Title: Numerical Methods Lecture - 230126

Speakers: Erik Schnetter

Collection: Numerical Methods (2022/2023)

Date: January 26, 2023 - 9:15 AM

URL: https://pirsa.org/23010007

Affine-Invariant Samplers

Dustin Lang
Perimeter Institute for Theoretical Physics

PSI Numerical Methods, 2023-01-26

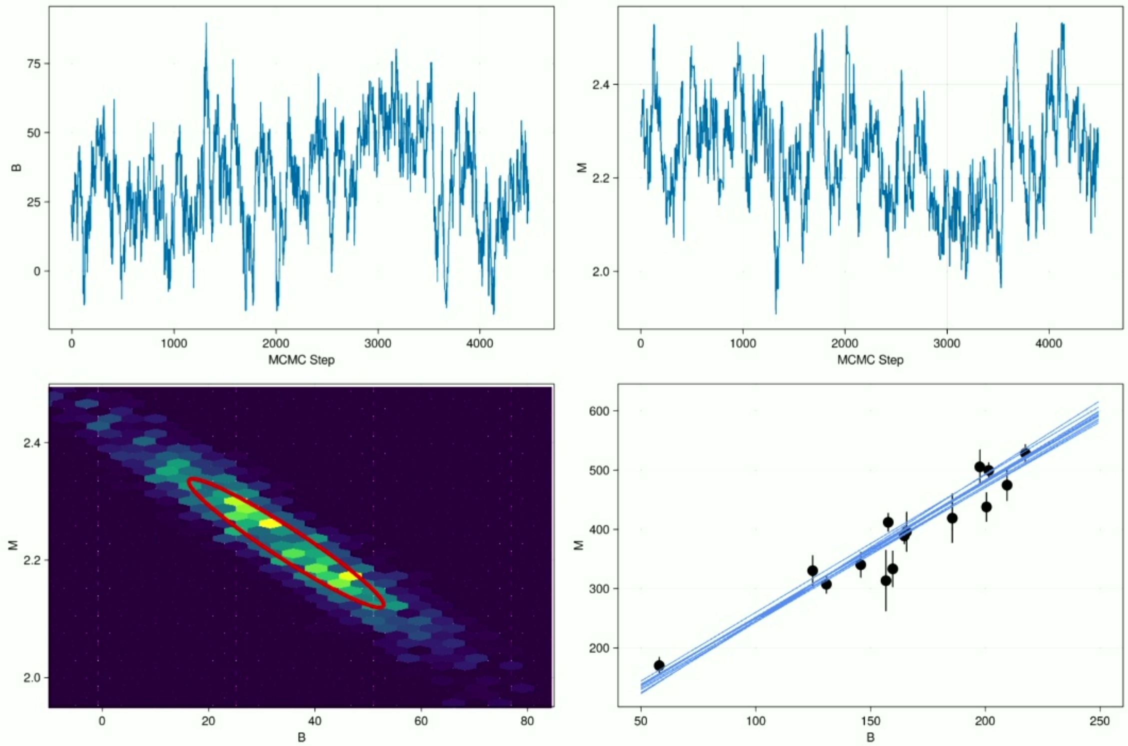
Borrowing heavily from Dan Foreman-Mackey's slides
https://speakerdeck.com/dfm/data-analysis-with-mcmc1
And Jonathan Pritchard's slides
https://www.imperial.ac.uk/media/imperial-college/research-centres-

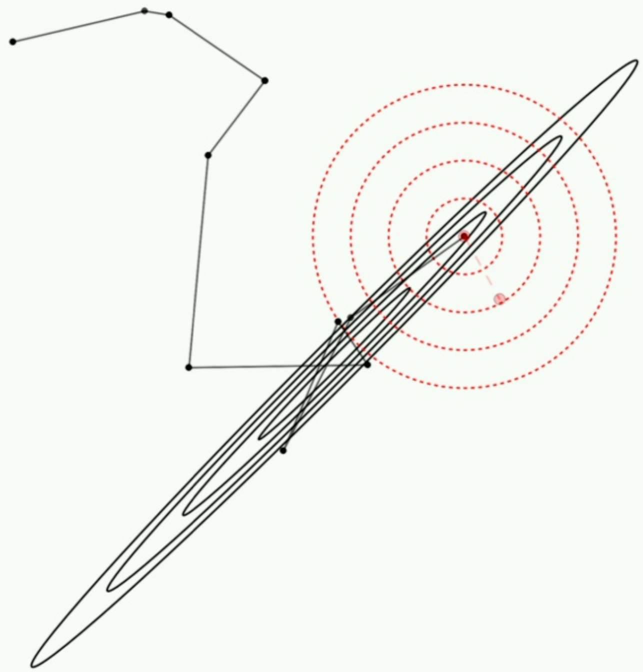
These slides are available at
https://github.com/dstndstn/MCMC-talk

The MCMC Algorithm

```
function mcmc(logprob_func, logprob_args,
              propose_func, propose_args,
              initial_pos, nsteps)
    p = initial_pos
    logprob = logprob_func(p, logprob_args)
    chain = zeros(Float64, (nsteps, length(p)))
    naccept = 0
    for i in 1:nsteps
        # propose a new position in parameter space
        p_new = propose_func(p, propose_args)
        # compute probability at new position
        logprob_new = logprob_func(p_new, logprob_args)
        # decide whether to jump to the new position
        if exp(logprob_new - logprob) > rand()
            p = p_new
            logprob = logprob_new
            naccept += 1
        end
        # save the position
        chain[i,:] = p
    end
    return chain, naccept/nsteps
end
```

