JAM : cosmological inference made simple

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Introduction

Several “CosmoBoxes” on the market :

- CosmoMC
- MontePython
- CosmoSIS
- Cobaya
- ...

...but none entirely satisfying for my needs

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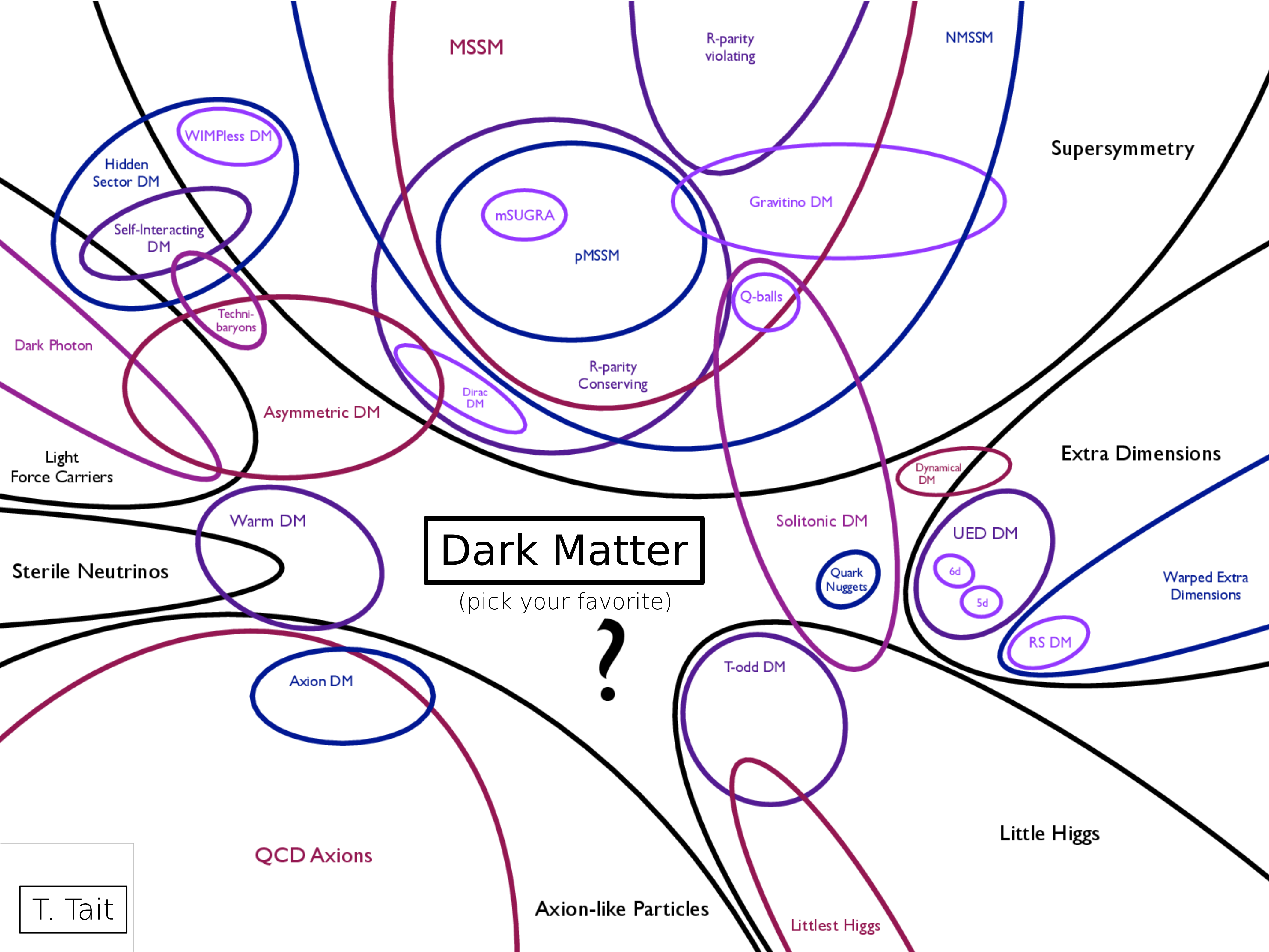
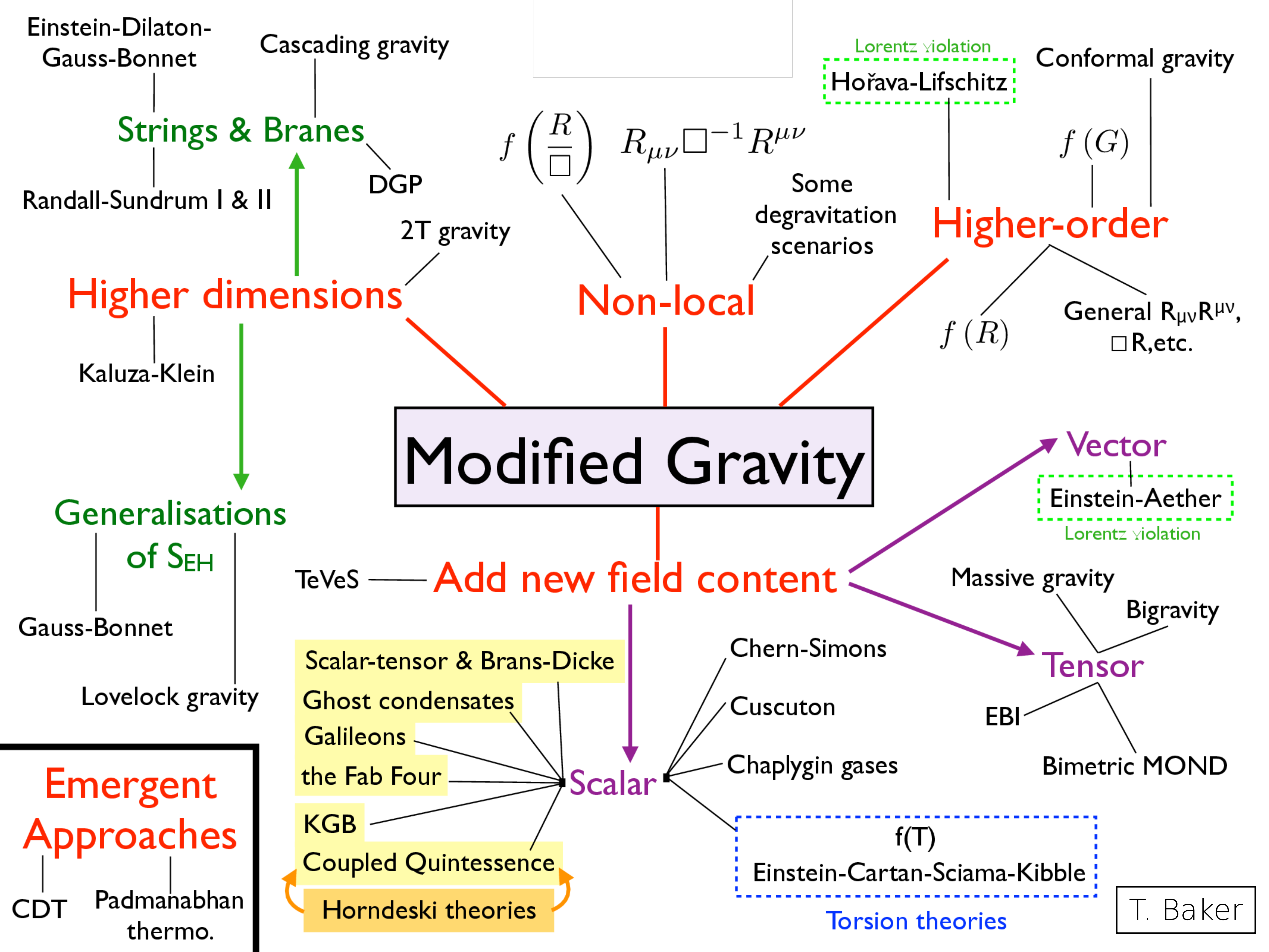

MSSM
R-parity violating
NMSSM
Supersymmetry
WIMPless DM
Hidden Sector DM
Self-Interacting DM
Techni-baryons
mSUGRA
pMSSM
Gravitino DM
Q-balls
R-parity Conserving
Dirac DM
Dark Photon
Asymmetric DM
Light Force Carriers
Extra Dimensions
Dynamical DM
Solitonic DM
UED DM
6d
5d
Warped Extra Dimensions
RS DM
Quark Nuggets
Warm DM
Sterile Neutrinos
Dark Matter
(pick your favorite)
?
Axion DM
T-odd DM
Little Higgs
QCD Axions
Axion-like Particles
Littlest Higgs
T. Tait


Einstein-Dilaton-Gauss-Bonnet
Cascading gravity
Strings & Branes
DGP
Randall-Sundrum I & II
2T gravity
Higher dimensions
Kaluza-Klein
Generalisations of S_{EH}
Gauss-Bonnet
Lovelock gravity
$f\left(\frac{R}{\Box}\right)$
$R_{\mu\nu}\Box^{-1}R^{\mu\nu}$
Some degravitation scenarios
Non-local
Lorentz violation
Hořava-Lifschitz
Conformal gravity
$f(G)$
Higher-order
$f(R)$
General $R_{\mu\nu}R^{\mu\nu}$, $\Box R$, etc.
Modified Gravity
Vector
Einstein-Aether
Lorentz violation
TeVeS
Add new field content
Massive gravity
Bigravity
Tensor
EBI
Bimetric MOND
Scalar-tensor & Brans-Dicke
Ghost condensates
Galileons
the Fab Four
KGB
Coupled Quintessence
Horndeski theories
Scalar
Chern-Simons
Cuscuton
Chaplygin gases
f(T)
Einstein-Cartan-Sciama-Kibble
Torsion theories
Emergent Approaches
CDT
Padmanabhan thermo.
T. Baker

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Introducing : NAME/ACRONYM PENDING

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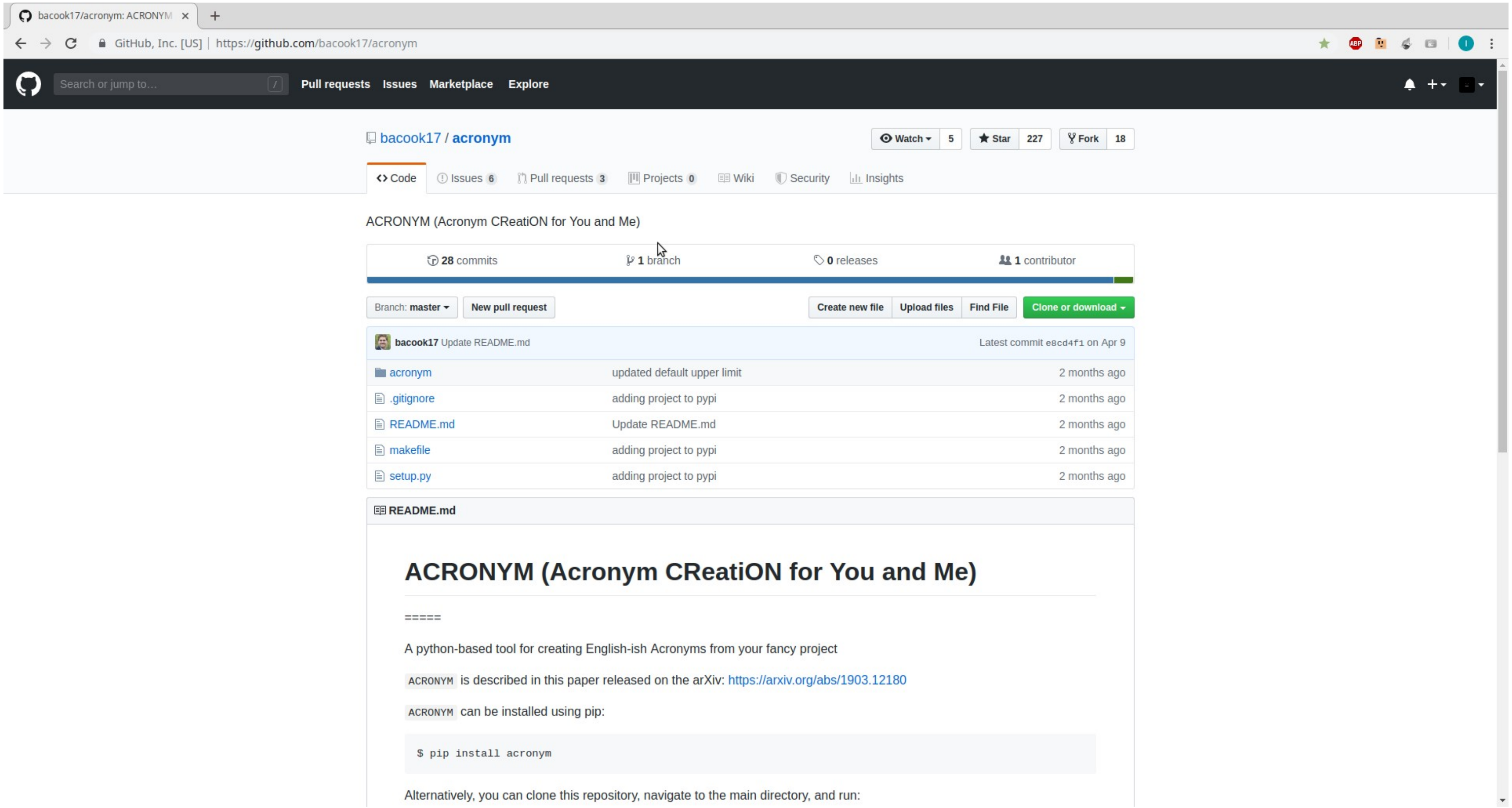
JAM ? (= Just A (simple) MCMC tool)

JUSTICE ? (= JUst a Simple Toolbox for InferenCE)

...



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- Two (fairly) short files in Python 2/3 : main (~200) & parser (~500)
- Human-readable/tweakable, well-commented (I hope !)

