12]:
165     pipeline('w01', snap=i, Ng=256, L=L, binsnum=100, BAO=True)
166     pipeline('nw01', snap=i, Ng=256, L=L, binsnum=100, BAO=True)
167
168
169
170
171 snap = 0
172 plt.figure(figsize=(7.5,6))
173 for j,snap in enumerate([0, 4, 8, 12]):
174     color = colors[snap]
175     pkw = np.loadtxt(os.path.join(OutBase, '{}_BAO_Ng{}_{}_snap{}.txt'.format('w01', 256, snap)))
176     pknw = np.loadtxt(os.path.join(OutBase, '{}_BAO_Ng{}_{}_snap{}.txt'.format('nw01', 256,
177                                     snap)))
178     S = (pkw[:,1] - pknw[:,1])/pknw[:,1]
179     plt.plot(pkw[:,0], S, color=color, label='redshift={}'.format(z[j]))
180     ind = np.argmax(S[8:12])
181     print(pkw[:,0][8:12][ind])
182 plt.xlim([1e-2, 0.5])
183 plt.xlabel(r'$wavenumber \ \ k[h\,Mpc^{-1}]$')
184 plt.ylabel(r'$P(k)/P^{\{smooth\}}(k)-1$')
185 plt.legend()
186 plt.show()

```

main.py

```

1 #!/usr/bin/env python
2 # coding=utf-8
3 import logging
4 import numpy as np
5
6 log = logging.info
7
8
9 class PowerSpectrum(object):
10     def __init__(self, L=300., Ng=128, **kwargs):
11         self.L = L
12         self.Ng = Ng
13         log('=' * 80)
14         log('parameters:')
15         log('N: %d, L: %f' % (self.Ng, self.L))
16         log('=' * 80)
17
18         self.Kf = 2 * np.pi / self.L
19         self.H = self.L / self.Ng
20         self.fn = np.fft.fftfreq(self.Ng, 1. / self.Ng)
21         # fn: 0,1,2,...,511,-512,-511,-510,...,-2,-1
22         self.k_ind = (self.fn[:, None, None]**2.
23                       + self.fn[None, :, None]**2.

```

```

24         + self.fn[None, None, :]**2)**(0.5)
25
26 def set_binsnum(self, num):
27     self.bins = num
28
29 def set_binstyle(self, style=''):
30     if style == 'log':
31         self.binspace = self.logspace_wrapper(np.logspace)
32     elif style == 'linear':
33         self.binspace = np.linspace
34     else:
35         raise ValueError('binstyle should be "log" or "linear".')
36
37 def set_binskrange(self, kmin, kmax):
38     """ input wave number, not grid index"""
39     self.bins_kmin = kmin
40     self.bins_kmax = kmax
41
42 def logspace_wrapper(self, func):
43     def wrapper(*args, **kwargs):
44         a = args[0]
45         b = args[1]
46         args = args[2:]
47         return func(np.log10(a), np.log10(b), *args, **kwargs)
48     return wrapper
49
50 def fft(self, data):
51     assert data.ndim == 3
52     datak = np.fft.fftn(data, norm=None)
53     return datak
54
55 def _DeWindow(self):
56     window = (np.sinc(1. / self.Ng * self.fn[:, None, None])
57              * np.sinc(1. / self.Ng * self.fn[None, :, None])
58              * np.sinc(1. / self.Ng * self.fn[None, None, :]))
59     return window
60
61 def AutoPS(self, delta, dew=True):
62     deltak = self.fft(delta)
63     if dew:
64         window = self._DeWindow()
65         deltak /= window ** 2 # CIC deconvolve window function
66     self.pk = np.abs(deltak)**2.
67
68 def get_bin1d(self):
69     try:
70         max = self.bins_kmax / self.Kf
71         min = self.bins_kmin / self.Kf
72     except AttributeError:
73         max = self.Ng/2
74         min = 1
75     try:
76         bin = self.binspace(min, max, self.bins+1, endpoint=True)
77     except AttributeError:
78         log('can not find parameter binstyle, \
79             use default logspace...')
80         bin = np.logspace(np.log10(min), np.log10(max),
81                           self.bins+1, endpoint=True)
82     n_bin = []
83     Pk_bin = []
84     k_bin = []
85     for i in range(self.bins):
86         bool = (bin[i] <= self.k_ind) * (self.k_ind < bin[i+1])
87         n_bin.append(bool.sum())
88         k_bin.append(self.k_ind[bool].astype(np.float64).mean())
89         Pk_bin.append(self.pk[bool].astype(np.float64).mean())
90     n_bin = np.array(n_bin)
91     k_bin = np.array(k_bin)
92     Pk_bin = np.array(Pk_bin)
93     n_bin[n_bin == 0] = 1.
94     k_bin *= self.Kf
95     Pk_bin *= self.L**3/self.Ng**6

```