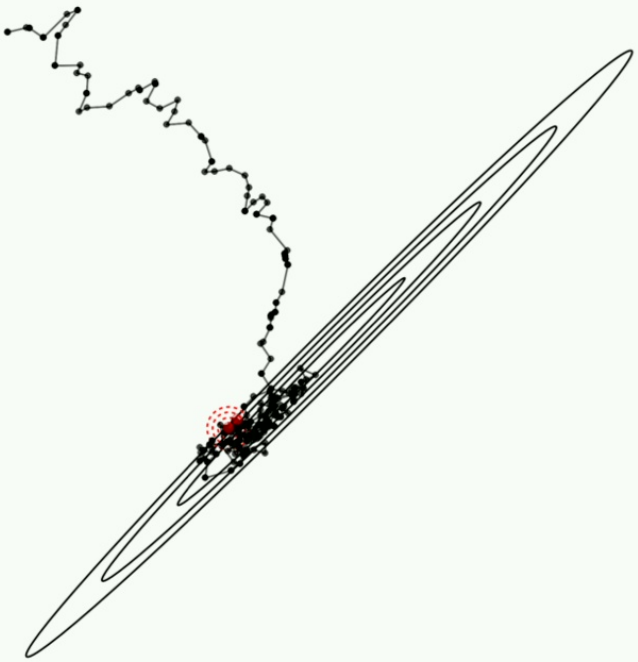
MCMC for model parameter inference





Metropolis–Hastings
in the real world

4



Metropolis–Hastings
in the real world

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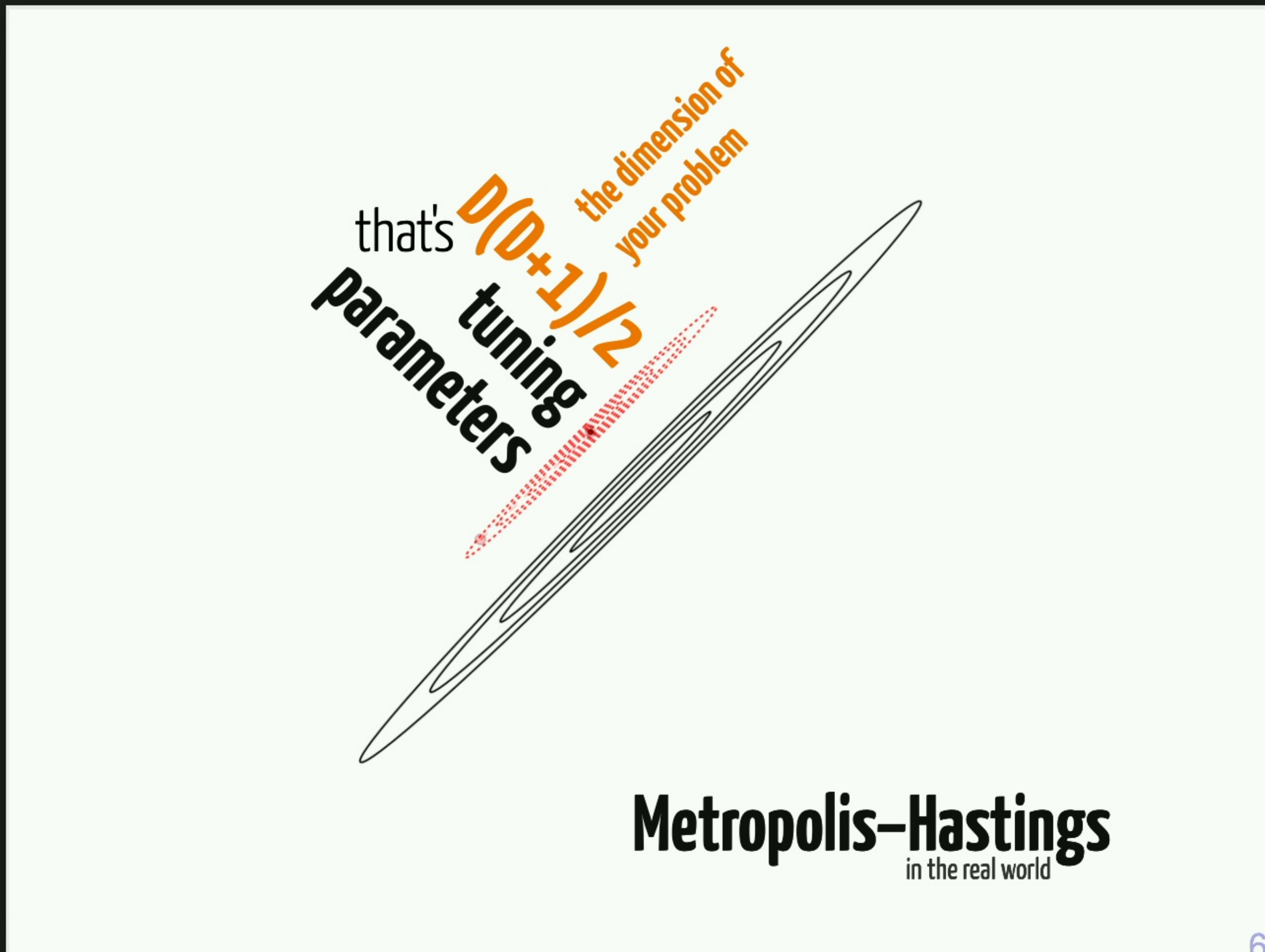
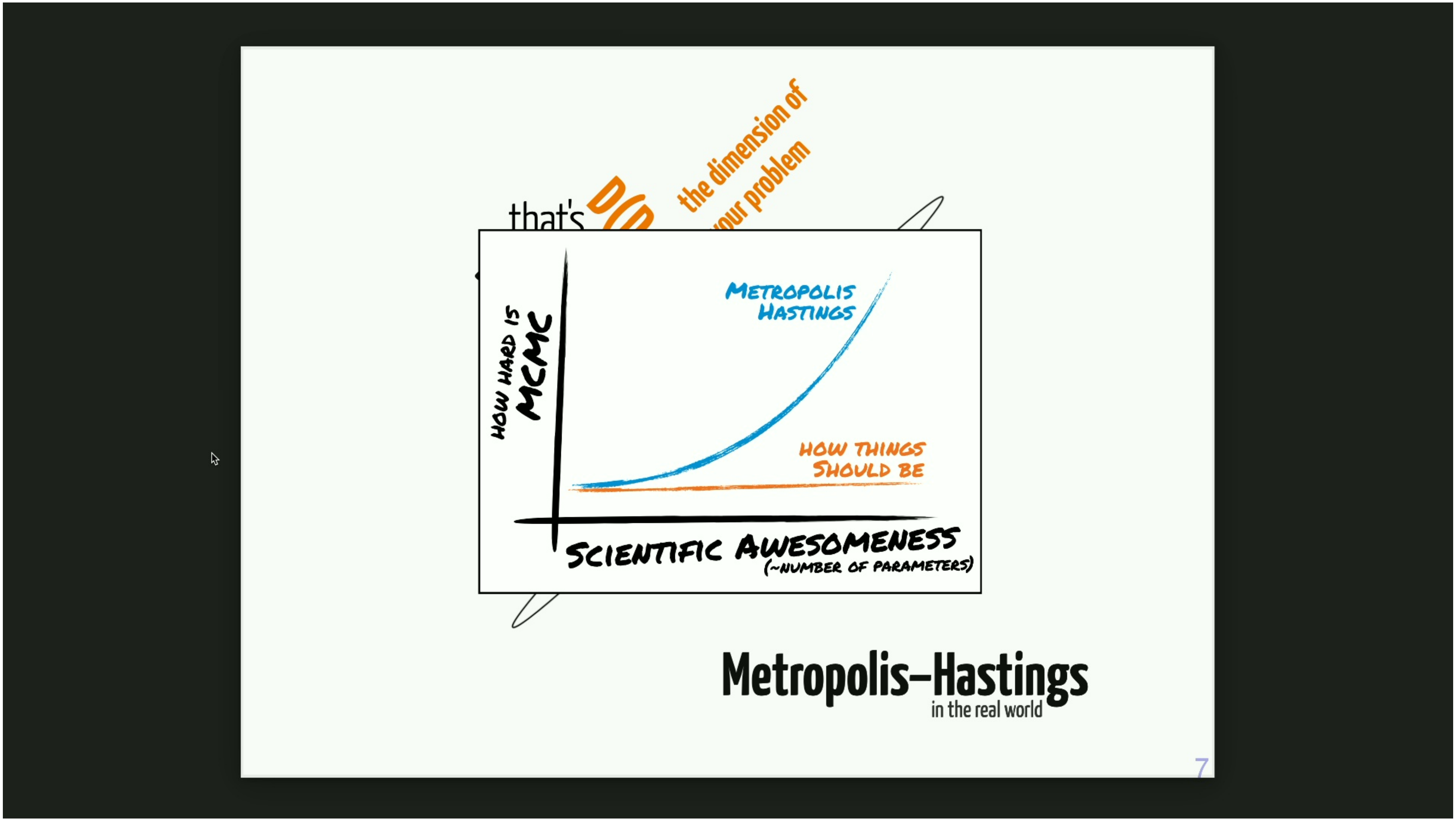

that's
D(D+1)/2
the dimension of
your problem
tuning
parameters
Metropolis–Hastings
in the real world
6


that's
the dimension of
METROPOLIS HASTINGS
HOW HARD IS MCMC
HOW THINGS SHOULD BE
SCIENTIFIC AWESOMENESS
(~NUMBER OF PARAMETERS)
Metropolis–Hastings
in the real world
7

