

Dynamic Nested Sampling with *dynesty*

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CENTER FOR

ASTROPHYSICS

HARVARD & SMITHSONIAN



UNIVERSITY OF
TORONTO



Banting

Postdoctoral Fellowships

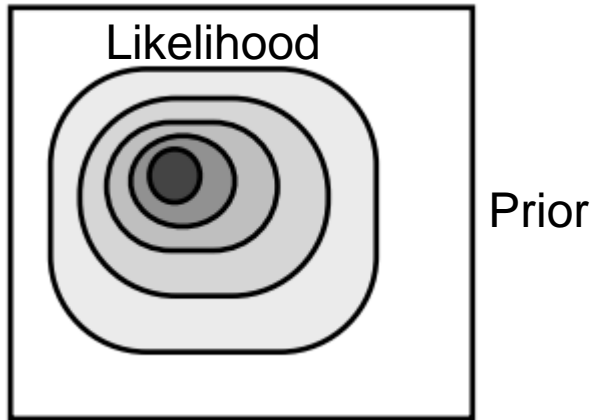
DUNLAP INSTITUTE
for **ASTRONOMY & ASTROPHYSICS**

Background

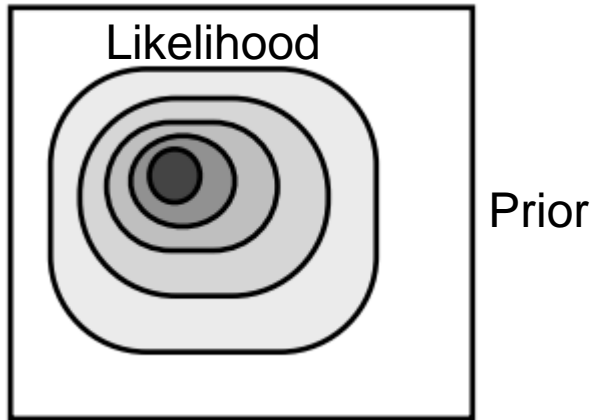
$$\text{Posterior} \quad \Pr(\Theta | \mathbf{D}, M) = \frac{\text{Likelihood} \quad \Pr(\mathbf{D} | \Theta, M) \quad \text{Prior} \quad \Pr(\Theta | M)}{\text{Evidence} \quad \Pr(\mathbf{D} | M)}$$

Bayes' Theorem

Motivation: Sampling the Posterior

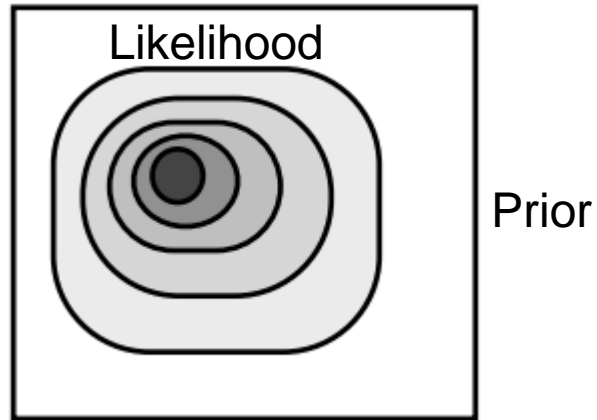


Motivation: Sampling the Posterior



Sampling directly from the likelihood $\mathcal{L}(\theta)$ is **hard**.

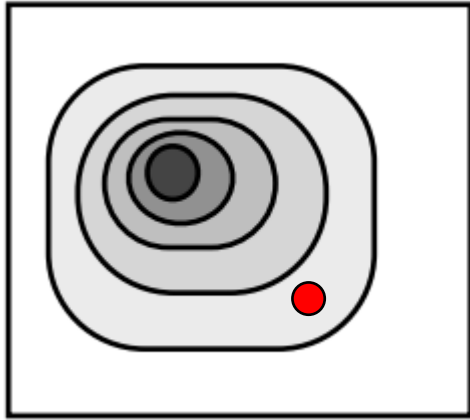
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MCMC: Solving a Hard Problem **once**.
(Markov Chain Monte Carlo)

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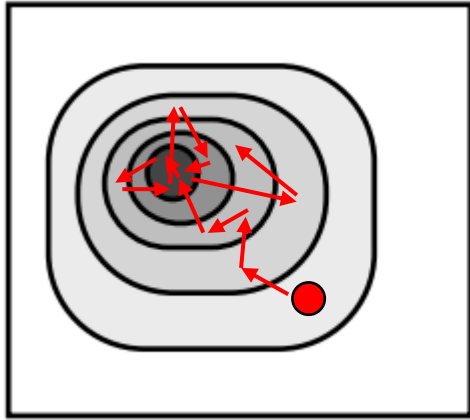
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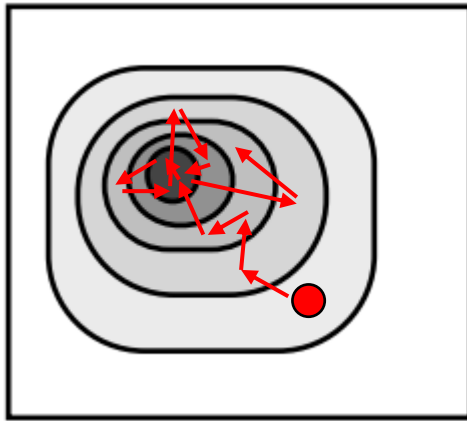
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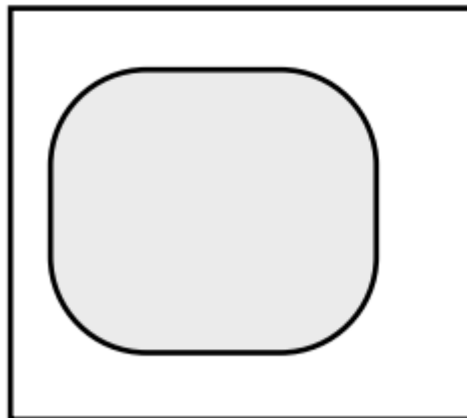
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Motivation: Sampling the Posterior



Sampling uniformly within
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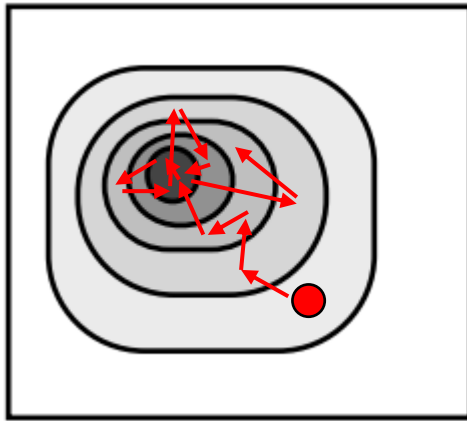


MCMC: Solving a Hard Problem **once**.

vs

Nested Sampling: Solving an Easier
Problem **many times**.

Motivation: Sampling the Posterior

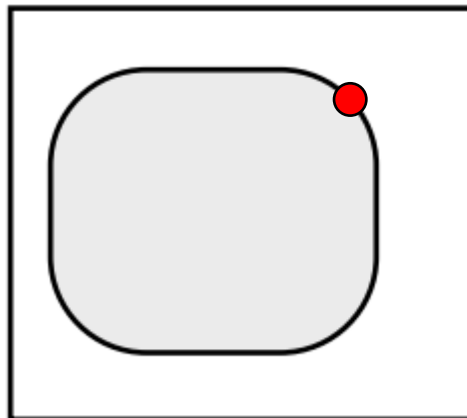


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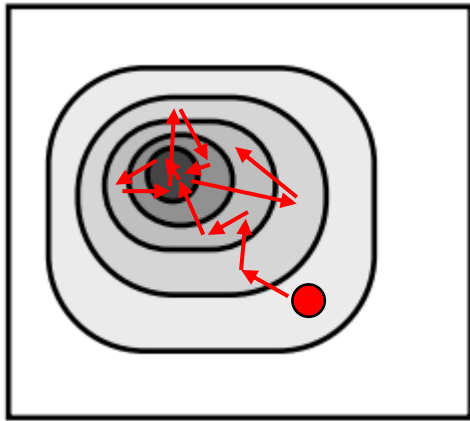
Nested Sampling: Solving an Easier Problem **many times**.

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X_{i-1}

Motivation: Sampling the Posterior

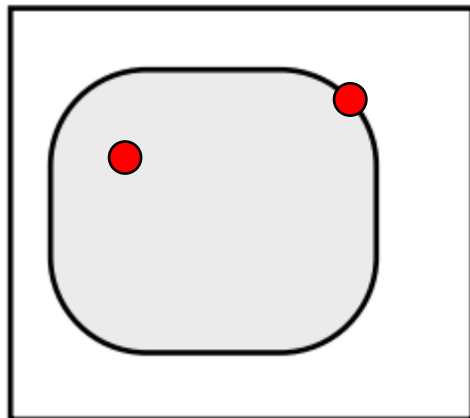


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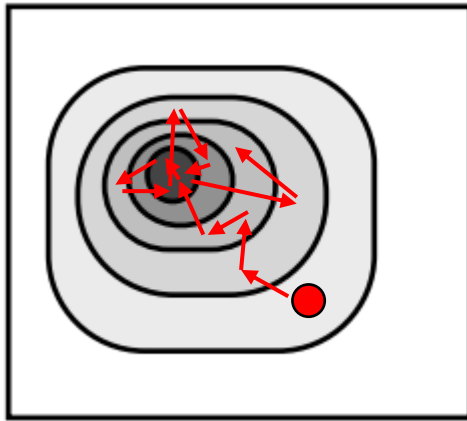
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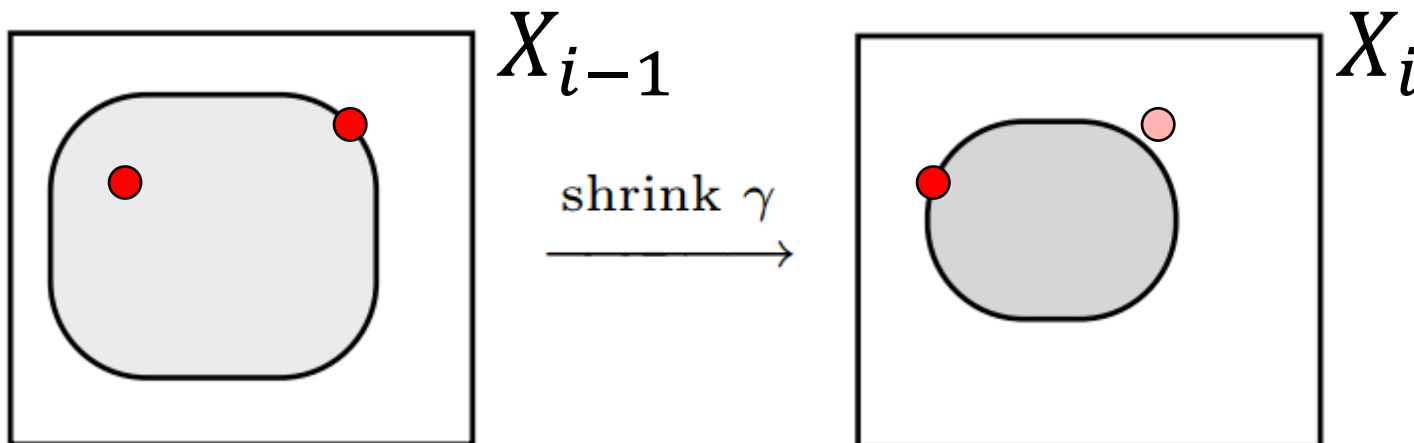


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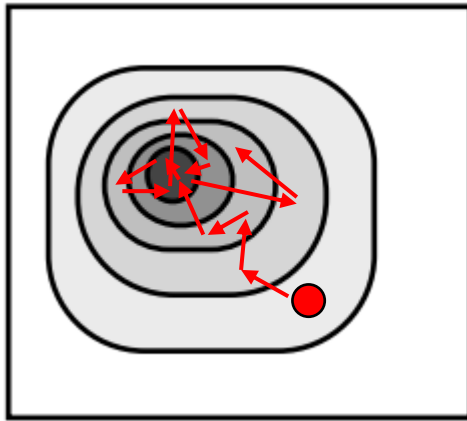
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Pictures adapted from [this 2010 talk](#) by John Skilling.

