In [1]:	<pre>import numpy as np import matplotlib.pyplot as plt from time import time import pandas as pd from scipy.constants import c</pre>
In [2]:	<pre># Import Hubble H(z) data hubble_data = pd.read_csv('hubble_data.csv', header=0) z_H = np.array(hubble_data['z'])</pre>
	<pre>H = np.array(hubble_data['H']) dH = np.array(hubble_data['dH']) plt.figure() plt.errorbar(z_H, H, yerr=dH, marker = '.', color='blue', ecolor='black', capsize=2, ls='none') plt.ylabel(r'\$H(z)\$') plt.xlabel(r'\$z\$')</pre>
	<pre>plt.show() # Import apparent magnitude m(z) data m_data = pd.read_csv('m_data.txt', sep = ' ', header = 0) m_sys_unc = pd.read_csv('m_sys_unc.txt', sep = ' ', header = 0) m_sys_unc = np.array(m_sys_unc['40']).reshape(40, 40)</pre>
	<pre>tot = m_sys_unc + np.diag(m_data['dmb']**2) z_m = np.array(m_data['zcmb']) m = np.array(m_data['mb']) dm = np.sqrt(np.diag(tot))</pre>
	<pre>plt.figure() plt.errorbar(z_m, m, yerr=dm, marker = '.', color='blue', ecolor='black', capsize=2, ls='none') plt.ylabel(r'\$m(z)\$') plt.xlabel(r'\$z\$') plt.show()</pre>
	<pre># Combine redshifts for likelihood computation later combined_z = [] combined_z.append(z_H) combined_z.append(z_m) # Combine data</pre>
	<pre>combined_data = [] combined_data.append(H) combined_data.append(m) # Combine uncertainties combined_unc = []</pre>
	combined_unc.append(dH) combined_unc.append(dm) 250 200
	50 - 10 1.5 2.0 z
	26 - 24 - 22 - 22 - 20 - 20 - 20 - 20 - 20
	18 -
In [3]:	<pre>"Define logarithmic Model' def logarithmic(z, params): H0 = params[0] b = params[1]</pre>
	<pre>f=b*np.log(1/(1+z)) + 1 return H0*np.sqrt(f*(1+z)**3) 'Define backreaction Model' def backreaction(z, params): H0 = params[0] OM = params[1]</pre>
	<pre>n = params[2] return H0*np.sqrt(OM*((1+z)**3)+(1-OM)*((1+z)**n)) 'Define apparent magnitude function' def ApparentMagnitude(z, Hubble, params):</pre>
	<pre>def integrand_dl(z, Hubble, params): #integrand of luminosity distance formula return params[0]/Hubble(z, params) def dl(z, Hubble, params): #dimensionless luminosity distance at redshift z (input array)</pre>
	<pre>rz_array = np.zeros(len(z)) for i in np.arange(len(z)): rz_each = quad(integrand_dl, 0, z[i],</pre>
In [6]:	<pre>return (1+z)*rz_array return 5*np.log10((c*100/params[0])*dl(z, Hubble, params)) - 19.25 params_logarithmic = [73.37, 0.22] params_backreaction = [73.37, 0.22, 1]</pre>
	<pre>plt.figure() plt.errorbar(z_H, H, yerr=dH, marker = '.', color='blue', ecolor='black', capsize=2, ls='none') plt.plot(z_H, logarithmic(z_H, params_logarithmic), color='red', ls='', label='Logarithmic') plt.plot(z_H, backreaction(z_H, params_backreaction), color='orange', label='Backreaction') plt.legend(loc='best') plt.ylabel(r'\$H(z)\$')</pre>
	<pre>plt.xlabel(r'\$z\$') plt.show() plt.figure() plt.errorbar(z_m, m, yerr=dm, marker = '.', color='blue', ecolor='black', capsize=2, ls='none') plt.plot(z_m, ApparentMagnitude(z_m, backreaction, params_backreaction), color='orange', label='Back Re</pre>
	<pre>action') plt.plot(z_m, ApparentMagnitude(z_m, logarithmic, params_logarithmic), color='red', ls='', label='Log arithmic') plt.legend(loc='best') plt.ylabel(r'\$m(z)\$') plt.xlabel(r'\$z\$') plt.xhow()</pre>
	400 350 - Logarithmic Backreaction
	150 - 100 -
	26 Back Reaction Logarithmic
	$\begin{array}{c} 24 \\ 22 \\ \\ \\ \\ \\ \\ \end{array}$
	16 - 14 - 0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 z