Jonathan Goodman

Jonathan Weare

"Ensemble samplers with affine invariance"

(dfm.io/mcmc-gw10)

introducing **emcee** the MCMC Hammer

arxiv.org/abs/1202.3665

dan.iel.fm/emcee

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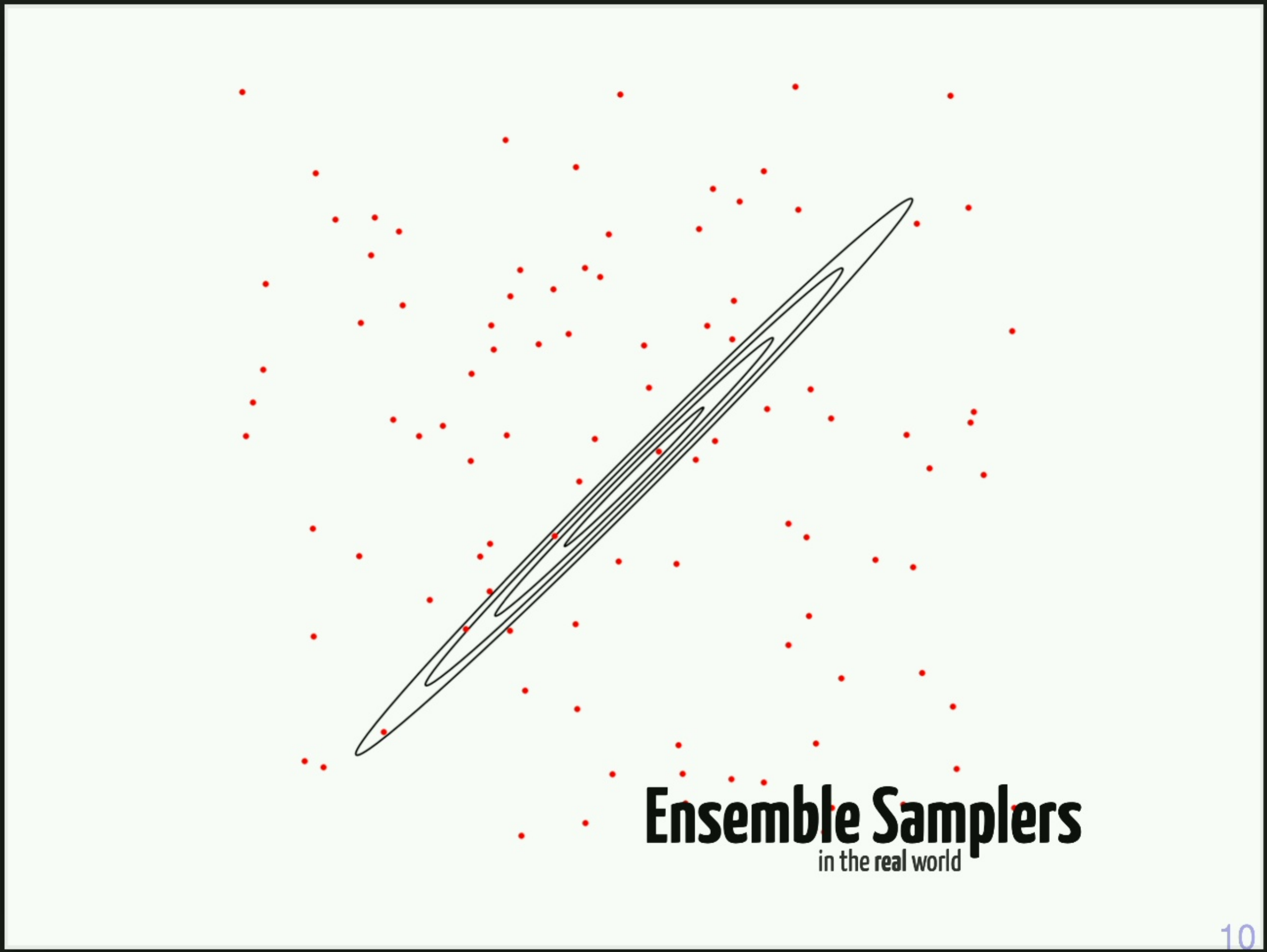
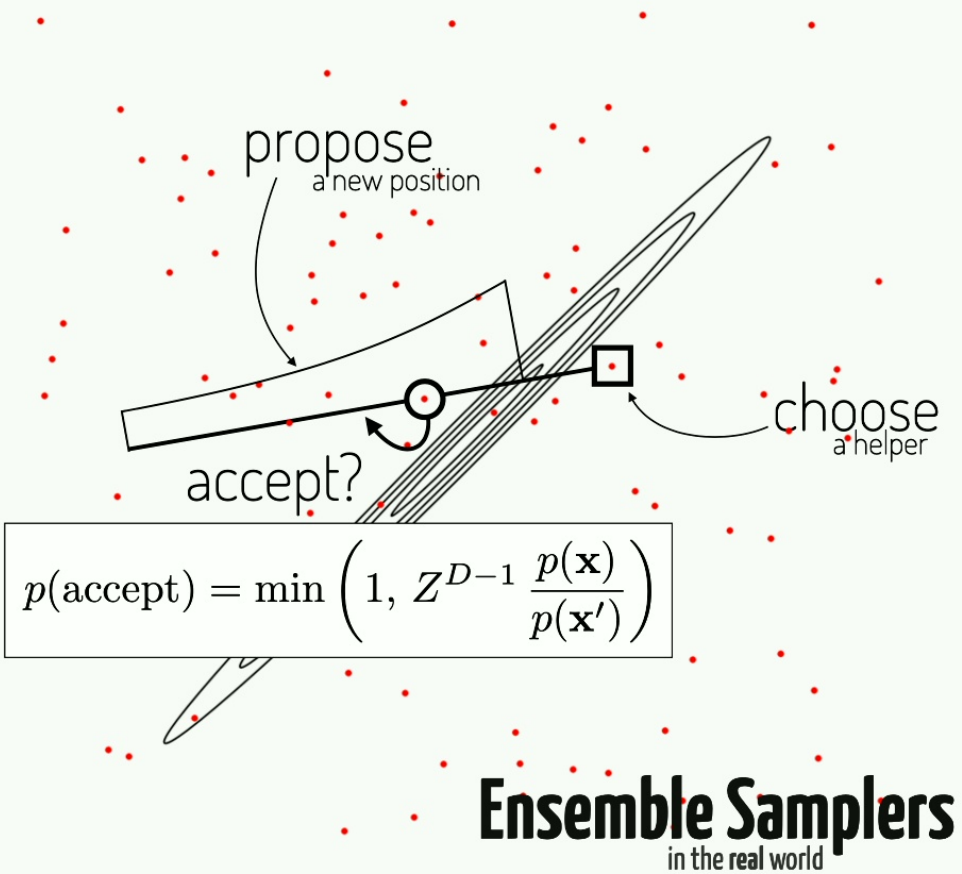
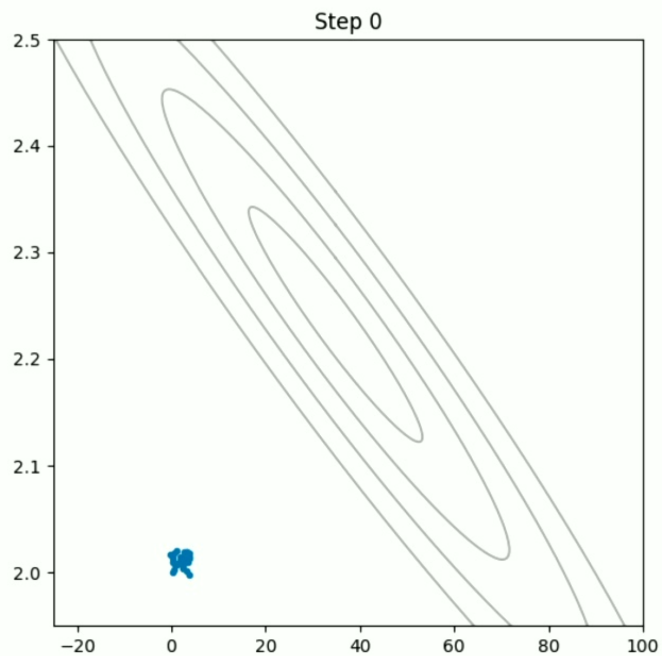