```
96 |         return k_bin, Pk_bin, n_bin
```

ps.py

```
1  #!/usr/bin/env python
2  # coding=utf-8
3  import numpy as np
4  import logging
5
6  logging.basicConfig(format='%(levelname)s: %(message)s', level=logging.INFO)
7
8
9  class ReadSnapshot():
10     'read data for L-Gadget'
11
12     def __init__(self, Path=''):
13         '''
14         usage:
15         Path='/data/dell1/userdir/output/gadget/test/snapdir_005/snapshot_005.'
16         NumOfFile=64
17         '''
18         self.Path = Path
19         self.dt = np.dtype([( 'head', np.int32, 1),
20                               ( 'npart', np.int32, 6),
21                               ( 'massarr', np.float64, 6),
22                               ( 'time', np.float64),
23                               ( 'redshift', np.float64),
24                               ( 'flag_sfr', np.int32),
25                               ( 'flag_feedback', np.int32),
26                               ( 'npartall', np.int32, 6),
27                               ( 'flag_cooling', np.int32),
28                               ( 'Nsubfiles', np.int32),
29                               ( 'BoxSize', np.float64),
30                               ( 'Omega0', np.float64),
31                               ( 'OmegaL', np.float64),
32                               ( 'H', np.float64),
33                               ])
34         f = open(self.Path + '0', 'r')
35         self.Info = np.fromfile(file=f, dtype=self.dt, count=1)
36         f.close()
37         self.Filenum = self.Info[ 'Nsubfiles' ][0]
38         # print 'Path:', Path
39         # print self.Info
40
41     def ReadPos(self, Filenum=np.int):
42         dtype_data = np.dtype([( 'pos', np.float32, 3)])
43         f = open(self.Path + '%d' % Filenum, 'r')
44         info = np.fromfile(file=f, dtype=self.dt, count=1)
45         length = info[ 'npart' ][0][1]
46         # print 'reading pos:'
47         f.seek(self.Info[ 'head' ][0] + 4 + 4)
48         a = np.fromfile(file=f, dtype=np.int32, count=1)[0]
49         pos = np.fromfile(file=f, dtype=dtype_data, count=info[ 'npart' ][0][1])
50         b = np.fromfile(file=f, dtype=np.int32, count=1)[0]
51         f.close()
52         if not (a == b and a == (length * 4 * 3)):
53             logging.info('error in pos!')
54             logging.info(a)
55             logging.info(b)
56         else:
57             return pos
58
59     def ReadVel(self, Filenum=np.int):
60         dtype_data = np.dtype([( 'vel', np.float32, 3)])
61         f = open(self.Path + '%d' % Filenum, 'r')
62         info = np.fromfile(file=f, dtype=self.dt, count=1)
63         length = info[ 'npart' ][0][1]
64         logging.info('reading vel:')
65         f.seek(self.Info[ 'head' ][0] + 4 + 4 + length * 4 * 3 + 4 + 4)
66         a = np.fromfile(file=f, dtype=np.int32, count=1)[0]
67         vel = np.fromfile(file=f, dtype=dtype_data, count=info[ 'npart' ][0][1])
68         b = np.fromfile(file=f, dtype=np.int32, count=1)[0]
```