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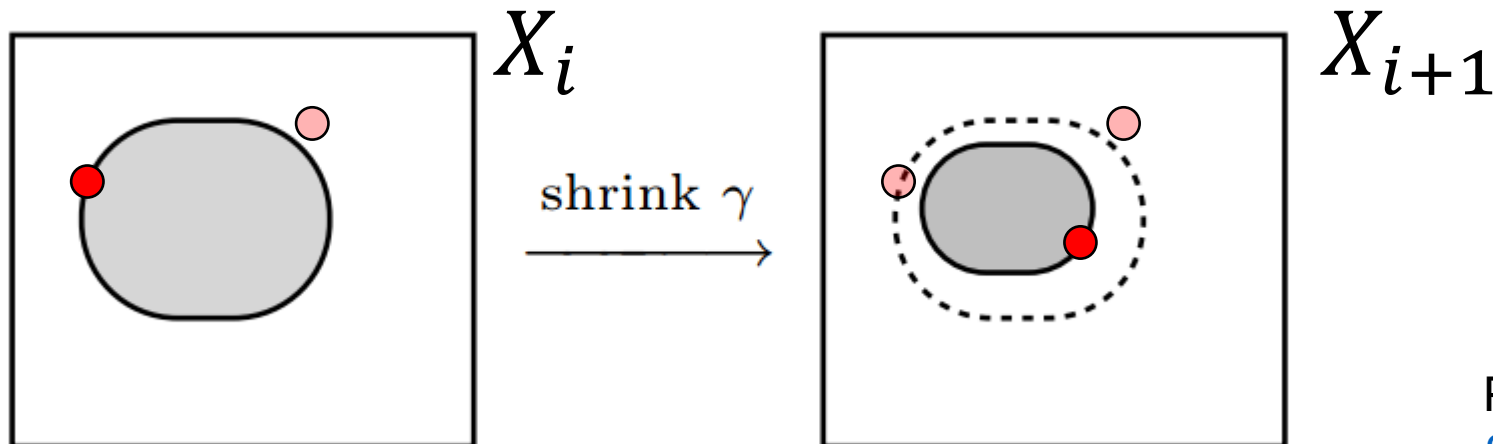


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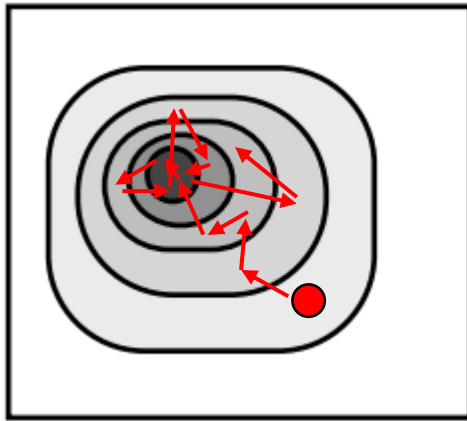
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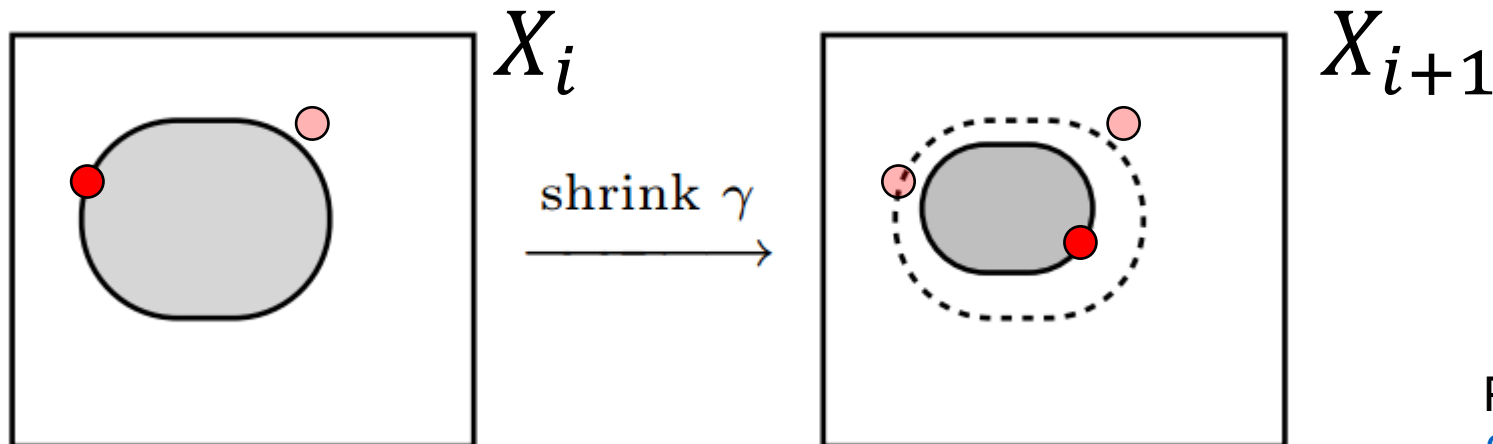


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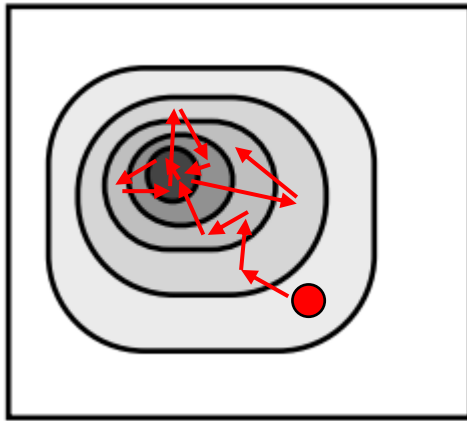
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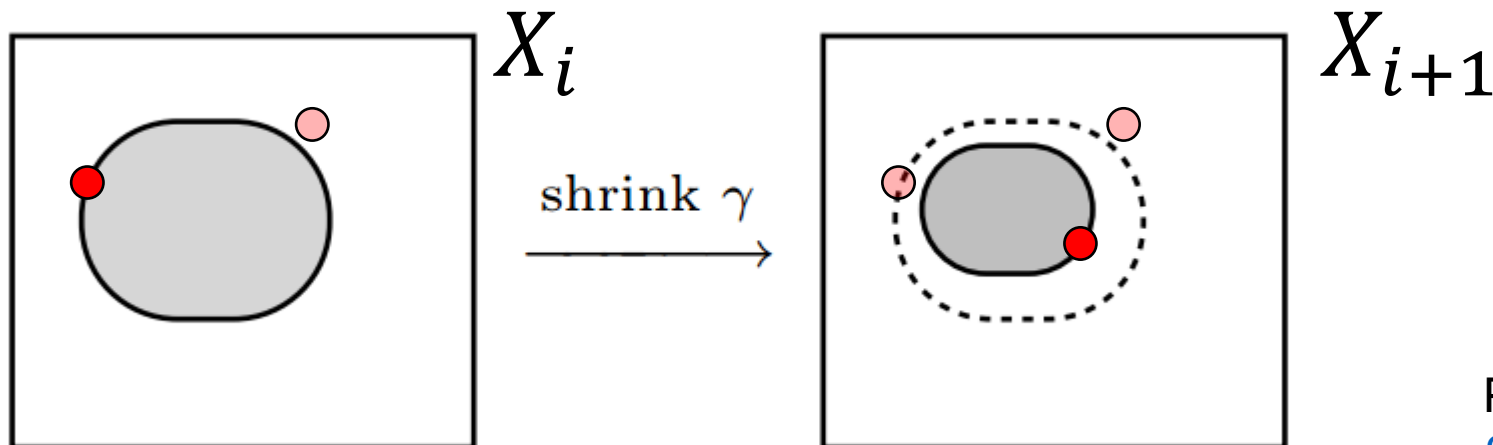
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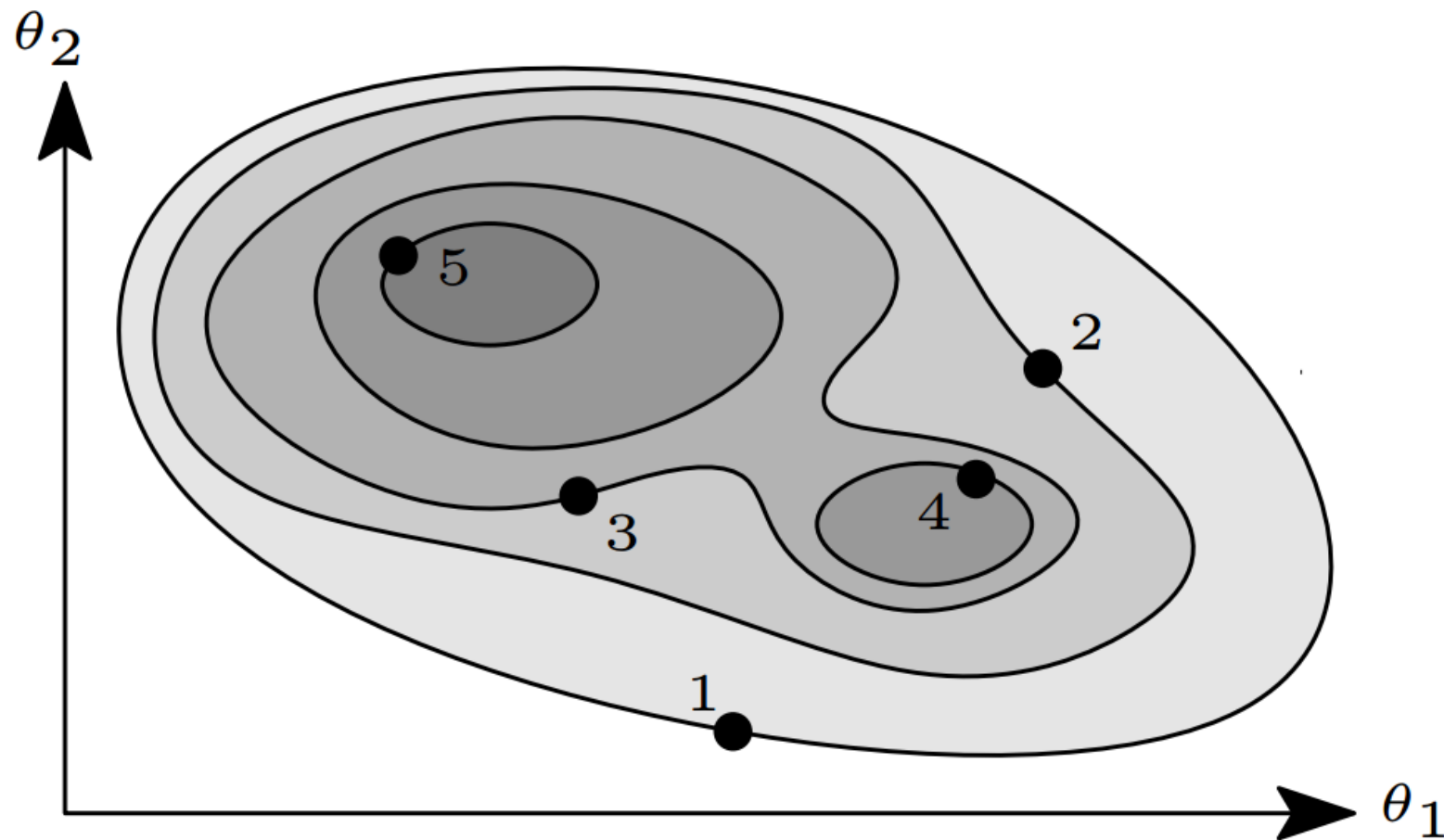
Nested Sampling: Solving an Easier Problem **many times**.

