

Cosmology School in the Canary Islands Fuerteventura, 18-22 September 2017

Bayesian estimation of cosmological parameters with CosmoMC & MontePython

Antonio J. Cuesta Universidad de Córdoba, Spain Cosmology School in the Canary Islands, Fuerteventura 18/09/2017



1.02

0.04

1.038 1.040 1.042

0.225 0.0250 0.027 Ω. h²

 $\Omega_{-}h^{2}$

190 3.04 3.

5.20 0.93 0.90

.02 0.04 0.08 0.12

Outline (keeping it simple...)

- Motivation & Initial remarks
- Generic steps when running MCMC's
- Introduction to MontePython
- Introduction to CosmoMC

Introduction & Motivation

What is all this about?

- Cosmological models have parameters (matter density Ω_m , Hubble constant H₀, ...) For example, $\Lambda CDM = \{ \Omega_b h^2, \Omega_c h^2, H_0 \text{ (or } \theta_s), A_s \text{ (or } \ln 10^{10}A_s), n_s, \tau_{reio} \}$
- We want to know the value and the error of those parameters (mean and rms).
- Ideally, we want the full probability distribution function (pdf) for each parameter, and even the full joint distribution for all the parameters together $P(\theta_1, \theta_2, \theta_3, ...)$
- The limits on the possible values of those parameters (Isigma=68.3% confidence, 2sigma=95.4%, 3sigma=99.7%...) can be obtained in a Bayesian way, in which the prior knowledge of the parameters will play an important role $P(\theta|\mathbf{x})=P(\theta)\mathscr{L}(\mathbf{x}|\theta)$

What is all this about?

- The resulting constraints on each parameter will depend on these two ingredients: the DATA you input (each experiment targets a different cosmological probe) the MODEL studied (each model contains a different number of free parameters)
- In general, a model with *more* free parameters will usually provide *weaker* constraints, but also provides a better fit: more parameters can accommodate more features, (hence returning a lower χ^2) although not necessarily will improve the *bayesian evidence*

Cosmological parameter estimation

You can estimate parameters by eye (not recommended)...

CMB Simulator

Use the sliders below to change the constituents of the Universe and see how it affects the Cosmic Microwave Background. You can toggle the power spectrum using the middle of the three buttons in the top right.

Normal Matter ((Ω _b = 0.05)	
Dark Matter (Ω _c	; = 0.25)	
Dark Energy (Ω,	∧ = 0.7)	
600		Our univers
R	Star 2 Star	Our univers
		Our univers
		Our univer

This tool was created for a Planck exhibit at the Royal Society Summer Science Exhibition 2013. You can see details of how it was written on Stuart Lowe's blog. If you'd like to use it elsewhere, then you can embed it in your site, or download the source-code from the Github repository.

http://planck.cf.ac.uk/cmb-sim

Cosmological parameter estimation

Or we can estimate parameters quantitatively In cosmology there are two major codes for this: CosmoMC and MontePython (& Cosmosis, PICO,...)



http://cosmologist.info/cosmomc/

Monte Python

The Monte Carlo code for CLASS in Python

http://baudren.github.io/montepython.html

Why CosmoMC?

- It has been used in many papers! (2000+ citations to Lewis & Bridle 2002)
- Usually new data (likelihood codes) are typically available first in CosmoMC
- It has a GUI to analyze the chains!! (but you can use it for MontePython chains too)
- Its Boltzmann solver, CAMB (based on CMBFAST) has been extensively used for a long time

• Lots of tools to run this code in a cluster Capabilities to run batches of models, MPI/OpenMP parallelization

Why MontePython?

- It is very easy to get started! (we'll see that in the afternoon hands-on session)
- It is written in Python: the code is easy to read and easy to modify
- Its Boltzmann solver (the code to compute the evolution of perturbations) is CLASS: (or hi-class) a direct transcript of the equations in <u>astro-ph/9506072</u> (Ma & Bertschinger 1995) very well commented, so less pain to implement new physics (if not already built-in)
- It is completely agnostic about cosmology: if you define a new parameter in CLASS, you don't need to modify MontePython

Running Markov Chain Monte Carlo (MCMC)

MCMC: How-To? Breaking the code into individual tasks

- <u>Step I</u>: Choose a point in the parameter space (*walk* the parameter space)
- <u>Step 2</u>: Solve the Boltzmann equations for those values of the parameters which are translated into the observables P(k), D(z), C_{ℓ} ...
- <u>Step 3</u>: Evaluate the likelihood of this point for each dataset (CMB, BAO, SNe...) by comparing observables with the measurements (evaluation of χ^2)
- <u>Step 4</u>: Compute the total likelihood, and Accept the point if the likelihood is larger (-Inlike smaller), or reject it otherwise, then move to another point (step I)
- <u>Step 5</u>: After you have RUN the chains (i.e. after getting enough points to sample the posterior distribution) the final step is to do an ANALYSIS of the results

Step I: walk a parameter space (low-d case)

• If the number of dimensions d is small (ID or 2D), then a grid (discretized) would suffice, but this is not true in cosmology (even ACDM has already 6 parameters)



Number of (potentially) visited points: N^d (grows exponentially with d).
 N depends on how fine the spatial discretization (resolution) you want it to be.
 Usually one computes the distribution in all the points (even away from the peak).

Step I: walk a parameter space (high-d case)

• If the number of dimensions is large, it is not feasible nor efficient to do a grid



unimodal distribution \rightarrow different initial conditions will converge to the same region

 It is better to do a *random walk*, in which there is some kind of "dragging force" towards the high likelihood region plus a thermal bath to move around the peak (the goal is not to find the maximum -- it is to sample points from the distribution)

The Metropolis-Hastings algorithm

This is exactly what the Metropolis-Hastings algorithm does:

If you are at location x, pick a location y (within some search radius from x):

- If P(y) > P(x), jump there, and store y in the list of visited points
- If P(y) < P(x), then pick a uniform random number r between 0 and 1:
 - If r < P(y)/P(x), jump there, and store y to the list of visited points
 - If r > P(y)/P(x), do not jump there, and store x (again) to the list of visited points

Cycle over this loop until you get enough points (~10⁵), or better, until a *convergence criterion* is achieved (see next slide)

Remember: In general x and y will be *d*-dimensional vectors, with as many components as parameters you want to determine

When MCMC is considered "converged"?

- The most common criterion is the R diagnostic by Gelman & Rubin (1992).
 This diagnostic is defined for each parameter, so we focus on a single parameter θ.
- Suppose all chains have length N (each chain has N steps) and we have run M chains.
- Each chain "m" will return a different mean μ_m and variance σ^2_m for the parameter θ .
- The variance of the means μ_m (times N) is called the variance "between chains" B.
- The mean of the variances σ^{2}_{m} is called the variance "within chains" W.
- The R parameter is then defined as (see Brooks & Gelman 2007 for exact formulae):

$$\hat{R} = \sqrt{1 + (1/N)(B/W)}$$

Typically, a *R-1* value of <0.03 (ideally <0.01) for <u>all parameters</u> is considered good enough

So when all chains return roughly the same $\mu_m \& \sigma_m$ if the Central Limit Theorem applies (so $B \simeq W$) we have that R-1 goes to zero as N goes to ∞

Step 2: Solve the Boltzmann equations

(already covered in the previous sessions...)