```

69         f.close()
70         if not (a == b and a == (length * 4 * 3)):
71             logging.info('error in pos!')
72             logging.info(a)
73             logging.info(b)
74         else:
75             return vel
76
77     def ReadPID(self, Filenum=np.int):
78         f = open(self.Path + '%d' % Filenum, 'r')
79         info = np.fromfile(file=f, dtype=self.dt, count=1)
80         length = info['npart'][0][1]
81         logging.info('reading PID:')
82         f.seek(
83             self.Info['head'][0] + 4 + 4 +
84             length * 4 * 3 + 4 + 4 +
85             length * 4 * 3 + 4 + 4
86         )
87         a = np.fromfile(file=f, dtype=np.int32, count=1)
88         PID = np.fromfile(file=f, dtype=np.int64, count=info['npart'][0][1])
89         b = np.fromfile(file=f, dtype=np.int32, count=1)
90         f.close()
91         if not (a == b and a == (length * 4 * 2)):
92             logging.info('error in PID!')
93             logging.info(a)
94             logging.info(b)
95         else:
96             return PID
97
98
99 if __name__ == '__main__':
100     import sys
101     Path = sys.argv[1]
102     NumOfFile = 64
103     f = ReadSnapshot(Path)
104     logging.info(f.Info)
105     logging.info(f.Info.dtype)

```

read\_snapshot.py

```

1  #!/usr/bin/env python
2  # coding=utf-8
3  import numpy as np
4  import matplotlib.pyplot as plt
5  import hmf
6  from astropy.cosmology import FlatLambdaCDM
7
8
9
10 name='WMAP9'
11
12 ips_camb = np.loadtxt('WMAP9_matterpower.dat')
13
14 # no-wiggle
15 from nowigglePS import TF
16 k = ips_camb[:,0]
17 pk = ips_camb[:,1]
18 TFnw = TF(my_k = k,
19           sigma_8=0.821, n=0.972, z=0,
20           lnk_min=np.log(1e-3), lnk_max=np.log(1e3), dlnk=0.05,
21           transfer_model=hmf.transfer.models.EHNoBAO,
22           cosmo_model=hmf.cosmo.WMAP9,
23           )
24 pk = TFnw.SmoothWiggle(pk, la=0.25)
25
26 pk *= k**3./(2*np.pi**2.)
27 ips_nw = np.c_[k,pk]
28 bool = (ips_nw[:,0]>1e-3)*(ips_nw[:,0]<80)
29 ips_nw = ips_nw[bool]
30 ips_nw = np.log10(ips_nw)
31 np.savetxt('./inips/nowiggle-%s.dat'%(name), ips_nw)
32 # no-wiggle

```

```

33
34
35 ips_camb[:,1] *= ips_camb[:,0]**3./((2*np.pi**2.)
36 ips_camb = np.log10(ips_camb)
37 ips_camb = ips_camb[bool]
38 np.savetxt('./inips/wiggle.%s.dat'%(name), ips_camb)
39 if __name__ == "__main__":
40     plt.figure('ps')
41     plt.plot(ips_camb[:,0], ips_camb[:,1], 'r-')
42     plt.plot(ips_nw[:,0], ips_nw[:,1], 'b--', label='nw')
43     plt.legend()
44     plt.figure('BAO')
45     plt.plot(ips_nw[:,0], 10**ips_camb[:,1]/10**ips_nw[:,1])
46     plt.show()

```

create\_PS-GadgetIC-WMAP.py

```

1 #!/usr/bin/env python
2 # coding=utf-8
3 import hmf
4 import numpy as np
5 import matplotlib.pyplot as plt
6 from scipy import interpolate
7
8 class TF(hmf.transfer.Transfer):
9     def __init__(self, my_k, **kwargs):
10         super(TF, self).__init__(**kwargs)
11         self.my_k = my_k
12         self.PS_EH()
13         self.PS_EHnw()
14         self.PS_BBKS()
15
16     def interpolate(self, x_new):
17         tck = interpolate.splrep(self.inpo_x, self.inpo_y)
18         y_bspline = interpolate.splev(x_new, tck)
19         return y_bspline
20
21     def PS_EH(self):
22         self.transfer_model = hmf.transfer_models.EH
23         self.PkEH = self.power.copy()
24         self.inpo_x = np.log(self.k)
25         self.inpo_y = np.log(self.PkEH)
26         self.my_EH = np.exp(self.interpolate(np.log(self.my_k)))
27
28     def PS_EHnw(self):
29         self.transfer_model = hmf.transfer_models.EHNoBAO
30         self.PkEHnw = self.power.copy()
31         self.inpo_x = np.log(self.k)
32         self.inpo_y = np.log(self.PkEHnw)
33         self.my_EHnw = np.exp(self.interpolate(np.log(self.my_k)))
34
35     def PS_BBKS(self):
36         self.transfer_model = hmf.transfer_models.BBKS
37         self.PkBBKS = self.power.copy()
38         self.inpo_x = np.log(self.k)
39         self.inpo_y = np.log(self.PkBBKS)
40         self.my_BBKS = np.exp(self.interpolate(np.log(self.my_k)))
41
42     def SmoothWiggle(self, pk, la=0.25):
43         Pk_approx = self.my_EHnw
44         klog = np.log10(self.my_k)
45         pk = pk/Pk_approx
46         factor = 1./np.sqrt(2*np.pi)/la
47
48         dqlog = np.zeros_like(klog)
49         dqlog[1:-1] = (klog[2:] - klog[:-2])/2.
50         dqlog[0] = klog[1] - klog[0]
51         dqlog[-1] = klog[-1] - klog[-2]
52         #convolve...
53         pnw = np.zeros_like(pk)
54         norm = np.zeros_like(pk)
55         for i in range(len(pnw)):

```



