Monte Python

the way back from cosmology to Fundamental Physics

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IFT School on Cosmology Tools

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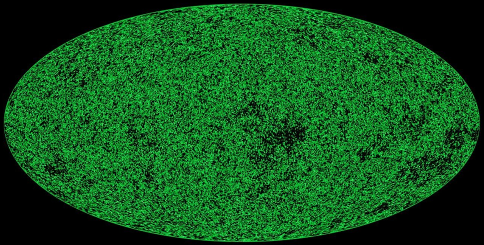
Related Tools

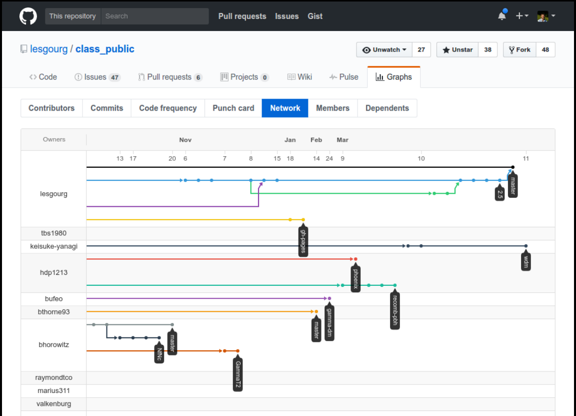


Version control and Python interfacing

PLANCK

Version control: GIT + github

- GIT: access all previous versions, restore, compare, branch...
- Github: website + interface
  - Network: users, branches intermediate versions



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- GIT: access all previous versions, restore, compare, branch...
- Github: website + interface
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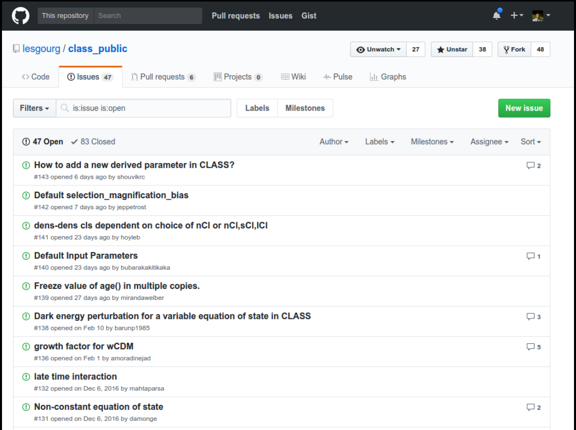
  - Issues: troubleshooting, forum/improvements



Python interfacing with classy

- classy → use CLASS as a Python module
  - Required for MCMC (tomorrow!)
  - Useful for plotting

```
from classy import Class
import numpy as np
import matplotlib.pyplot as plt
cosmo = Class ()
cosmo.set ({'output': 'tCl, pCl, lCl', 'lensing': 'yes'})
cosmo.compute ()
l = np.array ( range (2 ,2501) )
factor = l*(l +1) /(2*np.pi )
lensed_cl = cosmo.lensed_cl (2500)
#then just plot lensed_cl...
```

Python interfacing with `classy`

- `classy` $\rightarrow$ use CLASS as a Python module
  - Required for MCMC (tomorrow!)
  - Useful for plotting
- `IPython` $\rightarrow$ Interactive Python frontend
  - TAB auto-completion

```
miguel@Goedel:~$ ipython
Python 2.7.6 (default, Oct 26 2016, 20:30:19)
Type "copyright", "credits" or "license" for more information.

IPython 5.1.0 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

In [1]: from classy import Class

In [2]: c = Class()

In [3]: c.
         c.age                             c.h                      c.Omega_nu
         c.angular_distance                c.Hubble                 c.pars
         c.baryon_temperature              c.ionization_fraction    c.pk
         c.compute                         c.lensed_cl              c.raw_cl
         c.density_cl                      c.luminosity_distance    c.rs_drag
         c.empty                           c.n_s                    c.set
         c.get_background                  c.Neff                   c.set_default
         c.get_current_derived_parameters  c.nonlinear_method       c.sigma8
         c.get_perturbations               c.nonlinear_scale        c.state
         c.get_pk                          c.Omega0_m               c.struct_cleanup
         c.get_primordial                  c.Omega_b                c.T_cmb
         c.get_thermodynamics              c.omega_b                c.z_of_r
         c.get_transfer                    c.Omega_m
```

Python interfacing with `classy`

- `classy` → use CLASS as a Python module
  - Required for MCMC (tomorrow!)
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- `IPython` → Interactive Python frontend
  - TAB auto-completion
- `Jupyter` → Notebook interface (Julia+Pyton+R)

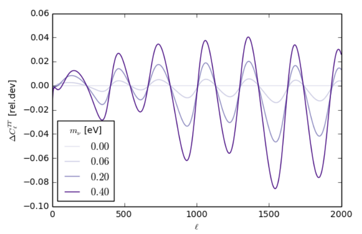
Jupyter example

You can write $\LaTeX$ and awesome equations like $m_\nu \gtrsim 60$ meV. **And plot the effect of m_ν in few lines**

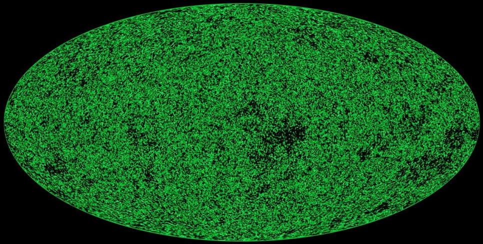
```
cm = plt.get_cmap('Purples')
c = Class()
cl = {} #dictionary for output
for m in [0.0, 0.06, 0.2, 0.4]:
    c.set({'N_ncdm':1, 'N_ur':2.033,'m_ncdm':m,'output':'tCl'})
    c.compute()
    cl[m] = c.raw_cl(2000)
    plt.plot(cl[m]['ell'][2:],cl[m]['tt'][2:]/cl[0]['tt'][2:]-1.,
             color=cm((m+0.1)/0.5),label=r'$%.2f$'%(m))
    c.empty()

plt.xlabel(r'$\ell$')
plt.ylabel(r'$\Delta C_\ell^{TT}$ [rel.dev]')
plt.legend(loc='lower left',fontsize = 12,title= r'$m_\nu$ [eV]')
```

```
<matplotlib.legend.Legend at 0x7fc7b75d5810>
```



Monte Python



from cosmology back to fundamental physics

PLANCK

DISCLAIMER: Short time!

$\lesssim 3h$ course $\Rightarrow$ overview and basic usage

Learn further:

- MontePython slides by Sebastien Clesse ($\ll 1h$?)

  https://lesgourg.github.io/class-tour/16.06.02_Lisbon_intro.pdf

- MontePython course ($\sim 5h$)

  https://lesgourg.github.io/class-tour-Tokyo.html

- Links to extra resources in exercise sheet

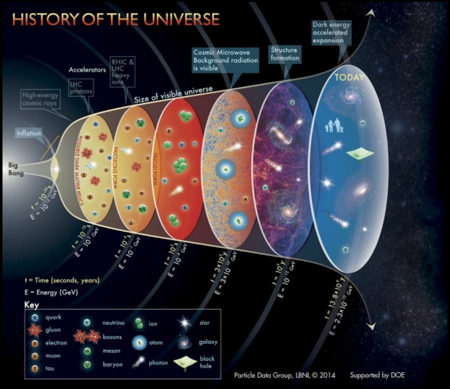
IMPORTANT DISCLAIMER:

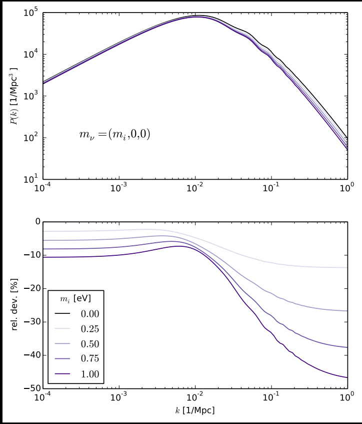
$\downarrow$ I'm mainly a user with little experience developing!

$\uparrow$ Help from experts:

Thejs Brinckmann, Carlos Garcia, Deanna Hooper & Vivian Poulin

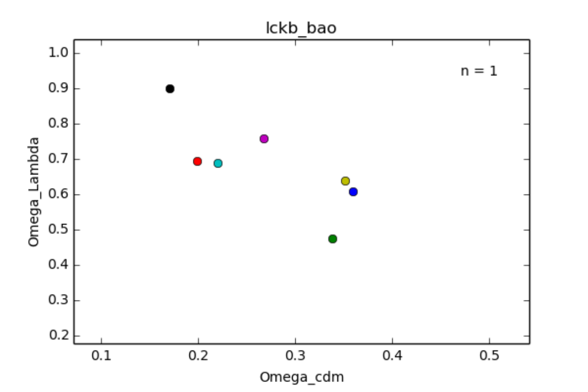
Fundamental physics and cosmology





Initial conditions, Dark Matter, Neutrinos, Dark Energy, Gravity...

Scan space of parameters



(recall lecture by Will Handley)

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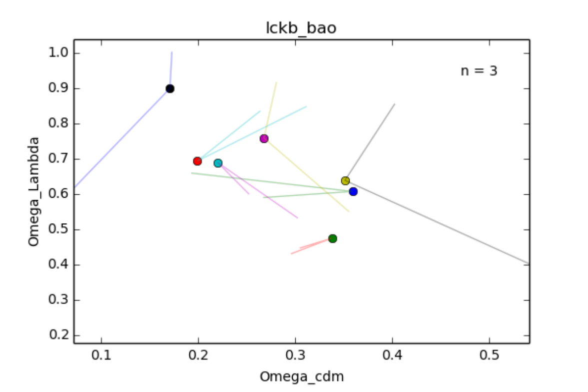

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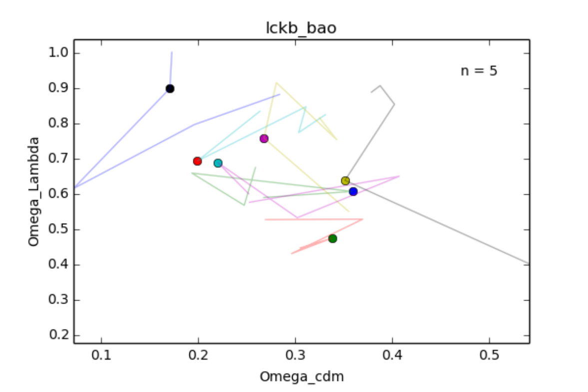

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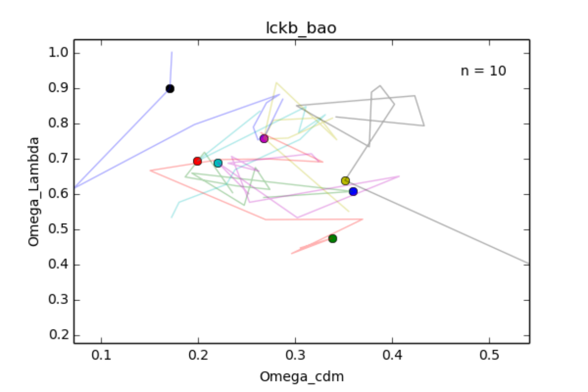

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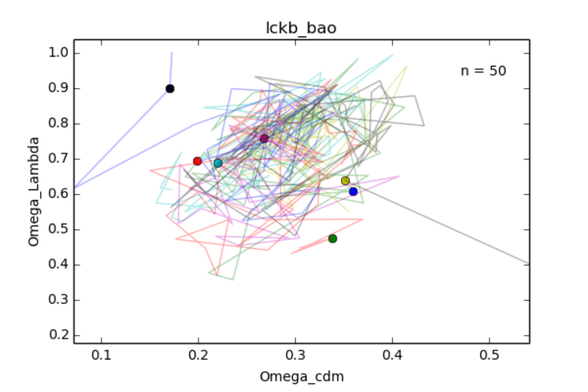

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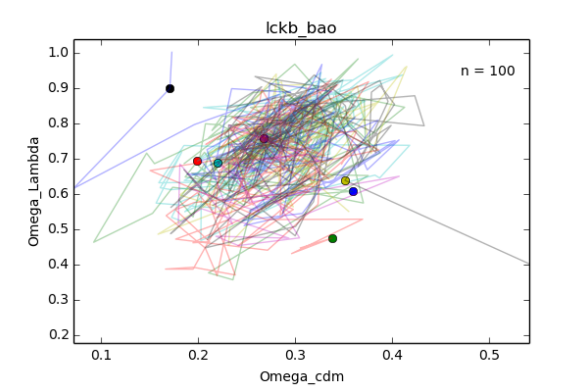

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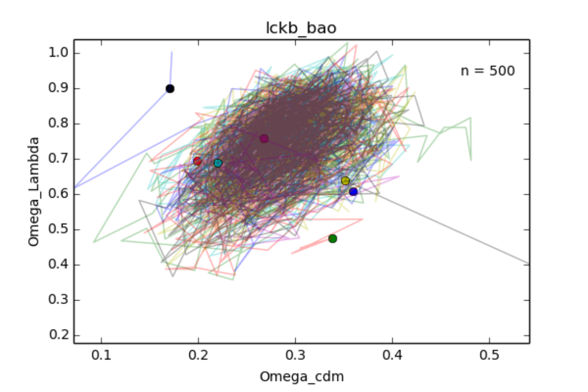

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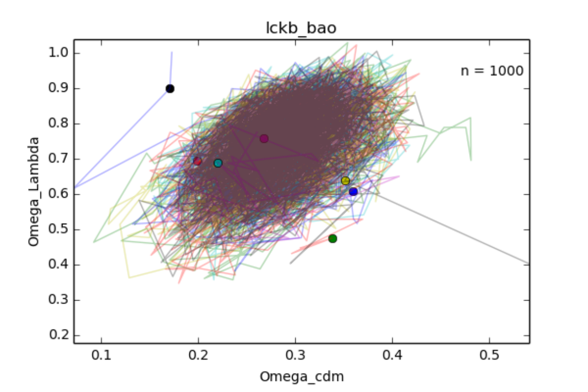

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MontePython

An Markov Chain Monte Carlo engine for parameter extraction:

Features

- Written in Python
  - Python is practically magic!
  - imports routines from `numpy` and `scipy`
  - useful outside academia, standard for Big Data

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  - likelihoods for new experiments
  - features for sampling, plotting...

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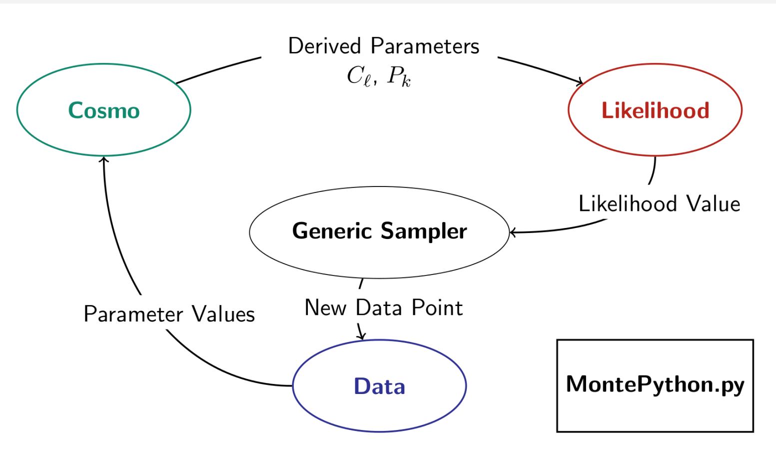
- Uses CLASS through the *classy* wrapper
- Modular, easy to add
  - likelihoods for new experiments
  - features for sampling, plotting...
- Easy to use, intensively documented
- Parallelization is optional
  - simpler to install
  - runs in old/separate computers, short queue

Modular Structure



(from B. Audren's Monte Python slides)

Defining a run (model.param)

- List of experiments

```
data.experiments=['Planck_highl','Planck_lowl','Planck_lensing']
```

Collected in montepython/likelihoods:

```
miguel@Goedel:~/code/montepython_zuma/montepython/likelihoods$ ls
acbar                       clik_wmap_full          __init__.py          quad
bao                         clik_wmap_lowl          __init__.pyc         sdss_lrgDR4
bao_boss                    cosmic_clocks_BC03      JLA                  sn
bao_boss_aniso              cosmic_clocks_BC03_all  JLA_simple           spt
bao_boss_aniso_gauss_approx cosmic_clocks_MaStro    lowlike              spt_2500
bao_known_rs                da_rec                  Planck_actspt        test_gaussian
bicep                       euclid_lensing          Planck_highl         test_nuisance1
bicep2                      euclid_pk               Planck_highl_lite    test_nuisance2
boomerang                   fake_desi               Planck_highl_TTTEEE  timedelay
cbi                         fake_planck_bluebook    Planck_lensing       WiggleZ
CFHTLens                    gunn_peterson           Planck_lowl          WiggleZ_bao
CFHTLens_correlation        hst                     Planck_SZ            wmap
clik_fake_planck            igm_temperature         polarbear            wmap_9yr
```

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- Cosmological parameters

```
                      #  [mean, (bounds) , SIGMA,scale, type ]
data.parameters['n_s']=[0.96, None,None, 0.008, 1 , 'cosmo']
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Fixed values:

- set SIGMA $= 0$
- `data.cosmo_arguments['N_ncdm'] = 1`

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- set SIGMA $= 0$
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- Derived and Nuisance parameters

```
data.parameters['sigma8'] = [0, None, None, 0, 1, 'derived']
data.parameters['A_cib_217'] = [61,0,200,7,1,'nuisance']
```

Defining a run (model.param)

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```

- MCMC parameters: `data.N=10`, `data.write_step=5` ...

Running Monte Python (run)

Single chain:

```
python montepython/MontePython.py run \
       -p model.param \
       -o output_directory  (...)
```

Parallel run (4 chains):

```
mpirun -nc 4 python (...)
```

Some options:

```
 /!\ Appending to an existing folder: using the log.param instead of
     input/lambda_bao_b.param
Running Monte Python v2.2.2

with CLASS v2.4.5

Testing likelihoods for:
 -> bao_boss, bao_boss_aniso

 /!\ excluding isotropic CMASS measurement
Creating chains/lcdmk_bao_b/2017-03-12_100__2.txt

Creating error file chains/lcdmk_bao_b/error_log.txt


Deduced starting covariance matrix:
['omega_b', 'Omega_cdm', 'Omega_k']
[[ 0.  0.  0.]
 [ 0.  0.  0.]
 [ 0.  0.  0.]]

#  -LogLkl      1e+02omega_b    Omega_cdm       Omega_k         Omega_Lambda
3  11.9558      2.221160e+00    3.132032e-01    -1.692095e-02   6.553103e-01
1  12.7946      2.262336e+00    3.271086e-01    2.742679e-02    5.961614e-01
1  12.0403      2.256136e+00    2.494162e-01    1.271974e-01    5.742182e-01
3  11.6619      2.286805e+00    2.308487e-01    1.014554e-01    6.178604e-01
2  11.4992      2.275734e+00    2.108346e-01    5.439644e-02    6.851744e-01
1  11.1477      2.309970e+00    2.013242e-01    3.477642e-02    7.135600e-01
3  7.83276      2.297757e+00    2.751741e-01    9.733703e-02    5.774153e-01
14  6.96653     2.302347e+00    2.748664e-01    5.921469e-02    6.157454e-01
4  6.46121      2.372939e+00    2.523288e-01    2.276382e-02    6.731983e-01
13  6.9573      2.334726e+00    2.363992e-01    -3.071722e-02   7.434402e-01
4  8.883        2.350200e+00    2.572473e-01    -3.956319e-02   7.311015e-01
14  7.19446     2.380873e+00    2.210523e-01    -2.615132e-02   7.532173e-01
2  6.95177      2.359364e+00    2.629244e-01    7.590971e-02    6.097521e-01
6  7.18606      2.339764e+00    2.595452e-01    8.159985e-02    6.078676e-01
1  6.44771      2.353985e+00    2.392110e-01    3.775342e-02    6.717389e-01
4  8.22755      2.328585e+00    2.075475e-01    -2.491768e-03   7.442001e-01
1  7.89432      2.390601e+00    2.076928e-01    -2.671562e-02   7.669296e-01
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1  7.37498      2.406336e+00    2.207678e-01    4.592705e-02    6.808696e-01
2  10.6892      2.439808e+00    1.946383e-01    5.075931e-02    7.014388e-01
3  11.7196      2.476394e+00    2.298767e-01    1.535277e-01    5.626362e-01
1  12.3995      2.441832e+00    3.239238e-01    2.005879e-01    4.222807e-01
3  10.2062      2.420720e+00    2.880782e-01    1.751385e-01    4.840349e-01
1  7.3809       2.439488e+00    2.699004e-01    7.482511e-02    6.021178e-01
3  7.25137      2.437977e+00    2.578430e-01    2.764030e-02    6.613929e-01
1  6.83719      2.459588e+00    2.214344e-01    4.100809e-02    6.839635e-01

#  100 steps done, acceptance rate: 0.26
```

Running Monte Python (run)

Single chain:

```
python montepython/MontePython.py run \
       -p model.param \
       -o output_directory  (...)
```

Parallel run (4 chains):

```
 mpirun -nc 4 python (...)
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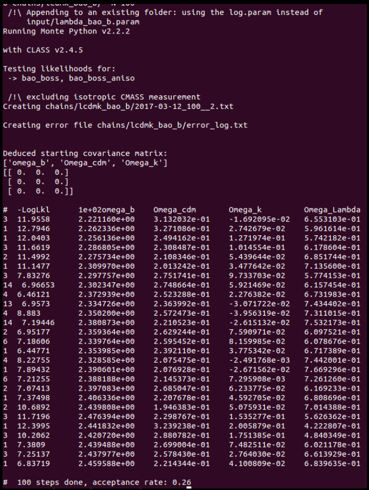
Some options:

- `-N` → # points
- `-C` → covariance matrix
- `-r` → restart from last point of chain
- `--update` → update sampling + covariance



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All options explained

```
python montepython/MontePython.py info --help
```

Analyzing results (`info`)

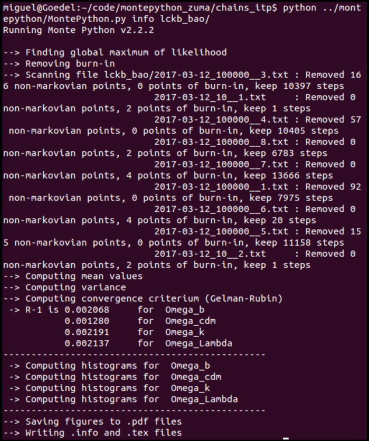
Single model/experiment:

```
python montepython/MontePython.py info \
       output_directory  (...)
```

Comparing several runs:

```
python montepython/MontePython.py info \
       output_1 output_2 output_3 (...)
```

Configuring the output/analysis



Analyzing results (info)

Single model/experiment:

```
python montepython/MontePython.py info \
       output_directory  (...)
```

Comparing several runs:

```
python montepython/MontePython.py info \
       output_1 output_2 output_3 (...)
```

Configuring the output/analysis

- --extra → file with plot options
- --bins → # bins for posterior
- --all → plot every subplot separately
- --no-mean → only marginalized in 1D

```
miguel@Goedel:~/code/montepython_zuma/chains_itp$ python ../mont
epython/MontePython.py info lckb_bao/
Running Monte Python v2.2.2

--> Finding global maximum of likelihood
--> Removing burn-in
--> Scanning file lckb_bao/2017-03-12_100000__3.txt : Removed 16
6 non-markovian points, 0 points of burn-in, keep 10397 steps
                           2017-03-12_10__1.txt     : Removed 0
non-markovian points, 2 points of burn-in, keep 1 steps
                           2017-03-12_100000__4.txt : Removed 57
 non-markovian points, 0 points of burn-in, keep 10405 steps
                           2017-03-12_100000__8.txt : Removed 0
non-markovian points, 2 points of burn-in, keep 6783 steps
                           2017-03-12_100000__7.txt : Removed 0
non-markovian points, 4 points of burn-in, keep 13666 steps
                           2017-03-12_100000__1.txt : Removed 92
 non-markovian points, 0 points of burn-in, keep 7975 steps
                           2017-03-12_100000__6.txt : Removed 0
non-markovian points, 4 points of burn-in, keep 20 steps
                           2017-03-12_100000__5.txt : Removed 15
5 non-markovian points, 0 points of burn-in, keep 11158 steps
                           2017-03-12_10__2.txt     : Removed 0
non-markovian points, 2 points of burn-in, keep 1 steps
--> Computing mean values
--> Computing variance
--> Computing convergence criterium (Gelman-Rubin)
 -> R-1 is 0.002068     for  Omega_b
           0.001280     for  Omega_cdm
           0.002191     for  Omega_k
           0.002137     for  Omega_Lambda
----------------------------------------------
 -> Computing histograms for  Omega_b
 -> Computing histograms for  Omega_cdm
 -> Computing histograms for  Omega_k
 -> Computing histograms for  Omega_Lambda
----------------------------------------------
--> Saving figures to .pdf files
--> Writing .info and .tex files
```

All options explained

```
python montepython/MontePython.py info --help
```

A very minimal run

Write `lckb.param`:

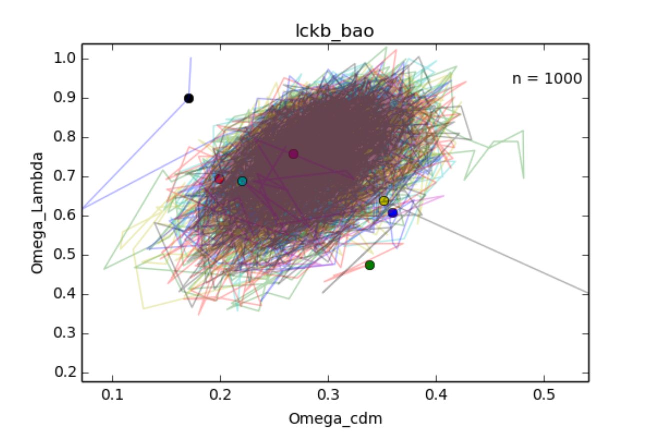
```
data.experiments=['bao_boss','bao_boss_aniso']
#Cosmo parameteress          [mean, min, max, sigma, scale, type]
data.parameters['Omega_b'] = [0.045,0.01, None,0.01,1,'cosmo']
data.parameters['Omega_cdm'] = [0.3, 0, None, 0.1, 1, 'cosmo']
data.parameters['Omega_k'] = [0.0, -0.5, 0.5, 0.1, 1, 'cosmo']
#Fixed parameters (sigma = 0)
data.parameters['H0'] = [67.8, None, None, 0, 1, 'cosmo']
data.cosmo_arguments['YHe'] = 0.24
#derived parameters
data.parameters['Omega_Lambda'] = [1,None,None,0,1,'derived']
#mcmc parameters
data.N=10
data.write_step=5
```

Run ~ 7 chains with

```
python montepython/MontePython.py run -o chains/lckb_bao \
                     -p lckb_param --update 300 -N 100000
```

A very minimal run

The 7 chains explore the parameter space



Chains named `yyyy-mm-dd_N_n.txt (date_points_id)`

A very minimal run

Analyze:

```
python montepython/MontePython.py info chains/lckb_bao
```

- lckb_bao.tex → table with MCMC results

Param	best-fit	mean$\pm\sigma$	95% lower	95% upper
Ω_b	0.03595	$0.03977^{+0.0095}_{-0.015}$	0.01662	0.06547
Ω_{cdm}	0.2931	$0.2872^{+0.049}_{-0.048}$	0.1892	0.3847
Ω_k	-0.1183	$-0.08087^{+0.11}_{-0.14}$	-0.3182	0.1755
Ω_Λ	0.7891	$0.7538^{+0.12}_{-0.091}$	0.542	0.9564

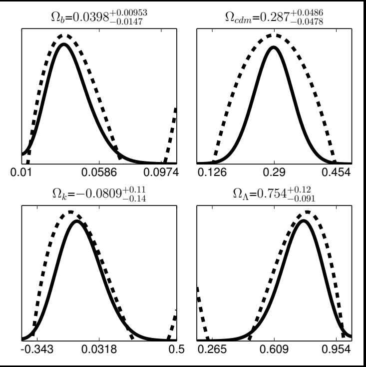
$-\ln\mathcal{L}_{\min} = 5.57269$, minimum $\chi^2 = 11.15$

- `lckb_bao.covmat` → covariance matrix
- `lckb_bao.bestfit` → best fit values

→ arguments for another run

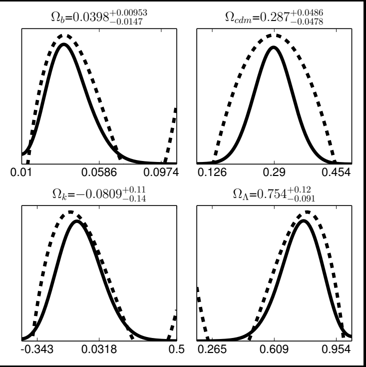
A very minimal run

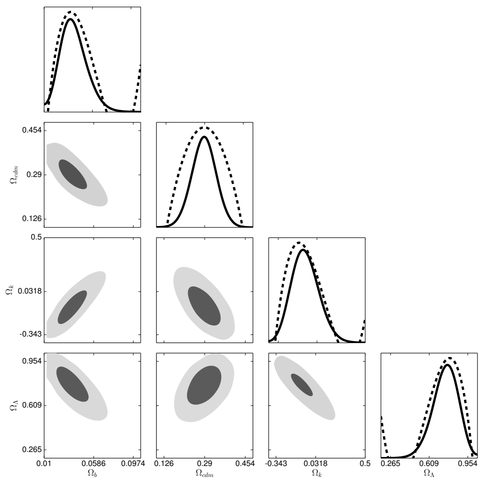
In `lckb_bao/plots`:



A very minimal run

In `lckb_bao/plots`:



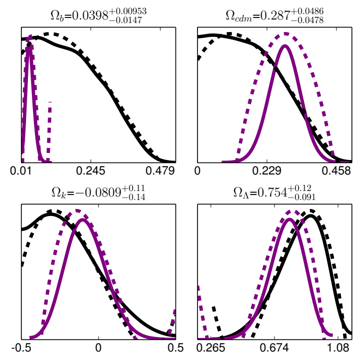


Comparing several runs

Run chains `lckb_sne` with `data.experiments=['sne']`

Analyze: `python ... info chains/lckb_sne chains/lckb_bao`

In `lckb_sne/plots`:

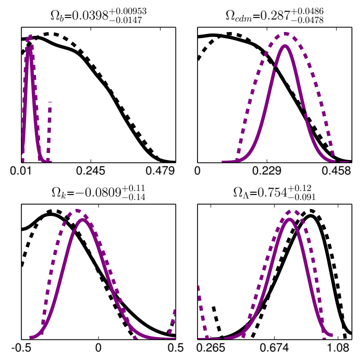


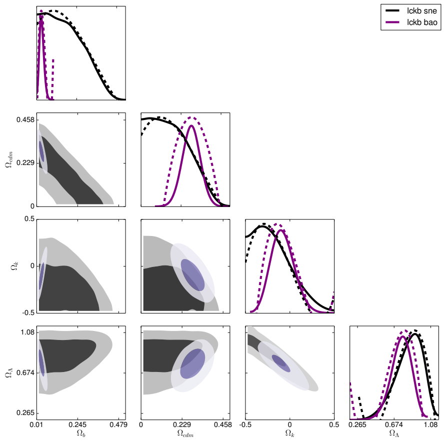
Comparing several runs

Run chains `lckb_sne` with `data.experiments=['sne']`

Analyze: `python ... info chains/lckb_sne chains/lckb_bao`

In `lckb_sne/plots`:





Experiments and Likelihoods

Simplest example ever: Prior on H_0 (1103.2976)

The Hubble Space Telescope measured $h_{obs} = 0.738 \pm 0.024$

$$\log(\mathcal{L}) = -\frac{1}{2}\frac{(h_{th} - h_{obs})^2}{\sigma_h^2}$$

Likelihood (`montepython/likelihoods/hst/__init__`):

```
from montepython.likelihood_class import Likelihood_prior
class hst(Likelihood_prior):
    def loglkl(self, cosmo, data):
        h = cosmo.h()
        loglkl = -0.5 * (h - self.h) ** 2 / (self.sigma ** 2)
        return loglkl
```

Data (`montepython/likelihoods/hst/hst.data`):

```
# Values for Hubble Space Telescope (following 1103.2976)
hst.h     = 0.738
hst.sigma = 0.024
```

Likelihood rules

- Likelihoods in directory `montepython/likelihoods/l_name`
- Needed files: `__init__.py` and `l_name.data`
- `__init__.py` defines a class, inheriting from `Likelihood`
- Contains function `loglkl` $\rightarrow \log(\mathcal{L})$

Introducing your own Likelihoods

- Follow the above rules
- Inspire yourself with the examples
- $\exists$ similar likelihood? $\rightarrow$ you can inherit its methods!
- You can use additional python packages

(See also B. Audren's lecture on likelihoods)

Conclusions

- Brings all the power of CLASS to Python
- Easy to run chains and analyze likelihoods
- Many available experiments
- Advantages from object oriented features in python
  - Add likelihoods
  - Add samplers or other features
- This just scratches the surface, many more options!

(See also B. Audren's slides)

The hi_class academy

Coming soon!

- Set of interrelated projects:
  - ⋆ Theory & model building
  - ⋆ Implementation and phenomenology
  - ⋆ Compare with data
- Collaboration → Publishable results
  - ⋆ Review of models
  - ⋆ Observational constaints
- Stay tuned for more info!

www.hiclass-code.net