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If you have a **prior transform** that converts your priors to look uniform, then this case is equivalent.



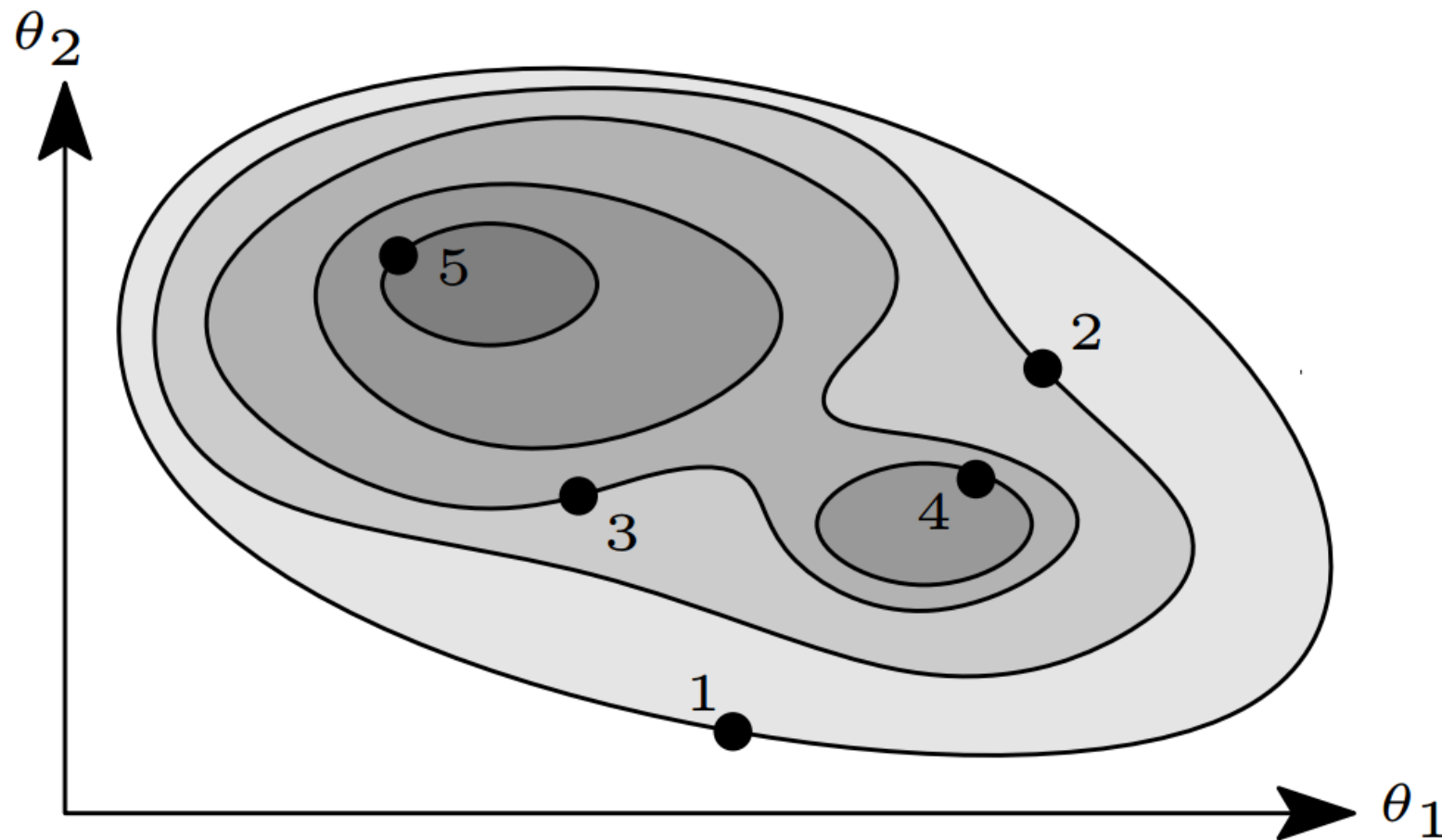
Nested Sampling In Practice



Higson et al. (2017)

[arxiv:1704.03459](https://arxiv.org/abs/1704.03459)

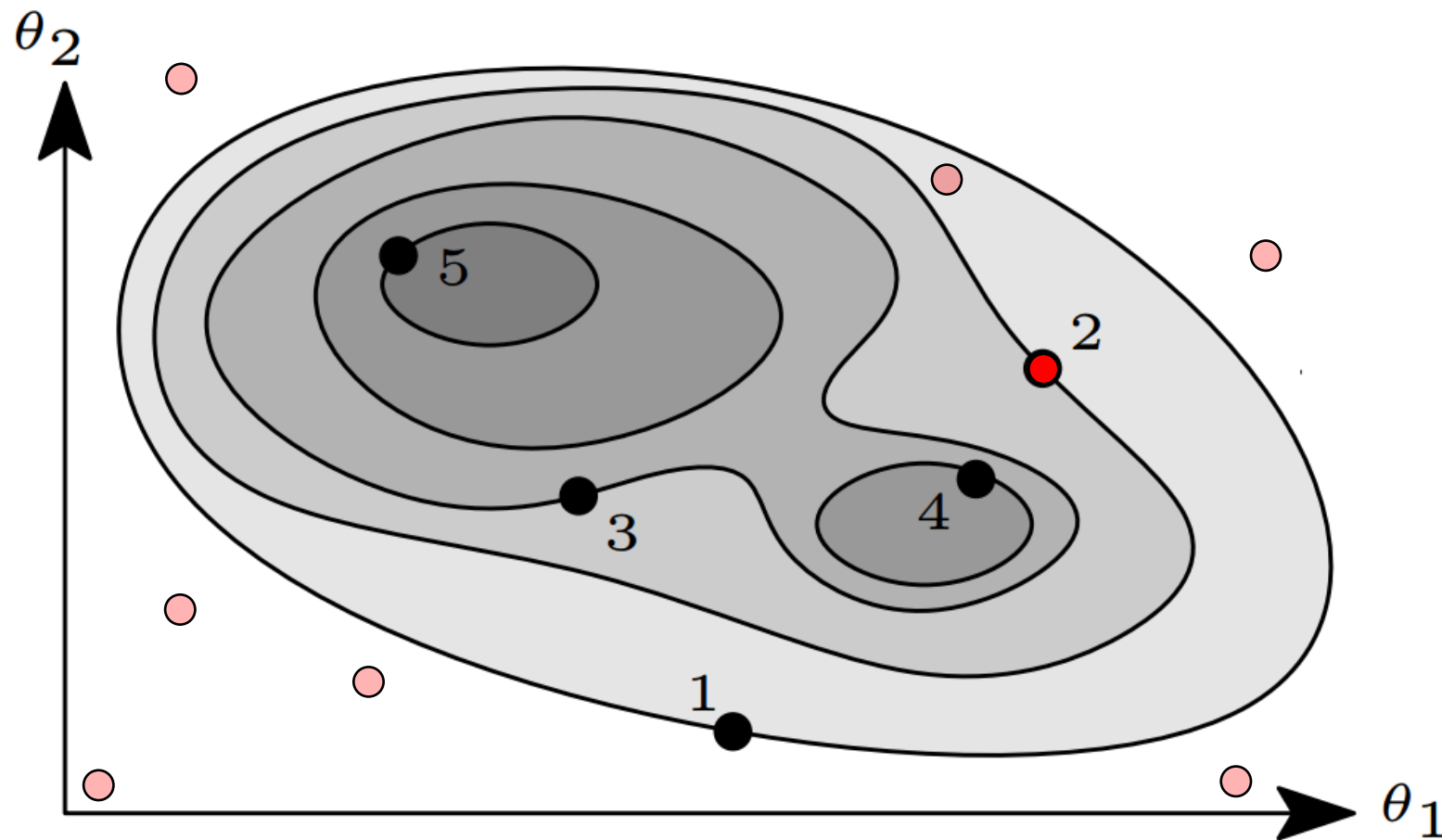
Naïve Approach: Sampling from the Prior



Higson et al. (2017)