• CAMB and CLASS are written to solve efficiently the evolution of each component (baryons, neutrinos, photons, dark matter, dark energy, metric...)

Synchronous gauge -

$$\begin{split} \dot{\delta} &= -(1+w)\left(\theta+\frac{\dot{h}}{2}\right) - 3\frac{\dot{a}}{a}\left(\frac{\delta P}{\delta\rho} - w\right)\delta\,, \\ \dot{\theta} &= -\frac{\dot{a}}{a}(1-3w)\theta - \frac{\dot{w}}{1+w}\theta + \frac{\delta P/\delta\rho}{1+w}\,k^2\delta - k^2\sigma\,, \end{split}$$

Conformal Newtonian gauge -

$$\begin{split} \dot{\delta} &= -(1+w)\left(\theta - 3\dot{\phi}\right) - 3\frac{\dot{a}}{a}\left(\frac{\delta P}{\delta\rho} - w\right)\delta\,, \\ \dot{\theta} &= -\frac{\dot{a}}{a}(1-3w)\theta - \frac{\dot{w}}{1+w}\theta + \frac{\delta P/\delta\rho}{1+w}\,k^2\delta - k^2\sigma + k^2\psi\,. \end{split}$$

and many others...



<u>http://class-code.net/</u>

• This is the part of the code you do not have to worry about (UNLESS you want to constrain non-standard cosmologies, which YOU will have to implement)

Step 3: Evaluate the likelihood(s)

likelihood value or Likelihood parameter values at this MCMC step chi-squared value code Ho Ω_{b} $\left(\frac{\text{theory value} - \text{measured value}}{\text{measured error}}\right)$ $2_{\rm m}$ ns As

CosmoMC and MontePython will report -In (likelihood) = $\chi^2/2$ (Gaussian case, Wick's Theorem) Here "value" can be a MCMC parameter (e.g. H₀) or a function of them (an observable, like P(k) or σ_8) WARNING: If "value" is NOT a MCMC parameter, it might depend on the (cosmological) model!

Cosmological probes (and most commonly used observables)



Cosmological probes (and most commonly used observables)

SS











Step 3: Evaluate the likelihood(s)

1. Release history

accepted):

likelihood code

V1 (January 2014,

paper submitted's

V2 (March 2014):

V4 (June 2014): V5 (March 2015):

V6 (March 2015): 2. Installation of the C++

Installation of the

cosmome plugir

V3 (April 2014, paper



http://pla.esac.esa.int/pla/#home



cosmological-data-products

SDSS-II/SNLS3 Joint Light-curve Analysis

This page contains links to data associated with the SDSS-II/SNLS3 Joint Light-Curve Analysis (Betoule et al. 2014, submitted to ABA).

The release consists in:

- The end products of the analysis and a C++ code to compute the likelihood of this data associated to a cosmological model. The code enables both evaluations of the complete likelihood, and fast evaluations of an approximate likelihood (see Betoule et al. 2014, Appendix E).
- The version 2.4 of the SALT2 light-curve model used for the analysis plus 200 random realizations usable for the propogation of model uncertainties.
- 3. The exact set of Supernovae light-curves used in the analysis.

We also deliver presentation material.

Since March 2014, the JLA likelihood plugin is included in the official release of cosmomc. For older versions, the plugin is still available (see below: Installation of the cosmomc plugin).

To analyze the JLA sample with SNANA, see \$SNDATA_ROOT/sample_input_files/JLA2014/AAA_README.

http://supernovae.in2p3.fr/ sdss snls jla/ReadMe.html

SDSS Summe Results Instruments Data Releases Education Collaboration Future Contact **BOSS** Publications and Results Science Results : Press Raleman SOSS-II Beg BOSS Overview Paper The motivation for BOSS and an overview of target selection, survey design, and observing strategy are described in Dawson et al. 2013, The Bar , published in the described in Dawson et al. 2013, The Baryon Capitation Spectroscopic Survey of SDSS-III, publis January 2013 issue of Astronomical Journal. A preprint style PDF of the paper is available on this site. --DR12 Galaxy Clustering Science Results I MARKED Here we list the series of papers that comprise the final data analysis of the BOSS galaxy survey, with links to measurements, covariance matrices, likelihoods, and figures. For quick reference, all files can be found on the SDSS SAS here. These papers represent analysis of the "combined" sample of DR12 galaxies. Previous DR12 - -: Image Gallery analyses (as well as the anisyses of data releases 9 through 11) split the BOSS galaxy sample into two main target classifications of LOWZ and CMASS. DR12 Combined-Sample Concensus Results and Support Papers · The clustering of galaxies in the completed SDSS-III Baryon Oscillation Spectroscopic Survey: cosmological analysis of the DR12 galaxy sample. Aliam et al 2016 (alphabetically authored paper). Gaussian likelihoods from the individual measurements of BAO and Full-shape analyses, and the final concensus likelihood, can be found here. A tarball of all figures presented in the paper can be found here.

http://www.sdss3.org/science/
boss publications.php

Built-in likelihoods in CosmoMC & MontePython

Lots of likelihoods to choose from!

(you can also write your own, if you have the data)

AJCuestaMacBookAir:~ ajcues	ta\$ ls ~/montepython_public/r	montepython/likelihoods/	AJCuestaMacBookAir:CosmoMC ajo	cuesta\$ ls batch2/	a literature constant
BK14	bao_boss	fake_planck_bluebook	BAO.ini	WLHeymans.ini	lowTEB.ini
BK14priors	bao_boss_aniso	gunn_peterson	BAODR11.ini	WLonly.ini	lowl.ini
CFHTLens	bao_boss_aniso_gauss_approx	hst	BAO_RSD.1n1	WLONLYHeymans.ini	lowL_old.ini
CFHTLens_correlation	bao_known_rs	hst_riess	BK14. ini	WMAPTER, ini	params CMR defaults ini
JLA	bicep	igm_temperature	BK14 README.txt	WMAP lowl.ini	pico, ini
JLA_simple	bicep2	lowlike	BK14only.ini	WMAP_tauprior.ini	planck_calibration.ini
Planck_SZ	boomerang	polarbear	BKPlanck	WiggleZ_MPK.ini	plik_dx11dr2_D5_v18_EE.ini
Planck_actspt	cbi	quad	BKPlanck.ini	abundances.ini	plik_dx11dr2_D5_v18_TE.ini
Planck_highl	clik_fake_planck	sdss_lrgDR4	BKPlanck_README.txt	accuracy.ini	plik_dx11dr2_DS_v18_TT.ini
Planck_highl_TTTEEE	clik_wmap_full	sn	HST ini	fix parame ini	plik_dx11dr2_US_V18_TTTEEE.Ini
Planck_highl_lite	clik_wmap_lowl	spt	HST Freeman12, ini	getdist background.ini	plik dx11dr2 HM v18 TE.ini
Planck_lensing	cmb_baryon	spt_2500	HST_GPE70p6.ini	getdist_base.ini	plik_dx11dr2_HM_v18_TT.ini
Planck_lowl	cosmic_clocks_BC03	test_gaussian	HST_GPE72p5.ini	getdist_common.ini	plik_dx11dr2_HM_v18_TTTEEE.ini
WiggleZ	cosmic_clocks_BC03_all	test_nuisance1	HST_high.ini	importance_sampling.ini	plik_lite_TT.ini
WiggleZ_bao	cosmic_clocks_MaStro	test_nuisance2	JLA.ini	lensing.ini	plik_lite_TTTEEE.ini
initpy	da_rec	timedelay	JLA_marge.ini	lensing_aggressive.ini	plik_v18_priors.ini
initpyc	euclid_lensing	wnap	SZ plus CMB, ini	likelihood, ini	zre prior, ini
acbar	euclid pk	wmap 9yr	S7 plus priors ini	lowER ini	ere_pravitana

MontePython likelihoods

fake desi

bao

CosmoMC likelihoods

lowLike, ini

CMB from Planck (TT,TE, EE) and others, BAO (eg. BOSS), SNe (JLA), matter power spectrum, Hubble constant, Bicep/Keck CMB B-modes, Euclid/DESI mock likelihoods (for forecasts),....

