In [4]: import numpy as np import matplotlib.pyplot as plt from time import time import pandas as pd from scipy.constants import c from scipy.integrate import quad #Nested sampling package import ultranest import corner I. Import data In [5]: # Import Hubble H(z) data hubble data = pd.read csv('hubble data.csv', header=0) z_H = np.array(hubble_data['z']) 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\$') 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) 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)) 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() # Combine redshifts for likelihood computation later combined z = []combined_z.append(z_H) combined z.append(z m) # Combine data combined data = [] combined data.append(H) combined data.append(m) # Combine uncertainties combined unc = [] combined_unc.append(dH) combined_unc.append(dm) 250 ł 200 150 1.0 1.5 0.0 0.5 2.0 26 24 22 (X) EL 20 18 16 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 II. Define models In [36]: 'Define Inverse Monomial model' def InverseMonomial(z, params): H0 = params[0]B = params[1]**return** H0*np.sqrt((1/(1+B*z))*(1+z)**3) 'Define Exponential Model' def Exponential(z, params): H0 = params[0]B = params[1]**return** H0*np.sqrt(np.exp(B*((1/(1+z))-1))*(1+z)**3) 'Define apparent magnitude function' def ApparentMagnitude(z, Hubble, params): 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) rz array = np.zeros(len(z)) for i in np.arange(len(z)): rz_each = quad(integrand_dl, 0, z[i], args = (Hubble, params))[0] rz_array[i] = rz_each return (1+z) *rz_array **return** 5*np.log10((c*100/params[0])*d1(z, Hubble, params)) - 19.25 In [43]: | params InverseMonomial = [72.21, 1] $params_Exponential = [73.37, 1.5]$ plt.figure() plt.errorbar(z_H, H, yerr=dH, marker = '.', color='blue', ecolor='black', capsize=2, ls='none') plt.plot(z H, InverseMonomial(z H, params InverseMonomial), color='red', label='InverseMonomial') plt.plot(z H, Exponential(z H, params Exponential), color='orange', label='Exponential') plt.legend(loc='best') plt.ylabel(r'\$H(z)\$') 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, InverseMonomial, params InverseMonomial), color='orange', label='I nverse Monomial') plt.plot(z_m, ApparentMagnitude(z_m, Exponential, params_Exponential), color='red', ls='--', label='Exp onential') plt.legend(loc='best') plt.ylabel(r'\$m(z)\$') plt.xlabel(r'\$z\$') plt.show() InverseMonomial 250 Exponential LogarithmicModel 200 100 50 0.5 1.0 1.5 2.0 0.0 26 Inverse Monomial Exponential --- LogarithmicModel 24 22 (Z) EL 20 18 16 14 0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 III. Nested Sampling: Inverse Monomial def Prior_InverseMonomial(cube): #H0 Prior: [0,100] $H0 \min = 0$ $H0 \max = 100$ #B Prior: [0,4] $B \min = 0$ $\mathsf{B}\ \mathsf{max}\ =\ 4$ #M Prior: [0,1] #M min = -21 $\#M \; max = -18$ #Extract values HOprime = cube[0]Bprime = cube[1]#OLprime = cube[2] #Mprime = cube[3] $H0 = H0prime*(H0_max-H0_min) + H0_min$ B = Bprime*(B_max-B_min) + B_min #OL = OLprime*(OL max-OL min) + OL min $\#M = Mprime*(M_max-M_min) + M_min$ return np.array([H0, B]) def LogLikelihood InverseMonomial(params): # calculate the model hubble_model = InverseMonomial(z_H, params) apparent_magnitude_model = ApparentMagnitude(z_m, InverseMonomial, params) #calculate the likelihood residual_H = H - hubble_model residual_m = m - apparent_magnitude_model sig H = 1/dHsig m = 1/dm $lnL_H = -0.5*np.sum((residual_H*sig_H)**2)$ $lnL_m = -0.5*np.sum((residual_m*sig_m)**2)$ return lnL_H + lnL_m In [57]: | t i = time() sampler InverseMonomial = ultranest.ReactiveNestedSampler(['H0', 'B'], LogLikelihood InverseMonomial, P rior InverseMonomial) result_InverseMonomial = sampler_InverseMonomial.run() sampler_InverseMonomial.print_results() t f = time()print('Sampling time: {} s'.format(t_f-t_i)) [ultranest] Sampling 400 live points from prior ... [ultranest] Explored until L=-5e+01 [-53.9015..-53.9015]*| it/evals=5294/7293 eff=76.8026% N=400[ultranest] Likelihood function evaluations: 7296 [ultranest] logZ = -62.53 + -0.0995[ultranest] Effective samples strategy satisfied (ESS = 1561.6, need >400) [ultranest] Posterior uncertainty strategy is satisfied (KL: 0.46+-0.07 nat, need <0.50 nat) [ultranest] Evidency uncertainty strategy is satisfied (dlogz=0.20, need <0.5) [ultranest] logZ error budget: single: 0.14 bs:0.10 tail:0.01 total:0.10 required:<0.50 [ultranest] done iterating. logZ = -62.531 + - 0.179single instance: logZ = -62.531 + -0.139bootstrapped : logZ = -62.532 +- 0.179: logZ = +- 0.010insert order U test : converged: True correlation: inf iterations ΗO 72.93 +- 0.30В 1.970 +- 0.076 Sampling time: 46.60527491569519 s In [58]: points_InverseMonomial= np.array(result_InverseMonomial["weighted_samples"]["points"]) weights_InverseMonomial= np.array(result_InverseMonomial["weighted_samples"]["weights"]) scaledweights_InverseMonomial = weights_InverseMonomial / weights_InverseMonomial.max() mask_InverseMonomial = np.random.rand(len(scaledweights_InverseMonomial)) < scaledweights_InverseMonomi</pre> al samples_InverseMonomial = points_InverseMonomial[mask_InverseMonomial, :] In [59]: # Open saved samples def open samples(file): 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 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 # Extract and compile chains InverseMonomial_chain_1 = samples_InverseMonomial[:,0] # extract chain of HO values InverseMonomial_chain_2 = samples_InverseMonomial[:,1] # extract chain if OM values #lcdm_chain_3 = samples_LCDM[:,2] # extract chain if OL values InverseMonomial_samples = np.vstack((InverseMonomial_chain_1, InverseMonomial_chain_2)).T # Save chains and evidence (do not forget) np.savetxt('InverseMonomial_chains.csv', InverseMonomial_samples, delimiter=",") np.savetxt('InverseMonomial Z.csv', [[result InverseMonomial['logz'] , result InverseMonomial['logzerr' # Open saved chains #samples_open = open_samples('InverseMonomial_chains_Aug11_9PM.csv') fig = corner.corner(InverseMonomial_samples, labels=[r"\$H_0\$", "b"],color='blue', label_kwargs={"fontsi ze": 20}, quantiles=[0.16, 0.5, 0.84], show_titles=True, title_kwargs={"fontsize": 20}) fig.savefig('InverseMonomial.pdf') $H_0 = 72.92^{+0.30}_{-0.28}$ $b = 1.97^{+0.08}_{-0.07}$ v q H_0 b IV. Nested Sampling: Exponential Model In [60]: def Prior_Exponential(cube): #H0 Prior: [0,100] $H0 \min = 0$ $H0 \max = 100$ #B Prior: [0,4] $B \min = 0$ $B_max = 4$ #M Prior: [0,1] #M min = -21 $\#M \; max = -18$ #Extract values HOprime = cube[0]Bprime = cube[1]#OLprime = cube[2] #Mprime = cube[3] $H0 = H0prime*(H0_max-H0_min) + H0_min$ B = Bprime*(B_max-B_min) + B_min #OL = OLprime*(OL_max-OL_min) + OL_min $\#M = Mprime*(M_max-M_min) + M_min$ return np.array([H0, B]) def LogLikelihood Exponential(params): # calculate the model hubble model = Exponential(z H, params) apparent_magnitude_model = ApparentMagnitude(z_m, Exponential, params) #calculate the likelihood residual H = H - hubble modelresidual_m = m - apparent_magnitude_model $sig_H = 1/dH$ $sig_m = 1/dm$ $lnL_H = -0.5*np.sum((residual_H*sig_H)**2)$ $lnL_m = -0.5*np.sum((residual_m*sig_m)**2)$ return lnL H + lnL m In [61]: | t_i = time() sampler_Exponential = ultranest.ReactiveNestedSampler(['H0', 'B'], LogLikelihood_Exponential, Prior_Exp result_Exponential = sampler_Exponential.run() sampler_Exponential.print_results() $t_f = time()$ print('Sampling time: {} s'.format(t_f-t_i)) [ultranest] Sampling 400 live points from prior ... [ultranest] Explored until L=-4e+01 [-38.0629..-38.0629]*| it/evals=5360/7377 eff=76.8238% N=400 [ultranest] Likelihood function evaluations: 7396 [ultranest] logZ = -46.88 + -0.07376[ultranest] Effective samples strategy satisfied (ESS = 1553.8, need >400) [ultranest] Posterior uncertainty strategy is satisfied (KL: 0.46+-0.06 nat, need <0.50 nat) [ultranest] Evidency uncertainty strategy is satisfied (dlogz=0.17, need <0.5) [ultranest] logZ error budget: single: 0.14 bs:0.07 tail:0.01 total:0.07 required:<0.50 [ultranest] done iterating. logZ = -46.883 +- 0.168single instance: logZ = -46.883 +- 0.140bootstrapped : logZ = -46.883 + -0.168tail : logZ = +- 0.010insert order U test : converged: True correlation: inf iterations 73.31 +- 0.26 2.119 +- 0.050Sampling time: 39.31010365486145 s In [63]: points_Exponential = np.array(result_Exponential["weighted_samples"]["points"]) weights_Exponential = np.array(result_Exponential["weighted_samples"]["weights"]) scaledweights_Exponential = weights_Exponential/ weights_Exponential.max() mask_Exponential = np.random.rand(len(scaledweights_Exponential)) < scaledweights_Exponential samples_Exponential = points_Exponential[mask_Exponential, :] In [64]: # Open saved samples def open_samples(file): 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 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 # Extract and compile chains Exponential_chain_1 = samples_Exponential[:,0] # extract chain of HO values Exponential_chain_2 = samples_Exponential[:,1] # extract chain if OM values #lcdm chain 3 = samples LCDM[:,2] # extract chain if OL values Exponential_samples = np.vstack((Exponential_chain_1, Exponential_chain_2)).T # Save chains and evidence (do not forget) np.savetxt('Exponential_chains.csv', Exponential_samples, delimiter=",") np.savetxt('Exponential_Z.csv', [[result_Exponential['logz'] , result_Exponential['logzerr']]]) # Open saved chains #samples open = open samples('InverseMonomial chains Aug11 9PM.csv') fig = corner.corner(Exponential_samples, labels=[r"\$H_0\$", "b"],color='blue', label_kwargs={"fontsize": 20}, quantiles=[0.16, 0.5, 0.84], show titles=True, title kwargs={"fontsize": 20}) fig.savefig('Exponential.pdf') $H_0 = 73.31^{+0.26}_{-0.25}$ $b = 2.12^{+0.05}_{-0.05}$ 224 236 208 H_0 b