```

56         pnw[i] += factor*(dqlog*pk*np.exp(-0.5/la**2.*(klog-klog[i])**2.)).sum()
57         norm[i] += factor*(dqlog*np.exp(-0.5/la**2.*(klog-klog[i])**2.)).sum()
58     pnw /= norm
59     pnw = pnw*Pk_approx
60     return pnw
61
62     def testNW(self):
63         my_pknw = self.SmoothWiggle(self.my_EH)
64         plt.plot(self.k, self.PkEH/self.PkEHnw, 'g-', label='EH/EHnw')
65         plt.plot(self.my_k, self.my_EH/my_pknw, 'b-', label='EH/Mynw')
66         plt.hlines(1., self.k[0], self.k[-1], colors='k', linestyle='dashed')
67         plt.xscale('log')
68         plt.xlim([0.03,0.6])
69         plt.ylim([0.85,1.15])
70         plt.legend()
71         plt.show()
72
73 if __name__ == '__main__':
74     my_k = np.linspace(0.01,1,200)
75     params = {
76         'lnk_min': np.log(1e-3),
77         'lnk_max': np.log(10),
78         'dlnk':0.01,
79         'sigma_8':0.8344,
80         'n':0.9624,
81         'z':0.0,
82         'transfer_model':hmf.transfer_models.EHNoBAO,
83     }
84     #
85     tf=TF(my_k=my_k, **params)
86     hmf.transfer.Transfer.parameter_info()
87     exit()
88     #tf.SmoothWiggle(tf.PkEH)
89     tf.testNW()

```

nowigglePS.py

```

1  #!/usr/bin/env python
2  # coding=utf-8
3  import numpy as np
4  from libgrid._cic import lib, ffi
5
6
7  def cic(pos, Ng=32, L=300):
8      posx = pos[:, 0]
9      posy = pos[:, 1]
10     posz = pos[:, 2]
11     if not posx.flags['C_CONTIGUOUS']:
12         posx = np.ascontiguousarray(posx, dtype=pos.dtype)
13     if not posy.flags['C_CONTIGUOUS']:
14         posy = np.ascontiguousarray(posy, dtype=pos.dtype)
15     if not posz.flags['C_CONTIGUOUS']:
16         posz = np.ascontiguousarray(posz, dtype=pos.dtype)
17     pinx = ffi.cast("float *", posx.ctypes.data)
18     piny = ffi.cast("float *", posy.ctypes.data)
19     pinz = ffi.cast("float *", posz.ctypes.data)
20     out = np.zeros([Ng**3], dtype=np.float32)
21     pout = ffi.cast("float *", out.ctypes.data)
22     lib.CIC(Ng, L, len(pos), pinx, piny, pinz, pout)
23     return out.reshape(Ng, Ng, Ng)
24
25
26 if __name__ == "__main__":
27     import unittest
28     import numpy as np
29
30     class testcic():
31
32         def __init__(self):
33             self.Ng = 4
34             self.Boxsize = 4
35             pos = [

```