Ensemble Samplers
in the real world
10



$$p(\text{accept}) = \min\left(1,\ Z^{D-1}\,\frac{p(\mathbf{x})}{p(\mathbf{x}')}\right)$$

Emcee demo



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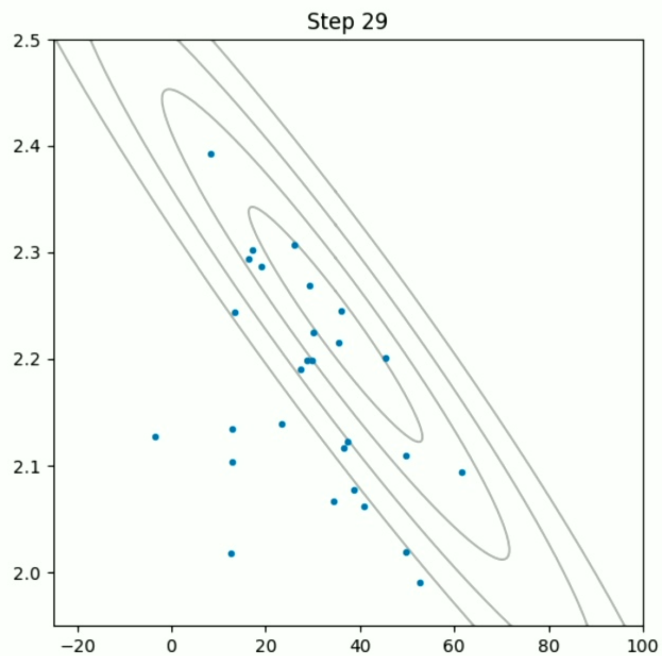
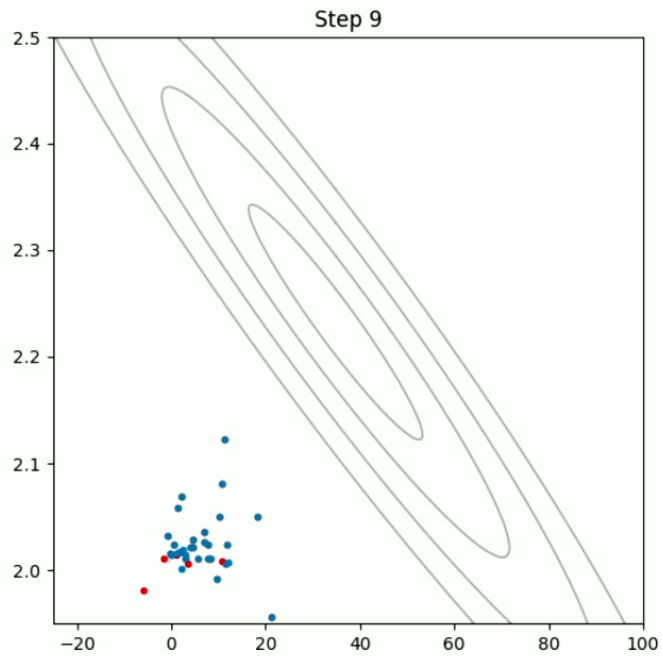
Emcee demo



Emcee demo



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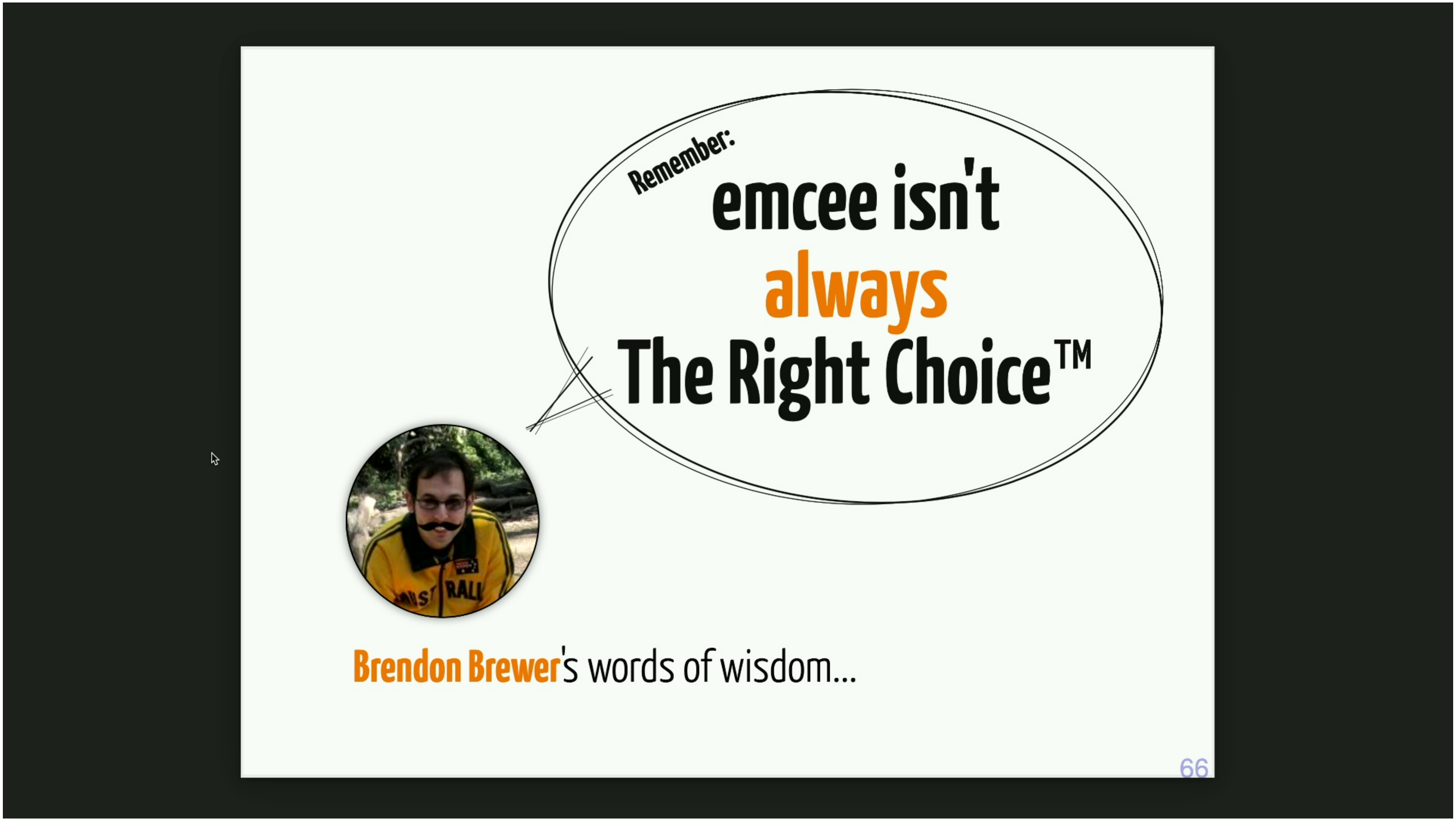
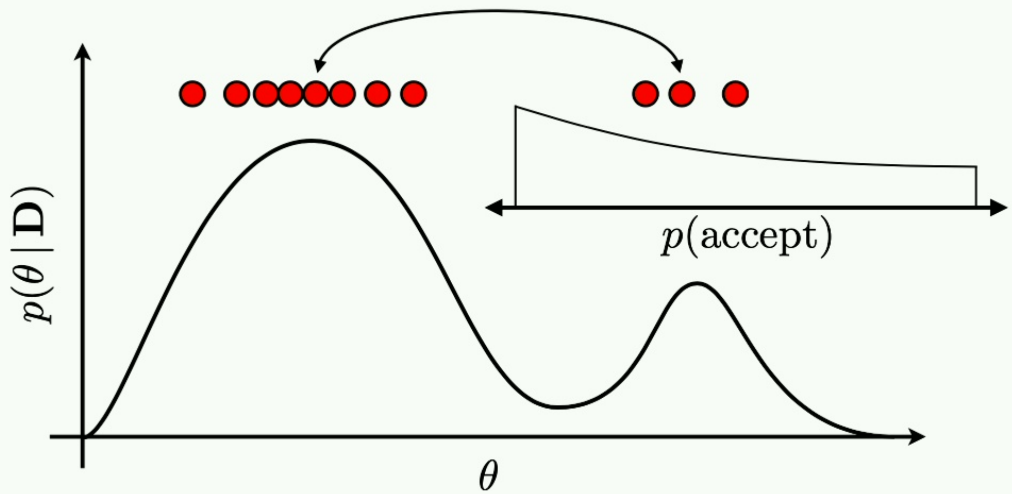