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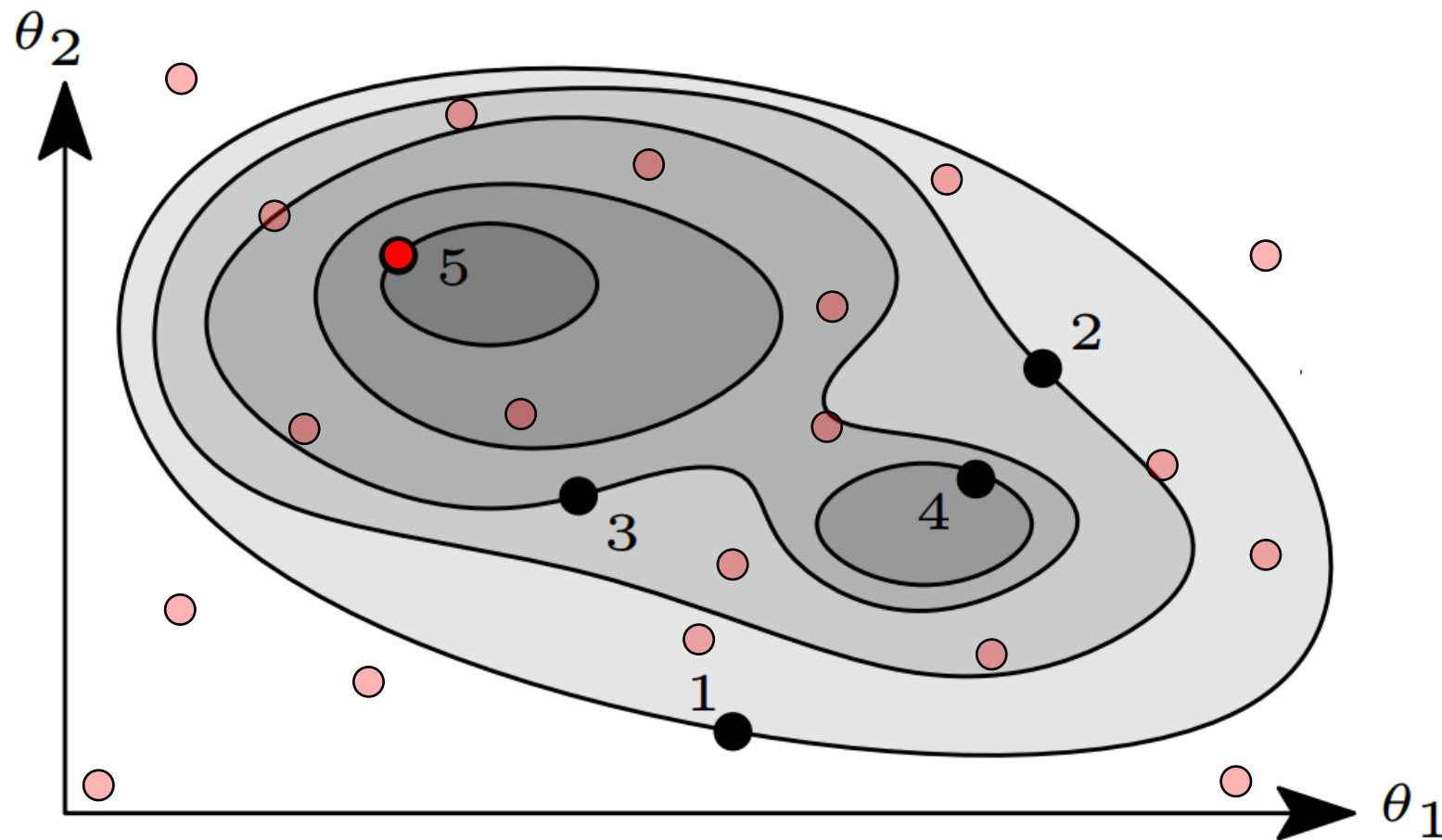
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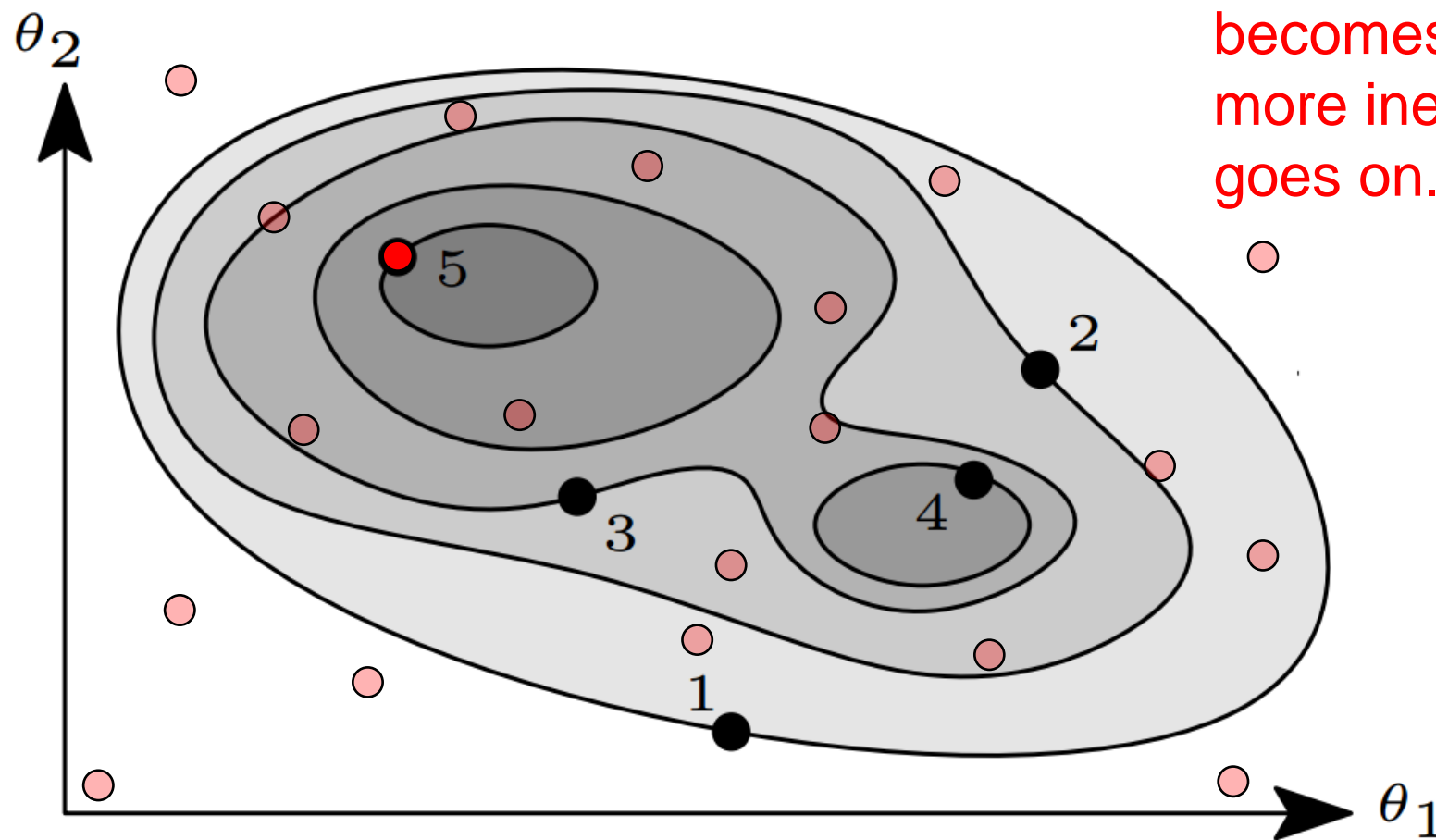


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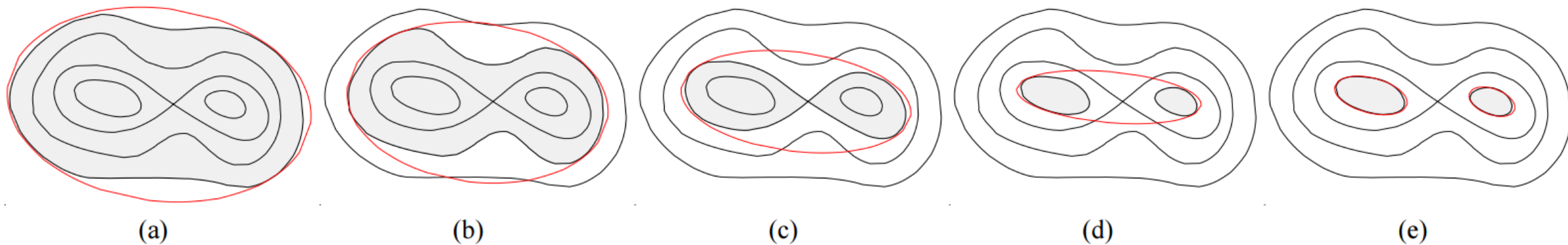
Sampling from the prior becomes **exponentially** more inefficient as time goes on.



Sampling from the Constrained Prior

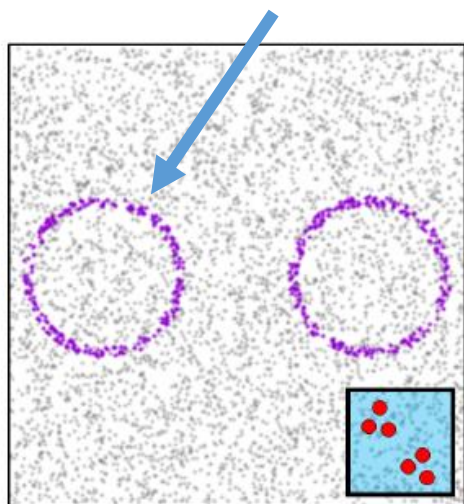
Proposal:

Try to bound the iso-likelihood contours in real time.

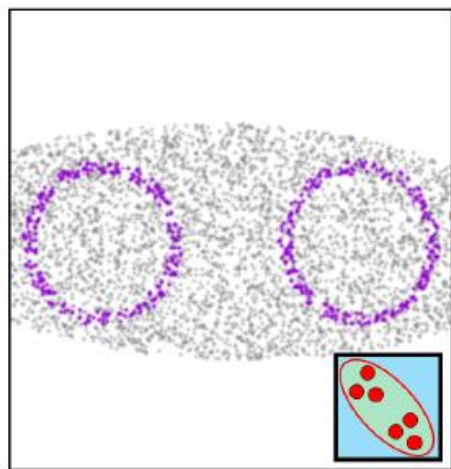


Examples of Bounding Strategies

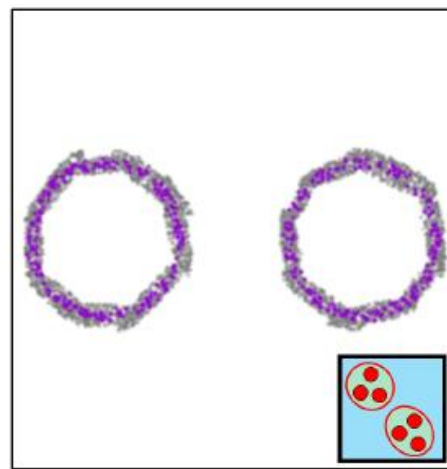
“Live points” (i.e. “chains”)



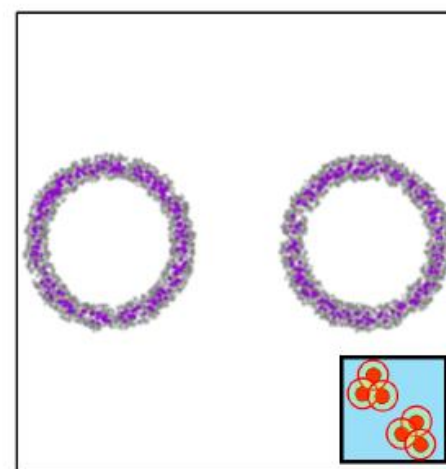
Unit Cube
(no bound)



