dessn Documentation

Release 0.0.1

dessn

March 02, 2016

CONTENTS

CHAPTER

ONE

DESSN PACKAGE

1.1 Subpackages

1.1.1 dessn.entry package

Submodules

dessn.entry.sim module

1.1.2 dessn.model package

Subpackages

dessn.model.nodes package

Submodules

dessn.model.nodes.cosmology module

class dessn.model.nodes.cosmology.**Cosmology**

Bases: *dessn.model.node.Node*

get_name()

class dessn.model.nodes.cosmology.**FlatWCDM**

Bases: *dessn.model.nodes.cosmology.Cosmology*

dessn.model.nodes.supernova module

class dessn.model.nodes.supernova.**Supernova**

Bases: *dessn.model.node.Node*

Abstract supernova which others must implement

type

class dessn.model.nodes.supernova.**SupernovaIa**(*log_luminosity*, *sigma_luminosity*)

Bases: object

Models a type Ia supernova

Models the luminosity distribution of type Ia supernovas statically (without internal parameters).

$$P(L) \sim N($$

Parameters **log_luminosity** : float

Represented by the variable μ

sigma_luminosity : float

Represented by the variable σ

get_luminosity_prob(*log_luminosity*)

type()

dessn.model.nodes.typeProb module

class dessn.model.nodes.typeProb.**TypeProbability**

Bases: *dessn.model.node.Node*

Abstract type probability node, from which all implementations should inherit

get_name()

class dessn.model.nodes.typeProb.**TypeProbabilitySimple**(*relative_rate=0.333*)

Bases: *dessn.model.nodes.typeProb.TypeProbability*

The Type probability node.

Takes *some information* to determine the probability of of the object in question being a type of supernova.

Parameters **relative_rate** : Optional[str]

Relative rate of SnIa / SnII

class dessn.model.nodes.typeProb.**Types**

Bases: enum.Enum

Possible target types

snII = <Types.snII: 2>

snIa = <Types.snIa: 1>

Submodules

dessn.model.abstracts module

dessn.model.model module

class dessn.model.model.**Model**

Bases: object

dessn.model.node module

class dessn.model.node.**Node**

Bases: object

add_dependency(*dependency_class*)

get_dependencies()

get_name()

1.1.3 dessn.simple package

This module is designed to give a step by step overview of a very simplified example Bayesian model.

The basic example model is laid out in the parent class *Example*, and there are three implementations. The first implementation, *ExampleIntegral*, shows how the problem might be approached in a simple model, where numerical integration is simply done as part of the likelihood calculation.

However, if there are multiple latent parameters, we get polynomial growth of the number of numerical integrations we have to do, and so this does not scale well at all.

This leads us to the implementation in *ExampleLatent*, where we use the MCMC algorithm to essentially do Monte Carlo integration via marginalisation. This means we do not need to perform the numerical integration in the likelihood calculation, however the cost of doing so is increase dimensionality of our MCMC.

Finally, the ExampleLatentClass implementation shows how the *ExampleLatent* class might be written to make use of Nodes. This is done in preparation for more complicated models, which will have more than one layer and needs to be configurable.

Submodules

dessn.simple.example module

class dessn.simple.example.**Example**(*n=300*, *theta_1=100.0*, *theta_2=30.0*)

Bases: object

Setting up the math for some examples.

Let us assume that we are observing supernova that are drawn from an underlying supernova distribution parameterised by θ, where the supernova itself simply a luminosity L. We measure the luminosity of multiple supernovas, giving us an array of measurements D. If we wish to recover the underlying distribution of supernovas from our measurements, we wish to find $P(\theta|D)$, which is given by

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

Note that in the above equation, we realise that $P(D|L) = \prod_{i=1}^{N} P(D_i|L_i)$ as our measurements are independent. The likelihood $P(D|\theta)$ is given by

$$P(D|\theta) = \prod_{i=1}^{N} \int_{-\infty}^{\infty} P(D_i|L_i)P(L_i|\theta)dL_i$$