Remember:
emcee isn't
always
The Right Choice™
Brendon Brewer's words of wisdom...
66

what about multimodal densities?



wh… es?

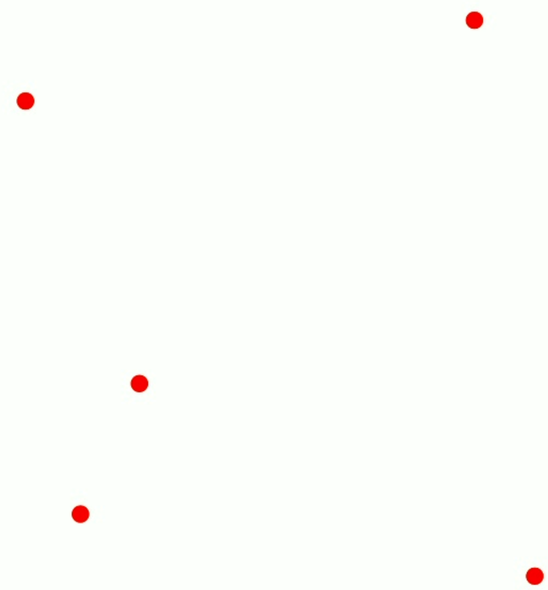
$p(\theta\,|\,\mathbf{D})$

θ

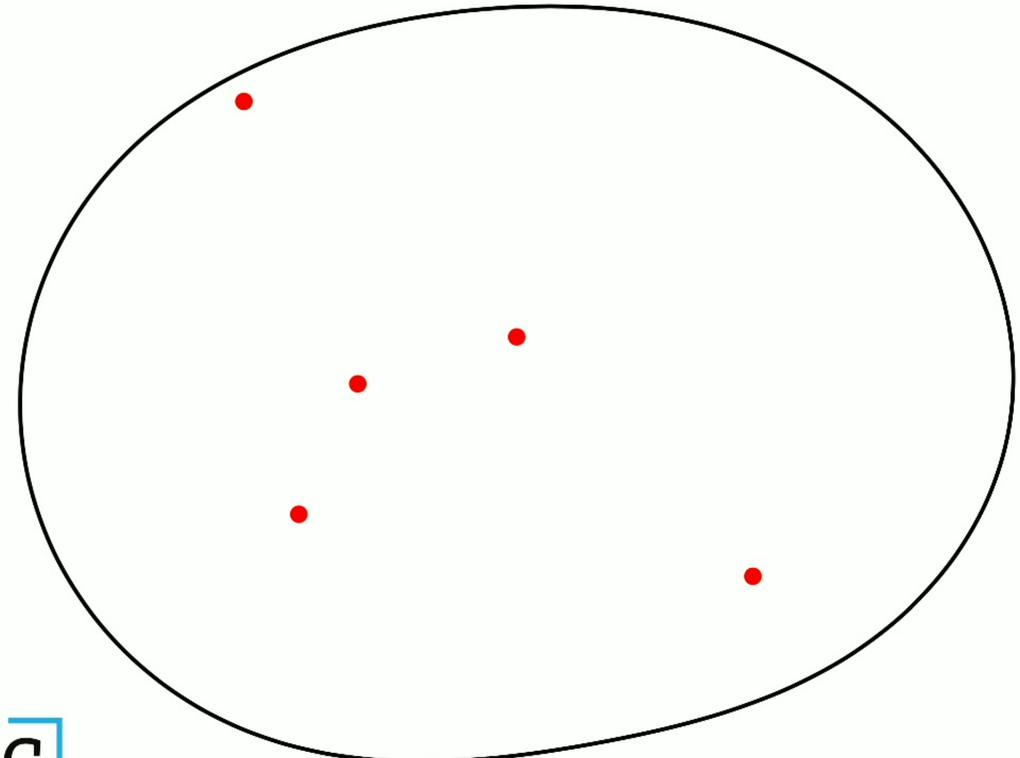
Nested Sampling

- An alternative to MCMC (and emcee)
- (Originally built for integrating the *evidence*)
- Idea: successively resample points, demanding they be above a minimum likelihood level
- Think of slowly raising the water level to find terrain contours

five live points chosen uniformly from prior



Select a new point uniformly sampled subject to requirement $L(X_{new})>L(X_{old})$