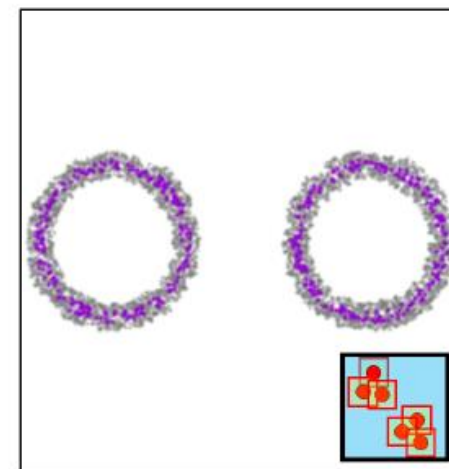
Single
Ellipsoid



Multiple
Ellipsoids



Overlapping
Balls

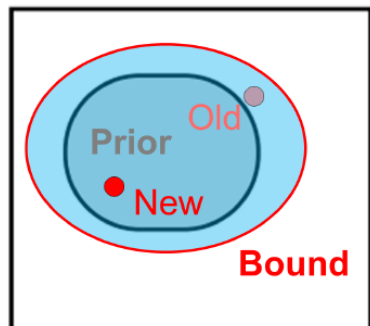


Overlapping
Cubes

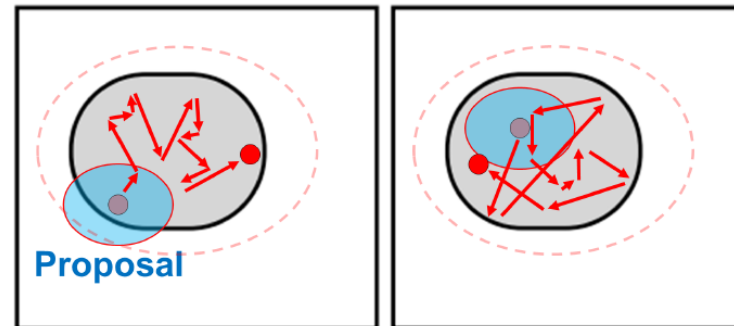
Bounding Method	Relevant Papers
Single ellipsoid (§4.1.2)	Mukherjee et al. (2006)
Multiple ellipsoids (§4.1.3)	Shaw et al. (2007), Feroz & Hobson (2008), Feroz et al. (2009, 2013), Handley et al. (2015)
Overlapping balls/cubes (§4.1.4, §4.1.5)	Buchner (2016, 2017)

Examples of Sampling Strategies

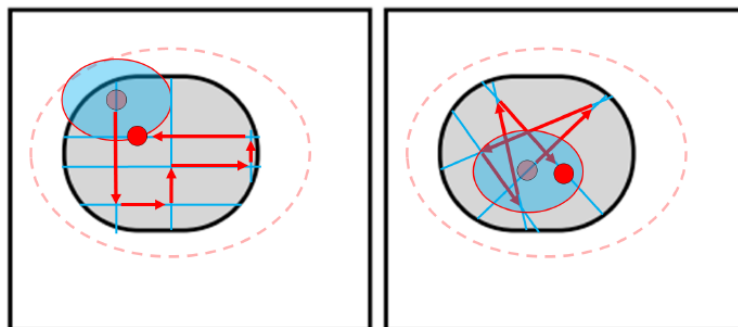
Uniform



Random Walk



Multivariate Slice



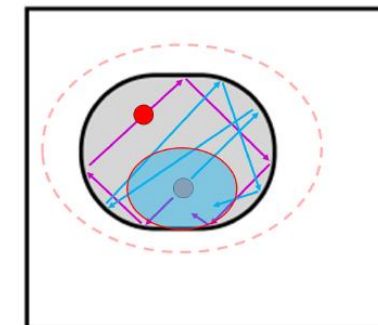
Principal Axes

Random

Fixed Scale

Variable Scale

Hamiltonian Slice



Sampling Method

Uniform Sampling (§4.2.1)

Random walks (§4.2.2)

Slice sampling (§4.2.3)

Hamiltonian slicing (§4.2.4)

Mukherjee et al. (2006), Feroz & Hobson (2008), Feroz et al. (2009), Buchner (2016)

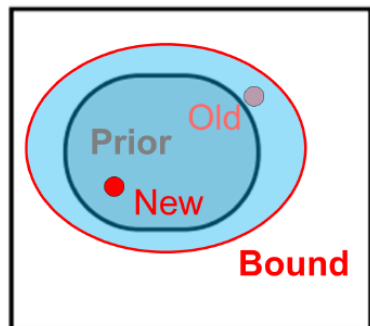
Skilling (2004), Skilling (2006)

Neal (2003), Handley et al. (2015)

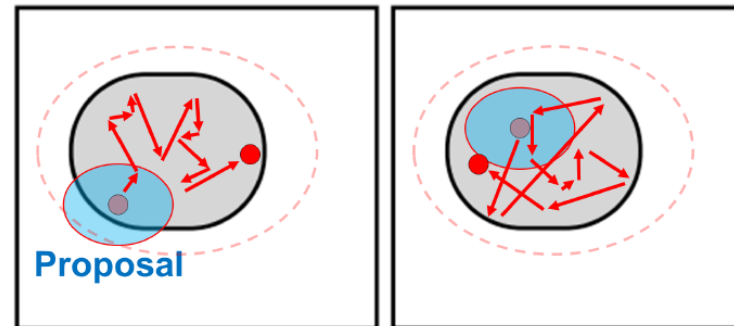
Neal (2003), Skilling (2012), Feroz & Skilling (2013), this work

Examples of Sampling Strategies

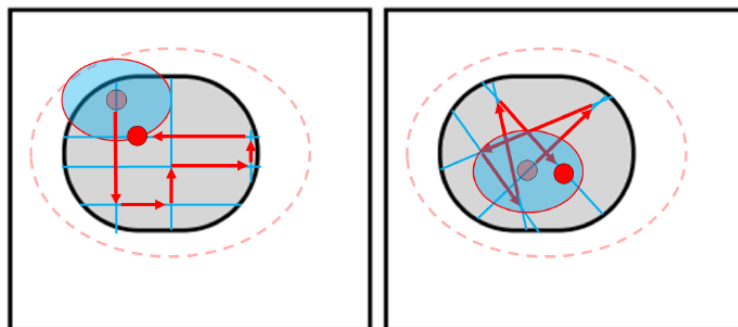
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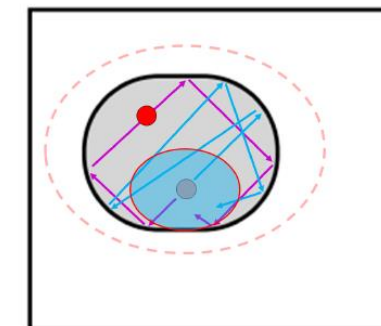
Principal Axes

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Uses “simple” MCMC to propose at each step

Sampling Method

Uniform Sampling (§4.2.1)

Random walks (§4.2.2)

Slice sampling (§4.2.3)

Hamiltonian slicing (§4.2.4)

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dynesty

Inspired by *emcee* (Foreman-Mackey et al. 2013)

- **Public, open source Python package** designed to make (Dynamic) Nested Sampling easy to use but also easy to customize.
- Designed to be **highly modular** and can mix-and-match methods.
- Includes **built-in plotting utilities** and post-processing tools.



Speagle (2020)

dynesty

```
import dynesty

# "Static" nested sampling.
sampler = dynesty.NestedSampler(loglike, ptform, ndim)
sampler.run_nested()
sresults = sampler.results

# "Dynamic" nested sampling.
dsampler = dynesty.DynamicNestedSampler(loglike, ptform, ndim)
dsampler.run_nested()
dresults = dsampler.results
```

dynesty

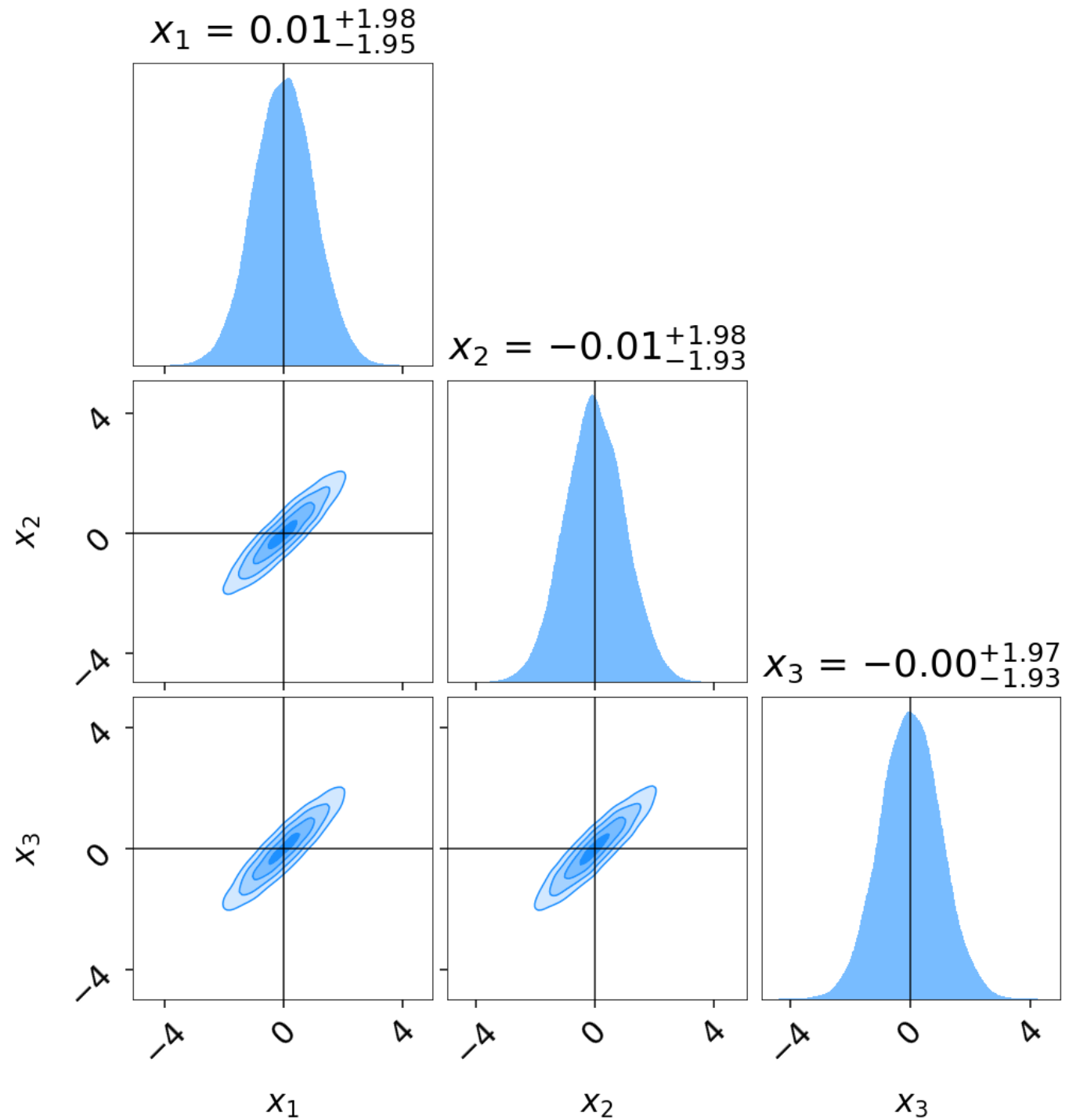
```
from dynesty import plotting as dyplot

# Plot a summary of the run.
rfig, raxes = dyplot.runplot(results)

# Plot traces and 1-D marginalized posteriors.
tfig, taxes = dyplot.traceplot(results)

# Plot the 2-D marginalized posteriors.
cfig, caxes = dyplot.cornerplot(results)
```