We now have two distributions to characterise. Let us assume both are gaussian, that is our observed luminosity x_i has gaussian error σ_i from the actual supernova luminosity, and the supernova luminosity is drawn from an underlying gaussian distribution parameterised by θ.

$$P(D_i|L_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x_i - L_i)^2}{\sigma_i^2}\right)$$
$$P(L_i|\theta) = \frac{1}{\sqrt{2\pi}\theta_2} \exp\left(-\frac{(L_i - \theta_1)^2}{\theta_2^2}\right)$$

This gives us a likelihood of

$$P(D|\theta) = \prod_{i=1}^{N} \frac{1}{2\pi\theta_2\sigma_i} \int_{-\infty}^{\infty} \exp\left(-\frac{(x_i - L_i)^2}{\sigma_i^2} - \frac{(L_i - \theta_1)^2}{\theta_2^2}\right) dL_i$$

Working in log space for as much as possible will assist in numerical precision, so we can rewrite this as

$$\log\left(P(D|\theta)\right) = \sum_{i=1}^{N}\left[\log\left(\int_{-\infty}^{\infty}\exp\left(-\frac{(x_i-L_i)^2}{\sigma_i^2}-\frac{(L_i-\theta_1)^2}{\theta_2^2}\right)dL_i\right)-\log(2\pi\theta_2\sigma_i)\right]$$

Parameters **n** : int, optional

The number of supernova to 'observe'

theta_1 : float, optional

The mean of the underlying supernova luminosity distribution

theta_2 : float, optional

The standard deviation of the underlying supernova luminosity distribution

do_emcee(*nwalkers=None*, *nburn=None*, *nsteps=None*)
Abstract method to configure the emcee parameters

get_likelihood(*theta*, *data*, *error*)
Abstract method to return the log likelihood

get_posterior(*theta*, *data*, *error*)
Gives the log posterior probability given the supplied input parameters.

Parameters **theta** : array of model parameters

data : array of length *n*

An array of observed luminosities

error : array of length *n*

An array of observed luminosity errors

Returns float

the log posterior probability

get_prior(*theta*)
Get the log prior probability given the input.

The prior distribution is currently implemented as flat prior.

Parameters **theta** : array of model parameters

Returns float

the log prior probability

plot_observations()
Plot the observations and observation distribution.

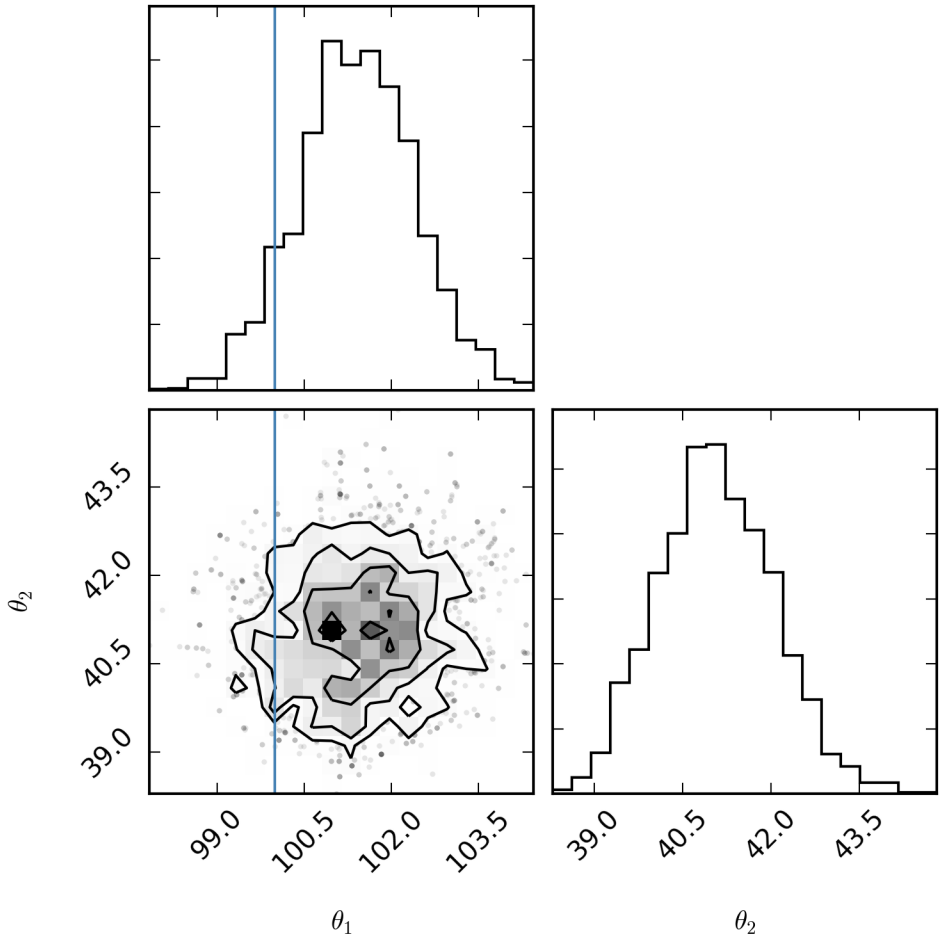
dessn.simple.exampleIntegral module

class dessn.simple.exampleIntegral.**ExampleIntegral**(*n=900*, *theta_1=100.0*, *theta_2=30.0*)

Bases: *dessn.simple.example.Example*

An example implementation using integration over a latent parameter.

Building off the math from *Example* Creating this class will set up observations from an underlying distribution. Invoke emcee by calling the object. In this example, we perform the marginalisation inside the likelihood


43.5
42.0
40.5
39.0
θ_2
99.0
100.5
102.0
103.5
θ_1
39.0
40.5
42.0
43.5
θ_2

calculation, which gives us dimensionality only of two (the length of the θ array). However, this is at the expense of performing the marginalisation over dL_i, as this requires computing n integrals for each step in the MCMC.

Parameters **n** : int, optional

The number of supernova to 'observe'

theta_1 : float, optional

The mean of the underlying supernova luminosity distribution

theta_2 : float, optional

The standard deviation of the underlying supernova luminosity distribution

do_emcee(*nwalkers=20*, *nburn=500*, *nsteps=2000*)

Run the *emcee* chain and produce a corner plot.

Saves a png image of the corner plot to plots/exampleIntegration.png.

Parameters **nwalkers** : int, optional

The number of walkers to use. Minimum of four.

nburn : int, optional

The burn in period of the chains.

nsteps : int, optional

The number of steps to run

get_likelihood(*theta*, *data*, *error*)

Gets the log likelihood given the supplied input parameters.

Parameters **theta** : array of size 2

An array representing $[\theta_1, \theta_2]$

data : array of length *n*

An array of observed luminosities

error : array of length *n*

An array of observed luminosity errors

Returns float

the log likelihood probability

dessn.simple.exampleLatent module

class dessn.simple.exampleLatent.**ExampleLatent**(*n=300*, *theta_1=100.0*, *theta_2=30.0*)

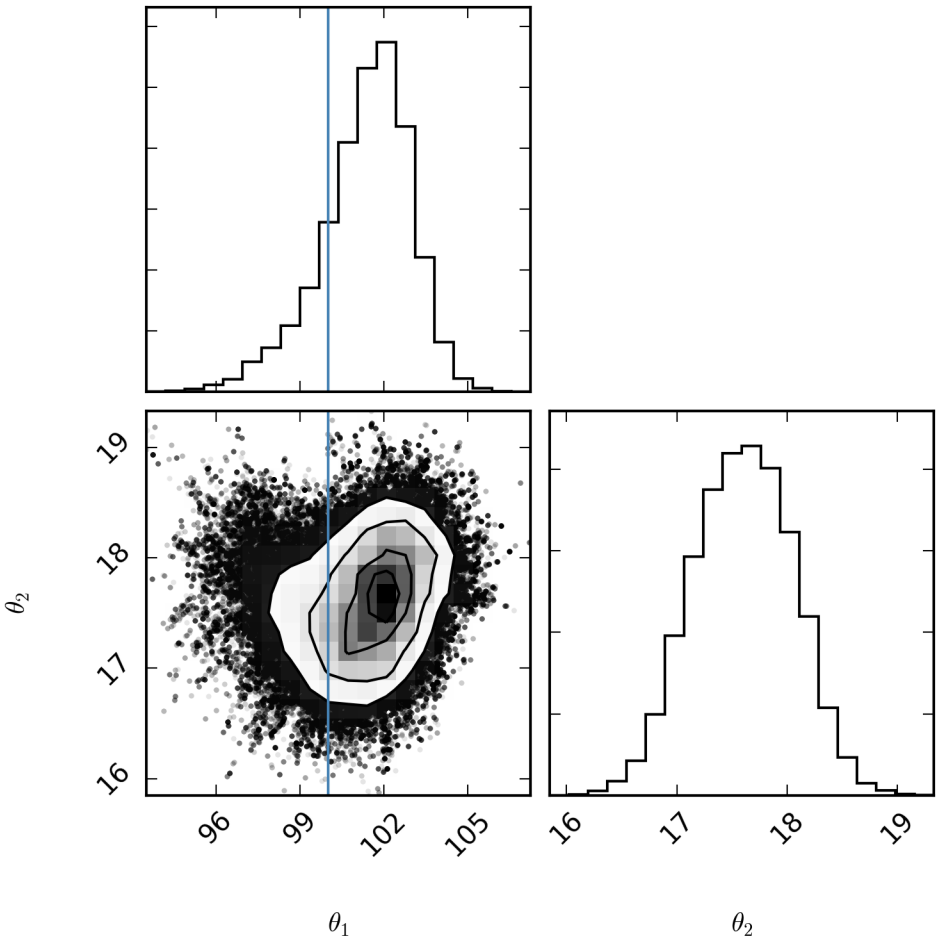
Bases: *dessn.simple.example.Example*

An example implementation using marginalisation over latent parameters.

Building off the math from *Example*, instead of performing the integration numerically in the computation of the likelihood, we can instead use Monte Carlo integration by simply setting the latent parameters $\vec{L}$ as free parameters, giving us

$$\log\left(P(D|\theta, \vec{L})\right) = -\sum_{i=1}^{N}\left[\frac{(x_i - L_i)^2}{\sigma_i^2} + \frac{(L_i - \theta_1)^2}{\theta_2^2} + \log(2\pi\theta_2\sigma_i)\right]$$

Creating this class will set up observations from an underlying distribution. Invoke `emcee` by calling the object. In this example, we marginalise over L_i after running our MCMC, and so we no longer have to compute integrals in our chain, but instead have dimensionality of $2 + n$, where n are the number of observations.



Parameters **n** : int, optional

The number of supernova to 'observe'

theta_1 : float, optional

The mean of the underlying supernova luminosity distribution

theta_2 : float, optional

The standard deviation of the underlying supernova luminosity distribution

do_emcee (*nwalkers=200*, *nburn=1000*, *nsteps=4000*)

Run the *emcee* chain and produce a corner plot.

Saves a png image of the corner plot to plots/exampleLatent.png.

Parameters **nwalkers** : int, optional

The number of walkers to use.

nburn : int, optional

The burn in period of the chains.

nsteps : int, optional

The number of steps to run

get_likelihood(*theta*, *data*, *error*)
Gets the log likelihood given the supplied input parameters.

Parameters **theta** : array of length 2 + n

An array representing $[\theta_1, \theta_2, \vec{L}]$

data : array of length n

An array of observed luminosities

error : array of length n

An array of observed luminosity errors

Returns float

the log likelihood probability

1.1.4 dessn.simulation package

Submodules

dessn.simulation.observationFactory module

class dessn.simulation.observationFactory.**ObservationFactory**(***kwargs*)
Bases: object

check_kwargs()

get_observations(*num*)
Still needs massive refactoring

dessn.simulation.simulation module

class dessn.simulation.simulation.**Simulation**
Bases: object

get_simulation(*num_trans=30*)

d

T