```

36         [1., 2., 3.], [0.3, 0., 0.], [3.9, 0.2, 2.6], [0., 0., 0.],
37         [0., 1., 0.], [4.0, 4., 4.], [2.6, 3.9, 2.2], [1.3, 2.5, 0.7],
38     ]
39     self.pos = np.array(pos, dtype=np.float32)
40
41     def weight_CIC(self, s):
42         w = np.zeros_like(s)
43         bool = np.abs(s) < 1.0
44         w[bool] += 1 - np.abs(s[bool])
45         return w
46
47     def GetWeight(self, gx, gy, gz, pos, window_func):
48         wx = window_func(gx - pos[0])
49         wy = window_func(gy - pos[1])
50         wz = window_func(gz - pos[2])
51         w = wx * wy * wz
52         return w
53
54     def CIC(self):
55         zeros = np.zeros(
56             [self.Ng + 2, self.Ng + 2, self.Ng + 2], dtype=np.float32)
57         gpos = np.arange(-1, self.Ng + 1) + 0.5
58         gx = gpos[:, None, None] + zeros
59         gy = gpos[None, :, None] + zeros
60         gz = gpos[None, None, :] + zeros
61         for i in range(self.pos.shape[0]):
62             weight = self.GetWeight(
63                 gx, gy, gz, self.pos[i], self.weight_CIC)
64             zeros += weight
65             zeros[1, :, :] += zeros[-1, :, :]
66             zeros[-2, :, :] += zeros[0, :, :]
67             zeros[:, 1, :] += zeros[:, -1, :]
68             zeros[:, -2, :] += zeros[:, 0, :]
69             zeros[:, :, 1] += zeros[:, :, -1]
70             zeros[:, :, -2] += zeros[:, :, 0]
71             grid = zeros[1:-1, 1:-1, 1:-1]
72             assert grid.sum() == self.pos.shape[0]
73             assert grid.shape == (self.Ng, self.Ng, self.Ng)
74             return grid
75
76     def testGrid_CIC_CA(self):
77         from CosmAna import CIC as Assign
78         self.pos[self.pos == self.Boxsize] -= self.Boxsize
79         grid = Assign(self.pos,
80                       Ng=self.Ng,
81                       L=self.Boxsize)
82         grid = grid.reshape(self.Ng, self.Ng, self.Ng)
83         assert grid.sum() == self.pos.shape[0]
84         grid_true = self.CIC()
85         assert np.allclose(grid, grid_true)
86
87     def testGrid_CIC_ffl(self):
88         self.pos[self.pos == self.Boxsize] -= self.Boxsize
89         grid = cic(self.pos,
90                   Ng=self.Ng,
91                   L=self.Boxsize)
92         print('+ '*80)
93         print('test:')
94         print(grid)
95         assert grid.sum() == self.pos.shape[0]
96         grid_true = self.CIC()
97         print(grid_true)
98         assert np.allclose(grid, grid_true)
99
100     t = testcic()
101     print(t.pos)
102     t.testGrid_CIC_ffl()
103     t.testGrid_CIC_CA()

```

cic.py

```

1 #include <stdio.h>
2 #include <stdlib.h>
3 #include <math.h>
4 #include <memory.h>
5
6 int Index(int N, int x, int y, int z);
7
8 int CIC(int N, int L, int SIZE, float* posx, float* posy, float* posz, float* pout)
9 {
10     int n;
11     int ibin, jbin, kbin, ibinm, ibinp, jbinm, jbinp, kbinm, kbinp;
12     float hx, hy, hz, hx0, hy0, hz0, hxp, hxm, hyp, hym, hzp, hzm;
13     float H = (float)L / (float)N;
14     double value = 1.;
15     double *gridP = (double *)malloc(N * N * N * sizeof(double));
16     memset(gridP, 0, sizeof(double) * N * N * N); // initialization
17
18     for (n = 0; n < SIZE; n++)
19     {
20         ibin = posx[n] / H;
21         jbin = posy[n] / H;
22         kbin = posz[n] / H;
23
24         hx = posx[n] / H - ibin - 0.5;
25         hy = posy[n] / H - jbin - 0.5;
26         hz = posz[n] / H - kbin - 0.5;
27
28         hx0 = 1. - fabs(hx);
29         hy0 = 1. - fabs(hy);
30         hz0 = 1. - fabs(hz);
31
32         if (hx > 0)
33         {
34             hxp = hx;
35             hxm = 0.;
36         }
37         else
38         {
39             hxp = 0.;
40             hxm = -hx;
41         }
42
43         if (hy > 0)
44         {
45             hyp = hy;
46             hym = 0.;
47         }
48         else
49         {
50             hyp = 0.;
51             hym = -hy;
52         }
53
54         if (hz > 0)
55         {
56             hzp = hz;
57             hzm = 0.;
58         }
59         else
60         {
61             hzp = 0.;
62             hzm = -hz;
63         }
64
65         ibinm = (ibin - 1 + N) % N;
66         ibinp = (ibin + 1 + N) % N;
67         jbinm = (jbin - 1 + N) % N;
68         jbinp = (jbin + 1 + N) % N;
69         kbinm = (kbin - 1 + N) % N;
70         kbinp = (kbin + 1 + N) % N;
71
72         gridP[Index(N, ibinm, jbinm, kbinm)] += hxm * hym * hzm * value;

```