dynesty



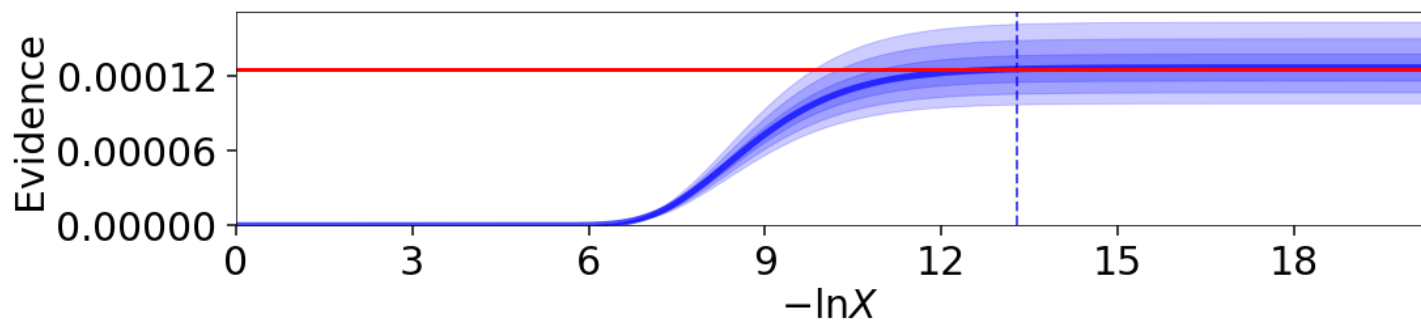
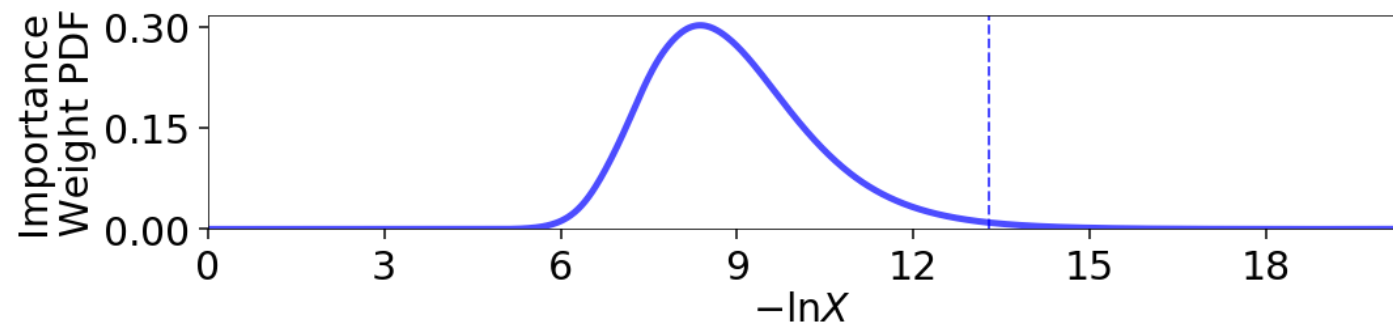
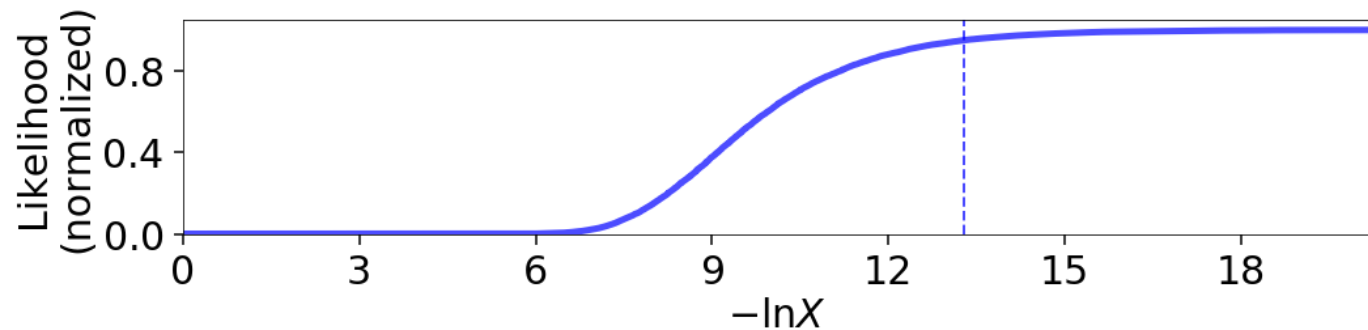
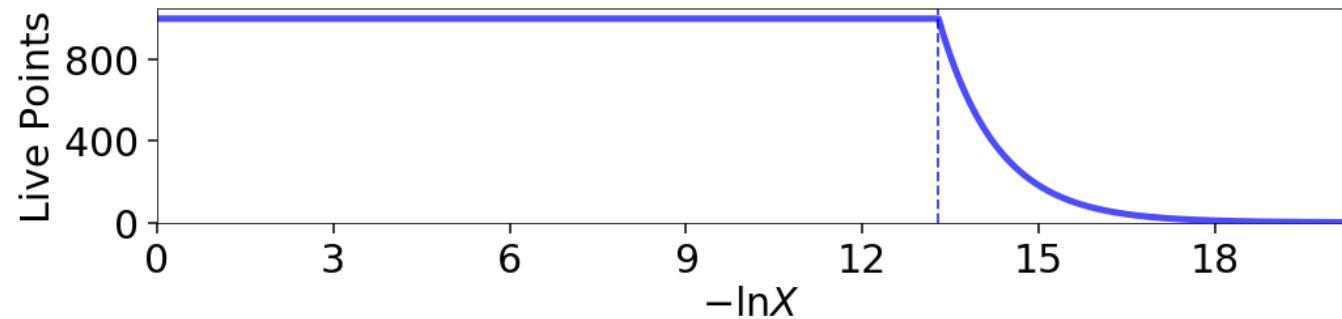
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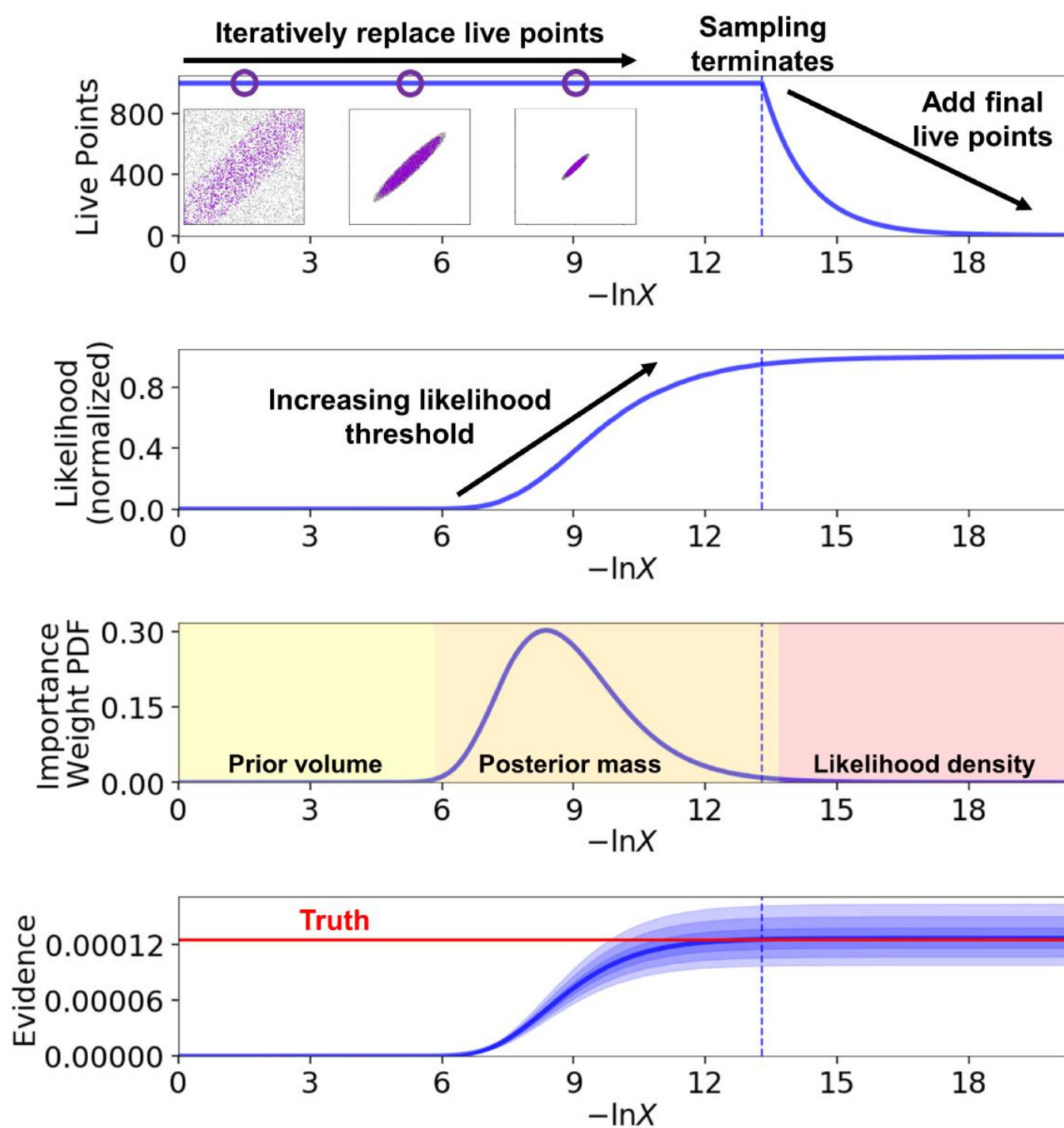
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dynesty

