

# Hz\_code

June 3, 2019

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In [1]: %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import scipy
import pandas as pd
import lmfit
import astropy
import astropy.units as u
import corner
from astropy.cosmology import FlatwOwaCDM

In [2]: # Astropy.cosmology version. Here I am using FlatwowaCDM because it has less parameters
def Hz1(z1, H01, Om1, w01, wa1):
    cosmo = FlatwOwaCDM(H0=H01* u.km / u.s / u.Mpc, Om0=Om1, w0=w01, wa=wa1)
    #the redshift dependence of the dark energy density:
    I = cosmo.de_density_scale(z1)
    E = np.sqrt((Om1*(1+z1)**3.) + (1.-Om1)*I)
    HZ1 = H01*E
    return HZ1

In [3]: #Define random redshifts
num_zs = 1000
zs = np.linspace(0.01, 3., num=num_zs)

In [4]: #From Planck observations for CPL mode
O_m= 0.3029
w_0= -0.9414
w_1= -0.4303
H_0= 68.5265

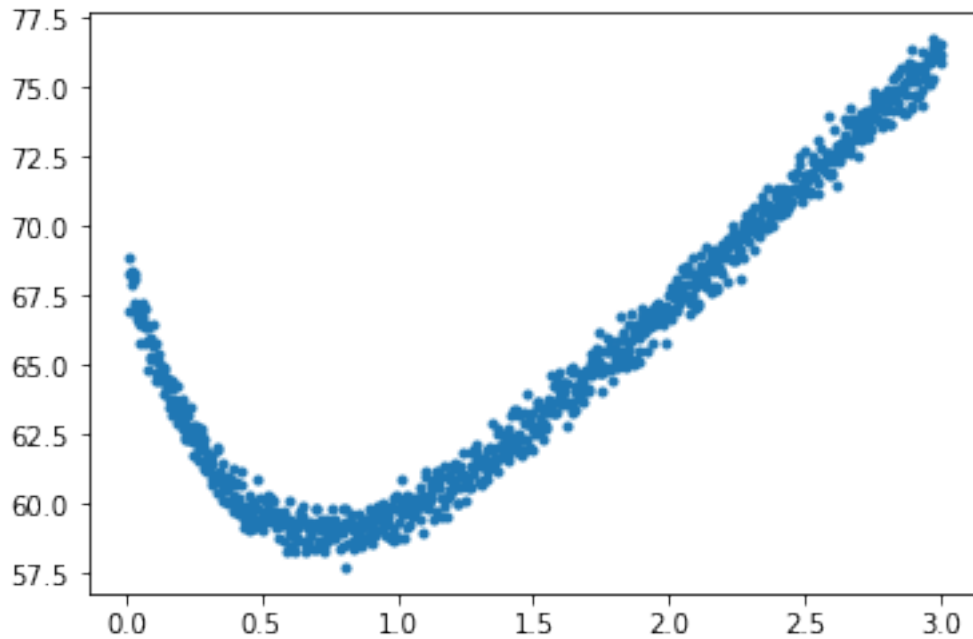
In [5]: #Hubble comoving parameter
Hz=Hz1(zs, H_0, O_m, w_0, w_1)/(1+zs)

In [6]: #random error for Hz
error_sigma = 0.5
e1 = np.random.normal(0., error_sigma, Hz.shape)

In [7]: H_zz= Hz + e1
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In [8]: plt.plot(zs,H_zz, '.')
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Out[8]: [<matplotlib.lines.Line2D at 0x7f0fc55d94d0>]
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In [9]: p = lmfit.Parameters()
p.add_many(('Om1',0.3,True,0.,2.),
           ('H01',70.0,True,50.,100.),
           ('w01',-1.0,True,-2.,2.),
           ('wa1',-0.1,True,-1.,1.))

def residual(p):
    v = p.valuesdict()
    return (Hz1(zs,v['H01'],v['Om1'],v['w01'],v['wa1'])-H_zz)/error_sigma