ICIC

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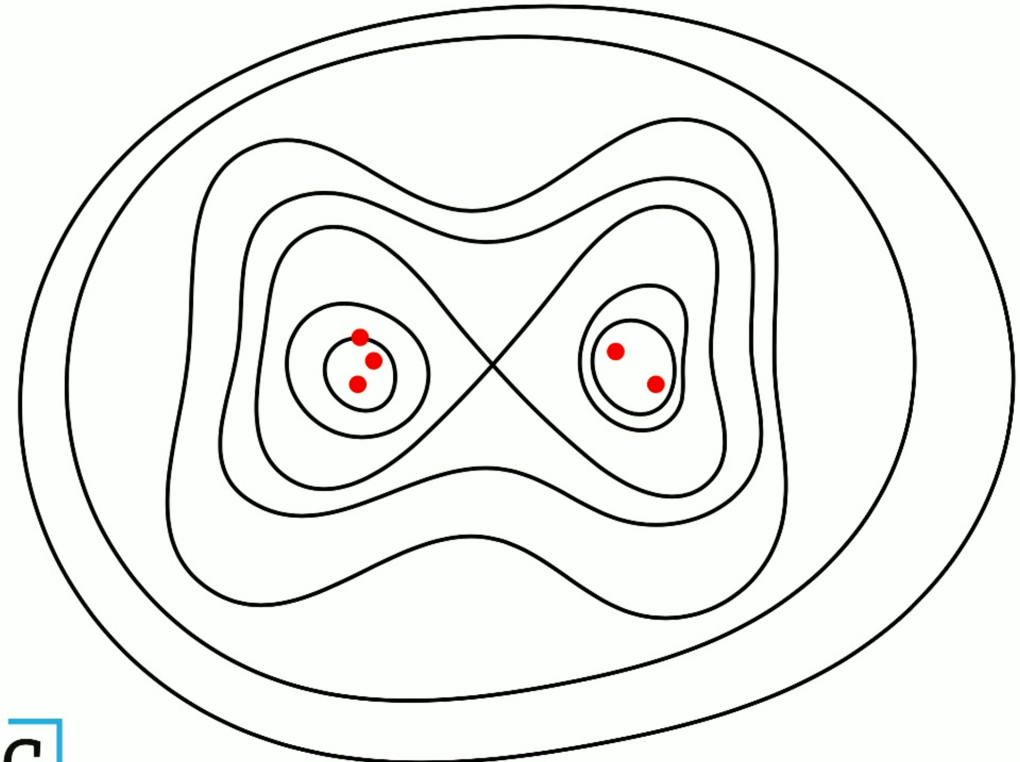
Successive points map likelihood in ordered way



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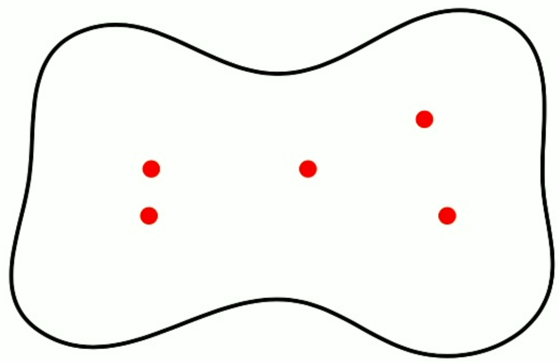

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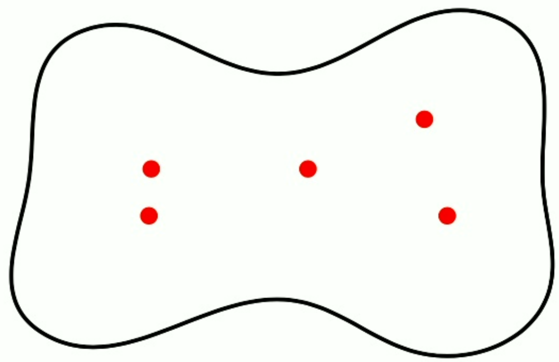

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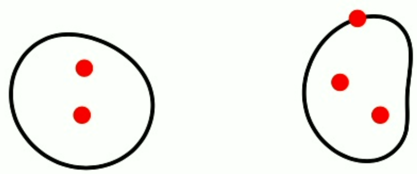

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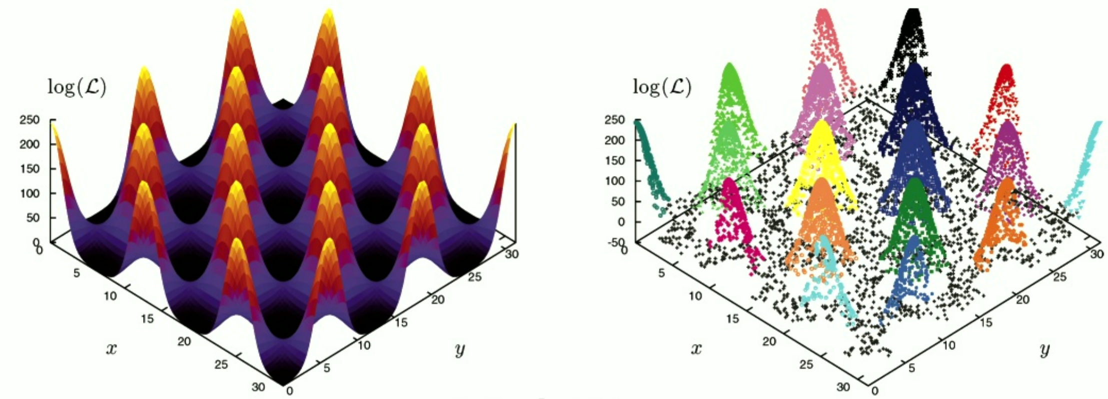
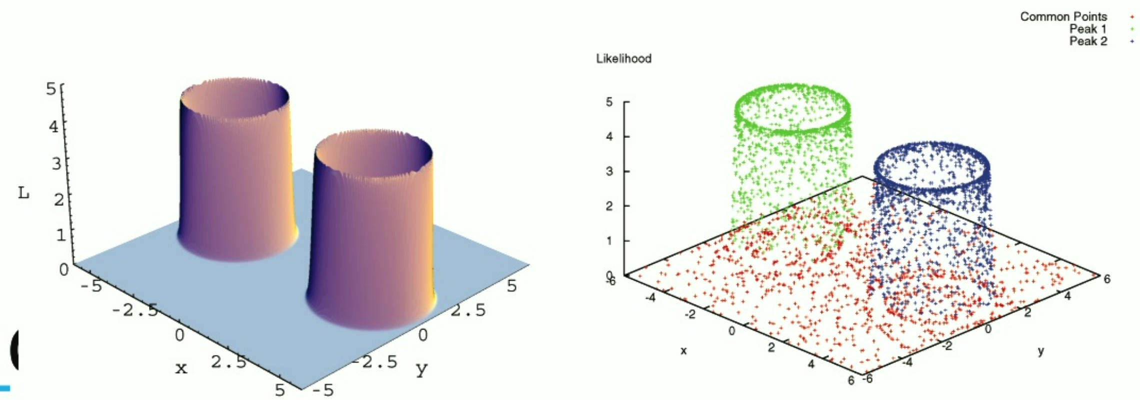


(a) (b)

MultiNest



(a) (b)