WL.ini

Tensions! why not use everything?



 When combining different datasets, one should always keep in mind that some pair of datasets can produce constraints that do not overlap in the d-dimensional parameter space (they might overlap in lower-dimensional plots)



 This can lead to multi-modal posteriors, (potentially) spurious constraints (e.g. claims of non-zero neutrino masses, dynamical dark energy, couplings in the dark sector,...) and to probably too many astro-ph.CO postings every day

try to be minimalistic!

Tensions!



- Well-known examples of dataset tensions are:
 - The Large-Scale Structure (LSS) measurements of matter fluctuation amplitude σ₈
 via weak lensing and those derived from the Cosmic Microwave Background (CMB)





DESY1, arXiv: 1708.01530

• The local measurement of H_0 and its extrapolation from CMB assuming ΛCDM



Bernal et al. arXiv:1607.05617

 Did we under-estimate uncertainties? Is ΛCDM wrong? Is GR/FLRW wrong? Is Planck wrong? (need for massive neutrinos / dark radiation / non-Λ dark energy / other extensions ?)

Step 4: Decide whether to accept the point & Write to file

- Assuming all datasets are independent, the total likelihood is the *product* of the individual likelihoods, so the -log(likelihoods) are *added*
- For a *fixed* model, different datasets will allow different regions of the parameter space. If we combine all datasets, the allowed region will be the *intersection* of the individual allowed regions
- Following the Metropolis-Hastings algorithm, we compare the total likelihood at the new point with the likelihood at the previous point.
- Depending on this comparison, it will move to the new point or otherwise, it will count the previous point twice (the *multiplicity* of the point will be >1)



Step 5: Analysis of the results

Once the chains have converged, we can make different types of summary figures or tables to convey the resulting information



This requires *marginalization*: integrate the *d*-dim PDF over all other parameters



ID Plot (mean values and standard deviations)

2D Plot (correlations, degeneracy directions)

Step 5: Analysis of the results

Once the chains have converged, we can make different types of summary figures or tables to convey the resulting information



This requires *marginalization*: integrate the *d*-dim PDF over all other parameters

se/WHA	◆ ▲ ● ● ●	Parameter	🔁 🔚 🗹 🔪 Parameter t	ables for: ba	se_nnu_mnu_pliki	IM_TTTEEE_I	owTEB	<u>* ^ 0</u>	S 🕂 💕 🛱 🖬 🖉
95%	99% 68% limits	Parameter	X Parameter t	ables for: ba	se_nnu_mnu_pliki	IM_TTTEEE_I	OWTEB		
rameter	68% limits	Parameter							
h ²	0.00045 1.0.000055		68% limits	Parameter	68% limits	Parameter	68% limits	Parameter	68% limits
	0.02215 ± 0.00025	A_{100}^{dustTT}	7.4 ± 1.9	C217	0.9960 ± 0.0015	D ₈₁₀	2535 ± 14	keq	0.01035 ± 0.00012
h^{*}	0.1191 ± 0.0031	$A_{143}^{{ m dust}TT}$	8.9 ± 1.8	H_0	$65.8^{+2.5}_{-1.8}$	D_{1420}	815.1 ± 4.9	$100\theta_{eq}$	0.8118 ± 0.0078
$0\theta_{MC}$	1.04081 ± 0.00045	$A_{143\times217}^{\mathrm{dust}TT}$	17.0 ± 4.2	Ω_{Λ}	$0.668^{+0.028}_{-0.012}$	D2000	230.6 ± 1.9	$100\theta_{s,eq}$	0.4488 ± 0.0040
	0.081 ± 0.018	A_{217}^{dustTT}	81.7 ± 7.4	Ω_m	$0.332^{+0.012}_{-0.028}$	n _{s,0,002}	0.9610 ± 0.0099	$r_{\rm drag}/D_V(0.57)$	$0.0706^{+0.0013}_{-0.00070}$
np	< 0.191	$A_{100}^{\mathrm{dust}EE}$	0.0809 ± 0.0056	$\Omega_m h^2$	$0.1430^{+0.0032}_{-0.0039}$	Yp	0.2443 ± 0.0029	H(0.57)	$91.8^{+1.8}_{-1.6}$
11	2.98 ± 0.20	$A_{100 \times 143}^{dust EE}$	0.0485 ± 0.0050	$\Omega_{\nu}h^2$	$0.00180^{+0.00030}_{-0.0018}$	Y_P^{BBN}	0.2456 ± 0.0029	$D_A(0.57)$	1417+29
$(10^{10}A_s)$	3.095 ± 0.039	$A_{100 \times 217}^{dust EE}$	0.0999 ± 0.033	$\Omega_m h^3$	0.0941 ± 0.0042	$10^5 D/H$	2.608 ± 0.047	$F_{AP}(0.57)$	0.6810+0.0032
	0.9610 ± 0.0099	AdustEE A143	0.0999 ± 0.0069	σ_8	$0.807\substack{+0.043\\-0.021}$	Age/Gyr	$13.95^{+0.22}_{-0.26}$	$f\sigma_{8}(0.57)$	$0.475^{+0.018}_{-0.010}$
d	1.0004 ± 0.0025	$A_{143 \times 217}^{\text{dust}EE}$	0.225 ± 0.047	$\sigma_8 \Omega_m^{0.5}$	0.464 ± 0.011	÷.	1090.07 ± 0.38	$\sigma_{8}(0.57)$	$0.597^{+0.036}_{-0.017}$
CIB	63.6 ± 6.6	AdustEE A217	0.65 ± 0.13	$\sigma_8 \Omega_m^{0.25}$	$0.612\substack{+0.022\\-0.013}$	r.,	145.2 ± 1.9	f_{2000}^{143}	29.4 ± 2.9
Z-CIB		$A_{100}^{{ m dust}TE}$	0.141 ± 0.038	$\sigma_{\rm s}/h^{0.5}$	$0.995^{+0.037}_{-0.019}$	1000,	1.04111 ± 0.00055	$f_{2000}^{143 \times 217}$	32.1 ± 2.2
SZ 43	5.4 ± 1.9	$A_{100 \times 143}^{{ m dust}TE}$	0.132 ± 0.029	$\langle d^2 \rangle^{1/2}$	2.509 ± 0.040	D_{Λ}/Gpc	13.95 ± 0.18	f ²¹⁷ ₂₀₀₀	105.8 ± 2.1
PS 00	259 ± 28	$A_{100\times217}^{{ m dust}TE}$	0.304 ± 0.084	STR.	$10.2^{+1.8}_{-1.5}$	drag	1059.31 ± 0.86	$\chi^2_{\rm low TEB}$	10498.6 ± 2.6
9 <u>S</u> 43	43 ± 8	$A_{143}^{{ m dust}TE}$	0.156 ± 0.054	$10^{9}A_{s}$	2.210 ± 0.085	rdeng	147.9 ± 2.0	$\chi^2_{\rm plik}$	2451.9 ± 7.2
25 43×217	40 ± 10	$A_{143\times217}^{{ m dust}TE}$	0.340 ± 0.080	$10^9 A_s e^{-2\tau}$	1.878 ± 0.018	$k_{\rm D}$	0.1401 ± 0.0014	$\chi^2_{\rm prior}$	19.2 ± 5.5
PS 17	98 ± 10	$A_{217}^{{ m dust}TE}$	1.68 ± 0.26	D_{40}	1246 ± 16	$100\theta_{\rm D}$	0.16079 ± 0.00043	$\chi^2_{\rm CMB}$	12950.5 ± 7.1
SZ	< 4.04	c100	0.99817 ± 0.00077	D220	5728 ± 39	heq	3408 ± 41	-11246223	
		Copy latex					Save lat	ex.	
	θ _{MC} ¹ _ν ff 10 ¹⁰ A _s) ¹ ¹ ¹ ¹ ² ² ³ ³ ³ ³ ³ ³ ³ ³	θ_{MC} 1.04081 ± 0.00045 0.081 ± 0.018 h_{ν} < 0.191	$\begin{array}{r c c c c c c c c c c c c c c c c c c c$	$\begin{array}{r c c c c c c c c c c c c c c c c c c c$	$\begin{array}{r c c c c c c c c c c c c c c c c c c c$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $

Planck's public chains

- Planck released their full analysis (done with CosmoMC) for a comprehensive combination of cosmological models and datasets
- They can be downloaded at <u>http://pla.esac.esa.int/pla</u> (Go to "Cosmology" and then click on "Cosmological parameters)
- The full grid shown in Planck 2015 Paper XIII can be found in the file COM_CosmoParams_base-plikHM_R2.00.tar.gz (3.6GB)
- More information can be found at the ESA/Planck wiki: <u>http://wiki.cosmos.esa.int/planckpla2015/index.php/Cosmological_Parameters</u>

← ⇒	C	pla.esac.esa.int/	pla/#cosmology				☆ ≡	← →	CD	pla.es	ac.esa.int/pla/#results					☆ =
EUROPE	EUROPEAN SPACE AGENCY 🖑 SCIENCE & TECHNOLOGY 🗗 SIGN IN					SIGN IN	EUROPEAN SPACE AGENCY de SCIENCE & TECHNOLOGY de						SIGN IN			
Pla	nck	Legacy A	Archive		-97	·e	esa	Pla	nck l	_eg	acy Archive				es	a
					Release	PR2 - 20	015 👻						Release	PR2 - 2	015	٣
# Q	Ω	PR2 - 2015 C	DSMOLOGY PRODUCTS	i.				11 Q	=	RES	ULTS Close All <<	< PR3	Cosmology #1		-	>
=						Explanate	ry Supplement •	=	Cos	molog	y products (5) X					
		Cosmological	CMB angular	Likelihood	Lensing products	Noise	covariance			0 selec	ted items		10	10	₫ 3	A
8		parameters	power spectra	Lincennood	Centimy products		natrices	8	0		File name	Size	Product type	R	elease	
9								9		-	COM_CosmoParams_base- lensonly_R2.00.tar.gz	13.5 MB	Cosmological Parameters		PR2	
	1	RESULTS								-	COM_CosmoParams_base- plikHM_R2.00.tar.gz	415.3 MB	Cosmological Parameters		PR2	
	17	RESULTS							0		COM_CosmoParams_base-plikHM-TT- lowTEB_R2.00.tar.gz	46.7 MB	Cosmological Parameters		PR2	
		0 selected items				10	II 4		0		COM_CosmoParams_base-r-plikHM- BKP_R2.00.tar.gz	173.4 MB	Cosmological Parameters		PR2	
		0	Description	envides C and	File name		Size		0		COM_CosmoParams_fullGrid_R2.00.tar	3.6 GB	Cosmological Parameters		PR2	
			Planck Likelihood Code. It ;	rovides C and									Parameters			

Grid of

chains

Likelihood

Code

Introduction to MontePython

The CLASSY interface: CLASS Python wrapper

- Since MontePython and CLASS are written in different languages (Python and C) MontePython needs a wrapper to communicate with CLASS at each MCMC step (there is also a pycamb interface to CAMB)
- Much like Montepython does to run, this wrapper can also be used stand-alone:

Terminal: write your_parameter_file.ini	Python: write a dictionary	Terminal:	Python:
h = 0.6774 onega b = 0.02230	parans = { "h": 0.6774.	From the to the base directory run	from classy import Class
Onega_cdm = 0.2603 Onega_fld = 0 Onega_smg = 0 #GR in hi_class background_verbose = 1 #info	"omega_b": 0.02230, "Omega_cdm": 0.2603, "Omega_fld" : 0, "Omega_sng" : 0, #GR in hi_class	./class your_parameter_file.ini	<pre>cosmos = class() #create universe cosmos.set(params) #feed params to cosmos cosmos.compute() #duh #play with the output</pre>
output = tCl,mPk #what to compute write background = y root = output/your_model_ #future files	"background_verbose" : 1, #info "output" : "tCl,mPk" #observables }	(plus an optional .pre precision file) Your output will be ready in the root address.	<pre>cosmo.struct_cleanup() #free memory cosmo.empty() #start over</pre>

(from Miguel Zumalacarregui's notes)

- To check if your installation works, open a python terminal and type: import classy
- More details can be found at: <u>https://github.com/lesgourg/</u> <u>class_public/wiki/Python-wrapper</u>

Running Montepython

The procedure is well described in the official documentation website: http://monte-python.readthedocs.io/en/latest/example.html

Monte Python 2.2.0 documentation »

Previous topic	Example of a complete work session
Getting Started	
Next topic	I just downloaded and installed Monte Python, read the previous pages, and I wish to launch and analyse my first run.
Using MultiNest with Monte	I can first create a few folders in order to keep my montepython directory tidy in the future. I do a
Quick search	<pre>\$ mkdir chains for storing all my chains</pre>
Go	\$ mkdir chains/planck if the first run I want to launch is based on the fake planck likelihood proposed in the example.param file
Enter search terms or a module, class or function name.	<pre>\$ mkdir input for storing all my input files</pre>
	<pre>\$ mkdir scripts for storing all my scripts for running the code in batch mode</pre>
	I then copy example.param in my input folder, with a name of my choice, e.g. lcdm.param, and edit it if needed:
	<pre>\$ cp example.param input/lcdm.param</pre>
	I then launch a short chain with
	<pre>\$ montepython/Montepython.py run -p input/lcdm.param -o chains/planck/lcdm -N 5</pre>

MontePython input file

The input file is where we specify:

- the experiments (cosmological datasets) we want to use (in folder montepython/likelihoods)
- the values of the parameters that we want fixed ("cosmo_arguments")
- the parameters we want to measure ("cosmo")
- the parameters required to be marginalized by some likelihoods ("nuisance")
- the extra parameters we want to be computed and written to file ("derived")
- other defaults like number of steps (override if specified), etc.

```
data.experiments = ['experiment1', 'experiment2', ...]
data.parameters['cosmo_name'] = [mean, min, max, sigma, scale, 'cosmo']
...
data.parameters['nuisance_name'] = [mean, min, max, sigma, scale, 'nuisance']
...
data.parameters['cosmo_name'] = [mean, min, max, sigma, scale, 'derived']
...
data.cosmo_arguments['cosmo_name'] = value
data.N = 10
data.write_step = 5
```