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```
# Plot a summary of the run.
```

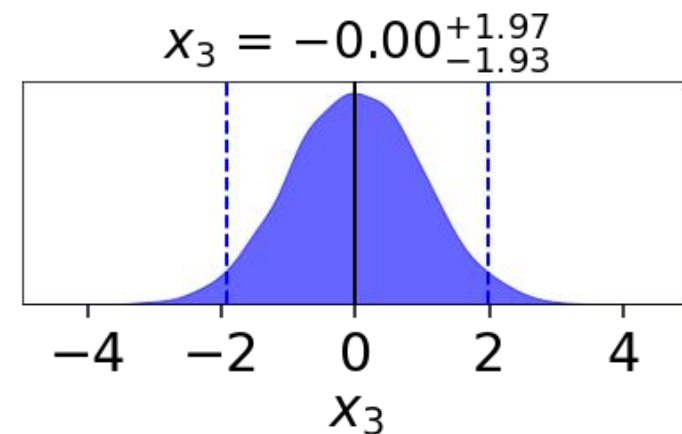
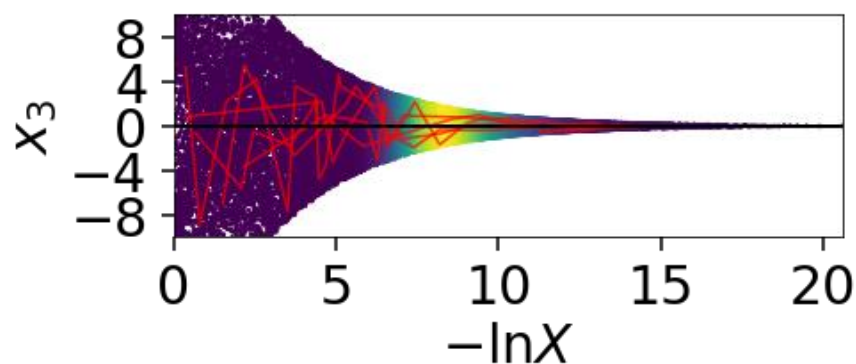
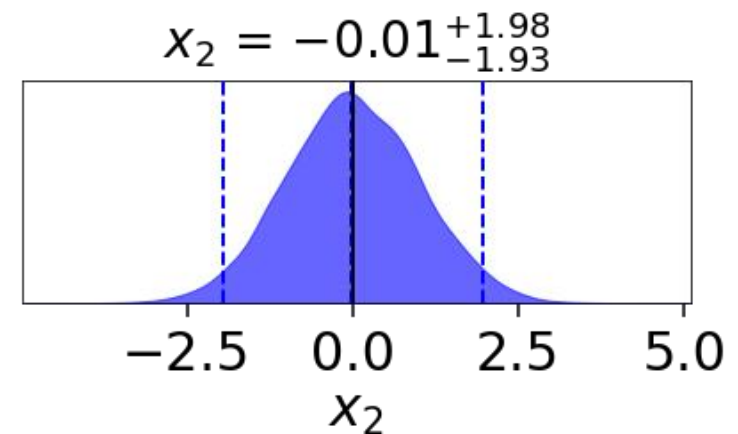
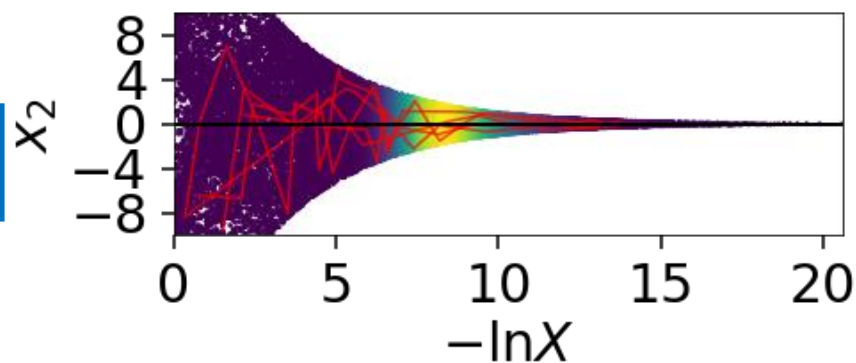
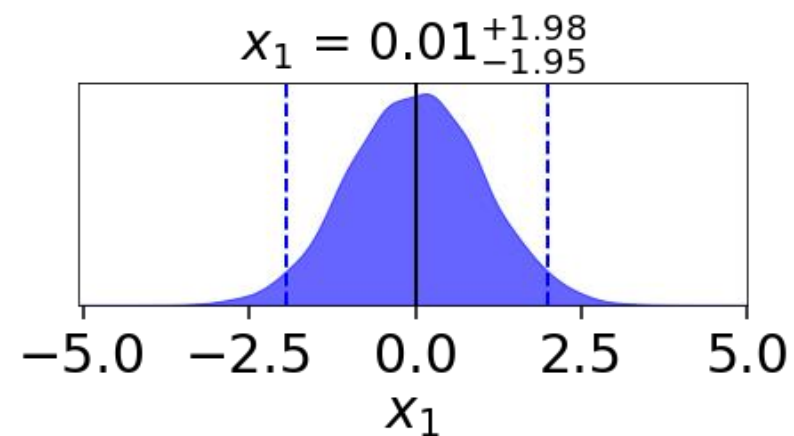
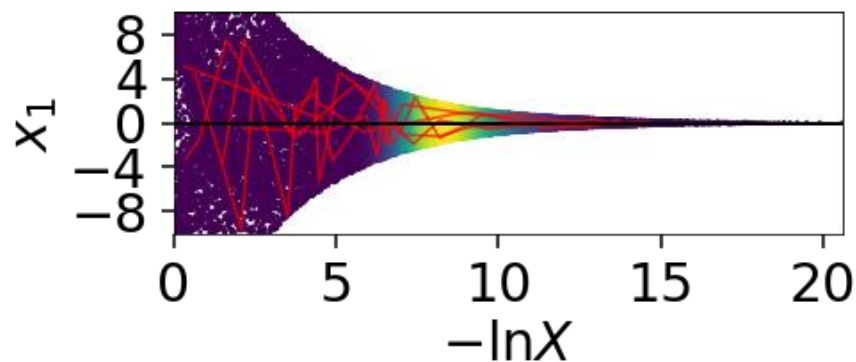
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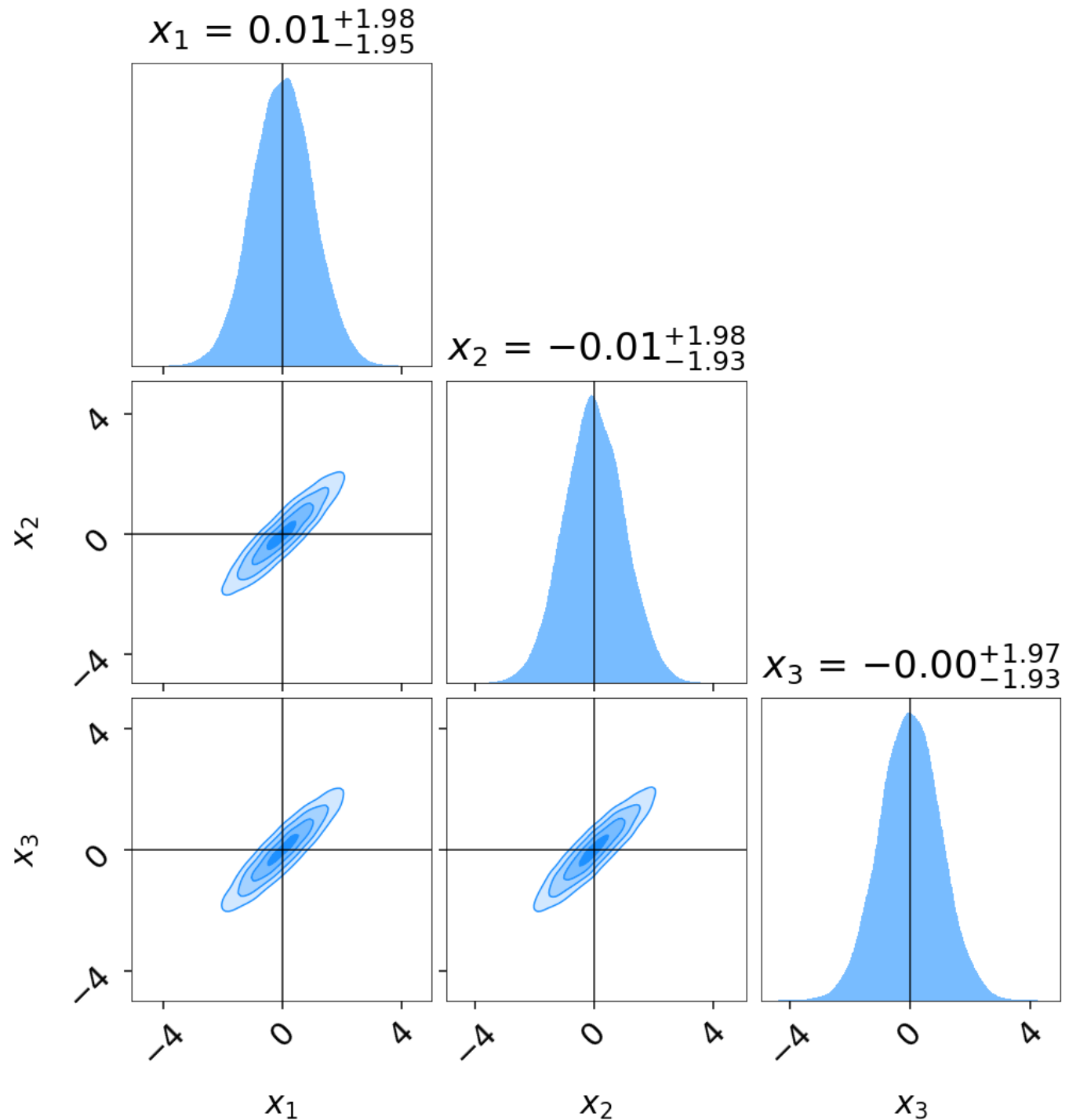