Introducing : JAM

```
############################
### Free MCMC parameters ###
############################
#----------------------------------------------------------------#
# Column order :                                                 #
# > type  name  start  min  max  width                           #
# Notes :                                                        #
# > "type" : "var_class" if a class parameter otherwise "var"    #
# > "width" : only used for initializing the walkers positions   #
#----------------------------------------------------------------#

### Class parameters
var_class  omega_b        0.02222   0.005   0.1   0.0001
var_class  omega_cdm      0.1197    0.1     0.13  0.002
var_class  H0            67.0      45.0    90.0   0.1
var_class  tau_reio       0.076     0.01    0.8   0.01
var_class  ln10^{10}A_s   3.096     2.0     4.0   0.01
var_class  n_s            0.977     0.8     1.2   0.01

### Calibration parameter common to all Planck 2015/18 likelihoods (incl. lensing)
var  A_planck  1.  0.9  1.1  0.002
```

Introducing : JAM

```
##########################
### Priors on parameters ###
##########################
#--------------------------------#
# Only Gaussian prior implemented #
# Column order :                  #
# > type  name  mean  stddev      #
#--------------------------------#

### Prior on calibration parameter common to all Planck 2015/18 likelihoods
gauss_prior  A_planck  1.  0.0025
```

Introducing : JAM

```
#######################
### Fixed parameters ###
#######################
#-------------------------------------------------------------#
# Column order :                                              #
# > type  name  value                                         #
# Notes :                                                     #
# > "type" : "fix_class" if a class parameter otherwise "fix" #
#-------------------------------------------------------------#

### Class parameters
#---------------------------------------#
# Note :                                #
# > "non_linear" instead of "non linear" #
#---------------------------------------#
fix_class  output         tCl pCl lCl mPk
fix_class  lensing        yes
fix_class  l_max_scalars  2508
fix_class  T_cmb          2.7255
fix_class  non_linear     halofit
fix_class  P_k_max_h/Mpc  1.
fix_class  N_ur           2.0328
fix_class  N_ncdm         1
fix_class  m_ncdm         0.06

### Planck 2015 full TT fixed nuisance parameters
### Additional fixed parameters for Planck 2015 full TTTEEE
fix  cib_index           -1.3
fix  galf_EE_index       -2.4
```

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Introducing : JAM

```
#############
### CLASS ###
#############

#----------------------------------------------------------------------#
# Select the version of CLASS to be used (give name of Python wrapper) #
#----------------------------------------------------------------------#
which_class  classy
```

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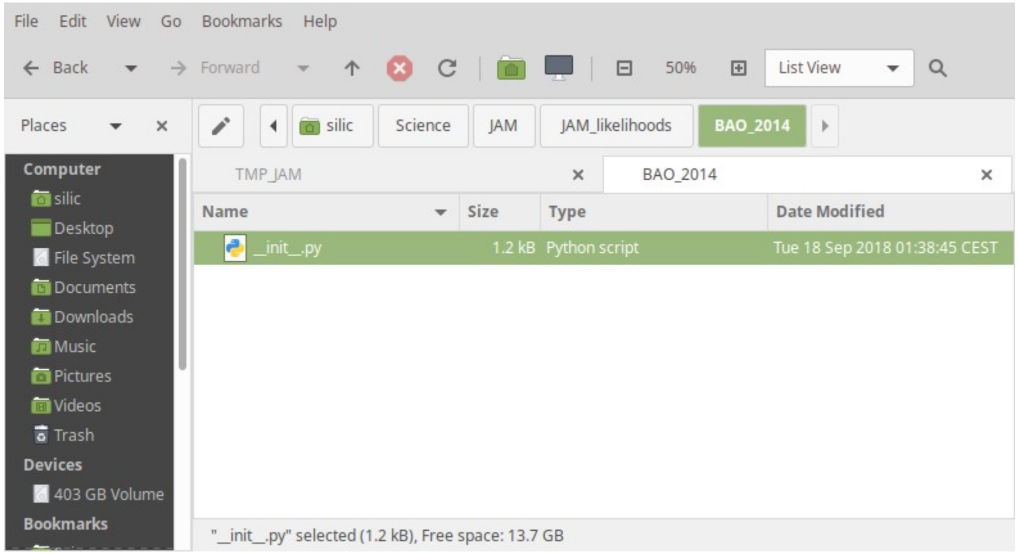
  (easy to add new ones)

Introducing : JAM

```
##################
### Likelihoods ###
##################

#---------------------------------------#
# Select the likelihoods to be combined #
#---------------------------------------#
# Current choices :                     #
# > BAO_2014                            #
# > H0_HST                              #
# > SN_JLA                              #
# > Planck2015_highTT                   #
# > Planck2015_highTTlite               #
# > Planck2015_highTTTEEE               #
# > Planck2015_highTTTEEElite           #
# > Planck2015_lensT                    #
# > Planck2015_lensTP                   #
# > Planck2015_lowTEB                   #
# > Planck2015_lowTT                    #
# > Planck2018_highTT                   #
# > Planck2018_highTTlite               #
# > Planck2018_highTTTEEE               #
# > Planck2018_highTTTEEElite           #
# > Planck2018_lensCMBdep               #
# > Planck2018_lensCMBmarg              #
# > Planck2018_lowBB                    #
# > Planck2018_lowEE                    #
# > Planck2018_lowEEBB                  #
# > Planck2018_lowTT                    #
#---------------------------------------#
likelihood  Planck2015_lowTEB
likelihood  Planck2015_TTTEEE
```

Introducing : JAM




```python
import numpy as np

### BAO "2014" data (used in Planck 2015 as ext. data)
def get_loglike(class_input, likes_input, class_run):
    lnl = 0.
    rs = class_run.rs_drag()
    # 6DF from 1106.3366
    z, data, error = 0.106, 0.327, 0.015
    da = class_run.angular_distance(z)
    dr = z / class_run.Hubble(z)
    dv = (da**2. * (1 + z)**2. * dr)**(1. / 3.)
    theo = rs / dv
    lnl += -0.5 * (theo - data)**2. / error**2.
    # BOSS LOWZ & CMASS DR10&11 from 1312.4877
    z, data, error = 0.32, 8.47, 0.17
    da = class_run.angular_distance(z)
    dr = z / class_run.Hubble(z)
    dv = (da**2. * (1 + z)**2. * dr)**(1. / 3.)
    theo = dv / rs
    lnl += -0.5 * (theo - data)**2. / error**2.
    z, data, error = 0.57, 13.77, 0.13
    da = class_run.angular_distance(z)
    dr = z / class_run.Hubble(z)
    dv = (da**2. * (1 + z)**2. * dr)**(1. / 3.)
    theo = dv / rs
    lnl += -0.5 * (theo - data)**2. / error**2.
    # SDSS DR7 MGS from 1409.3242
    z, data, error = 0.15, 4.47, 0.16
    da = class_run.angular_distance(z)
    dr = z / class_run.Hubble(z)
    dv = (da**2. * (1 + z)**2. * dr)**(1. / 3.)
    theo = dv / rs
    lnl += -0.5 * (theo - data)**2. / error**2.
    # Return log(like)
    return lnl
```

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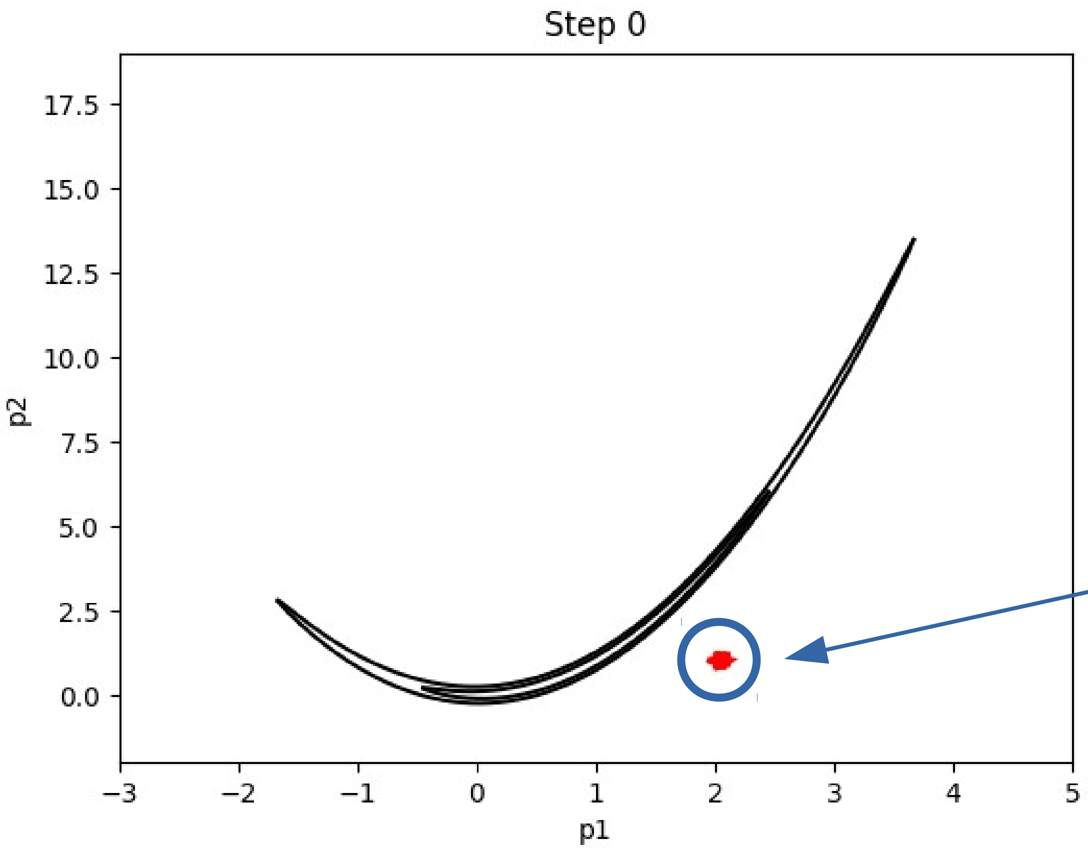
- MCMC algorithm : Affine-Invariant Ensemble sampling

Ensemble sampling

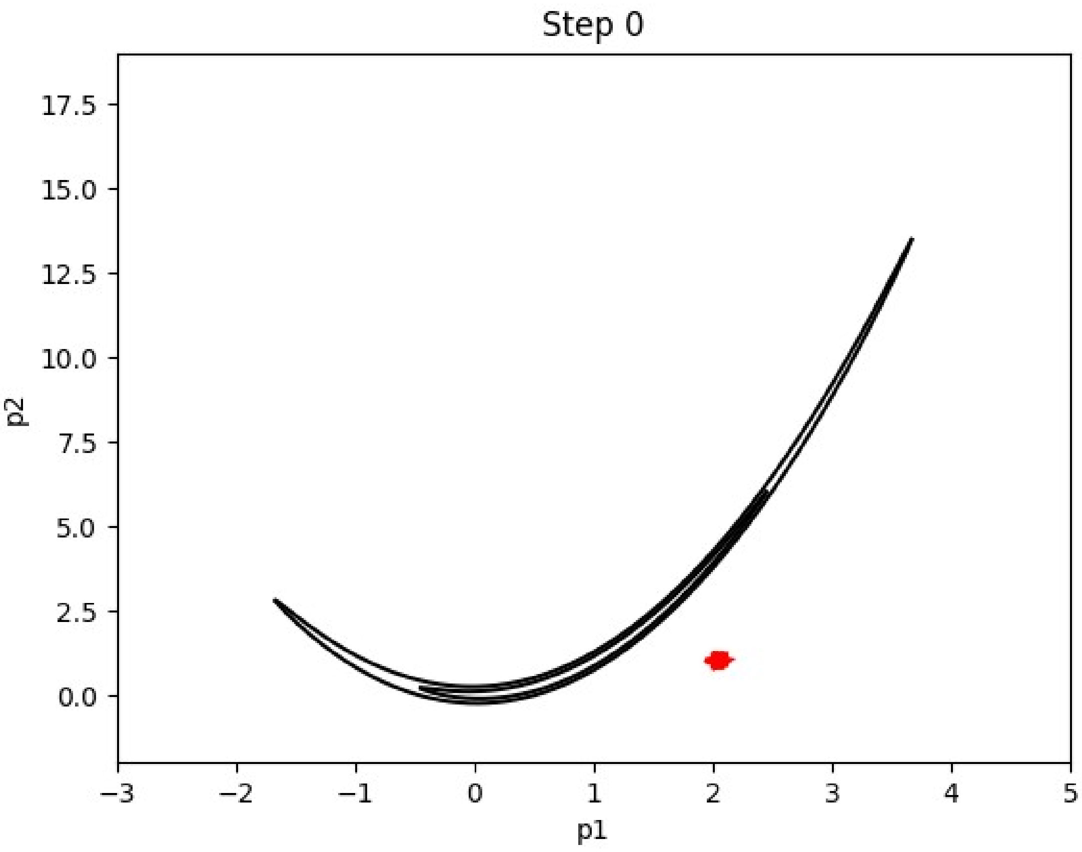
$$\pi(x) \propto \exp\left(\frac{-(x_1 - x_2)^2}{2\epsilon} - \frac{(x_1 + x_2)^2}{2}\right)$$



Collection of "walkers" initialized at random positions

Ensemble sampling

$$\pi(x) \propto \exp\left(\frac{-(x_1 - x_2)^2}{2\epsilon} - \frac{(x_1 + x_2)^2}{2}\right)$$



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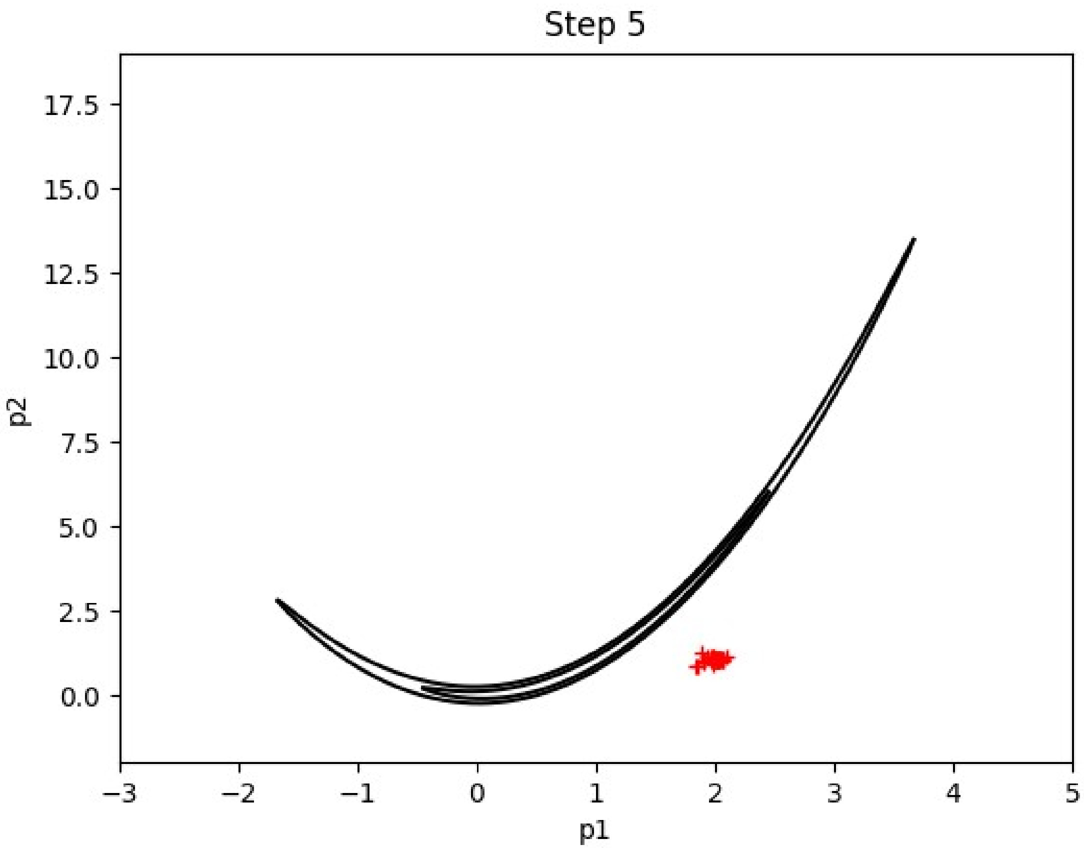

"Walkers" quickly spread throughout parameter space, using each other's position to propose jumps

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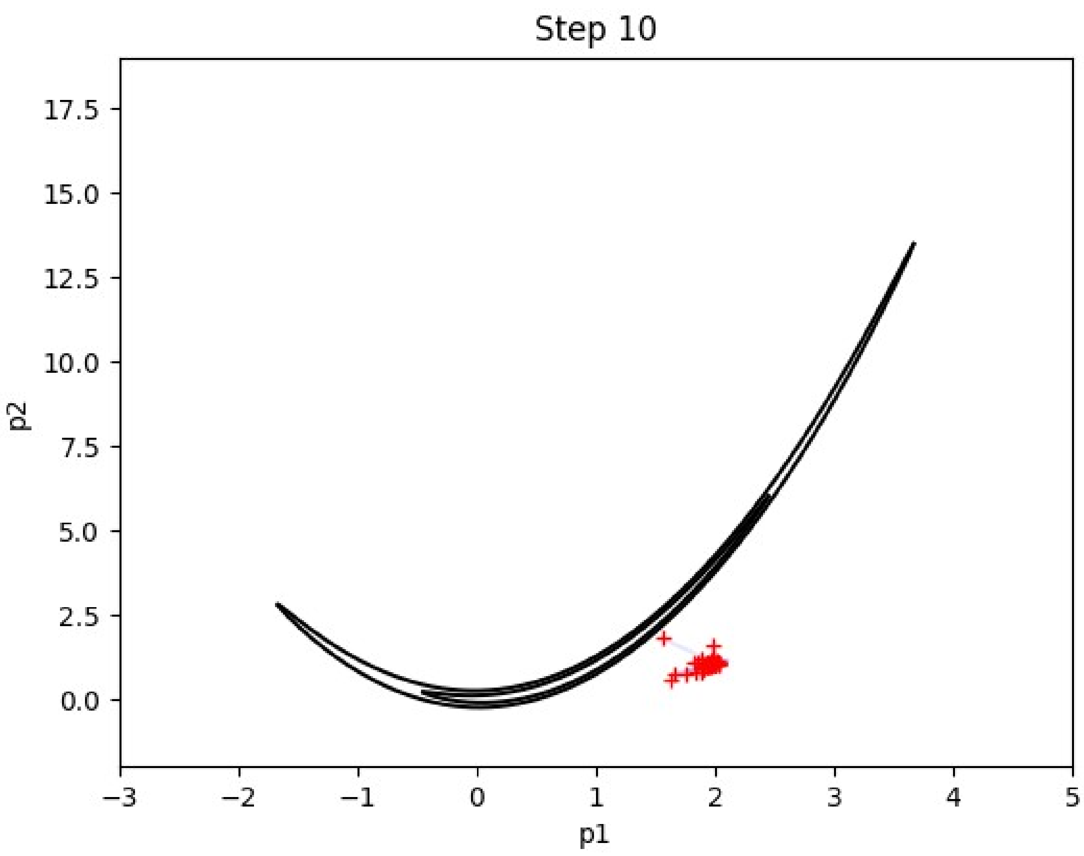

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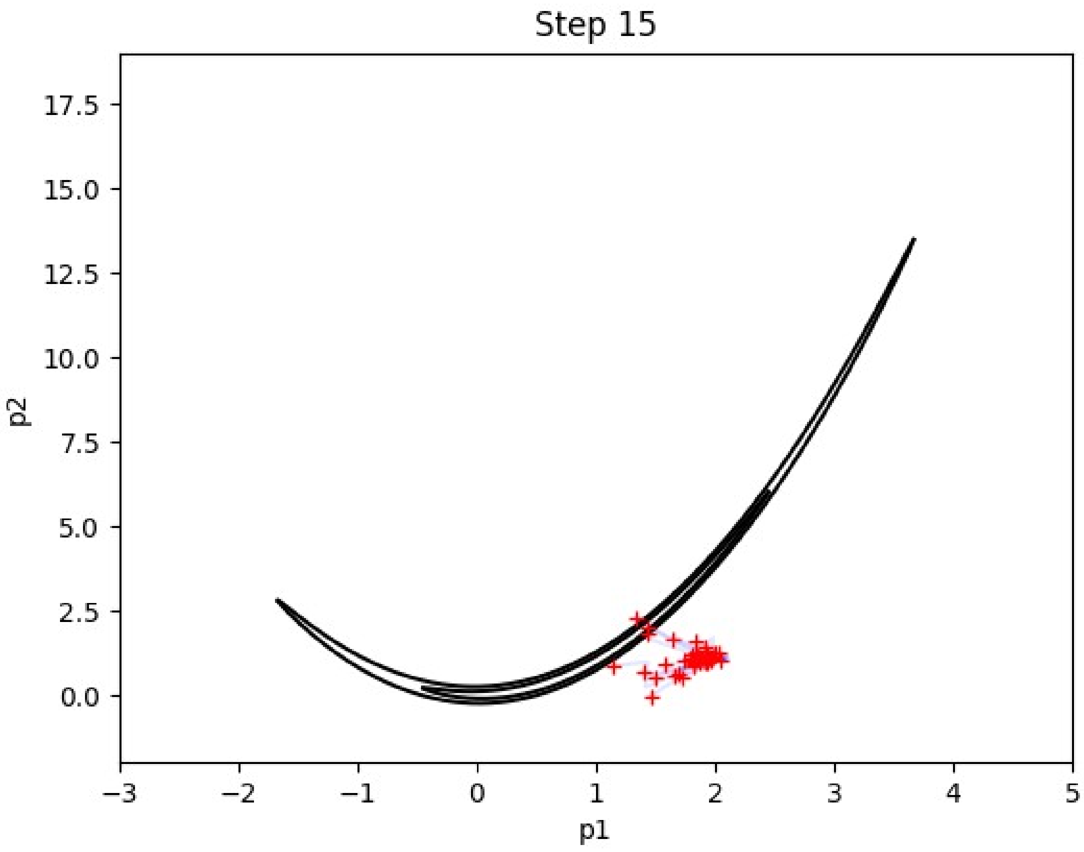

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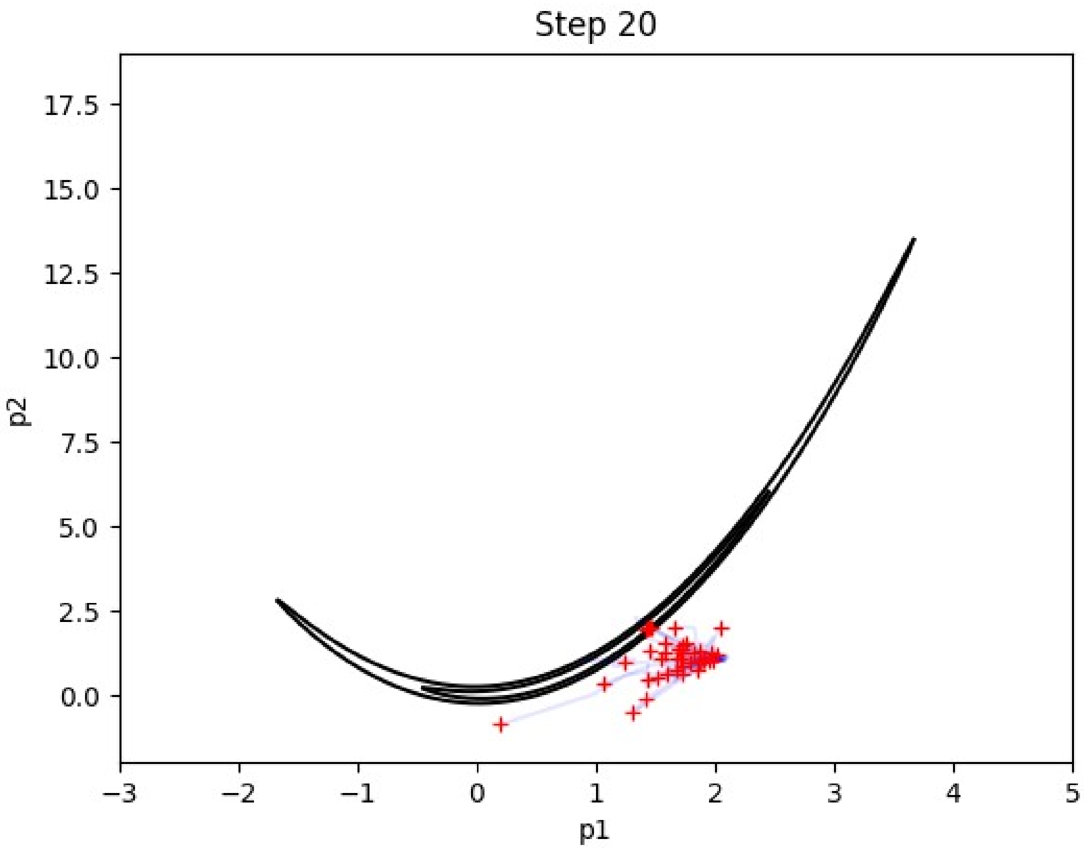

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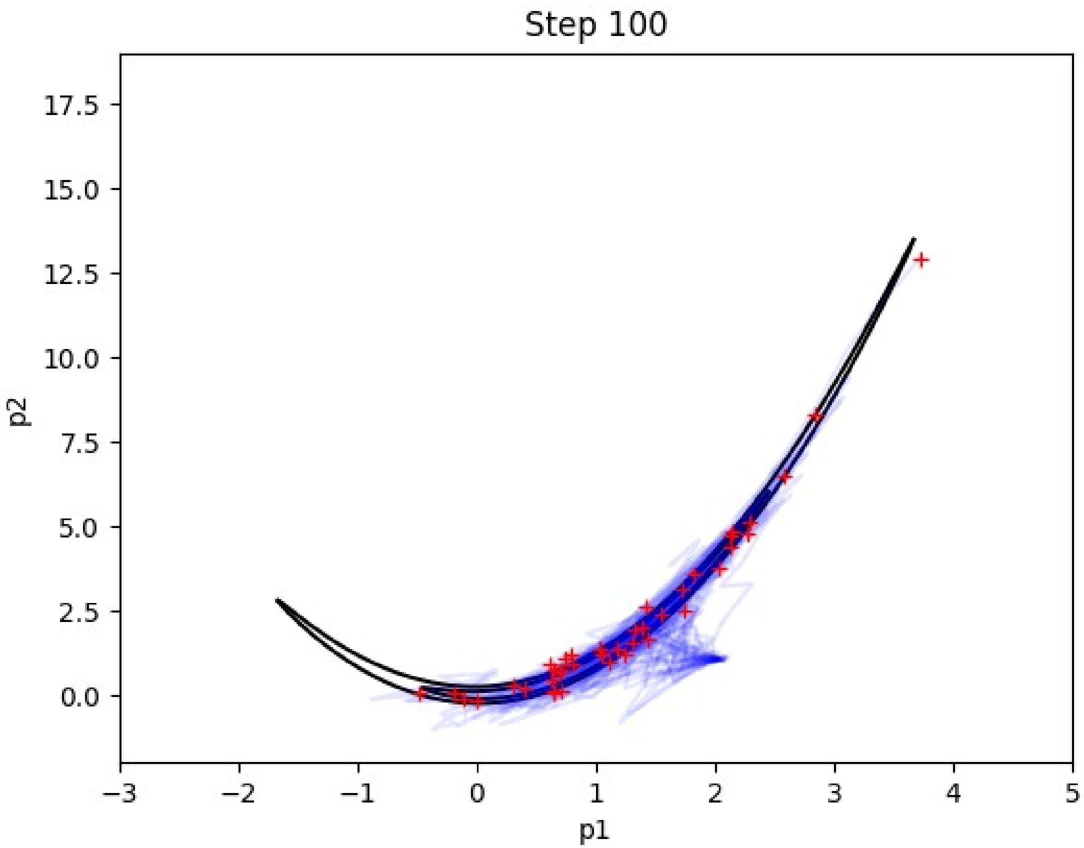
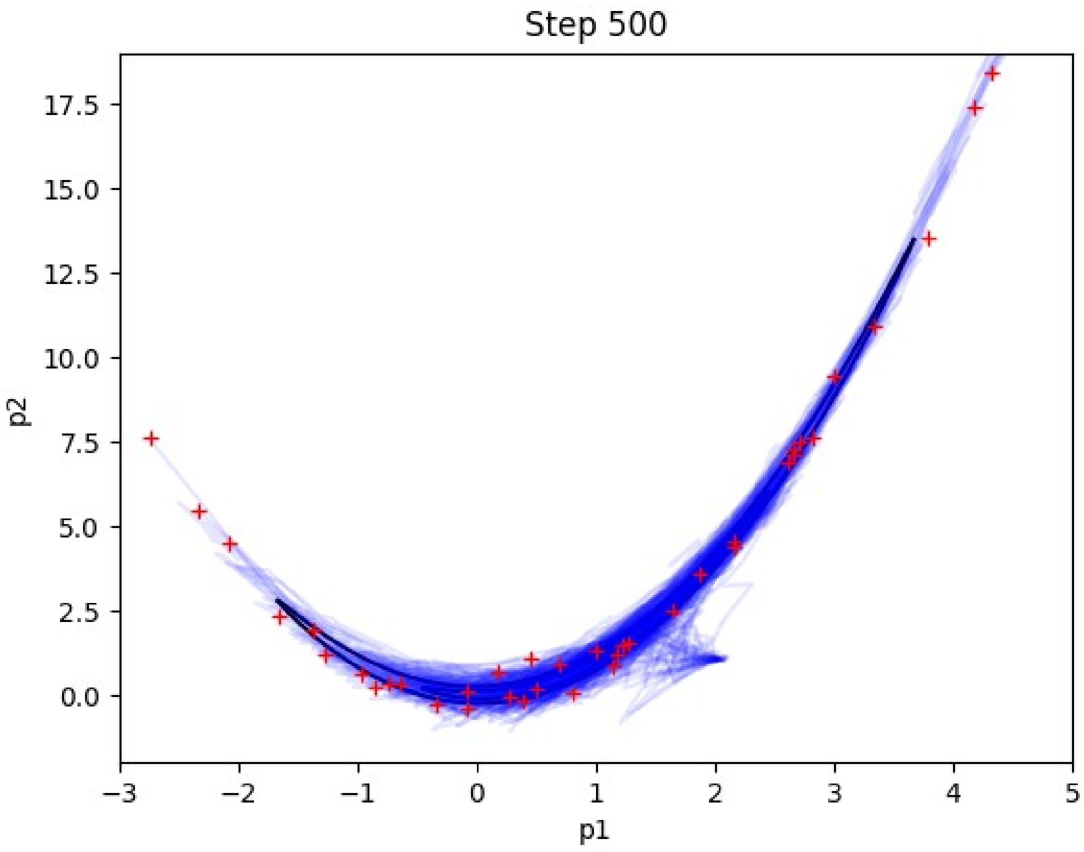


...and end up sitting in the "interesting" region of parameter space

Ensemble sampling

$$\pi(x) \propto \exp\left(\frac{-(x_1 - x_2)^2}{2\epsilon} - \frac{(x_1 + x_2)^2}{2}\right)$$



A single snapshot of walkers positions
=
A representative sample of the posterior distribution

Introducing : JAM

```
############
### MCMC ###
############

#-------------------------------#
# Setting for parallel computing #
#-------------------------------#----------------------------------#
# Current choices :                                                 #
# > "none": no parallelization                                      #
# > "multiprocessing N": OpenMP parallelization with N threads      #
# > "MPI": MPI parallelization (requires "schwimmbad" python module) #
#-------------------------------------------------------------------#
parallel  none

#-----------------------------------------------------------------------------#
# Number of walkers (has to be at least 2 times the number of free parameters) #
#-----------------------------------------------------------------------------#
# Current choices :                                                            #
# > "custom  X"  => fixed to X                                                 #
# > "prop_to  X" => X times the number of free parameters                      #
#-----------------------------------------------------------------------------#
#n_walkers  custom  1000
n_walkers  prop_to  4

#---------------------#
# Number of MCMC steps #
#---------------------#
n_steps  10000

#-------------------------------------------------#
# Thinning factor (i.e. keep only every X step) #
#-------------------------------------------------#
thin_by  1

#-------------------------#
# Temperature of the MCMC #
#-------------------------#
temperature  1.

#------------------------------------------------------------------------#
# Parameter for the "stretch move" of the Ensemble sampler (default is 2) #
#------------------------------------------------------------------------#
stretch  2.
```

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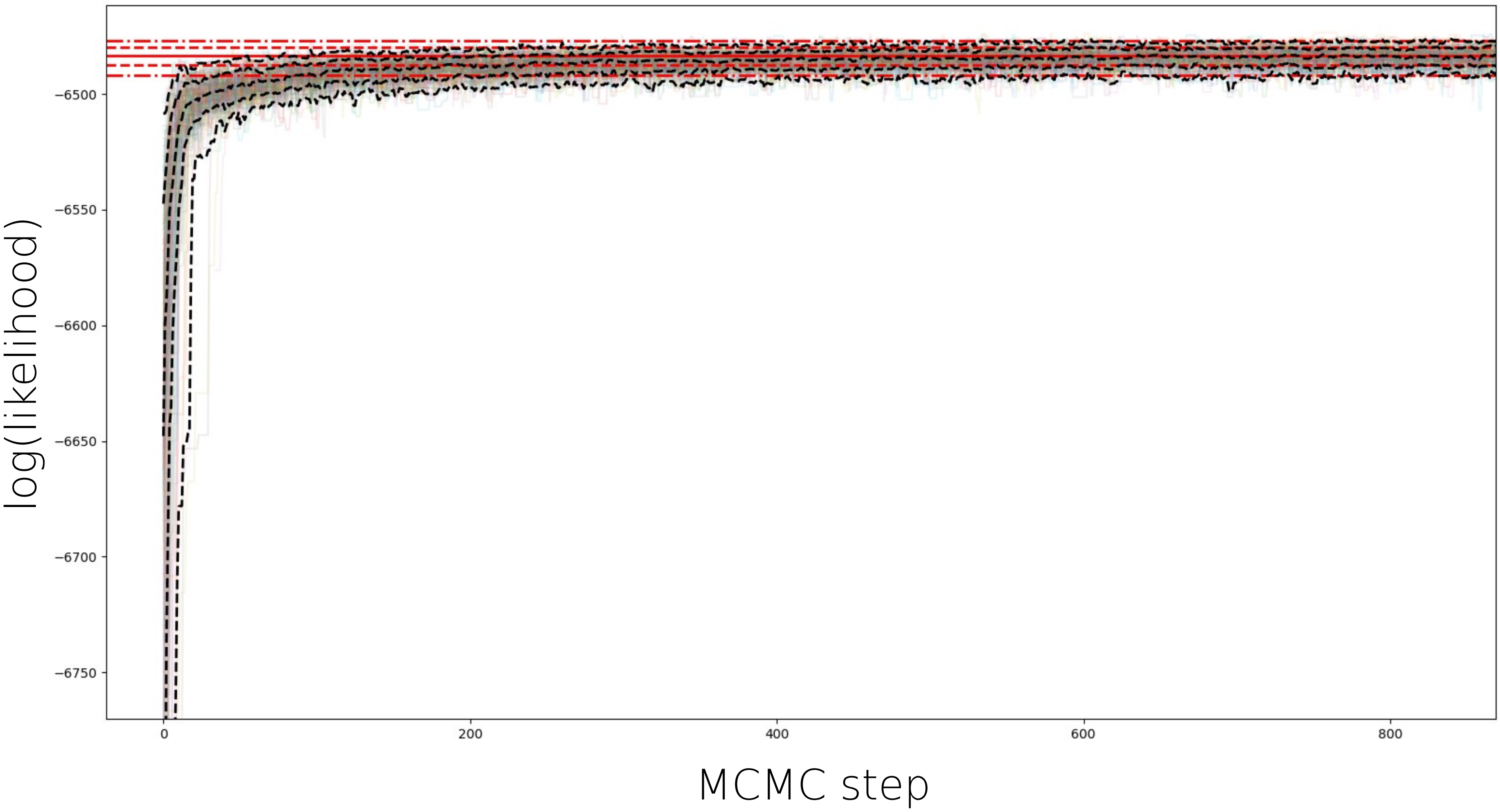
- Intuitive visualization scripts to assess convergence

Visualization tools



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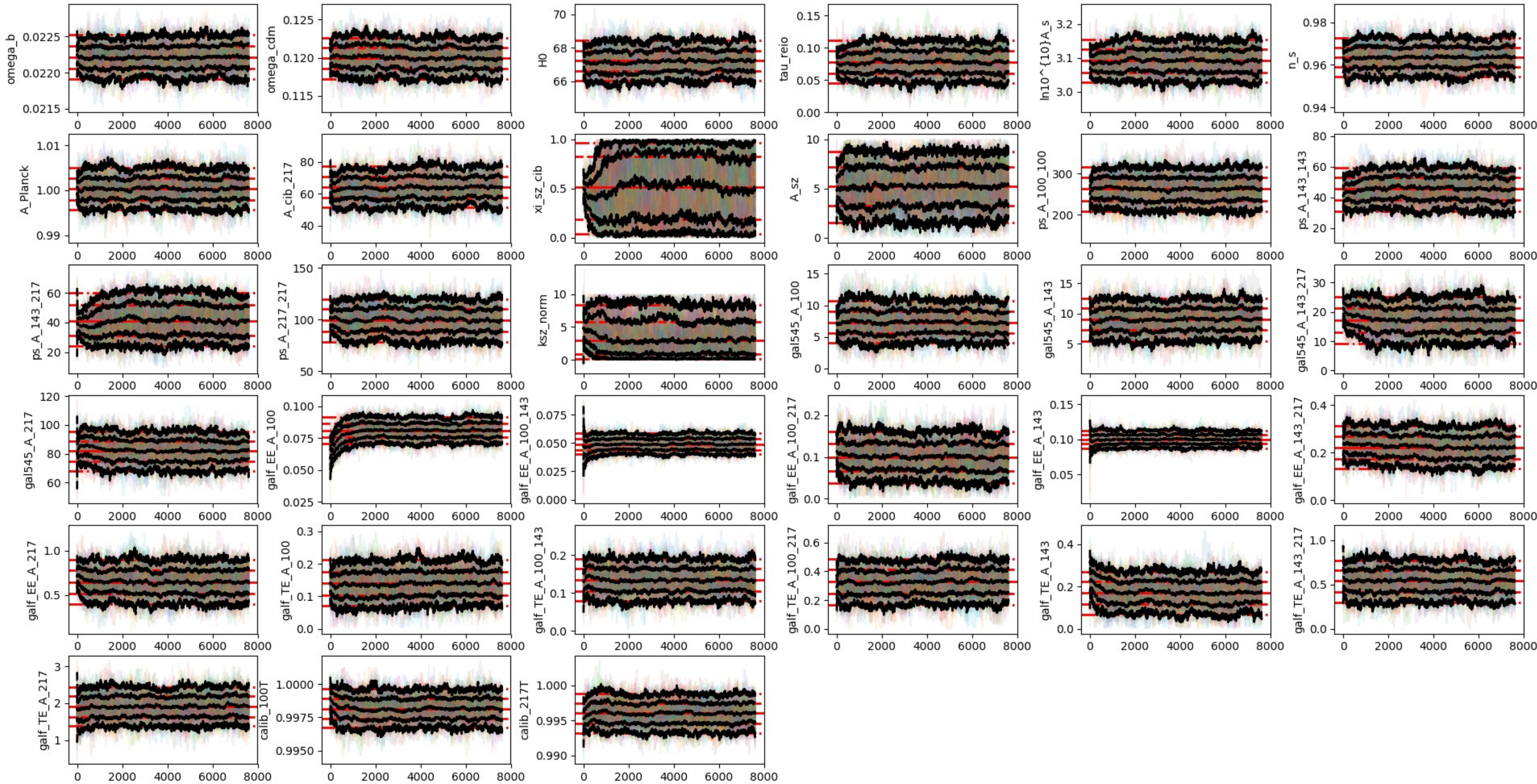
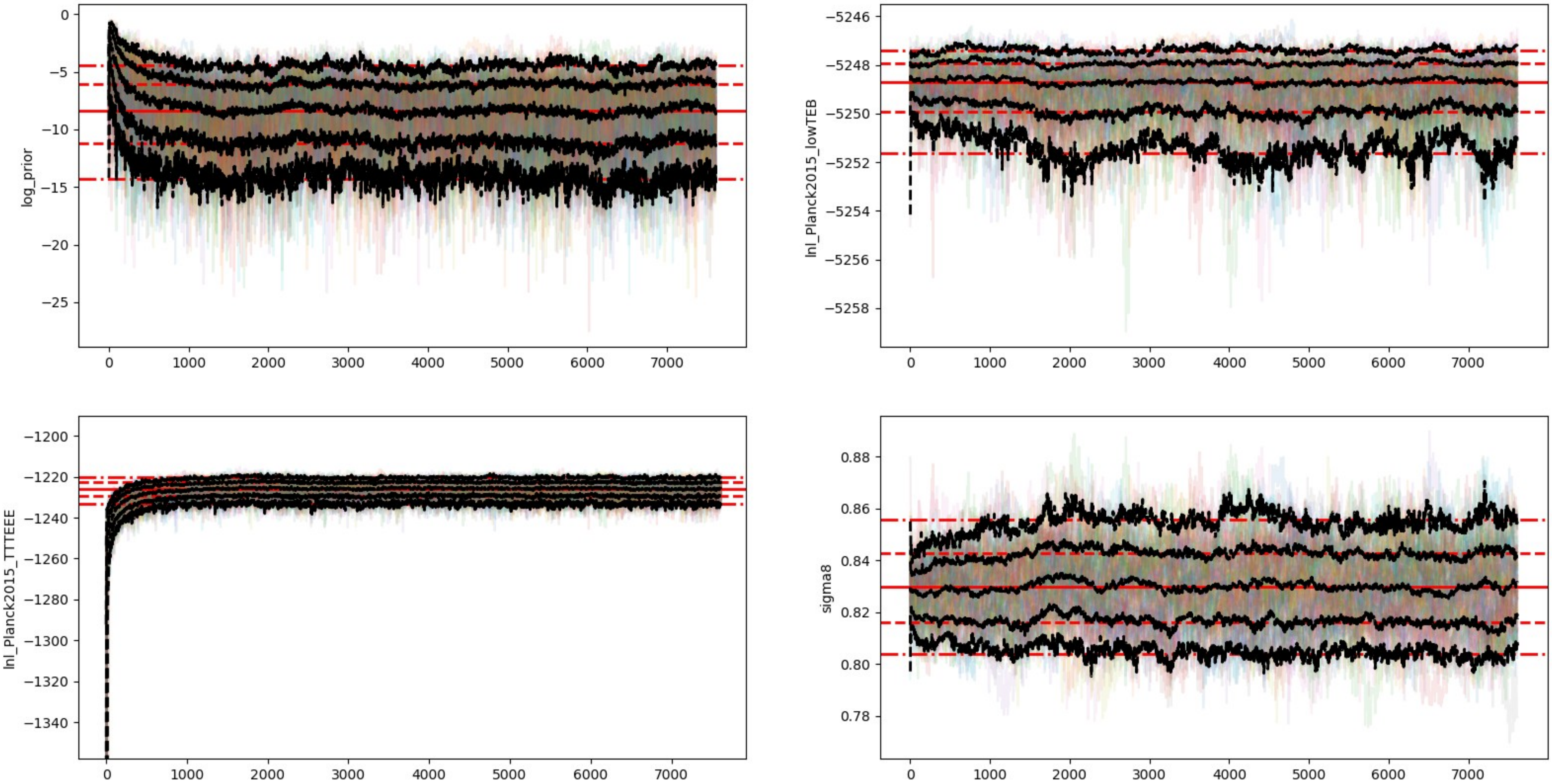


Visualization tools



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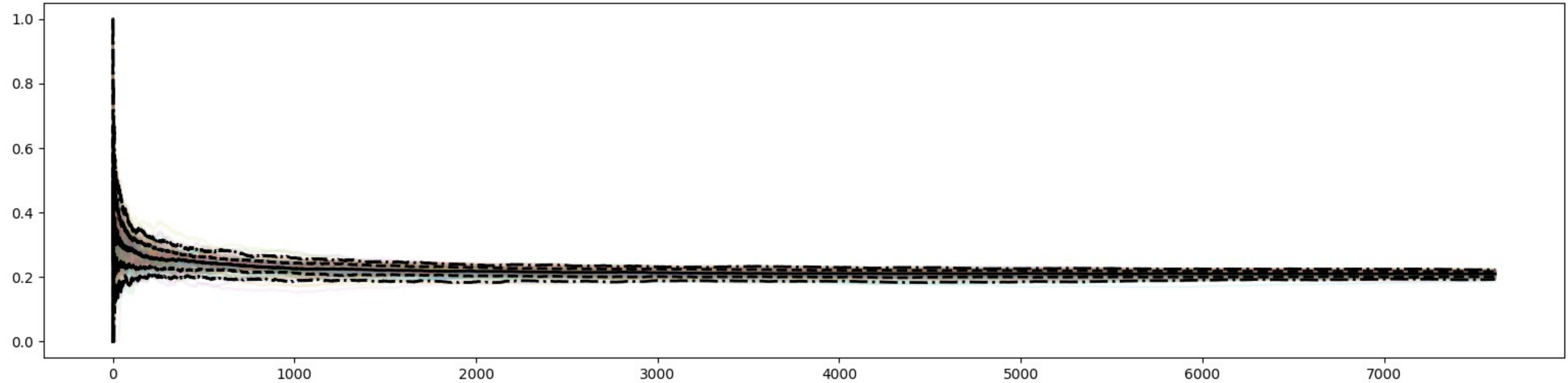

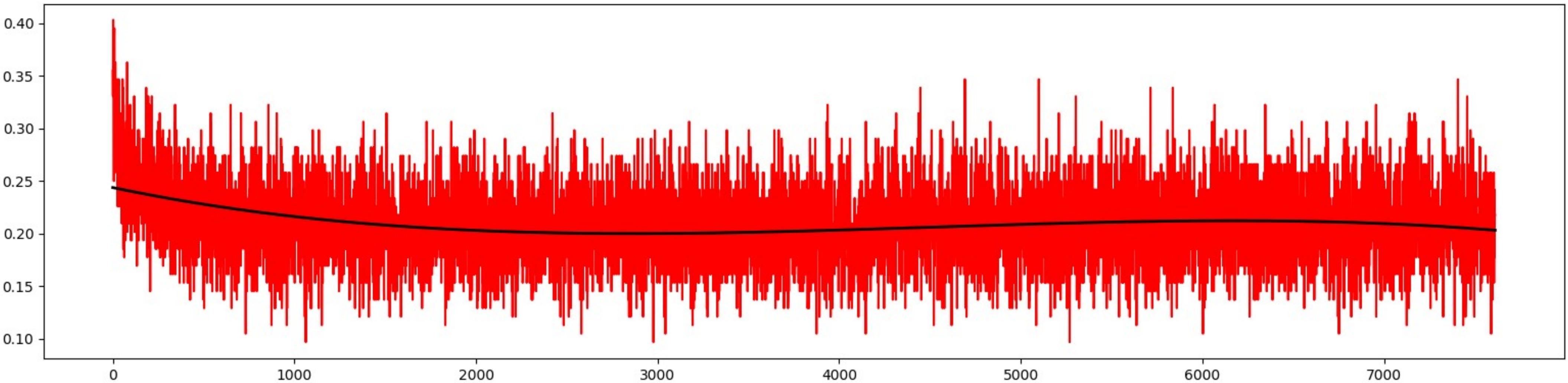

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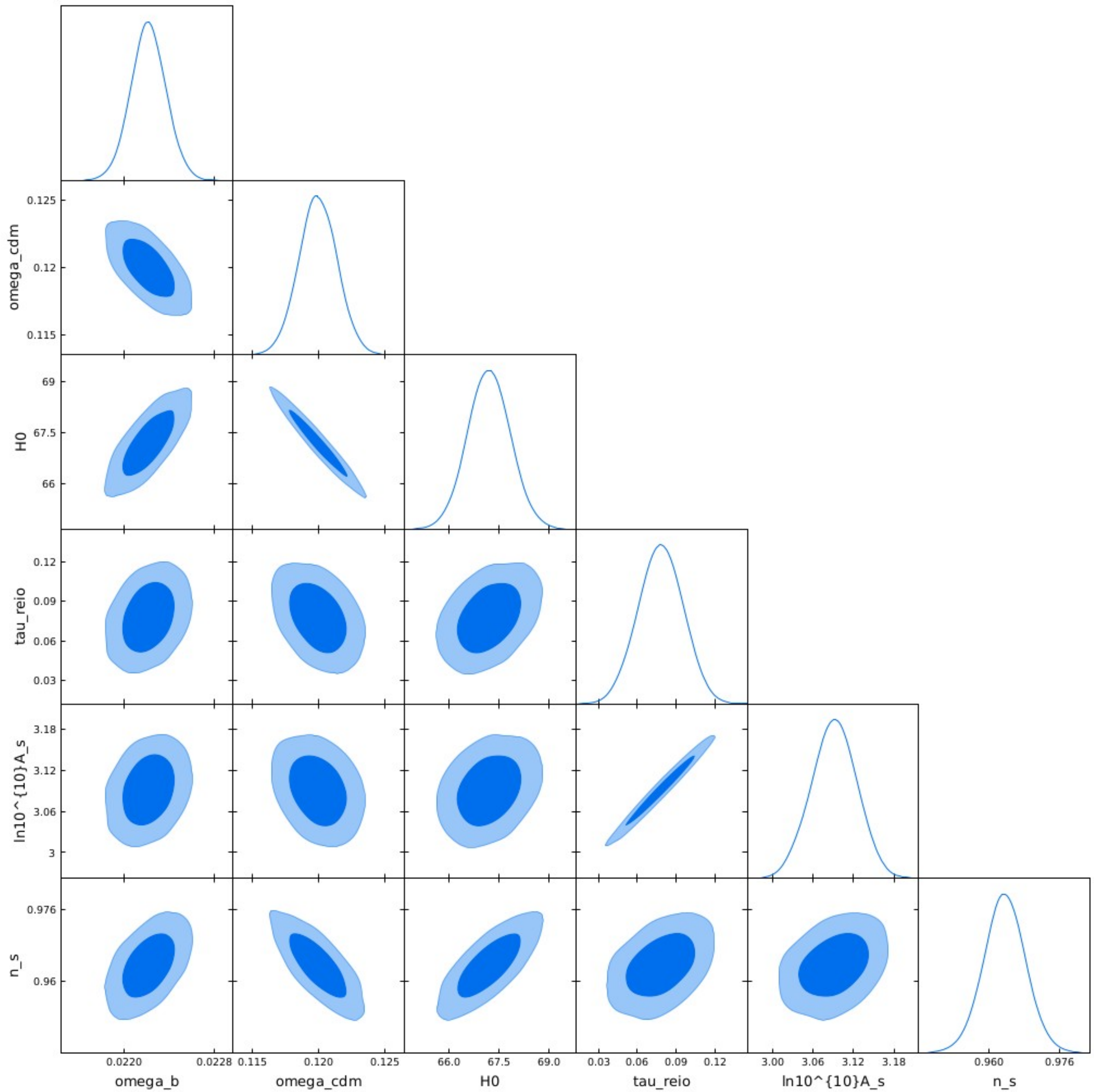
Contour plots



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- Convenient custom parser :“constraint” and “deriv” features

JAM parsing features

```
###################################
### Parameters special settings ###
###################################

#------------------------------#
# Put constraints on parameters #
#------------------------------#----------------------------------#
# Syntax :                                                        #
# > constraint  XXX  =  YYY                                       #
# > where XXX is the parameter forced to be equal to YYY          #
# Notes :                                                         #
# > YYY can be any fonction of any parameter                      #
# > in XXX and YYY, use syntax class[par_name] if class parameter #
# > in XXX and YYY, use syntax likes[par_name] otherwise          #
# Examples :                                                      #
# > class[omega_b]  =  class[omega_cdm]                           #
#-----------------------------------------------------------------#
#constraint  class[par_1] = class[par_2]+class[par_3]

#-------------------------------------------#
# Request some derived parameters in output #
#-------------------------------------------#----------------------------#
# Syntax :                                                               #
# > deriv  name  quantity_requested                                      #
# Notes :                                                                #
# > "name" == name of derived parameter in chain (should contain no space) #
# > "quantity_requested" can be any command one wants                    #
# > class wrapper accessible via "class_run" instance                    #
# > class background quantities accessible via "bg" dictionnary          #
# > class parameters accessible via "class_input" dictionnary            #
# > nuisance parameters accessible via "likes_input" dictionnary         #
# Examples :                                                             #
# > for H0 :      deriv  H0      bg['H [1/Mpc]'][-1]*299792.458          #
# > for sigma_8 :  deriv  sigma8  class_run.sigma8()                     #
# > for sum_nu  :  deriv  sum_nu  class_input['m_ncdm_val_0']+...        #
#------------------------------------------------------------------------#
# deriv  H0     bg['H [1/Mpc]'][-1]*299792.458
```

+ can put priors on any derived parameter

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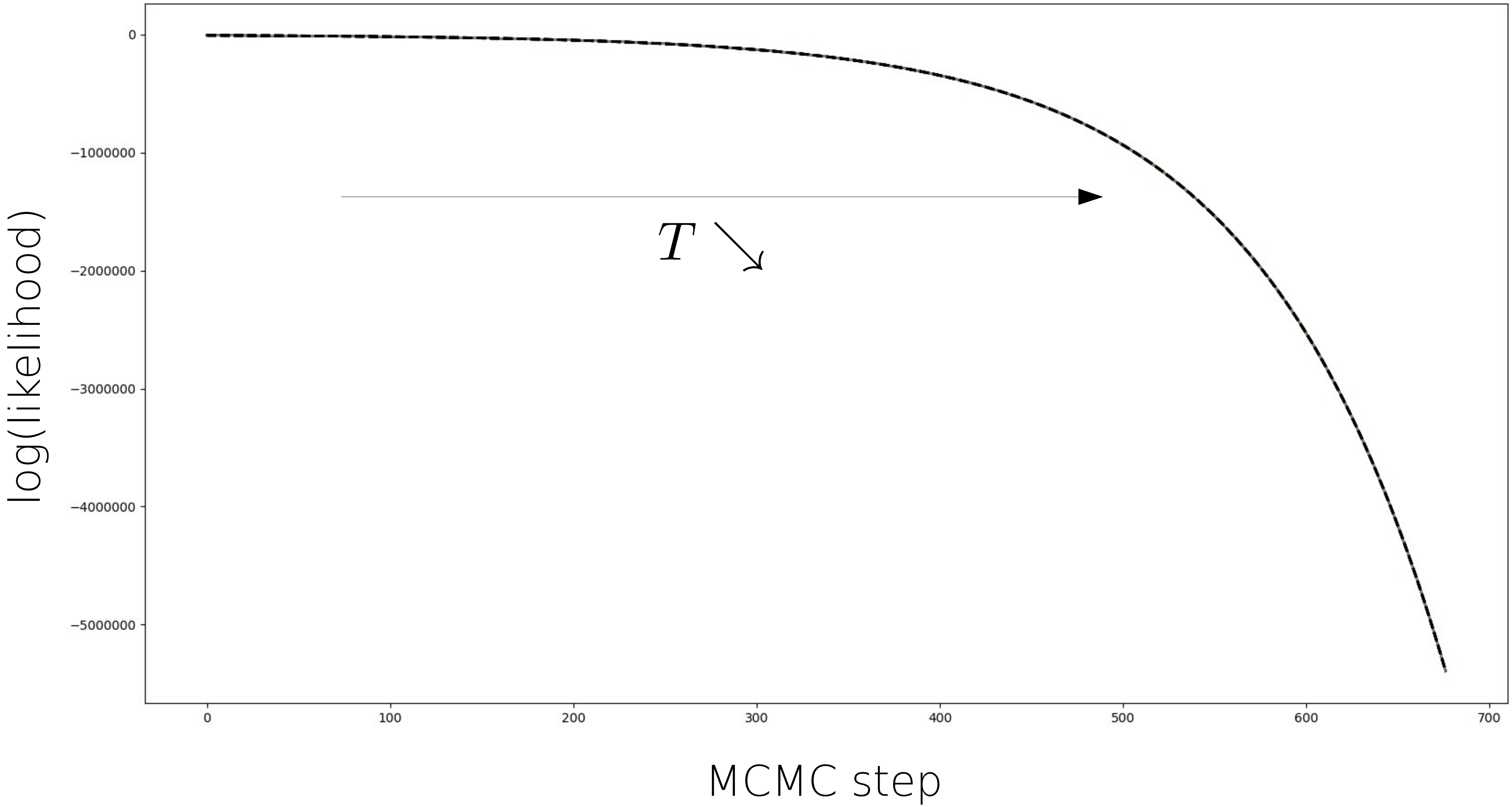
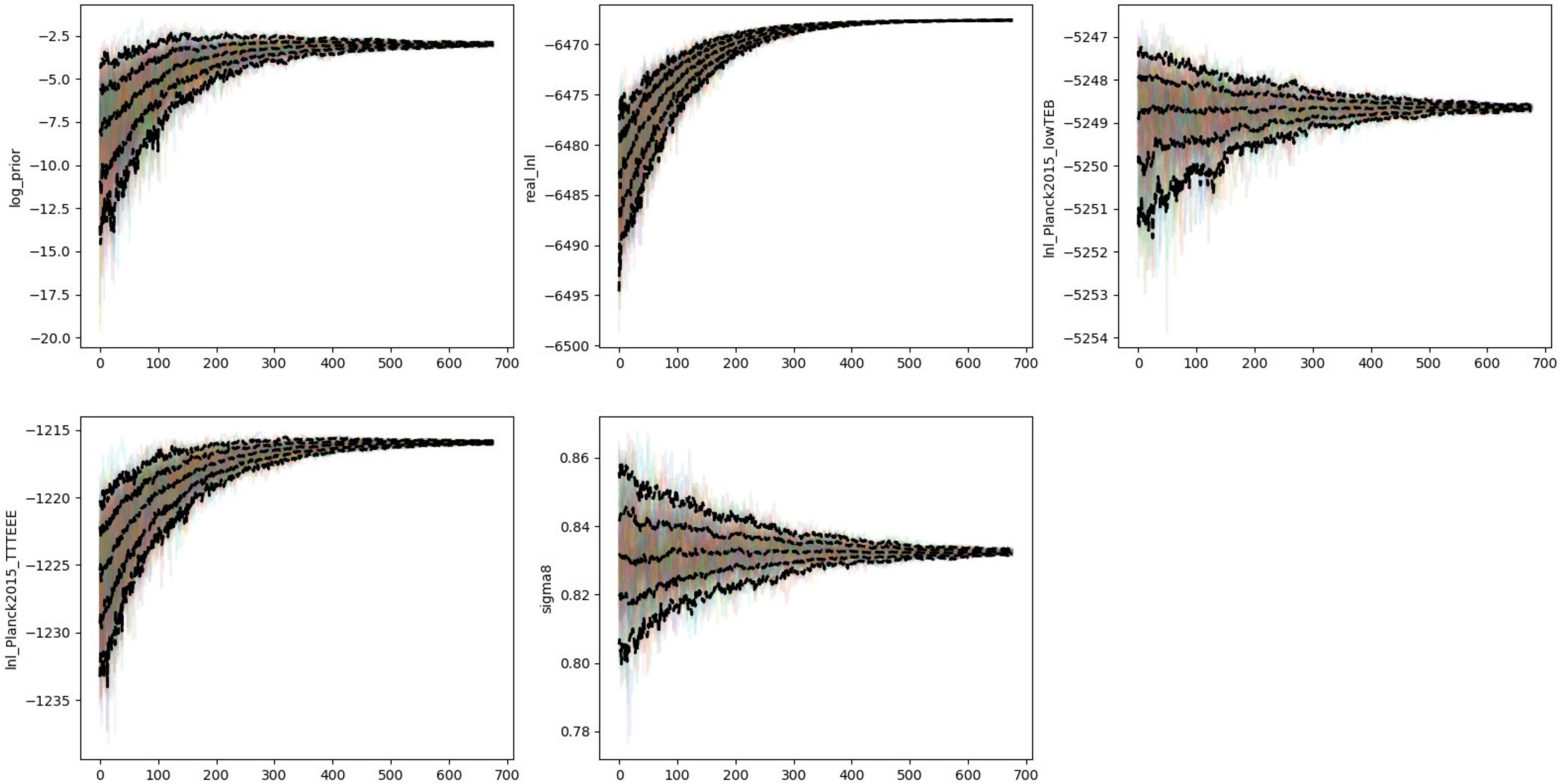
- Convenient custom parser :“constraint” and “deriv” features
- Robust minimizer combining simulated annealing & ensemble sampling (SAVES ?)

Minimizing with JAM

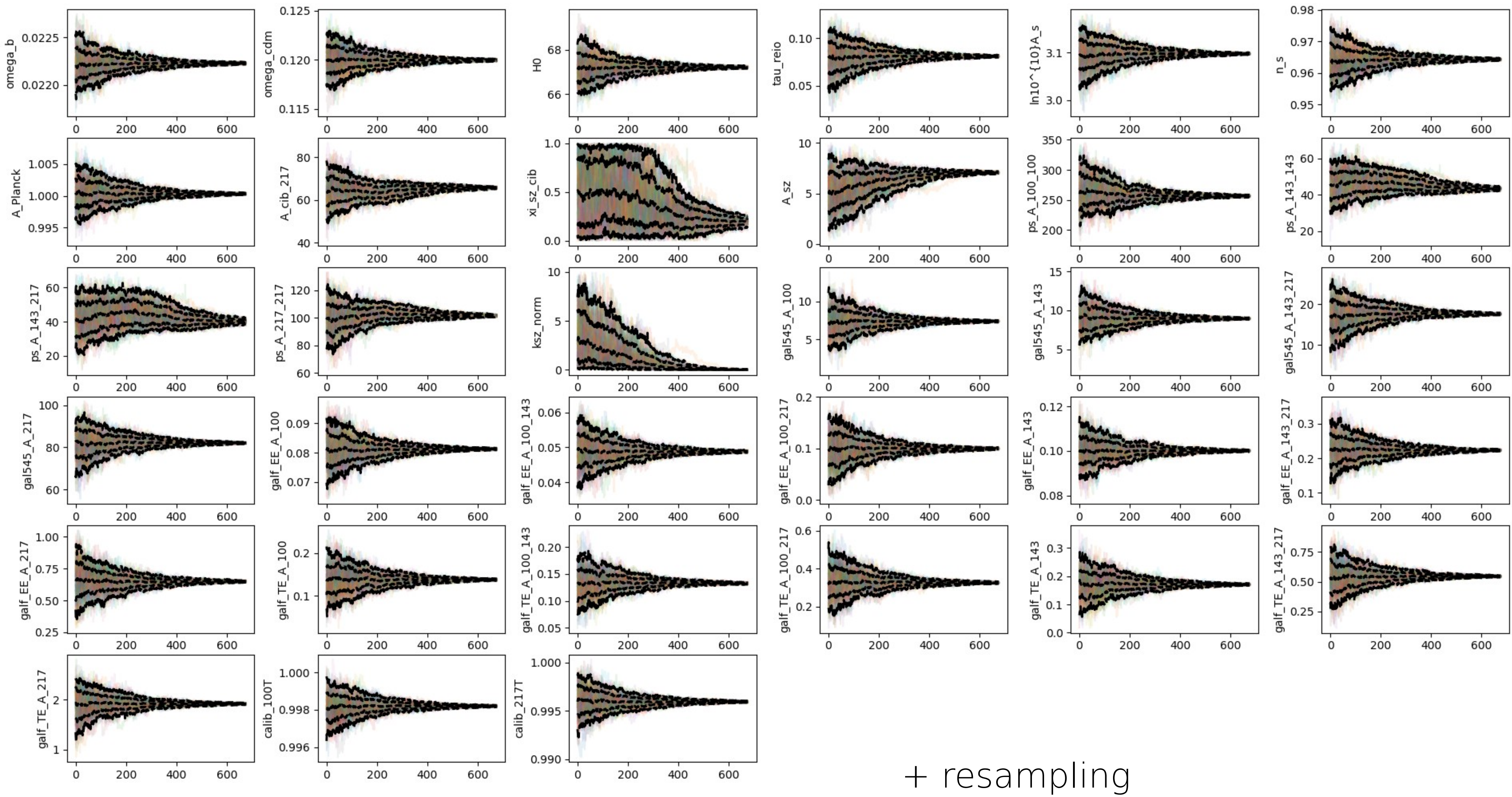
$$\mathcal{L} \longrightarrow \mathcal{L}^{1/T}$$



Minimizing with JAM



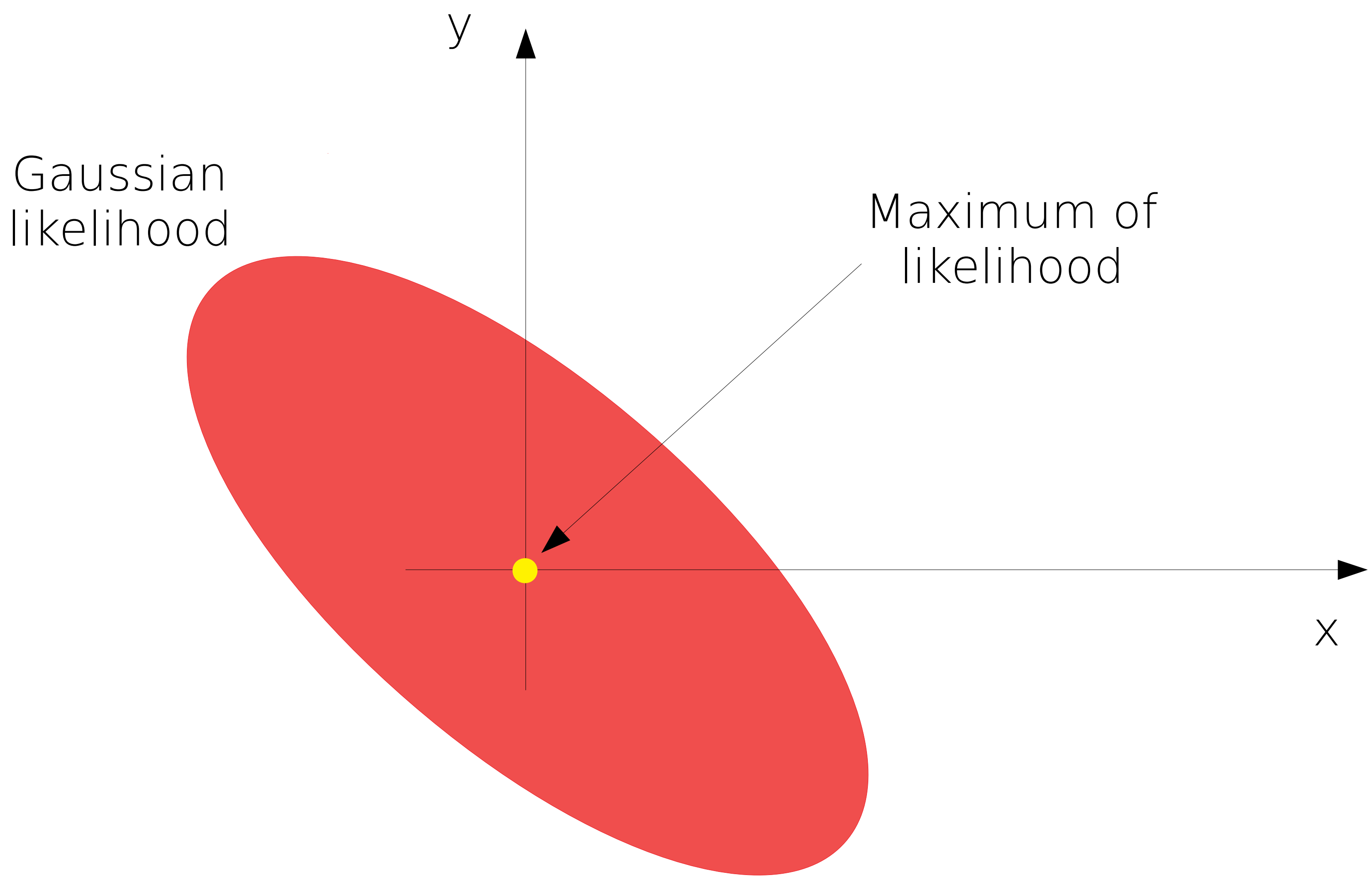
Minimizing with JAM



+ resampling
+ evidence computing

Identifying prior effects with JAM

Effects of priors



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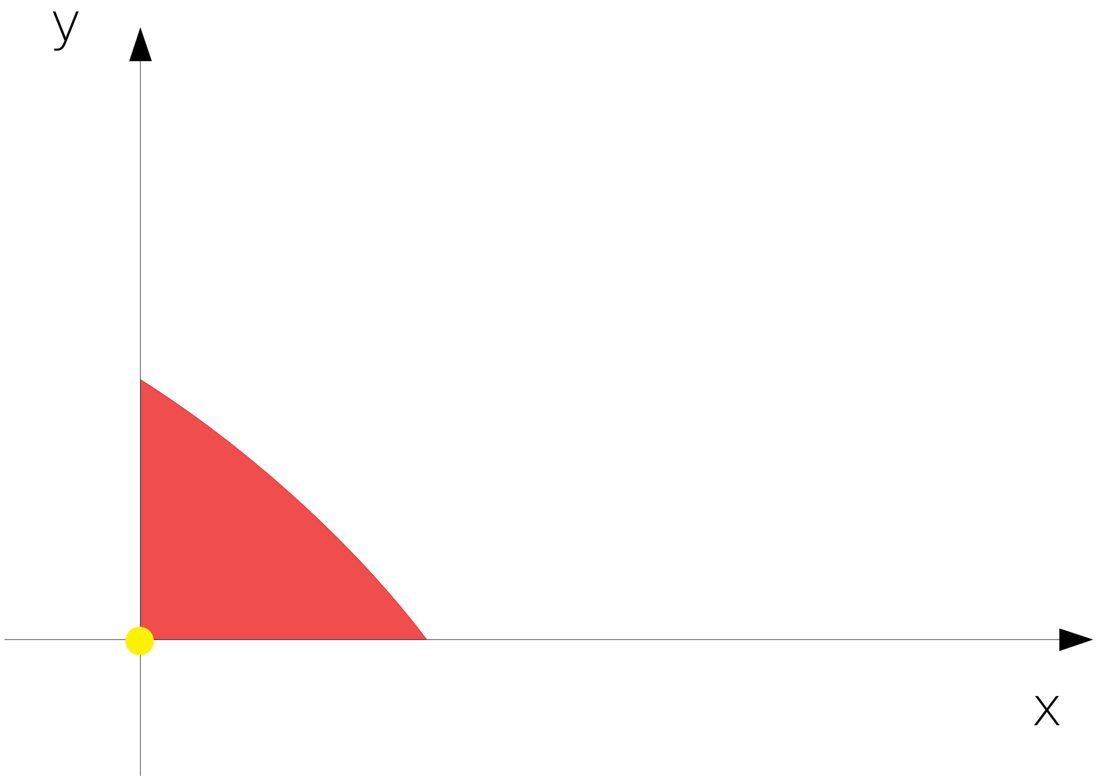

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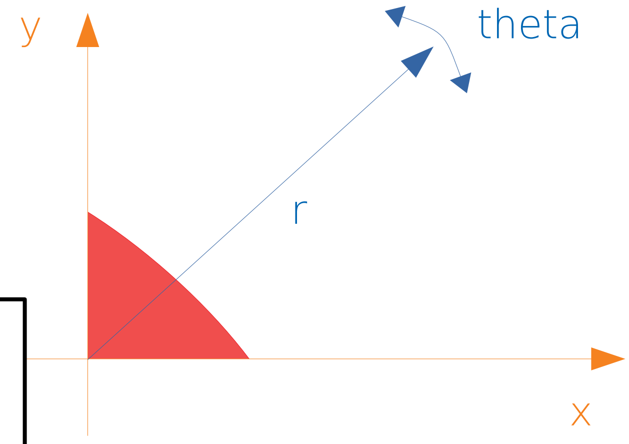
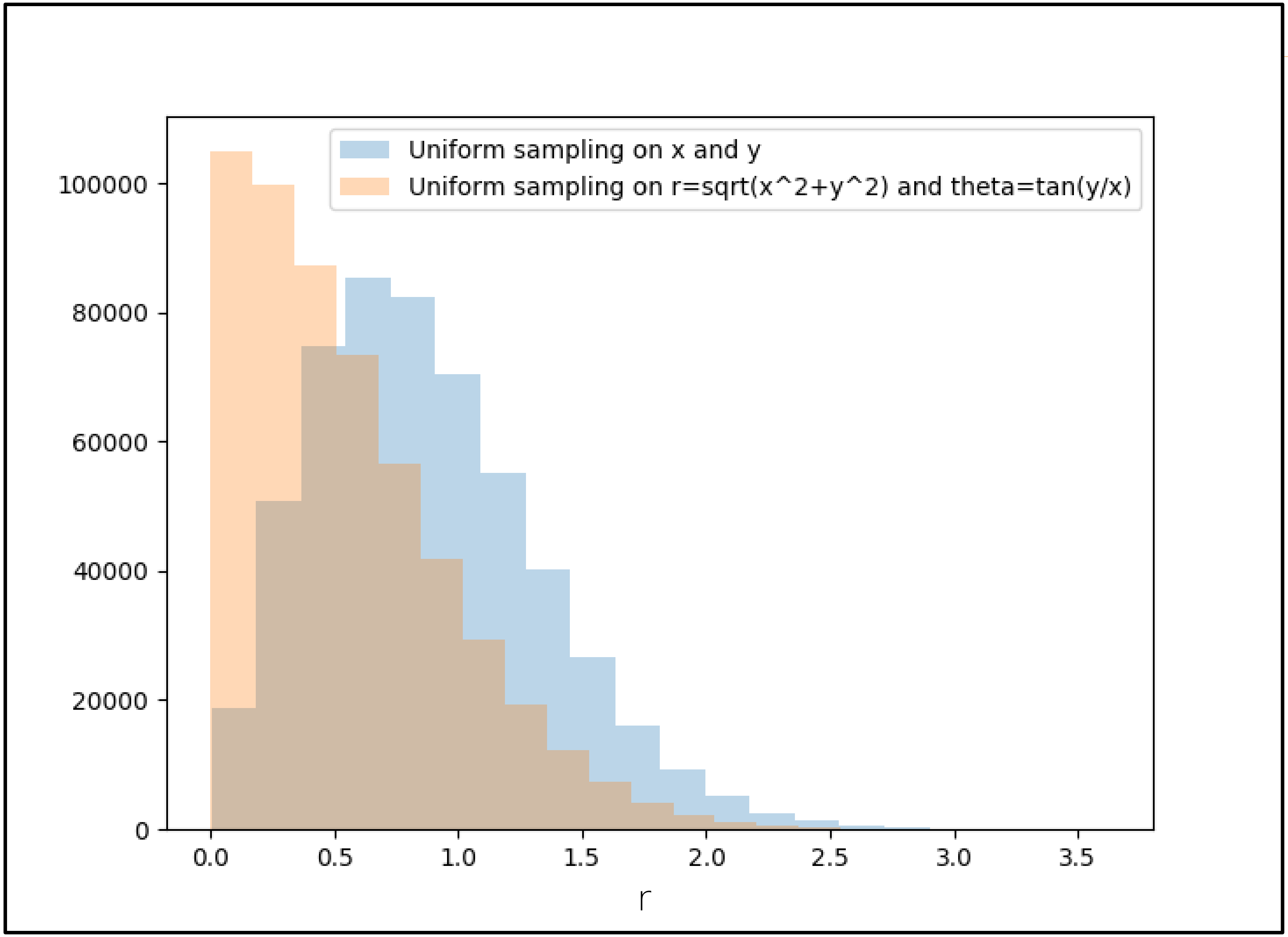


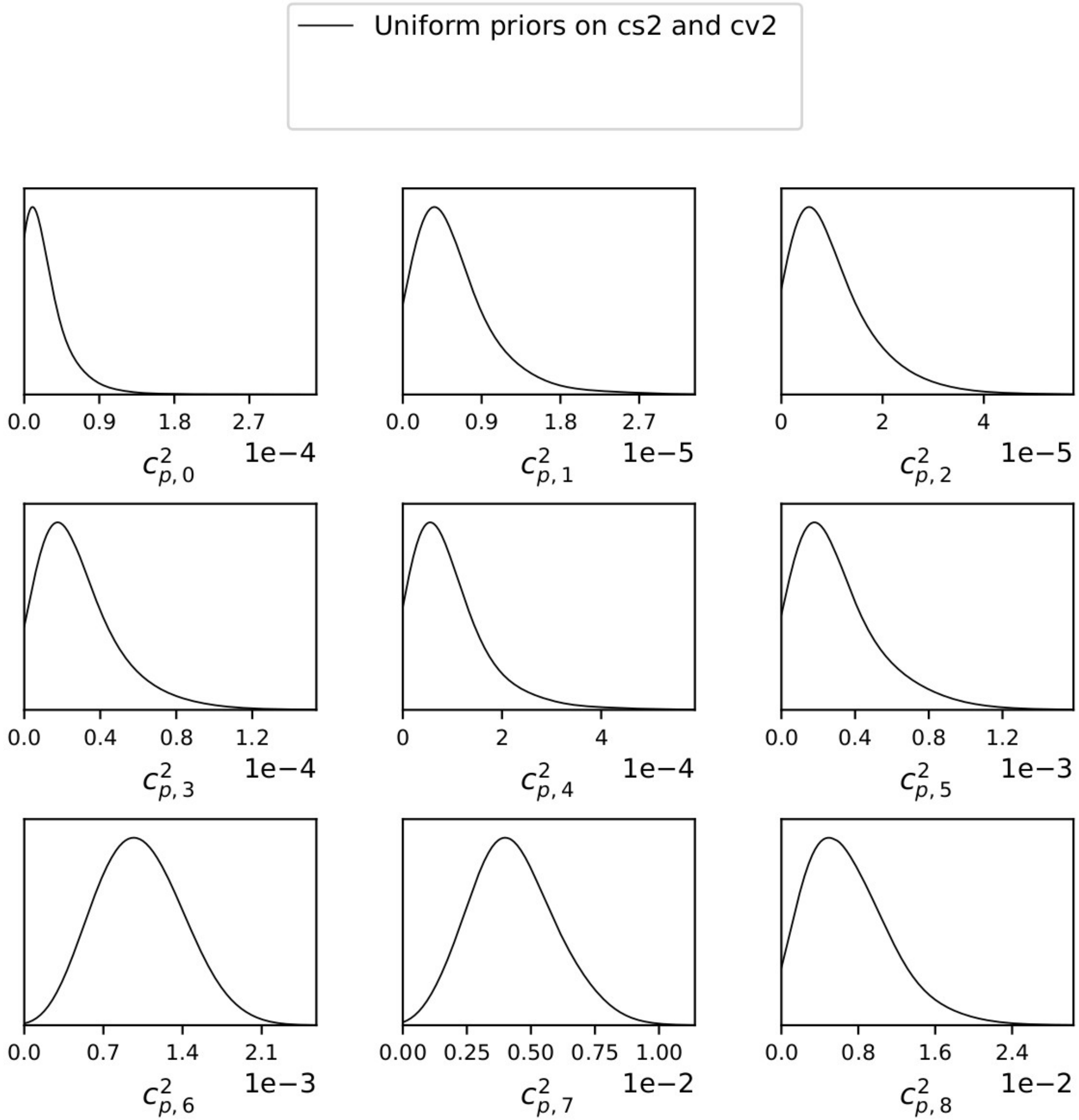


Effects of priors

Ilić et al, in prep

$$c_p^2 = c_s^2 + \frac{8}{15} c_v^2$$

$$(c_s^2, c_v^2) \quad > 0$$



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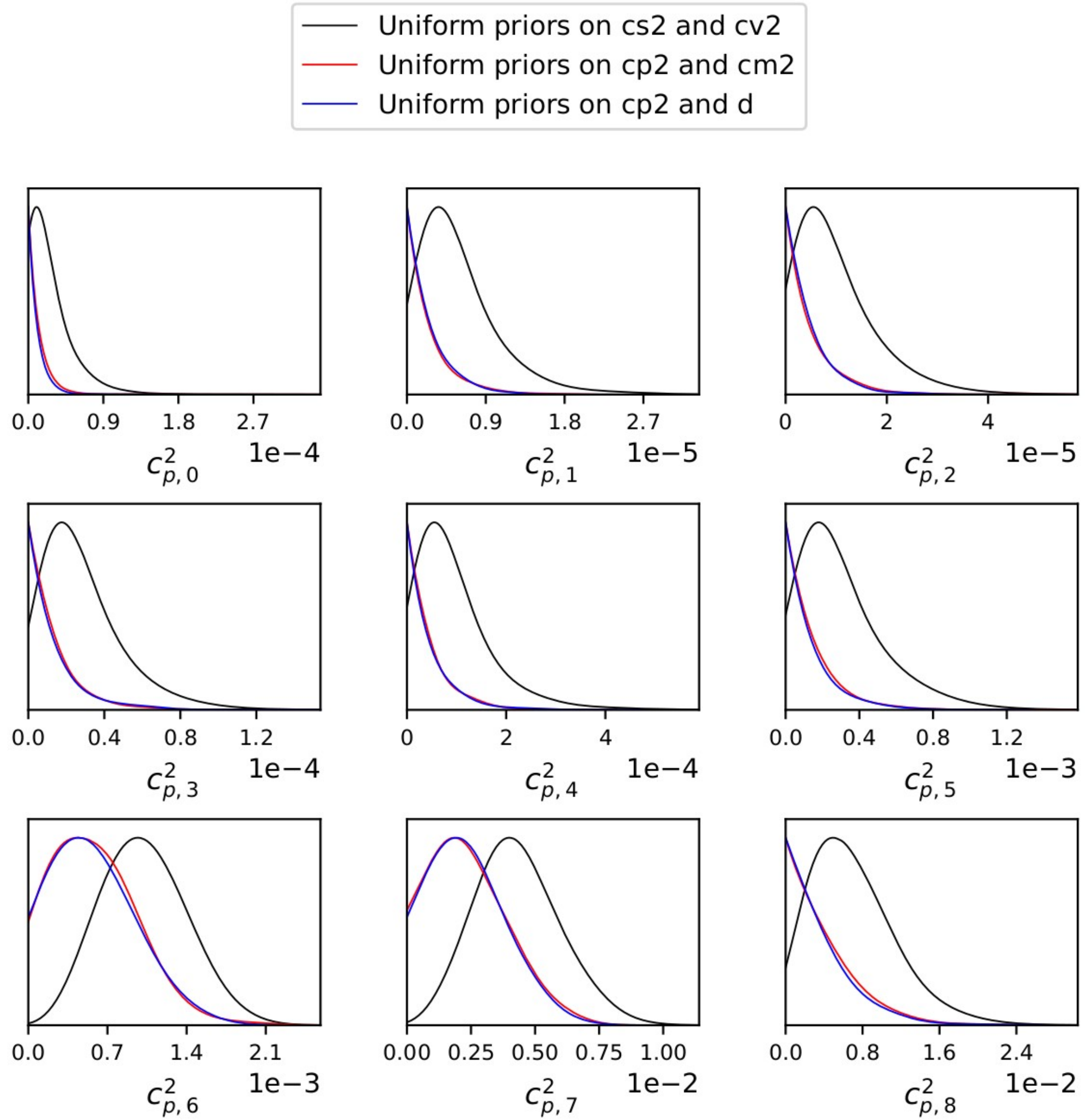
$$(c_s^2, c_v^2) \quad > 0$$

$$(c_p^2, c_m^2) \qquad\qquad (c_p^2, d)$$

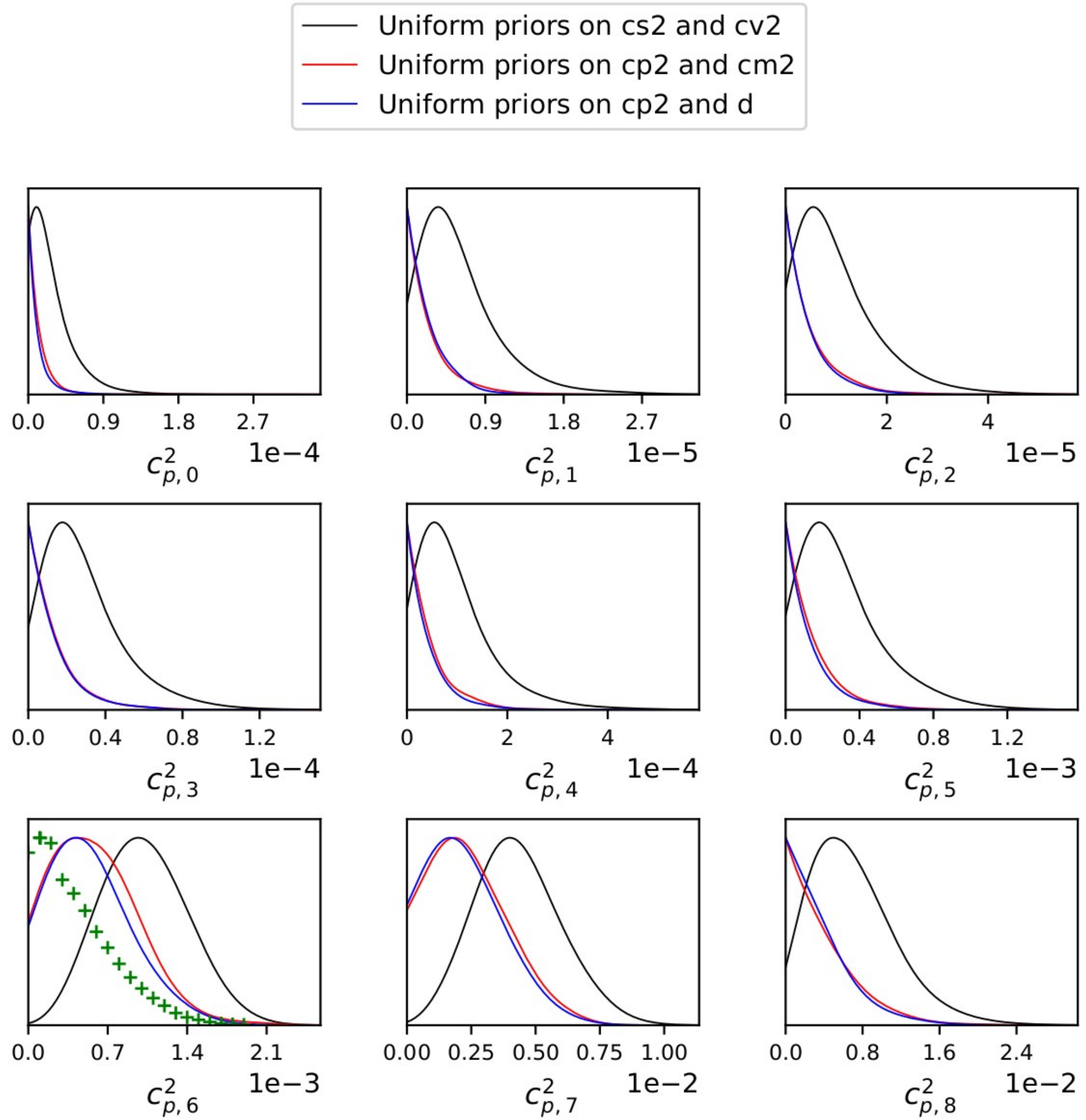
$$c_m^2 = \arctan\left(\frac{8}{15}\frac{c_v^2}{c_s^2}\right) \qquad\qquad d = \frac{c_s^2}{c_p^2}$$



Effects of priors

$$c_p^2 = c_s^2 + \frac{8}{15} c_v^2$$

Ilić et al, in prep



<u>Frequentist approach :</u>
Computation of the
"profile likelihood"
=
1D grid on given parameter,
minimize likelihood wrt
all other parameters

Identifying prior effects with JAM

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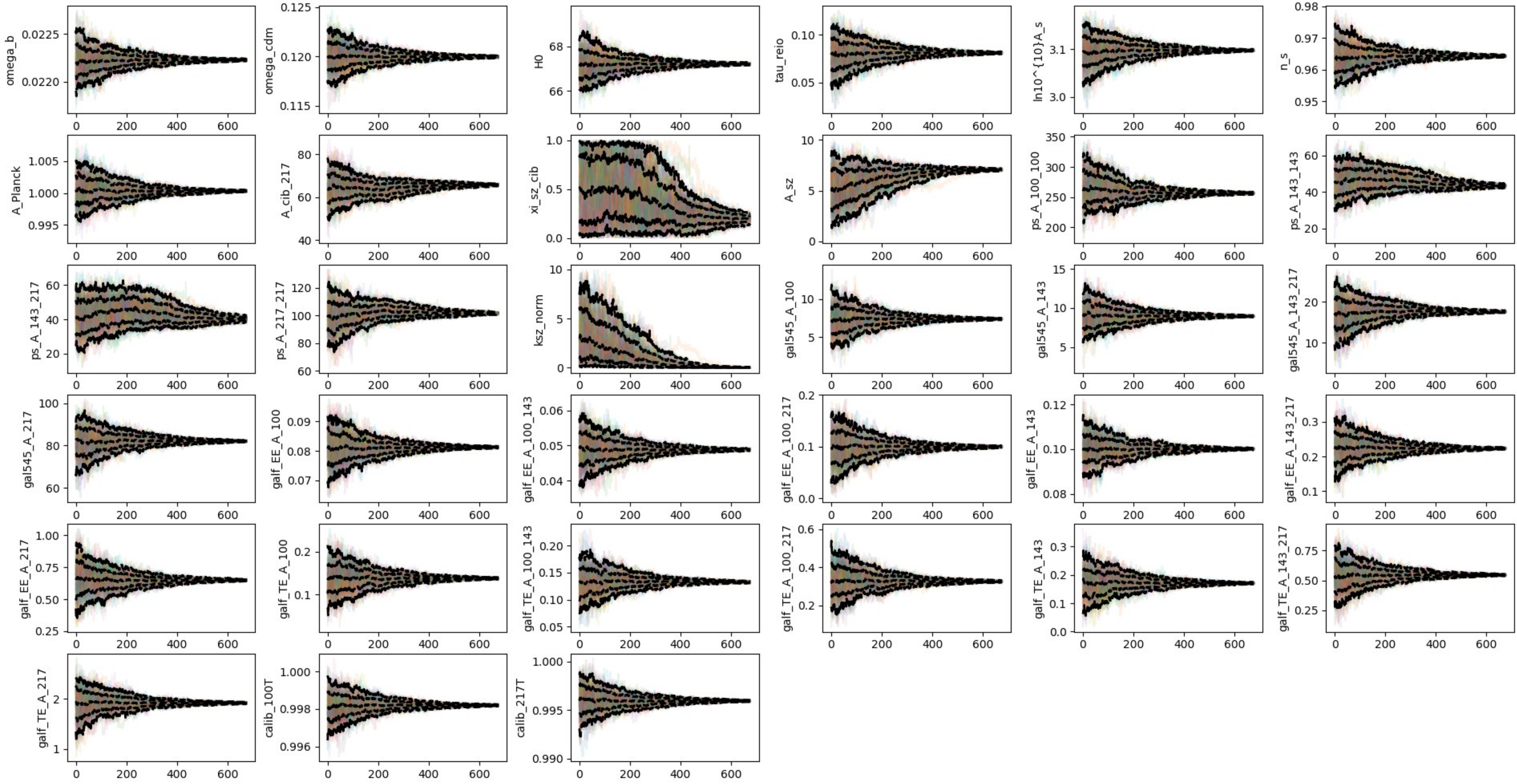
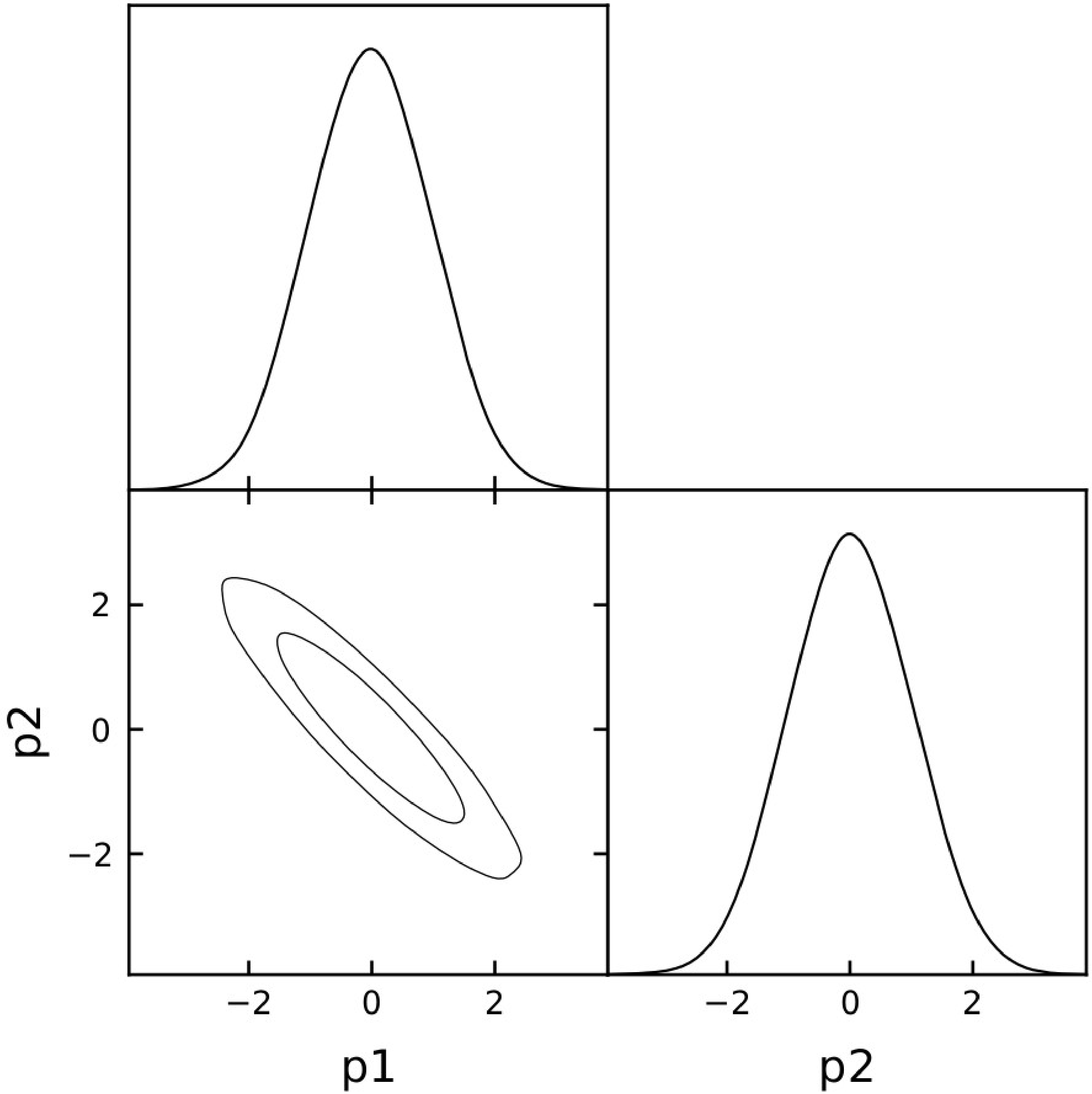
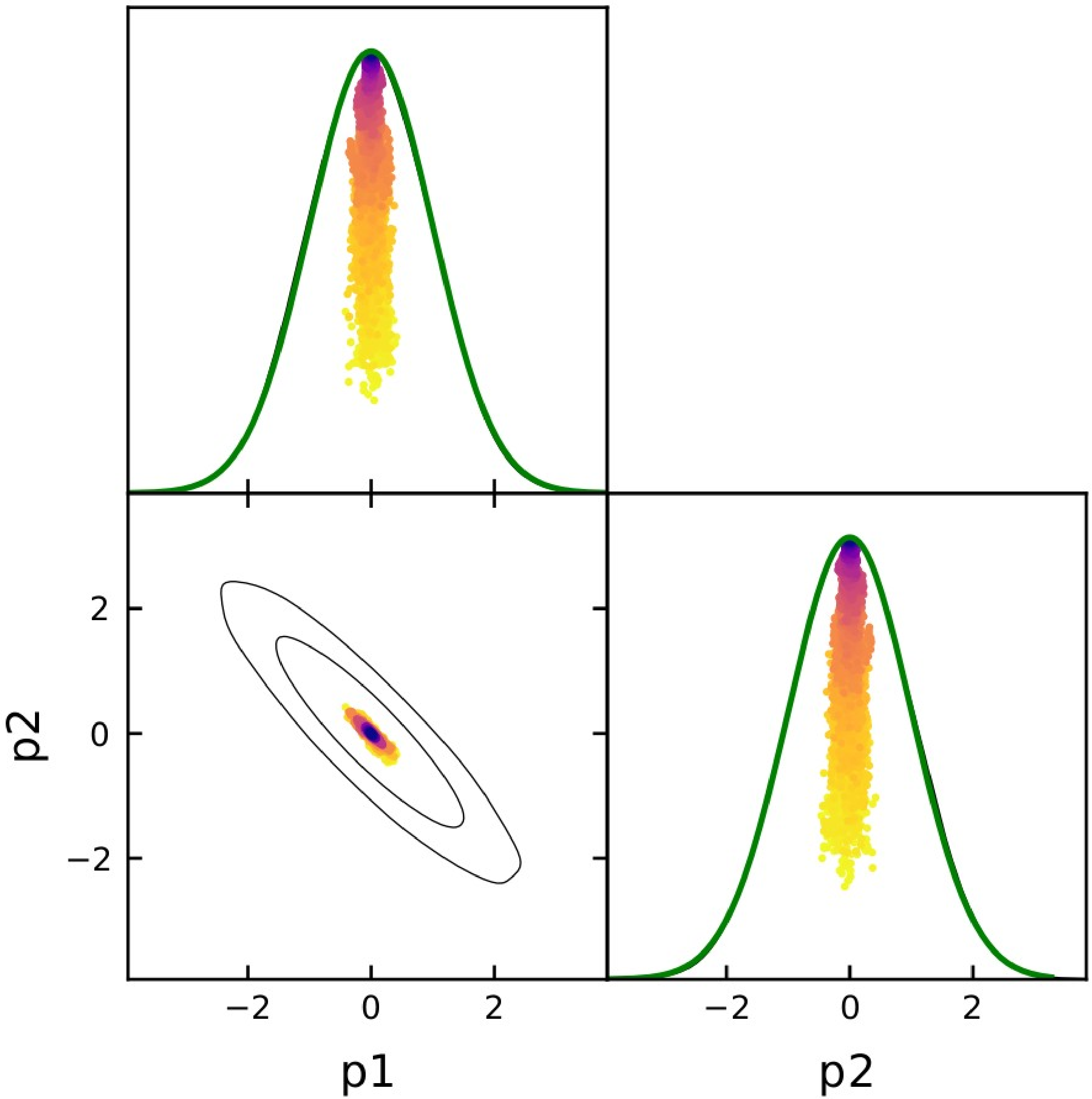


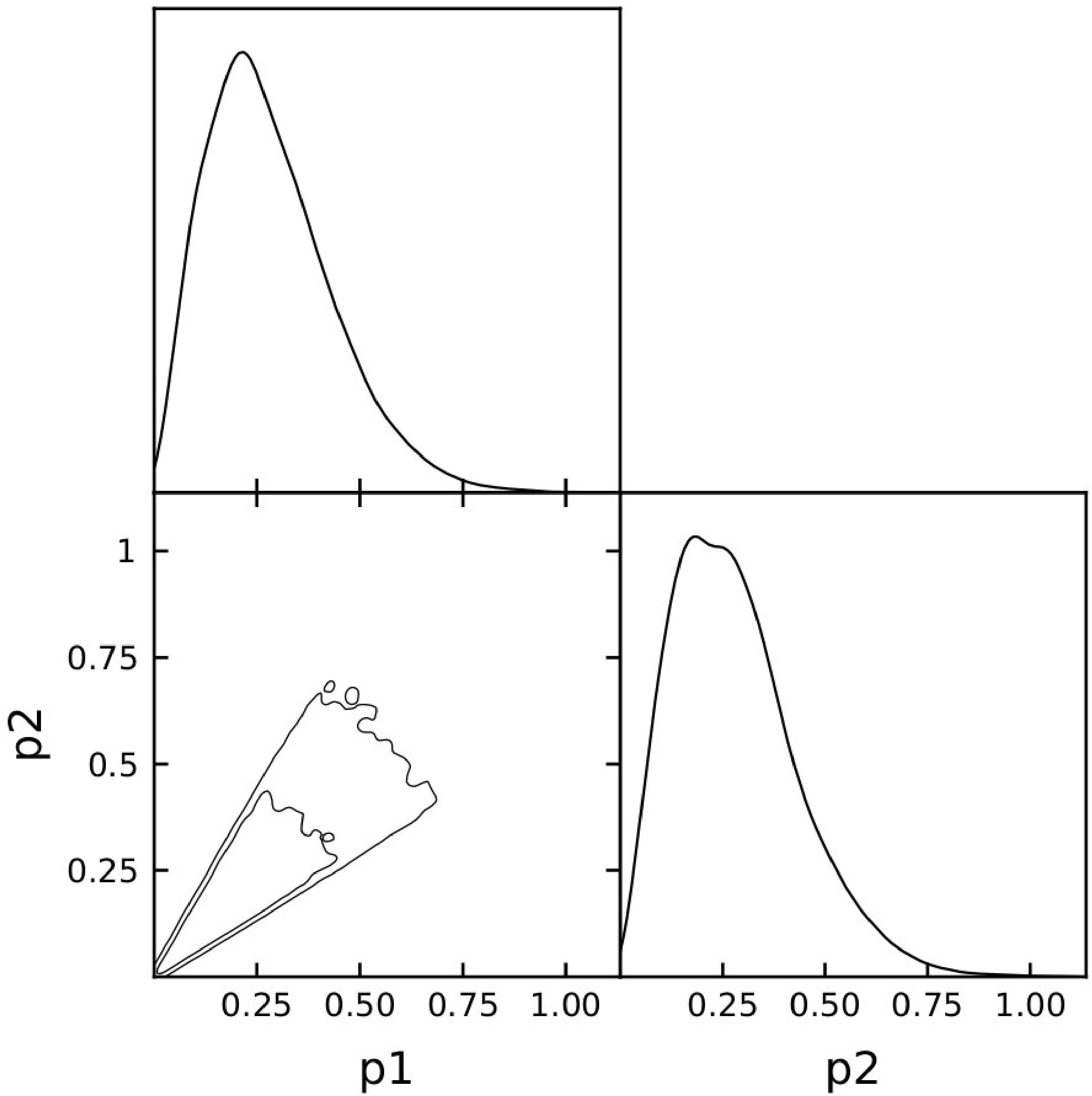
Identifying prior effects with JAM



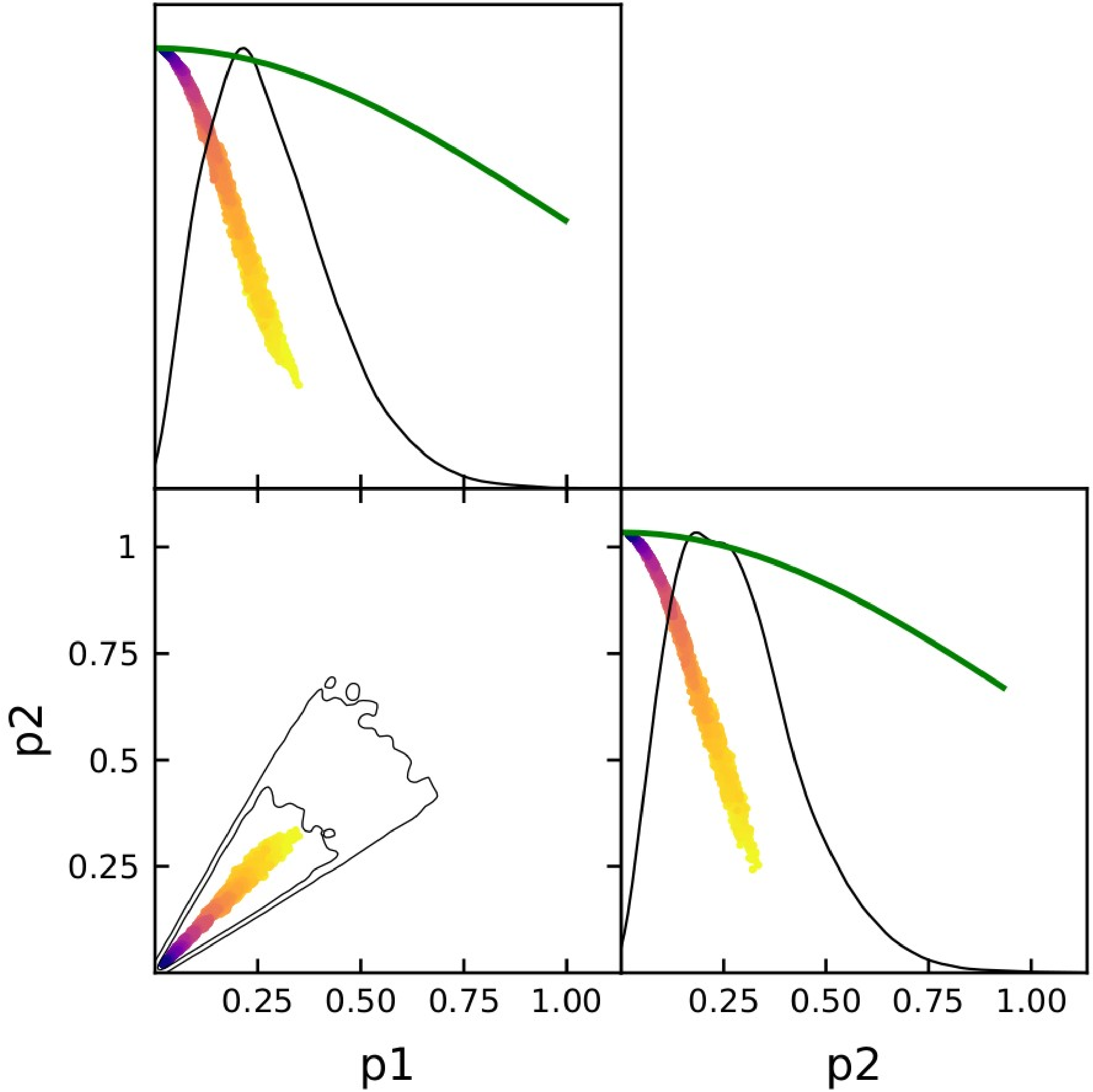
Identifying prior effects with JAM



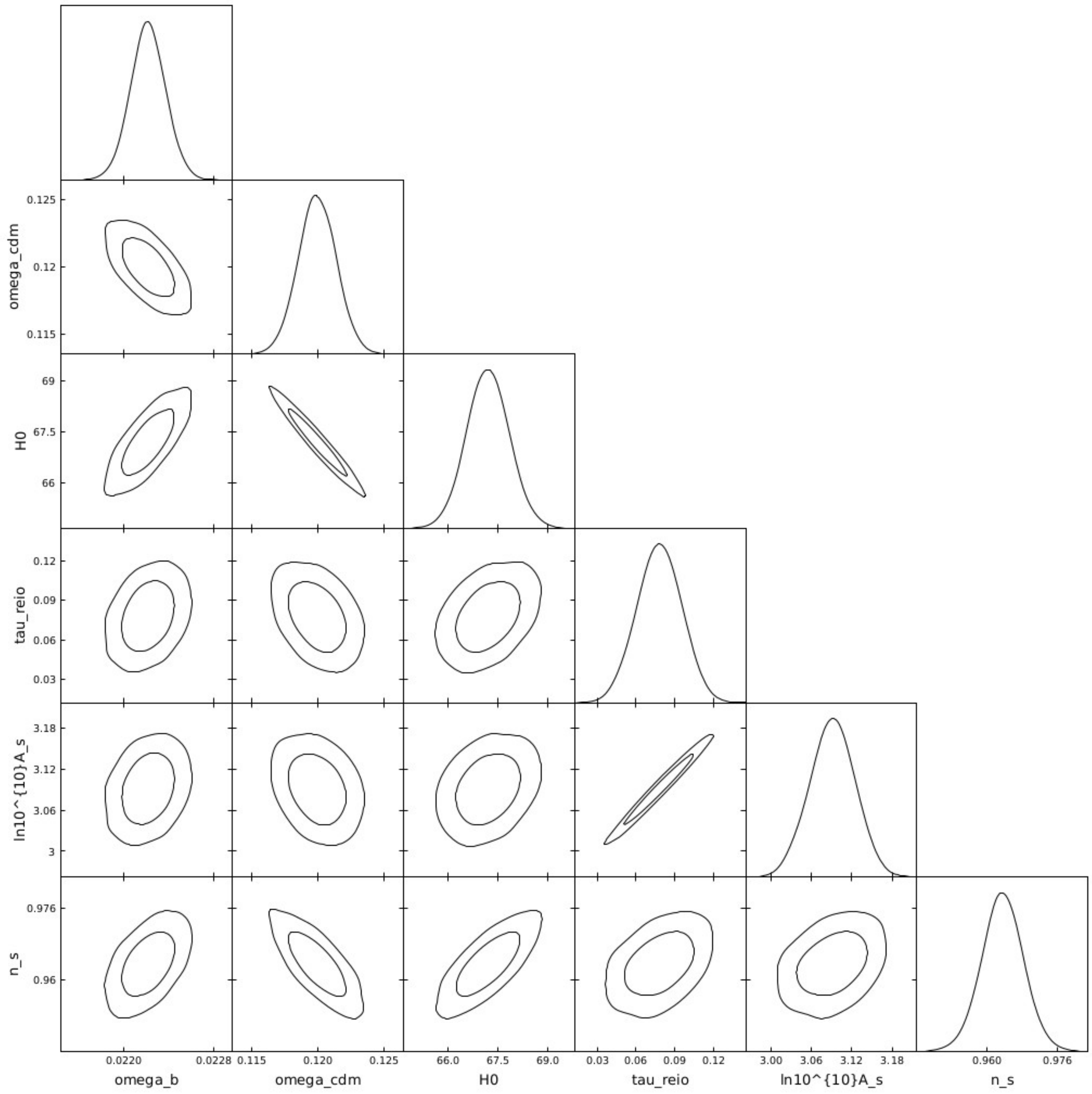
Identifying prior effects with JAM



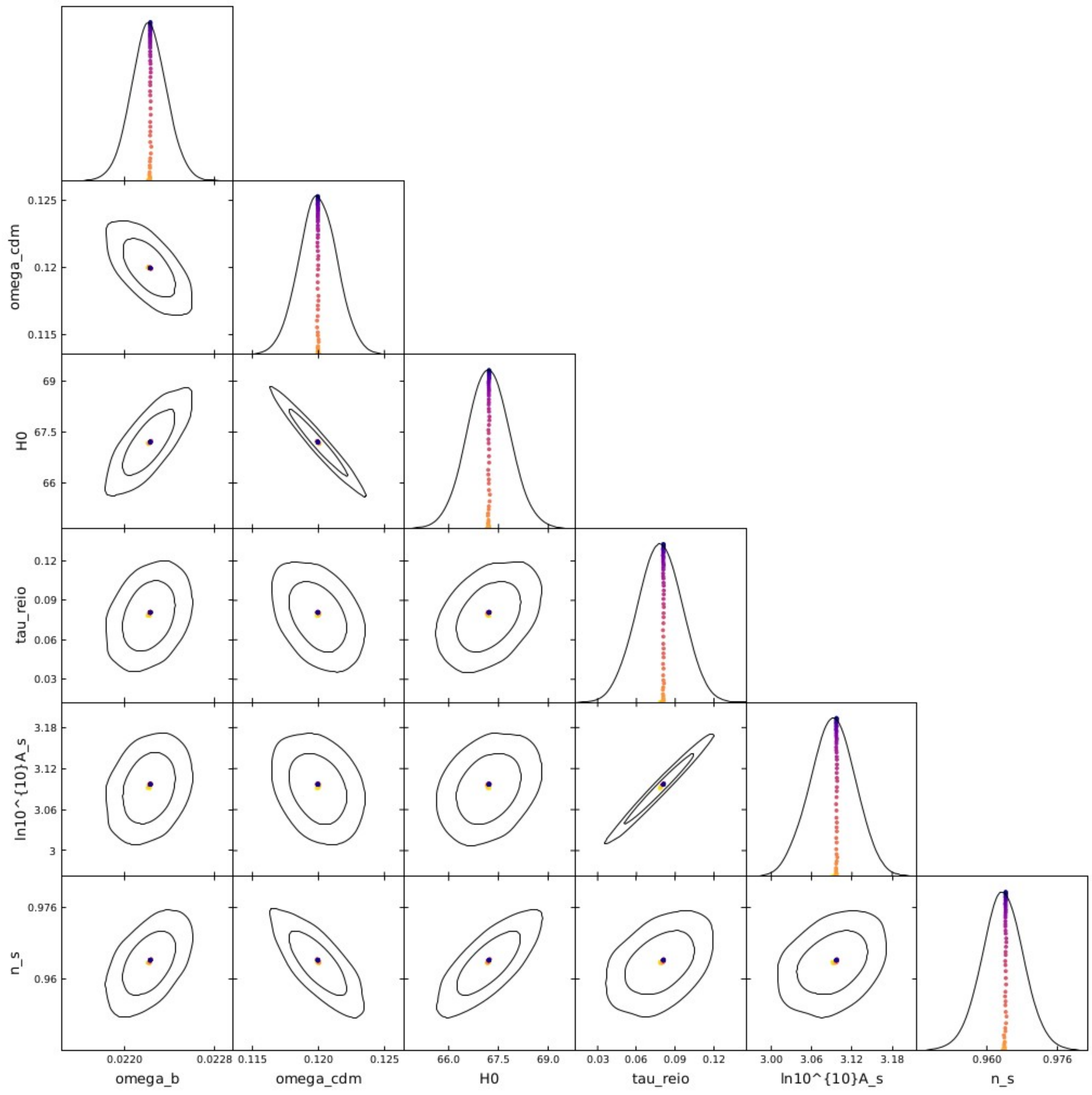
Identifying prior effects with JAM



Identifying prior effects with JAM



Identifying prior effects with JAM



Thank you
for your attention !