pyemcee Documentation

Release 0.2.0

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Oct 16, 2020

USER DOCUMENTATION

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CHAPTER ONE

INTRODUCTION

pyemcee is a Python implementation of the *affine-invariant Markov chain Monte Carlo (MCMC) ensemble sampler*, based on sl_emcee by M. A. Nowak, an S-Lang/ISIS implementation of the MCMC Hammer proposed by Goodman & Weare (2010), and also implemented in Python (emcee) by Foreman-Mackey et al. (2013).

CHAPTER TWO

INSTALLATION

To install the last version, all you should need to do is

```
$ python setup.py install
```

To install the stable version, you can use the preferred installer program (pip):

```
$ pip install pyemcee
```

or you can install it from the cross-platform package manager *conda*:

```
$ conda install -c conda-forge pyemcee
```

This package requires the following packages:

- NumPy
- SciPy
- Matplotlib

CHAPTER

THREE

USAGE

The Documentation of the functions provides in detail in the *API Documentation* (mcfit.github.io/pyemcee/doc). This Python library creates the MCMC sampling for given upper and lower uncertainties, and propagates uncertainties of parameters into the function

You need to define your function. For example:

```
def myfunc21(input1):
   result1 = np.sum(input1)
   result2 = input1[1] ** input1[0]
   return [result1, result2]
```

and use the appropriate confidence level and uncertainty distribution. For example, for a 1.645-sigma standard deviation with a uniform distribution:

```
clevel=.9 # 1.645-sigma
use_gaussian=0 # uniform distribution from min value to max value
```

for a 1-sigma standard deviation with a Gaussian distribution:

```
clevel=0.68268949 # 1.0-sigma
use_gaussian=1 # gaussian distribution from min value to max value
```

and specify the number of walkers and the number of iterations:

```
walk_num=30
iteration_num=100
```

Now you provide the given upper and lower uncertainties of the input parameters:

```
input1 = np.array([1., 2.])
input1_err = np.array([0.2, 0.5])
input1_err_p = input1_err
input1_err_m = -input1_err
output1 = myfunc21(input1)
output1_num = len(output1)
```

You should load the **pyemcee** library class as follows:

```
import pyemcee
import numpy as np
```

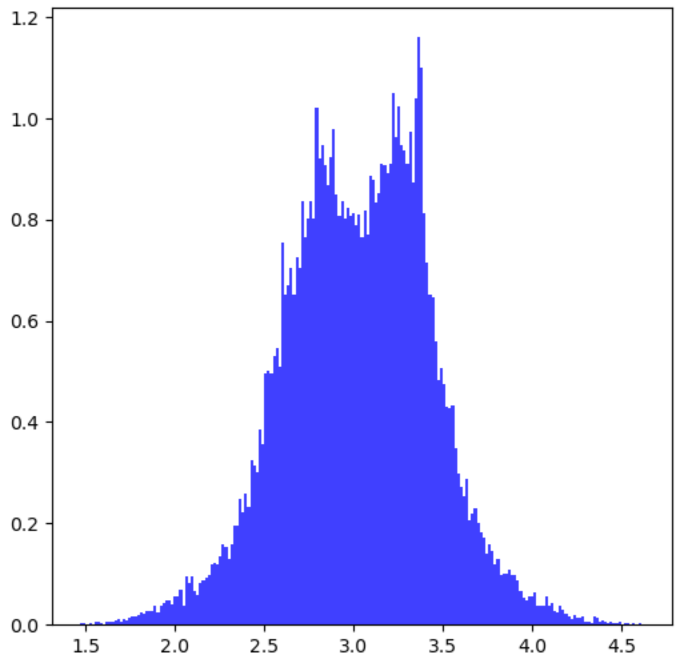
You can then create the MCMC sample and propagate the uncertainties of the input parameters into your defined functions as follows:

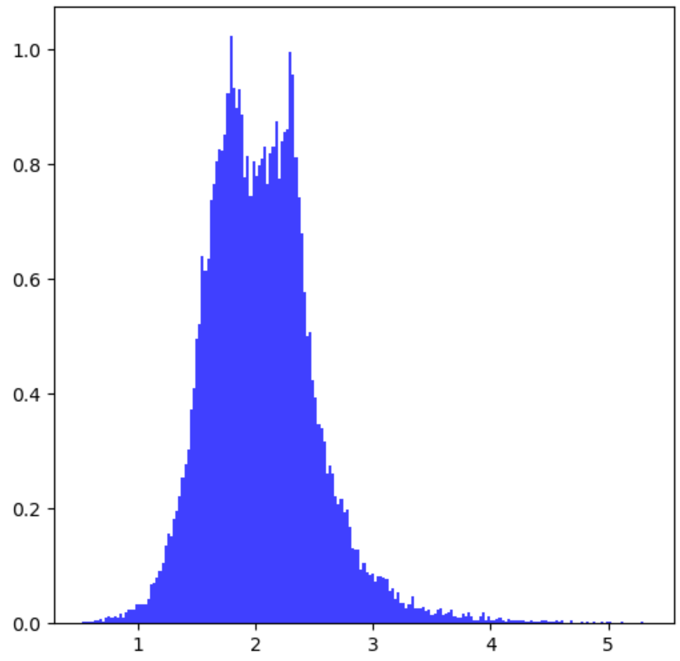
```
mcmc_sim = pyemcee.hammer(myfunc21, input1, input1_err_m,
                          input1_err_p, output1, walk_num,
                          iteration_num, use_gaussian)
```