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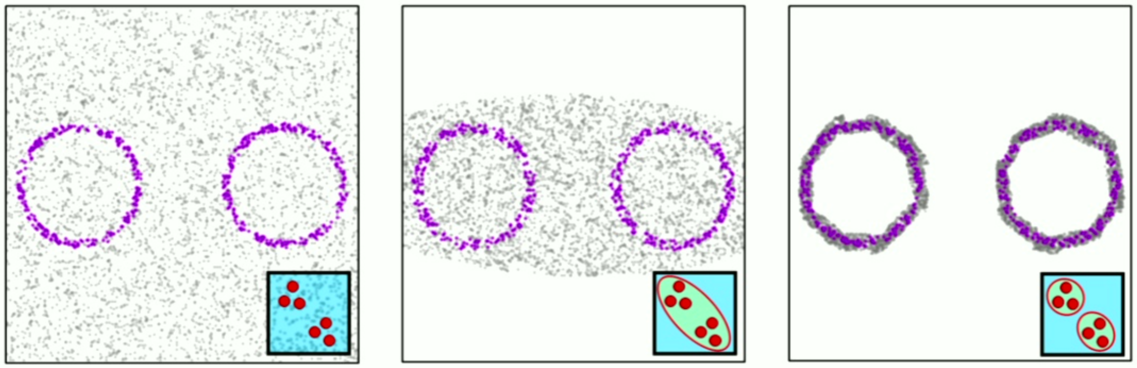
Dynamic Nested Sampling



Unit Cube (no bound) | Single Ellipsoid | Multiple Ellipsoids

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dynesty
stable

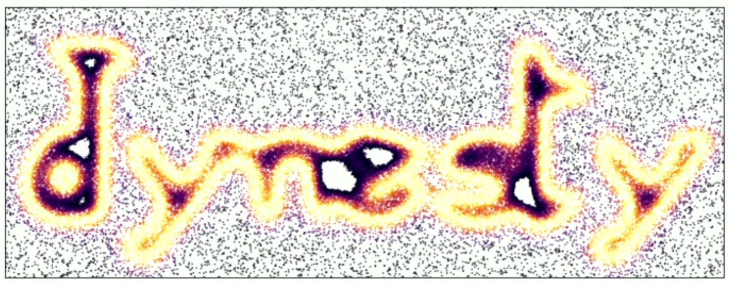
Search docs

- Crash Course
- Background
- Getting Started
- Dynamic Nested Sampling with dynesty
- Nested Sampling Errors
- Examples
- FAQ
- References and Acknowledgements
- API

Read the Docs v: stable

Docs » dynesty Edit on GitHub

dynesty



`dynesty` is a Pure Python, MIT-licensed Dynamic Nested Sampling package for estimating Bayesian posteriors and evidences. See Crash Course and Getting Started for more information. The latest development version can be found here.

The release paper describing dynesty 1.0 can be found here.

As a multi-purpose sampler, `dynesty` is designed to perform "reasonably well" across a large array of problems but is not optimized for any single one. In particular, please take caution when applying `dynesty` to estimate Bayesian posteriors and evidences for large-dimensional (>30 dimensions or so) problems.

Installation

`dynesty` is compatible wit Python 3.6+. It requires `numpy` (for arithmetic), `scipy` (for special

Real. Fake. Data.
Safe Synthetic Data Modeled After Yours
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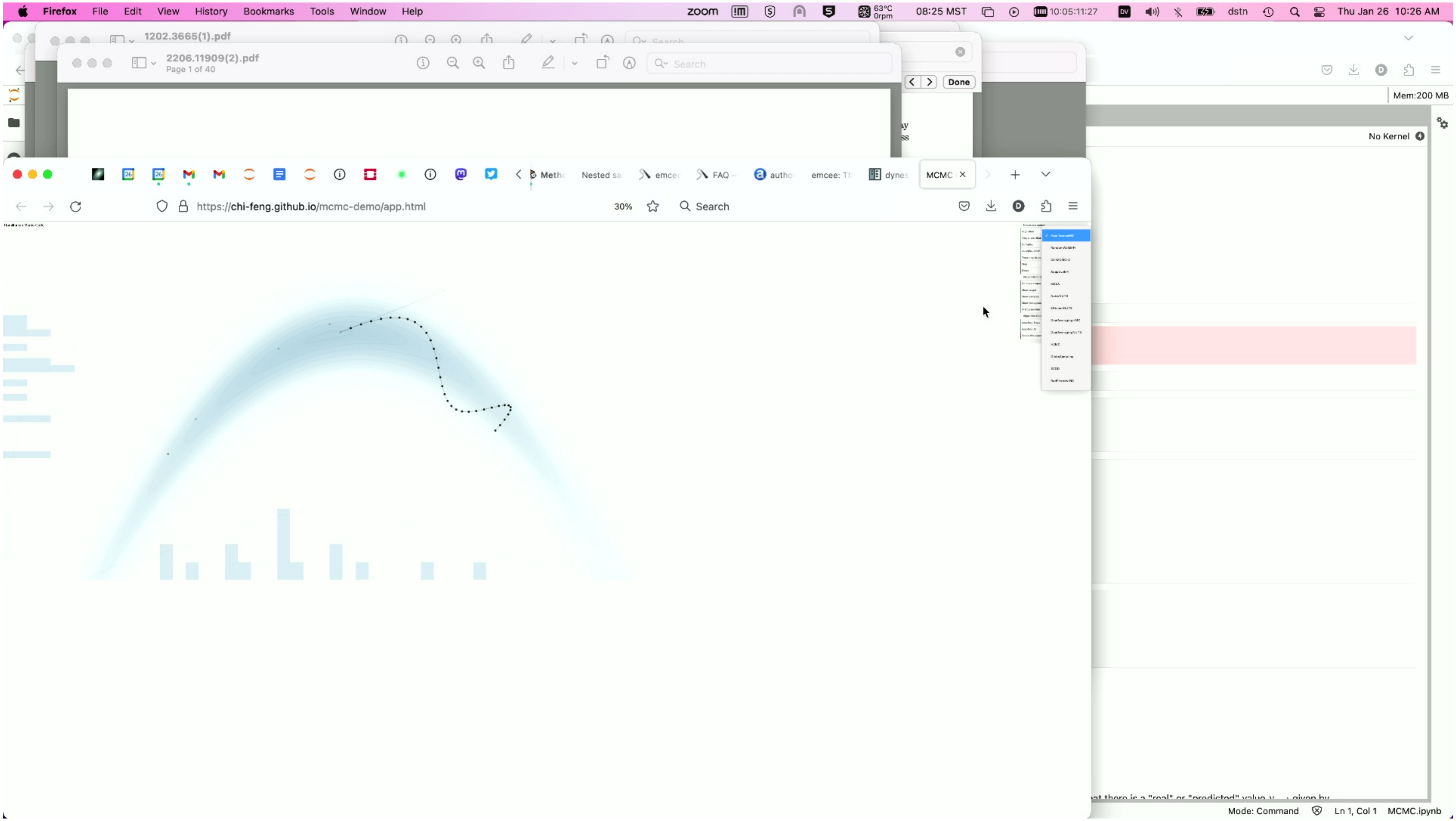
Dynamic Nested Sampling