Running chains with MontePython run

- Each instance of MontePython run will run only one chain, unless you run the command with MPI (requires the python module mpi4py)
- You can specify: an input file, an output folder, the number of steps (the code will not stop at convergence), the best fit point and a proposal covariance matrix (these two are needed for faster convergence, but you will have these files only if you did a previous shorter run or a similar run)
- You can also specify a step size (default -f 2.4, target should be ~20% to 25% acceptance rate), sampling method (e.g.MultiNest), and not use fast/slow sampling
- You can update the proposal covariance matrix every 500 steps with the option --update 500 (it will use *all* chains to recompute it, even without MPI)
- Example: if you want to run 4 chains with 10⁵ points each:

for n \$(seq 1 4); do python montepython/Montepython run \
 -o output_directory -N 100000 [other_options]; done

The first run creates a log.param file in the output folder, so that if you (mistakenly) try to run a chain in that folder with a different input file, the old configuration overrides the input file (prevents mix-ups)

Plotting your results with MontePython info

- Customize your plots!! (use the --extra option if you have saved these options into a file)
 - Lots of layout options: font size, legend style, line width, no-mean, ...
 - Change the number of bins for credible intervals (less bins = less resolution)
 - Do Gaussian smoothing or increase interpolation (for smoother plots)
 - To do operations with the parameters: info.redefine = {'new_param':'5*old_param+10'}
 - To rename a parameter in the output plots: info.to_change={'old_name':'new_name'}
 - To plot and compute credible intervals for only some specific parameters: info.to_plot=['new_param', 'new_name', 'old_param2',...]

Plotting your results with MontePython info

To compare the constraints on two different models from a fixed dataset (or on a single cosmological model from two different datasets)

python montepython/MontePython.py info experiment_1/ experiment_2/ ...



Creating tables from MontePython info

You can also use the output *tex files to compile LaTeX tables, including:

- All the parameters ('cosmo', 'derived', 'nuisance',...) especified in to_plot
- Their best-fit values and their mean values
- Their I-sigma and 2-sigma credible intervals (sigma and 95%)
- Other info like the maximum likelihood found and minimum value of χ^2

Param	best-fit	$mean \pm \sigma$	95% lower	95% upper
Ω_k	0.1984	$0.1619^{+0.26}_{-0.14}$	-0.2234	0.4994
Ω_m	0.2115	$0.2315_{-0.1}^{+0.072}$	0.07255	0.4076
Ω_{Λ}	0.59	$0.6065_{-0.16}^{+0.098}$	0.3697	0.8639

HELP!!!



- MontePython is well documented: http://monte-python.readthedocs.io/en/latest/
- Quick access to all the options in each mode:
 - The options to run chains are: python montepython/MontePython.py run --help
 - The options to plot and analyze chains are: python montepython/MontePython.py info --help

Introduction to CosmoMC

Running CosmoMC

- Running a set of N chains is as simple as executing the compiled code
 ./cosmomc with an input file params.ini in the command line
 (but you need to compile it first! Needs Intel Fortran 14 or GCC 6)
- CosmoMC also offers a simple way to generate job scripts and submit them to run the code in a computing cluster (e.g. Torque, MOAB, SLURM)

python python/runMPI.py --nodes 1 --chainsPerNode 8 --coresPerNode 16 --mem_per_node 40000 --walltime 480:00:00 --job_template job_script_hipatia --program ./cosmomc --queue batch ow0wacdmbaosn.ini

 When running in a cluster, each chain will be parallelized (using OpenMP) over a number of processors equal to coresPerNode over chainsPerNode The communication between chains will be done via MPI communication

CosmoMC input file

The input file for CosmoMC is named params.ini where we can set up:

<pre>#Folder where files (chains, checkpoir root_dir = chains/ #Root name for files produced file_root=planck15dr12</pre>	Output folder and	d chain <mark>file names</mark>	
<pre>#action= 0 runs chains, 1 importan #use action=4 just to quickly test action = 0</pre>	ce samples, 2 minimizes likelihoods	Execution mod	<mark>le</mark> (0=run chains)
<pre>#general settings #Bicep-Keck-Planck, varying cosmological pa #DEFAULT(batch2/BKPlanck.ini) #Planck 2015, default just include native 1 DEFAULT(batch2/plik_dx11dr2_HM_v18_TTTEEE.: DEFAULT(batch2/lowTEB.ini) #DEFAULT(batch2/lowl.ini) #DEFAULT(batch2/lensing.ini) #Other Likelihoods #DEFAULT(batch2/lensing.ini) #DEFAULT(batch2/Wl.ini) #DEFAULT(batch2/WiggleZ_MPK.ini) #DEFAULT(batch2/WFK.ini) #DEFAULT(batch2/WL.ini)</pre>	ikelihoods (others require c ini) Planck2015 highL tem Planck2015 lowL tem Planck2015 lowL tem Planck2015 CMB lens BAO from BOSS+MGS+ WiggleZ galaxy powe SDSS galaxy power sp CFHTLens weak lensi	hik) perature+polarization perature only ing -6dF(+WiggleZ) r spectrum pectrum ng Also, SNe from JLA, etc	Likelihoods (datasets) you want to include (each one is in turn a settings file)
<pre>#to vary parameters set param[name]= #param[mnu] = 0 0 0 0 0 param[omegak] = 0 -0.1 0.1 0.005 0.00</pre>	center, min, max, start	width, propose width	Model parameters: Values for fixed ones
param[w] = -1 -3 1 0.05 0.05 param[wa] = 0 -3 3 0.3 0.3 prior[omegabb2] = 0.0223 0.000	9 Fasily implement	Gaussian priors	and <mark>ranges</mark> for those to be measured

GetDist:Analysis of CosmoMC chains

CosmoMC's traditional (text-only) analysis tool is GetDist. Besides outputting info to the screen, it creates files with parameter bounds (margestats), covariance matrices, and python scripts to generate plots with matplotlib (in the plot_data folder) The analysis settings can be modified in the distparams.ini file

[acuesta@nova0 cosmomc2015jul]\$./getdist distparams.ini chains/lcdmbaosn Syntax: ./getdist distparams.ini chains/root
skipped unused params: omegak mnu nnu yhe Alens nrun r r02 parameters defined in distparams ini but not in the chains
reading chains/lcdmbaosn_1.txt
reading chains/lcdmbaosn_2.txt
reading chains/lcdmbaosn_3.txt
reading chains/lcdmbaosn_4.txt
reading chains/lcdmbaosn_5.txt number of chains road (check that these are all your chains)
reading chains/lcdmbaosn_6.txt Humber of Chams read (Check that these are an your chams)
reading chains/lcdmbaosn_7.txt
reading chains/lcdmbaosn_8.txt
Number of chains used = 8
var(mean)/mean(var), remaining chains, worst e-value: R-1 = 0.00666 MCMC Convergence status
RL: Thin for Markov: 30
RL: Thin for indep samples: 31
RL: Estimated burn in steps: 120 (50 rows)
mean input multiplicity = 2.39603247549020
using 65280 rows, processing 92 parameters number of parameters (cosmo+nuisance+der)
Approx indep samples: 5046
Best fit sample -log(Like) = 6822.3980000000
mean(-Ln(like)) = 6835,30173439549
-Ln(mean like) = 6830.18592659466
Warning: sharp edge in parameter chi2 JLA - check limits[chi2 JLA] or limits86 Warnings about non-
Warning: sharp edge in parameter chi2 6DF - check limits[chi2 6DF] or limits87
converged parameters