```

73     gridP[Index(N, ibinm, jbinm, kbin)] += hxm * hym * hz0 * value;
74     gridP[Index(N, ibinm, jbinm, kbinp)] += hxm * hym * hzp * value;
75     gridP[Index(N, ibinm, jbin, kbinm)] += hxm * hy0 * hzm * value;
76     gridP[Index(N, ibinm, jbin, kbin)] += hxm * hy0 * hz0 * value;
77     gridP[Index(N, ibinm, jbin, kbinp)] += hxm * hy0 * hzp * value;
78     gridP[Index(N, ibinm, jbinp, kbinm)] += hxm * hyp * hzm * value;
79     gridP[Index(N, ibinm, jbinp, kbin)] += hxm * hyp * hz0 * value;
80     gridP[Index(N, ibinm, jbinp, kbinp)] += hxm * hyp * hzp * value;
81
82     gridP[Index(N, ibin, jbinm, kbinm)] += hx0 * hym * hzm * value;
83     gridP[Index(N, ibin, jbinm, kbin)] += hx0 * hym * hz0 * value;
84     gridP[Index(N, ibin, jbinm, kbinp)] += hx0 * hym * hzp * value;
85     gridP[Index(N, ibin, jbin, kbinm)] += hx0 * hy0 * hzm * value;
86     gridP[Index(N, ibin, jbin, kbin)] += hx0 * hy0 * hz0 * value;
87     gridP[Index(N, ibin, jbin, kbinp)] += hx0 * hy0 * hzp * value;
88     gridP[Index(N, ibin, jbinp, kbinm)] += hx0 * hyp * hzm * value;
89     gridP[Index(N, ibin, jbinp, kbin)] += hx0 * hyp * hz0 * value;
90     gridP[Index(N, ibin, jbinp, kbinp)] += hx0 * hyp * hzp * value;
91
92     gridP[Index(N, ibinp, jbinm, kbinm)] += hxp * hym * hzm * value;
93     gridP[Index(N, ibinp, jbinm, kbin)] += hxp * hym * hz0 * value;
94     gridP[Index(N, ibinp, jbinm, kbinp)] += hxp * hym * hzp * value;
95     gridP[Index(N, ibinp, jbin, kbinm)] += hxp * hy0 * hzm * value;
96     gridP[Index(N, ibinp, jbin, kbin)] += hxp * hy0 * hz0 * value;
97     gridP[Index(N, ibinp, jbin, kbinp)] += hxp * hy0 * hzp * value;
98     gridP[Index(N, ibinp, jbinp, kbinm)] += hxp * hyp * hzm * value;
99     gridP[Index(N, ibinp, jbinp, kbin)] += hxp * hyp * hz0 * value;
100    gridP[Index(N, ibinp, jbinp, kbinp)] += hxp * hyp * hzp * value;
101    }
102
103    for (n = 0; n < (N * N * N); n++)
104    {
105        pout[n] = gridP[n];
106    }
107    free(gridP);
108    return 0;
109 }
110
111 int Index(int N, int x, int y, int z)
112 {
113     return x * N * N + y * N + z;
114 }
115 }

```

cic.c

```

1  #!/usr/bin/env python
2  # coding=utf-8
3  from cffi import FFI
4  ffibuilder = FFI()
5
6  ffibuilder.cdef(
7      "int CIC(int N, int L, int SIZE, float* posx, float* posy, float* posz, float* pout);")
8
9  ffibuilder.set_source(
10     "_cic", # name of the output C extension
11     """
12     #include <stdio.h>
13     #include <stdlib.h>
14     #include <math.h>
15     #include <memory.h>
16     """ ,
17     sources=['cic.c'], # includes cic.c as additional sources
18     include_dirs=['./'],
19     # library_dirs=[],
20     libraries=['m']) # on Unix, link with the math library
21
22 if __name__ == "__main__":
23     ffibuilder.compile(verbose=True)

```

libgrid\_build.py