In [7]:	<pre># Logarithmic def Prior_log(cube): #H0 Prior: [0,100] H0_min = 0 H0_max = 100</pre>
	<pre>#b Prior: [0,1] b_min = 0 b_max = 0.8 #Extract values HOprime = cube[0]</pre>
	<pre>bprime = cube[0] bprime = cube[1] H0 = H0prime*(H0_max-H0_min) + H0_min b = bprime*(b_max-b_min) + b_min return np.array([H0, b])</pre>
	<pre>def LogLikelihood_log(params): # calculate the model hubble_model = logarithmic(z_H, params) apparent magnitude model = ApparentMagnitude(z m, logarithmic, params)</pre>
	#calculate the likelihood residual_H = H - hubble_model residual_m = m - apparent_magnitude_model sig_H = 1/dH sig_m = 1/dm
Tn [8]•	<pre>lnL_H = -0.5*np.sum((residual_H*sig_H)**2) lnL_m = -0.5*np.sum((residual_m*sig_m)**2) return lnL_H + lnL_m t i = time()</pre>
111 [0].	<pre>sampler_log = ultranest.ReactiveNestedSampler(['H0', 'b'], LogLikelihood_log, Prior_log) result_log = sampler_log.run() sampler_log.print_results() t_f = time() print('Sampling time: {} s'.format(t_f-t_i))</pre>
	[ultranest] Sampling 400 live points from prior [ultranest] Explored until L=-3e+02 .70 [-258.7123258.7123]* it/evals=5529/7581 eff=76.9948% N=4 00 0 00 [ultranest] Likelihood function evaluations: 7588
	<pre>[ultranest] logZ = -267.9 +- 0.09277 [ultranest] Effective samples strategy satisfied (ESS = 1585.2, need >400) [ultranest] Posterior uncertainty strategy is satisfied (KL: 0.46+-0.08 nat, need <0.50 nat) [ultranest] Evidency uncertainty strategy is satisfied (dlogz=0.23, need <0.5) [ultranest] logZ error budget: single: 0.14 bs:0.09 tail:0.01 total:0.09 required:<0.50 [ultranest] done iterating.</pre>
	logZ = $-267.938 +- 0.232$ single instance: logZ = $-267.938 +- 0.144$ bootstrapped : logZ = $-267.930 +- 0.232$ tail : logZ = $+- 0.010$ insert order U test : converged: True correlation: inf iterations
In [9]:	<pre>b</pre>
In [11]:	<pre>mask_log = np.random.rand(len(scaledweights_log)) < scaledweights_log samples_log = points_log[mask_log, :] # Open saved samples def open_samples(file):</pre>
	<pre>chains = pd.read_csv(file) nparams = len(chains.columns) if nparams == 2: samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]))).T if nparams == 3:</pre>
	<pre>samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]), np.array(chains. iloc[:, 2]))).T if nparams == 4: samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]), np.array(chains.iloc[:, 2]), np.array(chains.iloc[:, 3]))).T return samples</pre>
	<pre># Extract and compile chains logarithmic_chain_1 = samples_log[:,0] # extract chain of HO values logarithmic_chain_2 = samples_log[:,1] # extract chain if OM values #logarithmic_chain_3 = samples_log[:,2] # extract chain if OL values logarithmic_samples = np.vstack((logarithmic_chain_1, logarithmic_chain_2)).T</pre>
	<pre># Save chains and evidence (do not forget) np.savetxt('logarithmic.csv', logarithmic_samples, delimiter=",") np.savetxt('logarithmicz.csv', [[result_log['logz'] , result_log['logzerr']]]) # Open saved chains samples_open = open_samples('logarithmic.csv')</pre>
	<pre>fig = corner.corner(samples_open, labels=[r"\$H_0\$", r"\$b\$", r"\$\Omega_d\$"],color='blue', label_kwargs={ "fontsize": 20},quantiles=[0.16, 0.5, 0.84],</pre>
	$H_0 = 68.47^{+0.16}_{-0.15}$
	$b = 0.68^{+0.01}_{-0.01}$
In [12]:	# Back Reaction def Prior bc (cube):