https://dynesty.readthedocs.io/en/stable/
https://chi-feng.github.io/mcmc-demo/app.html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Thu Jan 26 10:26 AM
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Page 1 of 40
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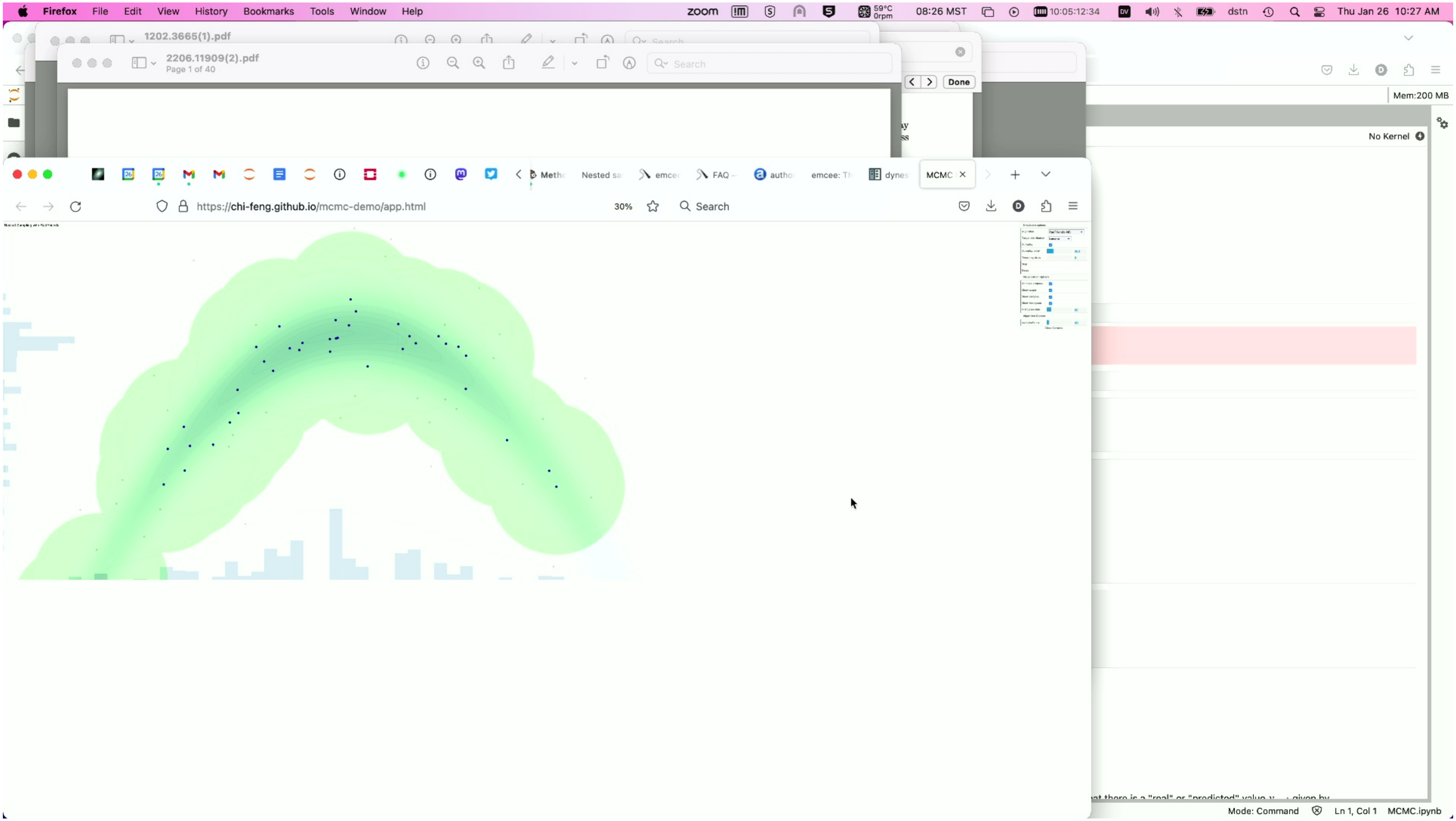
MCMC.ipynb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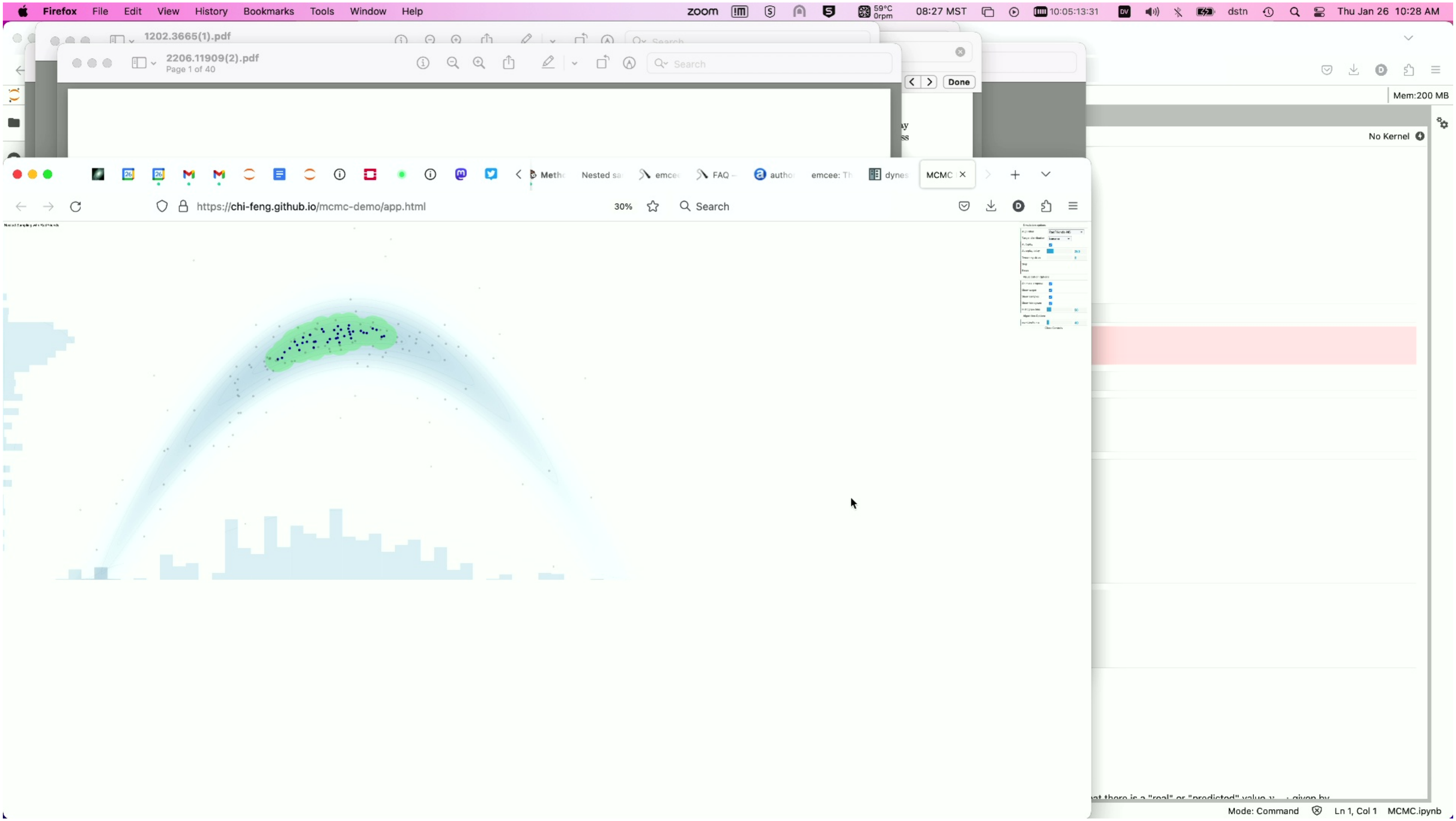
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FAQ
MCMC
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MCMC.ipynb

Dynamic Nested Sampling

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Emcee demo