GetDist: Analysis of CosmoMC chains

parameter	mean	sddev	lower1	upper1	limit1	lower2	upper2	limit2	lower3	upper3	limit3	
omegabh2	0.2227594E-01	0.1409804E-03	0.2213470E-01	0.2241652E-01	two	0.2200101E-01	0.2255144E-01	two	0.2191544E-01	0.2264190E-01	two	\Omega_b h^2
omegach2	0.1192956E+00	0.1068506E-02	0.1182545E+00	0.1203491E+00	two	0.1171635E+00	0.1213484E+00	two	0.1164438E+00	0.1221176E+00	two	\Omega_c h^2
theta	0.1040831E+01	0.2995374E-03	0.1040534E+01	0.1041130E+01	two	0.1040247E+01	0.1041420E+01	two	0.1040057E+01	0.1041614E+01	two	100\theta_{MC}
tau	0.8200741E-01	0.1643758E-01	0.6557802E-01	0.9862151E-01	two	0.4956239E-01	0.1138723E+00	two	0.4020595E-01	0.1240224E+00	two	\tau
logA	0.3097935E+01	0.3246072E-01	0.3065291E+01	0.3130707E+01	two	0.3034228E+01	0.3160888E+01	two	0.3013767E+01	0.3180444E+01	two	{\rm{ln}}(10^{10} A_s)
ns	0.9658500E+00	0.4063676E-02	0.9618321E+00	0.9698272E+00	two	0.9579955E+00	0.9740912E+00	two	0.9555469E+00	0.9768459E+00	two	n_s
calPlanck	0.1000465E+01	0.2516048E-02	0.9979804E+00	0.1002947E+01	two	0.9954956E+00	0.1005439E+01	two	0.9939398E+00	0.1007128E+01	two	y_{\rm cal}
acib217	0.6359261E+02	0.6577819E+01	0.5697960E+02	0.7011801E+02	two	0.5088221E+02	0.7649609E+02	two	0.4702681E+02	0.8075525E+02	two	A^{CIB}_{217}
xi	0.5220534E+00	0.2840235E+00	0.000000E+00	0.100000E+01	none	0.000000E+00	0.100000E+01	none	0.000000E+00	0.100000E+01	none	\xi^{tSZ-CIB}
asz143	0.5399273E+01	0.1871846E+01	0.3556131E+01	0.7442447E+01	two	0.1661532E+01	0.8952850E+01	two	0.7504497E+00	0.9658879E+01	two	A^{tSZ}_{143}
aps100	0.2590954E+03	0.2746669E+02	0.2316349E+03	0.2864320E+03	two	0.2053967E+03	0.3134392E+03	two	0.1890985E+03	0.3311659E+03	two	A^{PS}_{100}
aps143	0.4325286E+02	0.7687977E+01	0.3552913E+02	0.5095578E+02	two	0.2797599E+02	0.5791646E+02	two	0.2349064E+02	0.6198630E+02	two	A^{PS}_{143}
aps143217	0.4026165E+02	0.9948208E+01	0.3006222E+02	0.5063956E+02	two	0.2158706E+02	0.5957445E+02	two	0.1655117E+02	0.6414078E+02	two	A^{PS}_{143\times217}
aps217	0.9815534E+02	0.1100181E+02	0.8722243E+02	0.1092326E+03	two	0.7626975E+02	0.1192058E+03	two	0.6946944E+02	0.1255847E+03	two	A^{PS}_{217}
aksz	0.3160785E+01	0.2332050E+01	0.000000E+00	0.4034485E+01	>	0.000000E+00	0.7749367E+01	>	0.000000E+00	0.100000E+02	none	A^{kSZ}
[acuesta	@nova0 cosmon	mc2015jul]\$./getdist di	istparams.in:	i chai	ins/lcdmbaos	Syntax:	: ./ge	etdist dist	params.in	i chai	ins/root
skipped	unused para	ms: omegak m	nu nnu yhe A	Alens nrun r	r02	naramete	rs defined	l in d	istnaram	s ini but na	ot in t	the chains
reading	chains/lcdml	baosn 1.txt				paramoto			lotparant			
reading	chains/lcdml	baosn_2.txt										
reading	chains/lcdml	baosn_3.txt										
reading	chains/lcdml	baosn 4.txt										
reading	chains/lodm	bace 5 tyt		C 1					10 C			
reauing	chains/tcum	Dausi_J.txt	I numb	er ot cn	ain	s read (спеск 1	inat	t these	are all v	/our	' chains)
reading	chains/lcom	baosn_6.txt								···· ·		
reading	chains/lcdml	baosn_7.txt										
reading	chains/lcdml	baosn 8.txt										
Number	of chains us	ed =	8									
wanter	a) (mana (una)	cu -	chains lung	t a walwar I	1	0 000						
var(mea	in)/mean(var)	, remaining	chains, wors	st e-value:	K-1 =	0.000			Conve	rgence	stat	us
RL: Thi	In for Markov	: 30								•		
RL: Thi	in for indep	samples: 31										
RL: Est	imated burn	in steps: 12	0 (50 rows)									
mean in	nut multipli	city = 2	396032475490	120								
ucing	CEDOR	city - 2.	550052475450	02 025	motor	Joumb	or of no	ron	notore (oocmo	. nui	icanoo (dor)
using	05200	rows, proce	ssing	92 para	ameter		ei ui pa	all	161612 (CO2110.	tiui	sancetuer
Approx	indep sample:	s: 5	040						-			-
Best fi	it sample -log	g(Like) =	6822.398000	000000								
mean(-L	n(like)) =	6835.30173	439549									
-In/mea	n like) -	6830 18502	650466									
Wannia	u chara adar	10 0000.10092	c. chi2 11 A	chool: linit	te [ehi	2 1 41 47 1	imiteOf	14	arning	e ahout	nor	า_
warning	; sharp edge	in paramete	Chiz_JLA -	- check timi	L'S [Ch1	Z_JLAJ OF L	INICSOO	V		s about		•
Warning	: sharp edge	in paramete	r chi2_6DF -	 check limit 	tslchi	2_6DF] or l	imits87					
								CO	nverde	g parar	nete	ers

GetDist GUI: MCMC graphical analysis

- Getdist's graphical interface allows the interactive analysis of CosmoMC but also MontePython chains, making it easy to visually inspect the results
- It has an option to create tables with parameter bounds and export to LaTeX

	🔨 GetDist GUI	000			X Parameter t	ables for: bas	e_nnu_mnu_plikH	M_TTTEEE_	lowTEB		
Die Bata Spoors Beb		68% 95%	99%								
base_WMAP	<u> </u>	Parameter	68% limits	Parameter	68% limits	Parameter	68% limits	Parameter	68% limits	Parameter	68% limits
B base pikety TITEEE lowTEB X	base_plikHM_TTTEEE_lowTEB	$\Omega_b h^2$	0.02215 ± 0.00025	A_{100}^{dustTT}	7.4 ± 1.9	C217	0.9960 ± 0.0015	D ₈₁₀	2535 ± 14	keq	0.01035 ± 0.00012
Standard	0.150	$\Omega_c h^2$	0.1191 ± 0.0031	A_{143}^{dustTT}	8.9 ± 1.8	H_0	$65.8^{+2.5}_{-1.8}$	D_{1420}	815.1 ± 4.9	$100\theta_{eq}$	0.8118 ± 0.0078
	0.130	$100\theta_{MC}$	1.04081 ± 0.00045	$A_{143\times217}^{{ m dust}TT}$	17.0 ± 4.2	Ω_{Λ}	$0.668^{+0.028}_{-0.012}$	D_{2000}	230.6 ± 1.9	$100\theta_{s,eq}$	0.4488 ± 0.0040
		T	0.081 ± 0.018	A_{217}^{dustTT}	81.7 ± 7.4	Ω_m	$0.332^{+0.012}_{-0.028}$	n _{s,0.002}	0.9610 ± 0.0099	$r_{\rm drag}/D_V(0.57)$	$0.0706^{+0.0013}_{-0.00070}$
E Select All	0.125	Σm_{ν}	< 0.191	A_{100}^{dustEE}	0.0809 ± 0.0056	$\Omega_m h^2$	$0.1430_{-0.0039}^{+0.0052}$	Y_P	0.2443 ± 0.0029	H(0.57)	$91.8^{+1.8}_{-1.6}$
omegach2 i omegach2 i omegach2		Neff	2.98 ± 0.20	$A_{100\times143}^{\mathrm{dust}EE}$	0.0485 ± 0.0050	$\Omega_{\nu}h^{2}$	$0.00180\substack{+0.00030\\-0.0058}$	$Y_P^{\rm BBN}$	0.2456 ± 0.0029	$D_A(0.57)$	1417^{+29}_{-42}
L theta	0.100	$\ln(10^{10}A_s)$	3.095 ± 0.039	$A_{100\times217}^{\mathrm{dust}EE}$	0.0999 ± 0.033	$\Omega_m h^3$	0.0941 ± 0.0042	$10^5 D/H$	2.608 ± 0.047	$F_{AP}(0.57)$	$0.6810^{+0.0032}_{-0.0069}$
D ngh		n,	0.9610 ± 0.0099	A ^{dustEE}	0.0999 ± 0.0069	σ_8	$0.807\substack{+0.043\\-0.021}$	Age/Gyr	$13.95\substack{+0.22\\-0.26}$	$f\sigma_s(0.57)$	$0.475_{-0.010}^{+0.018}$
acib217 acib217	0.075	Meal	1.0004 ± 0.0025	AdustEE 143×217	0.225 ± 0.047	$\sigma_8 \Omega_m^{0.5}$	0.464 ± 0.011	5.	1090.07 ± 0.38	$\sigma_{s}(0.57)$	$0.597^{+0.036}_{-0.017}$
ast2143 ast2143 ast100		A ^{CIB} 217	63.6 ± 6.6	AdustEE 217	0.65 ± 0.13	$\sigma_8 \Omega_m^{0.25}$	$0.612^{+0.022}_{-0.013}$	r_{*}	145.2 ± 1.9	f_{29990}^{143}	29.4 ± 2.9
aps143 aps143 aps143217 aps143217	0.050	$\xi^{tSZ-CIB}$	-	A_{100}^{dustTE}	0.141 ± 0.038	$\sigma_{h}/h^{0.5}$	$0.995^{+0.037}_{-0.019}$	1000.	1.04111 ± 0.00055	$f_{2000}^{143 \times 217}$	32.1 ± 2.2
aps217 aps217 aks2		A ^{4.SZ} 143	5.4 ± 1.9	$A_{100\times143}^{\mathrm{dust}TE}$	0.132 ± 0.029	$\langle d^2 \rangle^{1/2}$	2.509 ± 0.040	D_{Λ}/Gpc	13.95 ± 0.18	f ²¹⁷ ₂₀₀₀	105.8 ± 2.1
kgal100 kgal200 kgal243 -	0.025	A_{100}^{PS}	259 ± 28	$A_{100\times217}^{{ m dust}TE}$	0.304 ± 0.084	1.00	$10.2^{+1.8}_{-1.5}$	1 drag	1059.31 ± 0.86	X ² _{lowTED}	10498.6 ± 2.6
kgal143217 kgal217 / Filed		A_{143}^{PS}	43 ± 8	A_{143}^{dustTE}	0.156 ± 0.054	$10^{9}A_{s}$	2.210 ± 0.085	rdeng	147.9 ± 2.0	χ^2_{plik}	2451.9 ± 7.2
gaffel00 C Line F Shaded	3.00 3.05 3.10 3.15 3.20	$A_{143 \times 217}^{PS}$	40 ± 10	$A_{143\times217}^{\mathrm{dust}TE}$	0.340 ± 0.080	$10^9 A_s e^{-2\tau}$	1.878 ± 0.018	$k_{\rm D}$	0.1401 ± 0.0014	χ^2_{prior}	19.2 ± 5.5
garte100217 Coor by process	$\ln(10^{\prime\prime}A_s)$	A_{217}^{PS}	98 ± 10	A_{217}^{dustTE}	1.68 ± 0.26	D_{40}	1246 ± 16	$100\theta_{\rm D}$	0.16079 ± 0.00043	$\chi^2_{\rm CMB}$	12950.5 ± 7.1
Make plot		A ^{kSZ}	< 4.04	c100	0.99817 ± 0.00077	D220	5728 ± 39	ing	3408 ± 41		
							_				
Gui selection Script Preview				Copy latex			Save latex				

More examples are shown at http://getdist.readthedocs.org/en/latest/plot_gallery.html

HELP!!!



- CosmoMC has a complete README website: <u>http://cosmologist.info/cosmomc/readme.html</u>
- It contains individual pages for many topics: Planck likelihood, Python modules, GetDist GUI, running grids of models/datasets,...
- See also the CosmoCoffee forum: <u>http://cosmocoffee.info/</u>

Thank you

ajcuesta@uco.es

Supplementary slides

Structure of a chain file

- A chain file is just a text file, you can open it with any editor or manipulate it through any python script (or the way that is most convenient for you)
- Each row is a MCMC step. Each column is each one of the parameters in this order: cosmological, nuisance, and derived. Check the *.paramnames file to find out the ordering
- The first two columns are the multiplicity (or number of steps spent in that point) and the $-\log(likelihood)$, or "loglike", which is just 0.5 times the total χ^2 value.

mult & loglike LCDM parameters

1MCMC step

0.2000000E+01 0.7432273E+04 0.2205772E-01 0.1223525E+00 0.1040409E+01 0.9243788E-01 0.3091427E+01 0.9585111E+00 0.9999859E+00 0.1381403E+00 0.3085730E+01 0.6719501E+02 0.16074 88E-01 0.2326024E+00 0.3234647E+03 0.4471673E+02 0.1465753E+02 0.8721921E+02 0.5519028E+01 0.4040853E+01 0.8603040E+01 0.2843156E+02 0.8216804E+02 0.6988734E-01 0.8529992E-01 0 .1473713E+00 0.1212628E+00 0.4138422E+00 0.5325758E+00 0.2066227E+00 0.2024037E+00 0.3101160E+00 0.2384299E+00 0.6598682E+00 0.1248762E+01 0.9968187E+00 0.9981910E+00 0.6611572E+ 02 0.6681633E+00 0.3318367E+00 0.1450554E+00 0.6451439E-03 0.9599442E-01 0.8370717E+00 0.4821974E+00 0.6533218E+00 0.1029462E+01 0.2543836E+01 0.1138763E+02 0.2200845E+01 0.182 9359E+01 0.1218436E+04 0.5524315E+04 0.2451456E+04 0.7855802E+03 0.219278E+03 0.9505111E+00 0.2452473E+00 0.2650759E+01 0.1385349E+02 0.1099526E+04 0.1440652E+03 0.10440627E+01 0.1384408E+02 0.1059361E+04 0.1468229E+03 0.1409091E+00 0.1510448E+00 0.3450975E+04 0.2465732E+00 0.2650759E+01 0.1385349E+02 0.1099526E+04 0.1440652E+03 0.10440627E+01 0.1384408E+02 0.1059361E+04 0.446829E+03 0.1409091E+00 0.1610448E+00 0.3450975E+04 0.1053267E-01 0.88034780E+00 0.4444658E+00 0.1137244E+00 0.7910790E+02 0.1009162 E+04 0.3515068E+00 0.7049756E-01 0.9239276E+02 0.1407670E+04 0.6811109E+00 0.4936407E+00 0.4937144E+00 0.4916913E+00 0.46178100E+00 0.3612763E+04 0.1049756E+05 0.6964181E+03 0.4 869998E+00 0.1972903E+00 0.1102911E+02 0.1891800E+01 0.4420137E+02 0.1411032E+05 0.1360520E+02

0.4000000E+01 0.7284871E+04 0.2198426E+01 0.1221917E+00 0.1040366E+01 0.1098112E+00 0.3125897E+01 0.9607862E+00 0.1000165E+01 0.1525372E+00 0.3207994E+01 0.8596888E+02 0.10553 51E+00 0.3467409E+01 0.2893997E+03 0.4493034E+02 0.2553329E+02 0.7202911E+02 0.6357391E+01 0.1250935E+02 0.8057744E+01 0.2133231E+02 0.6455248E+02 0.6871896E=01 0.7897106E=01 0 .1537515E+00 0.1198039E+00 0.4199892E+00 0.5379834E+00 0.1532049E+00 0.1571962E+00 0.4808829E+00 0.2579597E+00 0.7759683E+00 0.1462243E+01 0.9989428E+00 0.9984782E+00 0.6669619E+ 02 0.6685035E+00 0.314965E+00 0.1448211E+00 0.6451439E=03 0.9572121E=01 0.852054E+00 0.4408817E+00 0.6465344E+00 0.1040054E+01 0.2582354E+01 0.128300E+02 0.2278031E+01 0.182 8854E+01 0.1221446E+04 0.5509919E+04 0.2451231E+04 0.7856966E+03 0.2223143E+03 0.9607862E+00 0.2455387E+00 0.2465387E+00 0.2665888E+01 0.1386161E+02 0.1090666E+04 0.1441621E+03 0.1040593E+01 0.1385383E+02 0.1059208E+04 0.1469439E+03 0.107185E+00 0.1611494E+00 0.3445374E+04 0.1051558E=01 0.8042171E+00 0.4449052E+00 0.1137728E+00 0.1147728E+00 0.1040952E+02 0.1090666E+04 0.106104952E+02 0.1090666E+04 0.1441621E+03 0.1040593E+01 0.1385383E+02 0.1059208E+04 0.1408265E+04 0.6810272E+00 0.5074146E+00 0.5004196E+00 0.6465344E+00 0.2445387E+00 0.4449052E+00 0.1137728E+00 0.11097232E+02 0.1009537 E+04 0.3514796E+00 0.705297E-01 0.9234238E+02 0.1408265E+04 0.6810272E+00 0.5074146E+00 0.5004196E+00 0.640952E+00 0.312784E+04 0.1050066E+05 0.7015079E+03 0.4 721827E+00 0.2234966E+00 0.1081429E+02 0.1822413E+01 0.4143067E+02 0.1381347E+05 0.1333238E+02

List of CosmoMC's valid parameter names

You can see a complete list in the file paramnames/params_CMB.paramnames and also in Planck's documentation <u>http://wiki.cosmos.esa.int/planckpla2015/</u> <u>images/b/b9/Parameter_tag_definitions_2015.pdf</u>

omegabh2	\Omega_b h^2 #physical baryon density
omegach2	<pre>\Omega_c h^2 #physical CDM matter density</pre>
theta	100\theta_{MC} #100 times the ratio of the angular diameter distance to the LSS sound horizon
tau	\tau
omegak	\Omega_K
mnu	\Sigma m_\nu #sum of physical masses of standard neutrinos
meffsterile	<pre>m_{\nu,{\rm{sterile}}}^{\rm{eff}} #effective mass of sterile neutrino, \approx omeganuh2*94</pre>
W	w #equation of state parameter for scalar field dark energy today
wa	w_a #w_a variation
nnu	N_{eff} #effective number of neutrinos (only clearly defined for massless)
H0*	H_0 #hubble parameter is H0 km/s/Mpc
omegal*	\Omega_\Lambda
omegam*	\Omega_m

Parameter Covariance Matrix

- Choosing a good covariance matrix is important because it HELPS the chain to converge faster
- It gives you the optimal sampling step size in each direction of the parameter space (diagonal elements of the matrix)
- But also, if the parameters are correlated, it also gives the direction where to move when we change one of the parameters (off-diagonal elements)



 $R_{ij} = \frac{C_{ij}}{\sigma_{\theta_i}\sigma_{\theta_j}} = \begin{pmatrix} 1 & \rho_{\theta_1\theta_2} \\ \rho_{\theta_1\theta_2} & 1 \end{pmatrix}$

 $C_{ij} = \begin{pmatrix} \sigma_{\theta_1\theta_1} & \sigma_{\theta_1\theta_2} \\ \sigma_{\theta_1\theta_2} & \sigma_{\theta_2\theta_2} \end{pmatrix}$

Covariance matrix $\sigma_{\theta_i\theta_i} = \sigma_{\theta_i}^2$

Correlation matrix

Modifying a (simple) CosmoMC likelihood

 Let's make a copy of this likelihood to batch2/HSTnew.ini because we want to use the new 2.4% determination of H₀ by Riess et al. 2016 <u>http://arxiv.org/abs/1604.01424</u>

```
# Riess et al (2011) value of H0 = 73.8 +/- 2.4 km/s/Mpc
# Riess et al: 1103.2976
Hubble_zeff = 0.04
Hubble_angconversion = 11425.8
#angconversion converts inverse of the angular diameter distance at z = zeff to H0
#for the fiducial cosmology (omega_k = 0, omega_lambda = 0.7, w = -1)
#likelihood is in terms of inverse of the angular diameter distance, so includes the tiny cosmological
#dependence of the measurement (primarily on w) correctly.
Hubble_H0 = 73.8 
73.24
Hubble_H0_err = 2.4 
1.74 P(H_0) \propto e^{-0.5 \left(\frac{H_0 - 73.24}{1.74}\right)^2}
use_HST=T
```

• Now you can INCLUDE in your parameter file this new likelihood batch2/HSTnew.ini