	<pre>def Prior_bc(cube): #H0 Prior: [0,100] H0_min = 0 H0_max = 100 #OM Prior: [0,1]</pre>
	OM_min = 0 OM_max = 1 #n Prior: [-4,4] n_min = -4 n_max = 4
	<pre>#Extract values HOprime = cube[0] OMprime = cube[1] nprime = cube[2] HO = HOprime*(HO_max-HO_min) + HO_min OM = OMprime*(OM max-OM min) + OM min</pre>
	<pre># calculate the model hubble_model = backreaction(z_H, params) apparent_magnitude_model = ApparentMagnitude(z_m, backreaction, params) #calculate the likelihood residual_H = H - hubble_model</pre>
	<pre>residual_H = H - hubble_model residual_m = m - apparent_magnitude_model sig_H = 1/dH sig_m = 1/dm lnL_H = -0.5*np.sum((residual_H*sig_H)**2) lnL_m = -0.5*np.sum((residual_m*sig_m)**2)</pre>
In [13]:	<pre>return lnL_H + lnL_m t_i = time() sampler_bc = ultranest.ReactiveNestedSampler(['H0', 'OM', 'n'], LogLikelihood_bc, Prior_bc) result_bc = sampler_bc.run() sampler_bc.print_results()</pre>
	<pre>t_f = time() print('Sampling time: {} s'.format(t_f-t_i)) [ultranest] Sampling 400 live points from prior</pre>
	<pre>[ultranest] Explored until L=-4e+01 [-36.502136.5020]* it/evals=6619/13270 eff=51.4297% N=400</pre>
	<pre>[ultranest] logZ error budget: single: 0.16 bs:0.11 tail:0.01 total:0.11 required:<0.50 [ultranest] done iterating. logZ = -48.422 +- 0.262 single instance: logZ = -48.422 +- 0.162 bootstrapped : logZ = -48.413 +- 0.262 tail : logZ = +- 0.010</pre>
	insert order U test: converged: True correlation: inf iterations HO 73.52 +- 0.33 OM 0.230 +- 0.018 n 0.23 +- 0.17 Sampling time: 140.41255617141724 s
In [14]:	<pre>points_bc = np.array(result_bc["weighted_samples"]["points"]) weights_bc = np.array(result_bc["weighted_samples"]["weights"]) scaledweights_bc = weights_bc / weights_bc.max() mask_bc = np.random.rand(len(scaledweights_bc)) < scaledweights_bc samples_bc = points_bc[mask_bc, :]</pre>
In [15]:	<pre># Open saved samples def open_samples(file): chains = pd.read_csv(file) nparams = len(chains.columns)</pre>
	<pre>if nparams == 2: samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]))).T if nparams == 3: samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]), np.array(chains.iloc[:, 2]))).T if nparams == 4:</pre>
	<pre>samples = np.vstack((np.array(chains.iloc[:, 0]), np.array(chains.iloc[:, 1]), np.array(chains. iloc[:, 2]), np.array(chains.iloc[:, 3]))).T return samples # Extract and compile chains</pre>
	<pre>backreaction_chain_1 = samples_bc[:,0] # extract chain of HO values backreaction_chain_2 = samples_bc[:,1] # extract chain if OM values backreaction_chain_3 = samples_bc[:,2] # extract chain if n values backreaction_samples = np.vstack((backreaction_chain_1, backreaction_chain_2, backreaction_chain_3)).T # Save chains and evidence (do not forget) np.savetxt('backreaction.csv', backreaction_samples, delimiter=",") np.savetxt('backreactionz_csv', [[result_bc['logz']], result_bc['logzerr']]])</pre>
	<pre>np.savetxt('backreactionz.csv', [[result_bc['logz'] , result_bc['logzerr']]]) # Open saved chains samples_open = open_samples('backreaction.csv') fig = corner.corner(samples_open, labels=[r"\$H_0\$", r"\$\Omega_m\$", r"\$n\$"],color='blue', label_kwargs={</pre>
	<pre>fig = corner.corner(samples_open, labels=[r"\$H_0\$", r"\$\Omega_m\$", r"\$n\$"],color='blue', label_kwargs={ "fontsize": 20},quantiles=[0.16, 0.5, 0.84],</pre>
	$\Omega_{m} = 0.23^{+0.02}_{-0.02}$
	$n = 0.24^{+0.16}_{-0.16}$
	C or As
	H_0 Ω_m n