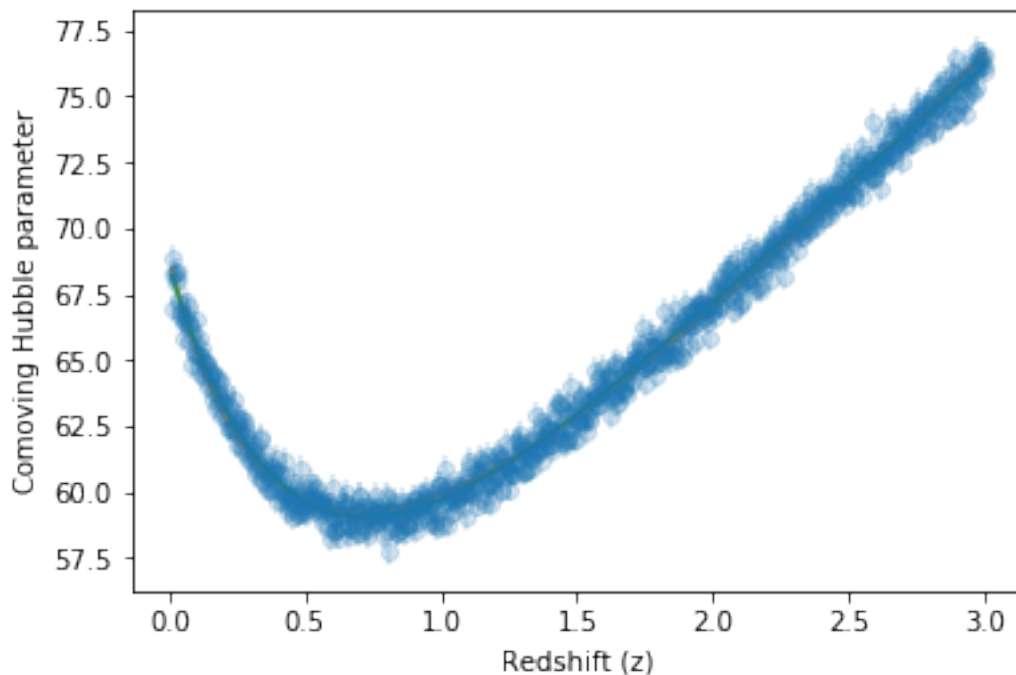
In [10]: mi = lmfit.minimize(residual, p, method='leastsq', nan_policy='omit')

