

Define a posterior: $P(\theta|D)$

Define a proposal density distribution (should be a symmetric function):

$$P(\theta_{i+1}|\theta_i)$$

Choose a starting point: $P(\theta_0)$

Given θ_i draw a new θ_{i+1}

Compute acceptance ratio

$$\alpha = \frac{P(\theta_{i+1}|D)}{P(\theta_i|D)}$$

if $\alpha \geq 1$ accept proposal and add θ_{i+1} to chain

if $\alpha < 1$ accept proposal with probability α

compare α to random number r

if $\alpha \geq r$ add θ_{i+1} to chain

else add θ_i to chain

emcee: The MCMC Hammer

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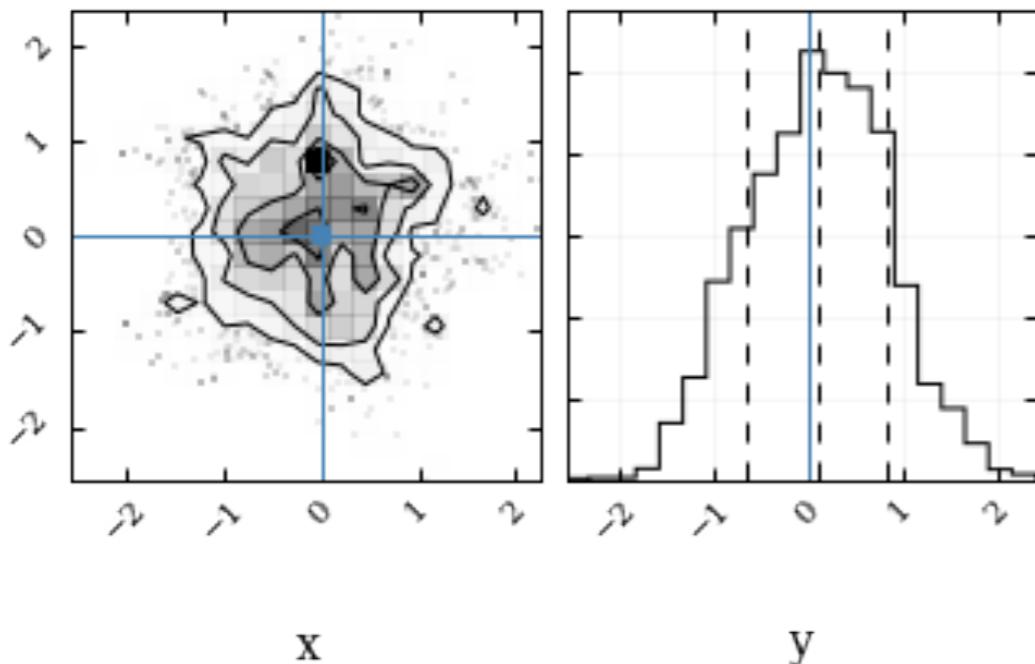
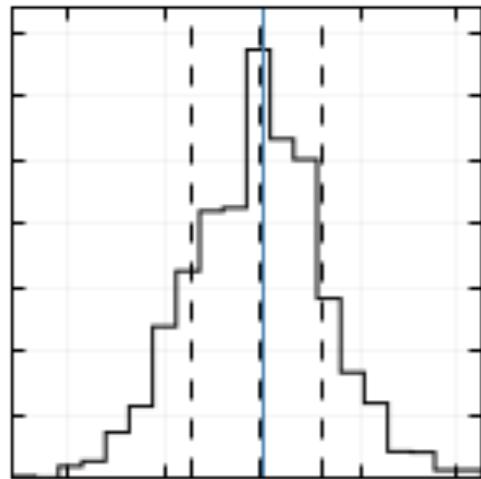
ABSTRACT

We introduce a stable, well tested Python implementation of the affine-invariant ensemble sampler for Markov chain Monte Carlo (MCMC) proposed by Goodman & Weare (2010). The code is open source and has already been used in several published projects in the astrophysics literature. The algorithm behind `emcee` has several advantages over traditional MCMC sampling methods and it has excellent performance as measured by the autocorrelation time (or function calls per independent sample). One major advantage of the algorithm is that it requires hand-tuning of only 1 or 2 parameters compared to $\sim N^2$ for a traditional algorithm in an N -dimensional parameter space. In this document, we describe the algorithm and the details of our implementation. Exploiting the parallelism of the ensemble method, `emcee` permits *any* user to take advantage of multiple CPU cores without extra effort. The code is available online at <http://dan.iel.fm/emcee> under the MIT License.

Joint distribution

$$P(x, y)$$

$$P(x, y|D)$$



Marginalized distribution

$$P(x) = \int P(x, y|D) dy$$