To determine the upper and lower errors of the function outputs, you need to run:

```
output1_error = pyemcee.find_errors(output1, mcmc_sim, clevel, do_plot=1)
```

which shows the following distribution histograms:





To print the results:

```
for i in range(0, output1_num):
   print(output1[i], output1_error[i,:])
```

which provide the upper and lower limits on each parameter:

```
3.0 [-0.35801017 0.35998471]
2.0 [-0.37573196 0.36297235]
```

For other standard deviation, you should use different confidence levels:

```
clevel=0.38292492 # 0.5-sigma
clevel=0.68268949 # 1.0-sigma
clevel=0.86638560 # 1.5-sigma
clevel=0.90       # 1.645-sigma
clevel=0.95       # 1.960-sigma
clevel=0.95449974 # 2.0-sigma
clevel=0.98758067 # 2.5-sigma
clevel=0.99       # 2.575-sigma
clevel=0.99730020 # 3.0-sigma
clevel=0.99953474 # 3.5-sigma
clevel=0.99993666 # 4.0-sigma
clevel=0.99999320 # 4.5-sigma
clevel=0.99999943 # 5.0-sigma
clevel=0.99999996 # 5.5-sigma
clevel=0.999999998# 6.0-sigma
```

CHAPTER FOUR

REFERENCES

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FIVE

PYEMCEE.MAIN PACKAGE

5.1 pyemcee main module

This module contains functions for the affine-invariant Markov chain Monte Carlo (MCMC) ensemble sampler proposed by Goodman & Weare (2010).

`pyemcee.`**`find_errors`**(*output*, *mcmc_sim*, *clevel*, *do_plot=None*, *image_output_path=None*)

This function returns the uncertainties of the function outputs based on the confidence level.

For example:

```
>> output_error=pyemcee.find_erros(output, mcmc_sim, clevel)
```

Returns This function returns uncertainties.

Return type arrays

Parameters

- **`do_plot`** (*`boolean`*) – set to plot a normalized histogram of the MCMC chain.
- **`image_output_path`** (*`str`*) – the image output path.
- **`output`** (*`arrays`*) – the output array returned by the calling function.
- **`mcmc_sim`** (*`arrays`*) – the results of the MCMC simulations from hammer().
- **`clevel`** (*`float`*) – the confidence level for the the lower and upper limits. clevel=0.38292492 (0.5-sigma); clevel=0.68268949 (1.0-sigma); clevel=0.86638560 (1.5-sigma); clevel=0.90 (1.645-sigma); clevel=0.95 (1.960-sigma); clevel=0.95449974 (2.0-sigma); clevel=0.98758067 (2.5-sigma); clevel=0.99 (2.575-sigma); clevel=0.99730020 (3.0-sigma); clevel=0.99953474 (3.5-sigma); clevel=0.99993666 (4.0-sigma); clevel=0.99999320 (4.5-sigma); clevel=0.99999943 (5.0-sigma); clevel=0.99999996 (5.5-sigma); clevel=0.999999998(6.0-sigma).

`pyemcee.`**`hammer`**(*fcn*, *input*, *input_err_m*, *input_err_p*, *output*, *walk_num*, *iteration_num*, *use_gaussian*, *functargs=None*)

This function runs the affine-invariant MCMC Hammer, and returns the MCMC simulations

For example:

```
>> mcmc_sim=pyemcee.hammer(myfunc, input, input_err, output,
>>                         walk_num, iteration_num, use_gaussian)
```

Returns This function returns the results of the MCMC simulations.

Return type arrays

Parameters

- **functargs** (*parameter, optional*) – the function arguments (not used for MCMC).
- **fcn** (*str*) – the calling function name.
- **input** (*float*) – the input parameters array used by the calling function.
- **input_err_m** (*float*) – the lower limit uncertainty array of the parameters for the calling function.
- **input_err_p** (*float*) – the upper limit uncertainty array of the parameters for the calling function.
- **output** (*arrays*) – the output array returned by the calling function.
- **walk_num** (*int*) – the number of the random walkers.
- **iteration_num** (*int*) – the number of the MCMC iteration.
- **use_gaussian** (*boolean*) – if sets to 1, the walkers are initialized as a gaussian over the specified range between the min and max values of each free parameter, otherwise, the walkers are initialized uniformly over the specified range between the min and max values of each free parameter.