In [11]: plt.errorbar(zs,H_zz,yerr=error_sigma,fmt='o',alpha=0.2)
bestOm1 = mi.params.valuesdict()['Om1']
bestH01 = mi.params.valuesdict()['H01']
bestw01 = mi.params.valuesdict()['w01']
bestwa1 = mi.params.valuesdict()['wa1']
plt.plot(zs,H_z1(zs,bestH01,bestOm1,bestw01,bestwa1))
plt.plot(zs,H_z)
plt.xlabel('Redshift (z)')
plt.ylabel('Comoving Hubble parameter')
lmfit.report_fit(mi)
```

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[[Fit Statistics]]
# fitting method      = leastsq
# function evals      = 63
# data points         = 1000
# variables            = 4
chi-square            = 1054.64781
reduced chi-square    = 1.05888334
Akaike info crit      = 61.2068816
Bayesian info crit    = 80.8379027
[[Variables]]
Om1:  6.2587e-04 +/- 3.3977e-04 (54.29%) (init = 0.3)
H01:  68.8925464 +/- 0.09522049 (0.14%) (init = 70)
w01: -1.41561150 +/- 0.00467824 (0.33%) (init = -1)
wa1:  1.00000000 +/- 0.00109956 (0.11%) (init = -0.1)
[[Correlations]] (unreported correlations are < 0.100)
C(Om1, wa1) = -0.959
C(w01, wa1) = -0.957
C(H01, w01) = -0.898
C(Om1, w01) =  0.839
C(H01, wa1) =  0.770
C(Om1, H01) = -0.613

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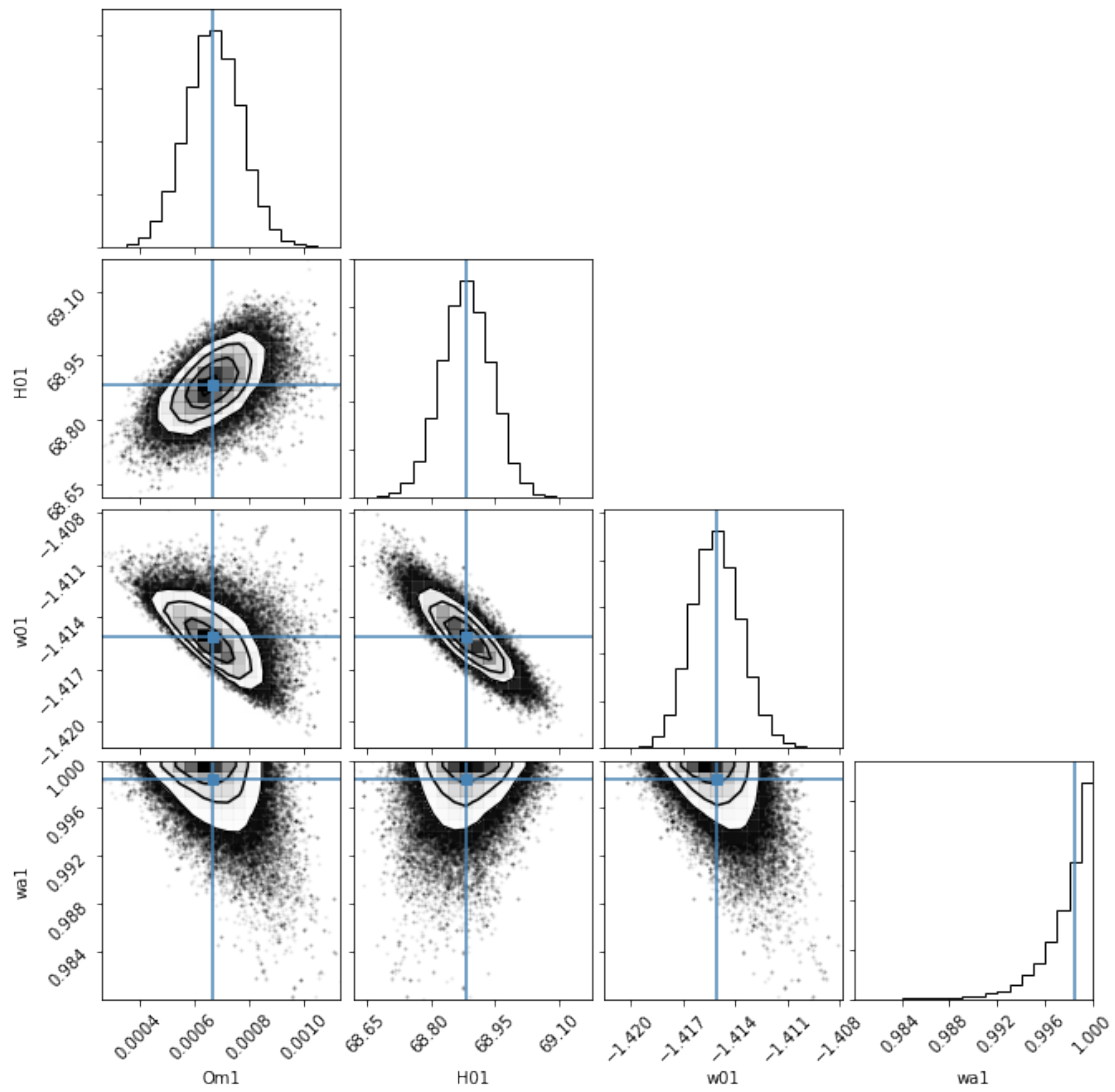
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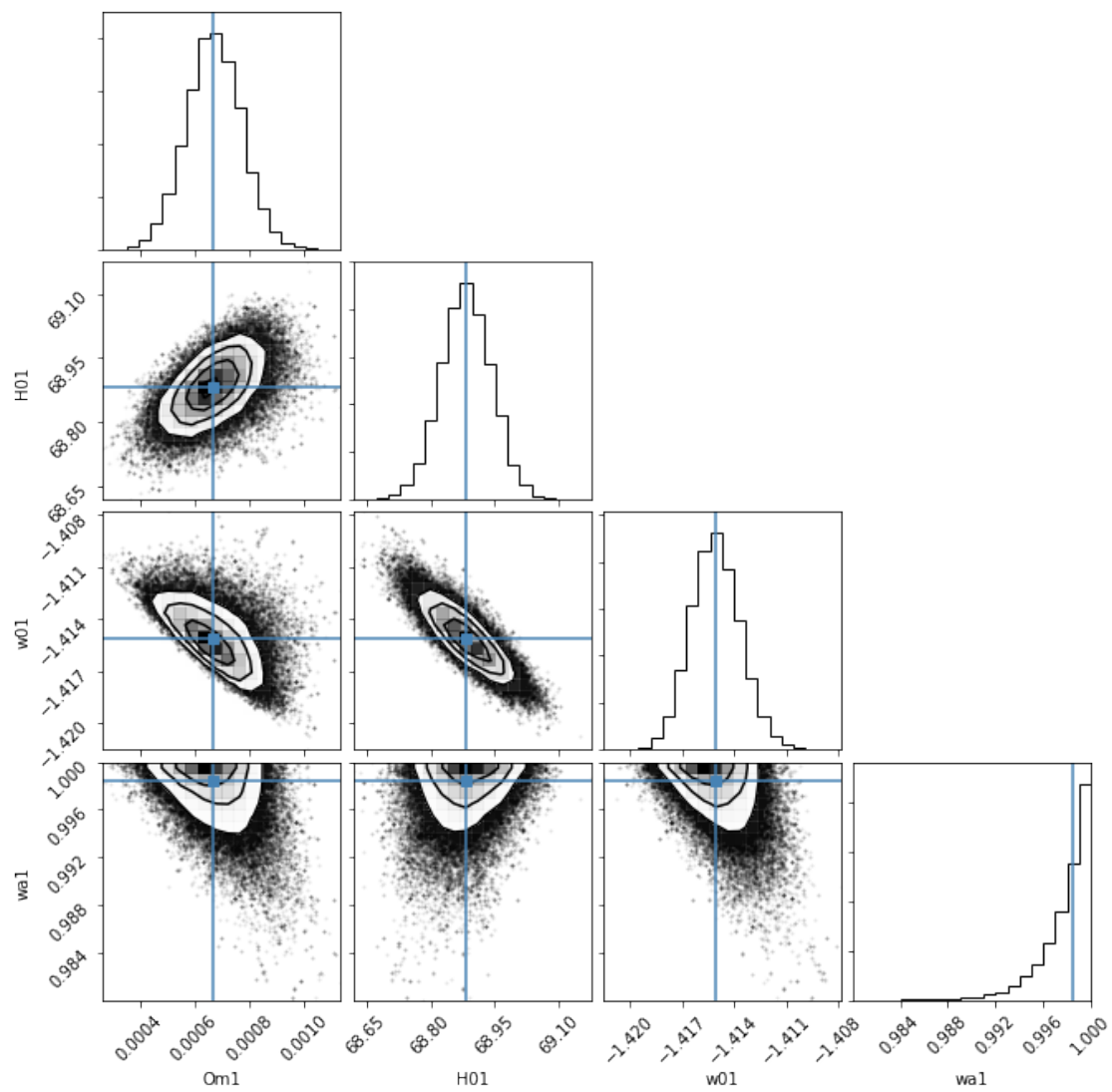
In [14]: res = lmfit.minimize(residual, method='emcee', nan_policy='omit', burn=300, steps=1500,
                             params=p, is_weighted=True)

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In [15]: corner.corner(res.flatchain, labels=res.var_names, truths=list(res.params.valuesdict()))
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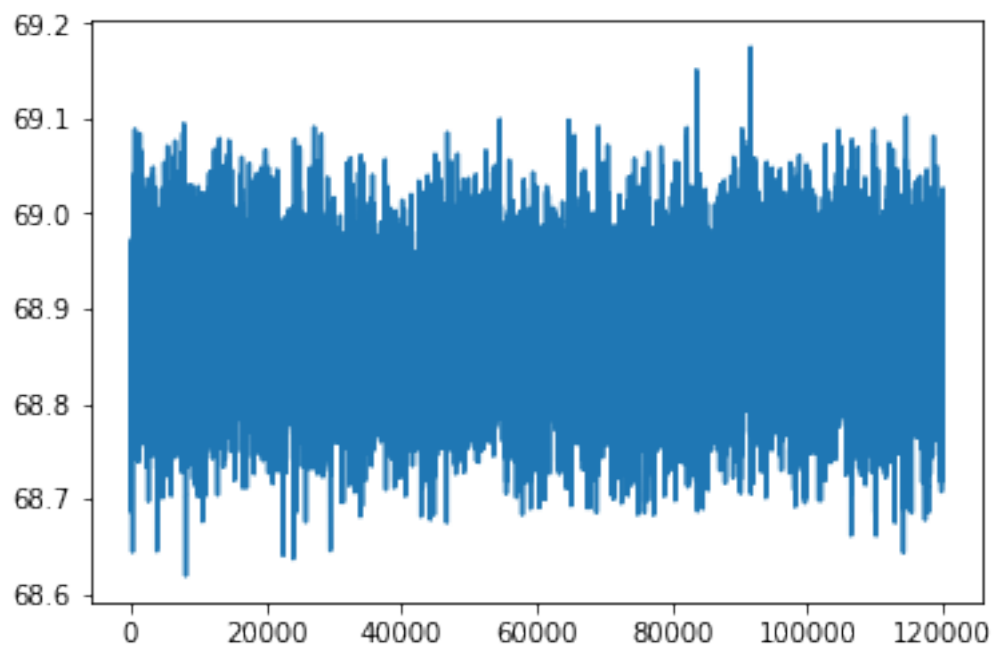
Out[15]:





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In [16]: plt.plot(res.flatchain.H01)
```

```
Out[16]: [<matplotlib.lines.Line2D at 0x7f0fc0f70090>]
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In [ ]: