Monte Python: basic runs

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Outline

- Monte Python
 - Goals
 - Design Strategy
- Basic Usage
 - Installation
 - Usage
 - Running strategies
 - Exercise

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- 2 Basic Usage

Wish list

• Interfacing with CLASS (C), other likelihoods

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- Easy to learn, easy to use

Goals



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Wish Tick list

- ✓ Interfacing with CLASS (C), other likelihoods
- √ Modular design (use other Boltzmann codes, algorithms)
- Readability (a code is read more than it is written)
- √ Manipulating files read, write, renaming
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Guidelines

• Modular structure: separate I/O, parser, data structures, sampler, interface with the cosmological module, plotting: **Thursday**

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- Convenient Plotting: since a folder will be self contained, with all the information, producing a plot out of this folder should be easy.

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- Using mock data: there must be a way to handle mock data easily.

Conclusion on design

You tell me!

We'll see in the coming days if it works!

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Installation

Compile the wrapper

```
cd class; make;
cd python; python setup.py install --user
```

Download

http://montepython.net or

https://github.com/baudren/montepython_public/releases

Unzip

```
bunzip2 montepython_v2.1.0.tar.bz2
tar -xvf montepython_v2.1.0.tar
```

Configure

cp default.conf.template default.conf
edit it to match your path

Two modes

Run

python montepython/MontePython.py run -h/--help

Info

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

Doing a run is choosing:

a set of experiments, ...

Planck, WiggleZ, BAO,...which might require nuisance parameters

sampled parameters, ...

 Ω_m , H_0 , A_s , r,...

an input covariance matrix

From a previous run

and some derived parameters.

 σ_8 , $log(10^{10}A_s)$, ...

And an output folder

Common arguments

python montepython/MontePython.py run plus...

• A minima: -o chains/planck -p example.param

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python montepython/MontePython.py run plus...

- A minima: -o chains/planck -p example.param
- -N 1000 Number of proposed steps

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python montepython/MontePython.py run plus...

- A minima: -o chains/planck -p example.param
- -N 1000
- -c covmat/old.covmat better proposal density

Common arguments

python montepython/MontePython.py run plus...

- A minima: -o chains/planck -p example.param
- -N 1000
- -c covmat/old.covmat
- -b bestfit/old.bestfit best-fit to start the chain

```
data.experiments=['Planck_highl','Planck_lowl','lowlike']
data.over sampling=[1, 4]
# Cosmological parameters list
data.parameters['omega_b'] = [2.2253, None, None, 0.028, 0.01, 'cosmo']
data.parameters['omega_cdm'] = [0.11919, None, None, 0.0027, 1, 'cosmo']
data.parameters['H0']
                          = [67.802, None, None, 1.2, 1, 'cosmo']
data.parameters['n_s'] = [2.2177, None, None, 0.055, 1.e-9, 'cosmo']
data.parameters['n_s'] = [0.96229, None, None, 0.0074, 1, 'cosmo']
data.parameters['tau_reio'] = [0.09463, None, None, 0.013, 1, 'cosmo']
# Nuisance parameter list, same call, except the name does not have to be a class name
data.parameters['A_ps_100'] = [145.83, 0, None, 61, 1, 'nuisance']
data.parameters['A_ps_143'] = [49.578, 0, None, 14, 1, 'nuisance']
# Derived parameters
data.parameters['z reio']
                                     = \lceil 1. \text{None. None. 0.} \rceil
                                                             1.
                                                                   'derived'l
data.parameters['Omega_Lambda']
                                     = [1, None, None, 0,
                                                                   'derived'l
                                                             1,
data.cosmo arguments['N eff'] = 2.03351
data.cosmo arguments['N ncdm'] = 1
```

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data.experiments=['Planck_highl','Planck_lowl','lowlike']
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# Cosmological parameters list
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                               f2.2253
                                         None.None. 0.028. 0.01. 'cosmo'l
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data.parameters['A_ps_100'] = [145.85,
                                                        61, 1, 'nuisance']
                                           v.wone.
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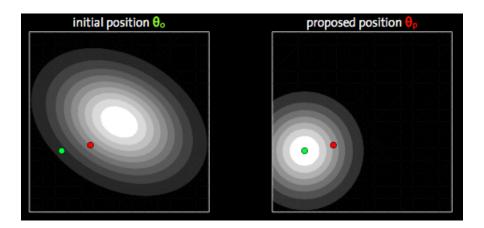
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                                                                            type name
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Reminder from lecture 1



cosmological

- known to Class (can define tricks)
- must be compatible (as in explanatory.ini)

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nuisance

- As the name indicates...
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nuisance

- As the name indicates...
- Needed pain

Warning!

Input parameter file and log.param

- When a folder is created, a file log.param is written, copying information from param and likelihoods.
- When a new chain is launched, the input file is not read any more, only the log.param

Configuration File

```
root = '/Users/benjaminaudren/Desktop/professional/codes'
path['cosmo'] = root+'/class/'
```

Usage: summary

After installation

- cp default.conf.template default.conf and edit
- python montepython/MontePython.py -o chains/test -p example.param

Running in parallel

Installing mpi

apt-get install python-mpi4py

Using mpi

mpirun -np N python montepython/Montepython run...

What Monte Python does for you

Convenience

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- Can use a covariance matrix with partial information

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Convenience

- No need to choose a name for your chain
- Can use a covariance matrix with partial information
- Can analyze a subset of chains

Running strategies

Starting

- Choosing experiments to combine careful with that
- Varying parameters, proposal distribution
- ullet After M ($\simeq 10$) chains of N ($\simeq 10000$) points, analyze

Analyzing (after the break)

python montepython/MontePython.py info folder

Main

- Feed the new found covariance matrix to new runs.
- Analyze only these new chains
- Compare best-fit likelihood, or evidence, read parameter constraints

Simple Exercise

Hst measurement (or at least a first approx)

• Model: H_0 varying.

• Data: hst

• Find the posterior distribution.

Advanced exercise for a laptop

Because there are no better feeling than sipping a coffee while a computer computes

Homogeneous cosmology constraints

- Let's confirm the contours of the recent **JLA** results on Ω_m .
- Use the JLA likelihood (find out the derived parameters requirements).

Advanced exercise for a laptop

Because there are no better feeling than sipping a coffee while a computer computes

Homogeneous cosmology constraints

- Let's confirm the contours of the recent **JLA** results on Ω_m .
- Use the JLA likelihood (find out the derived parameters requirements).
- There should be one main parameter, Ω_{cdm} , to reproduce Fig.15 from http://arxiv.org/abs/1401.4064
- we need derived parameter Ω_m , and fix CLASS parameters.
- Run over the break to have something to analyze while doing the next lecture.

Exercise for a laptop

Because there are no better feeling than sipping a coffee while a computer computes

```
data.experiments=['JLA']
# Cosmological parameters list
data.parameters['Omega cdm'] = [0.2562. None. None. 0.008. 1. 'cosmo']
# Nuisance
data.parameters['alpha'] = [0.15, None, None, 0.001, 1, 'nuisance']
data.parameters['beta'] = [3.559, None, None, 0.02, 1, 'nuisance']
data.parameters['M'] = [-19.02, None, None, 0.004, 1, 'nuisance']
data.parameters['Delta M'] = [-0.10, None, None, 0.004, 1, 'nuisance']
# Derived parameter list
data.parameters['Omega_m'] = [0, -1, -1, 0.1, 'derived']
data.cosmo_arguments['Omega_b'] = 0.05
data.cosmo arguments['h'] = 0.70
data.cosmo_arguments['T_cmb'] = 2.726
data.cosmo_arguments['N_eff'] = 3.046
data.cosmo arguments['N ncdm'] = 0
#---- Mcmc parameters ----
# Number of steps taken, by default (overwritten by the -N command)
data N=10
# Number of accepted steps before writing to file the chain. Larger means less
# access to disc, but this is not so much time consuming.
data.write_step=5
```

Commands

```
(mpirun -np 4) python montepython/MontePython.py -N 1000 -p jla.param -o chains/jla
python montepython/MontePython.py info chains/jla
cp chains/jla/jla.covmat chains
cp chains/jla/jla.bestfit chains
(mpirun -np 4) python montepython/MontePython.py -N 20000 -p jla.param -o chains/jla \
               -c chains/jla.covmat -b chains/jla.bestfit
```