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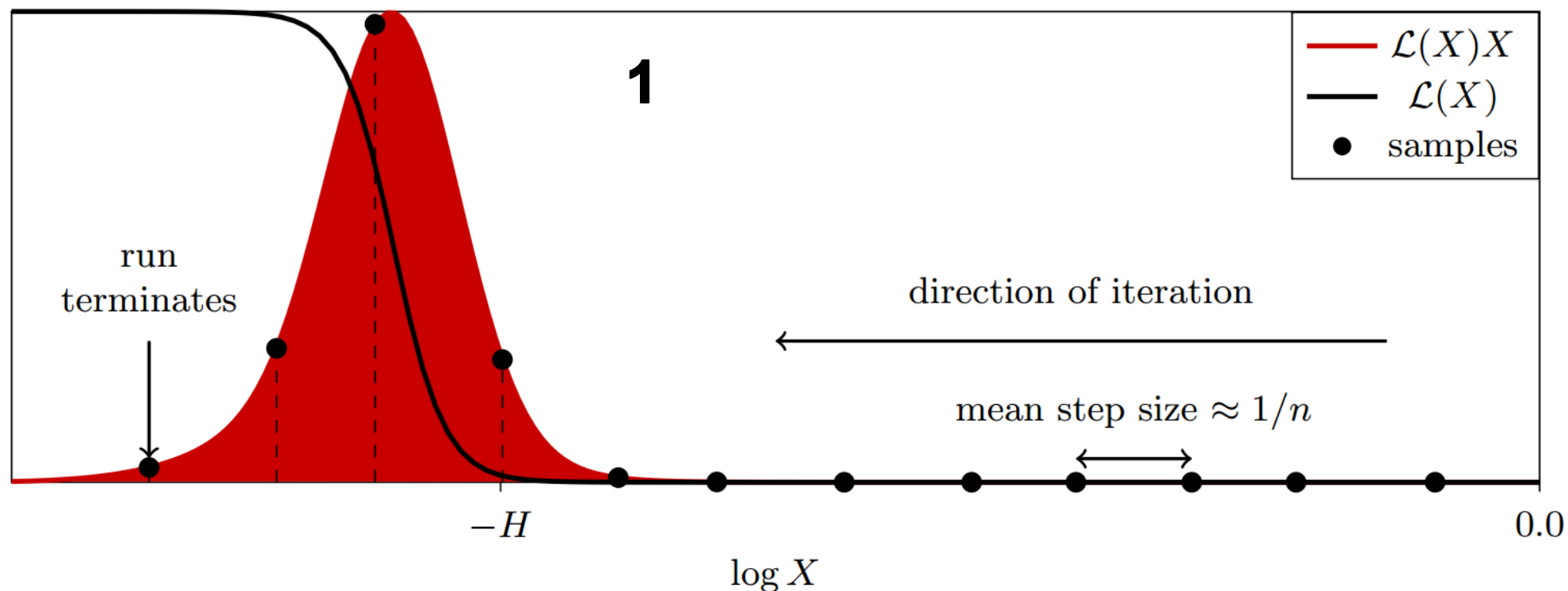
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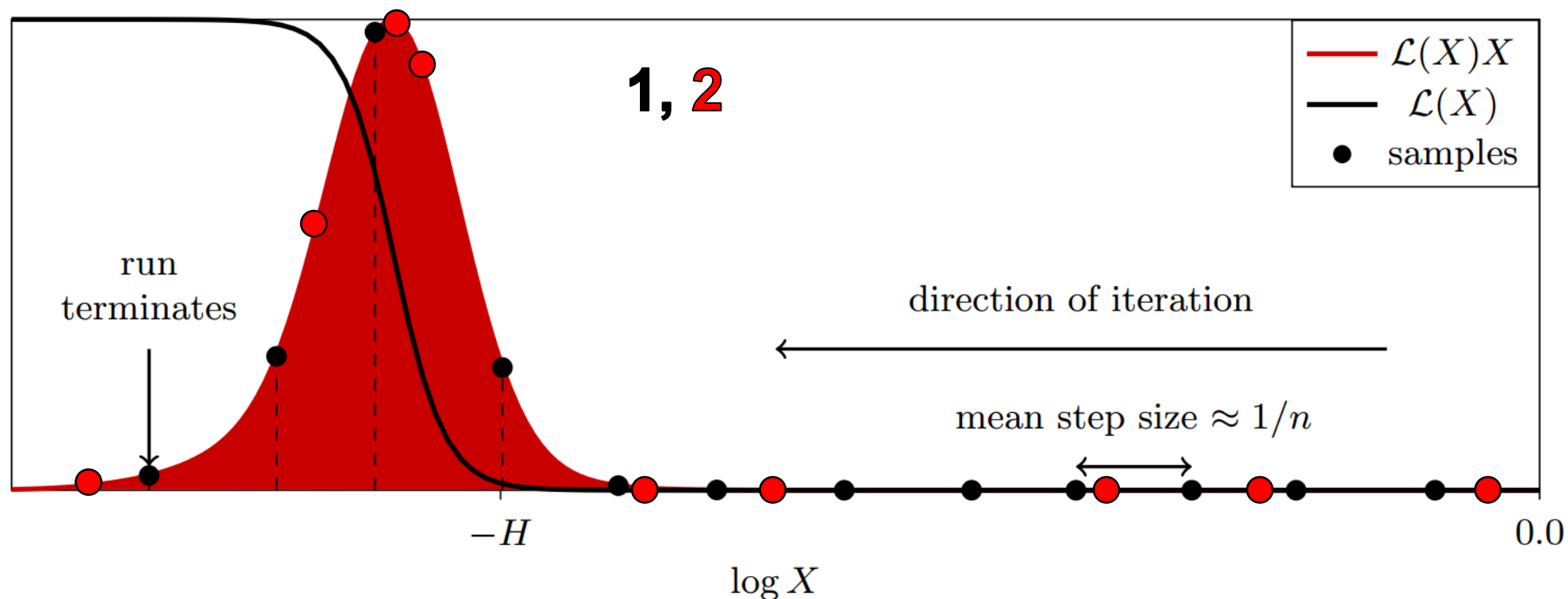


Dynamic Nested Sampling



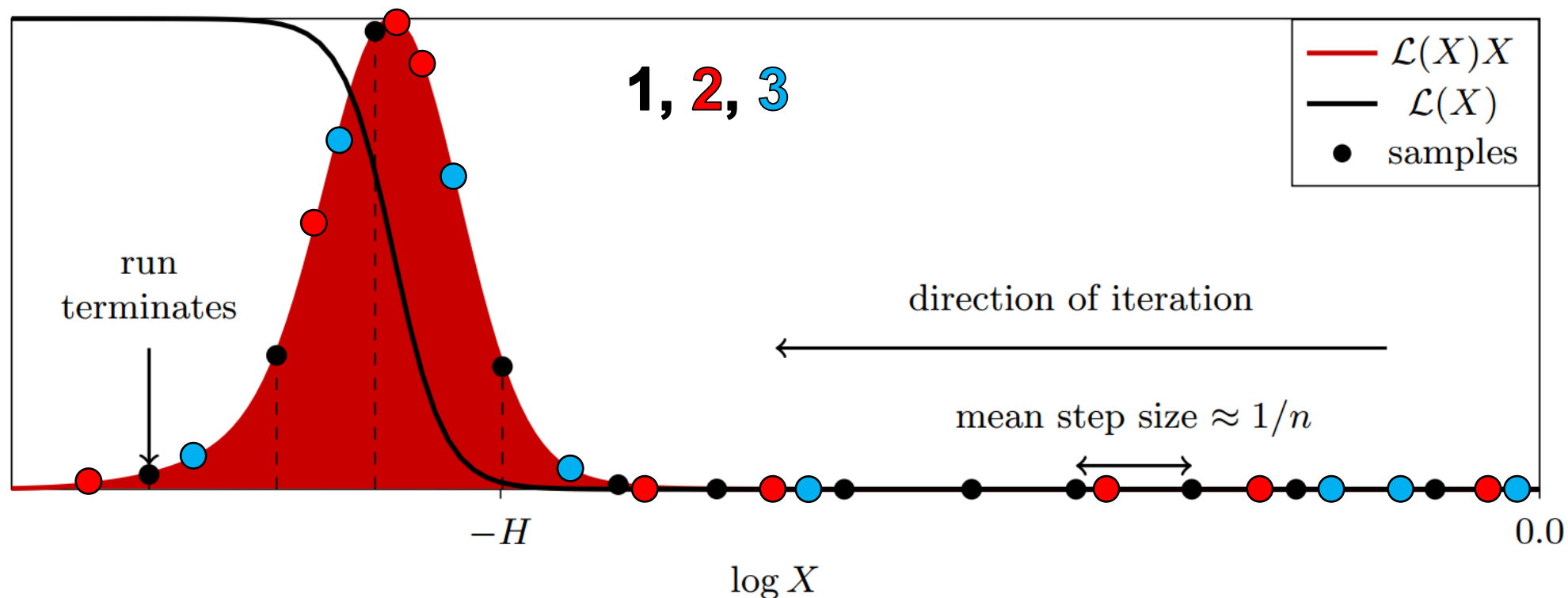
Higson et al. (2017)
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Dynamic Nested Sampling



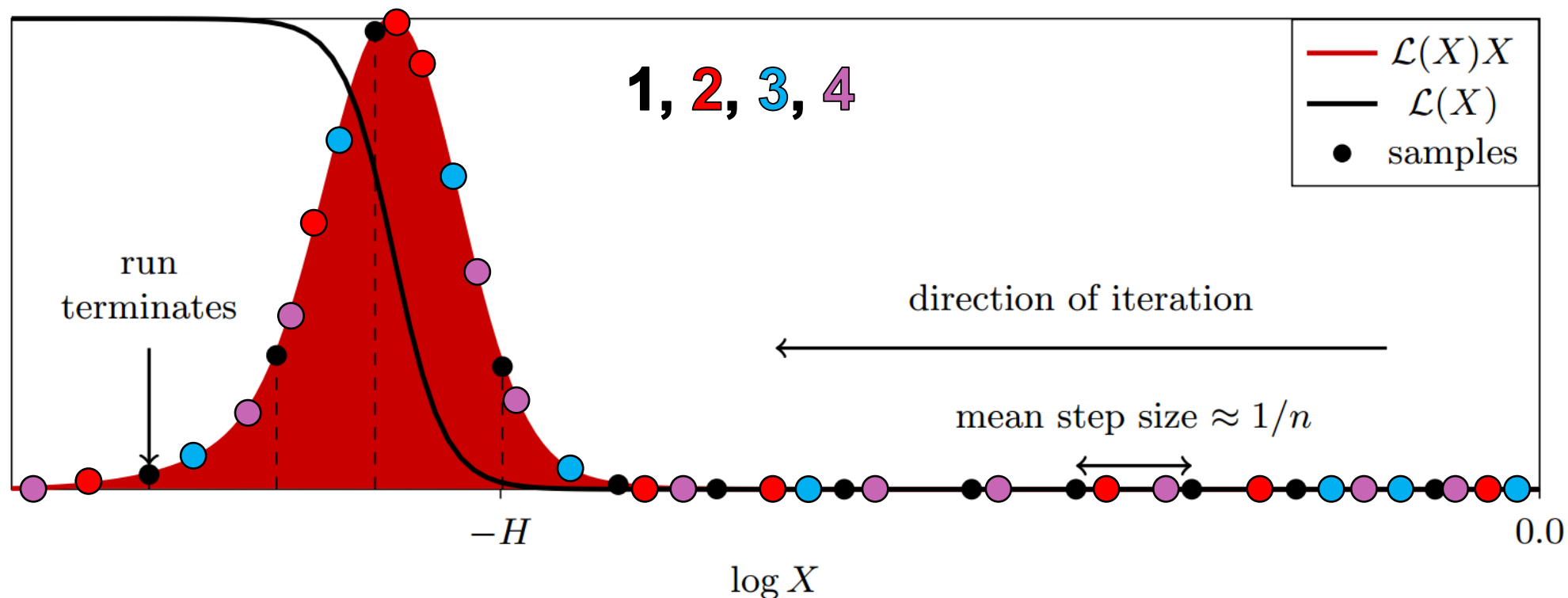
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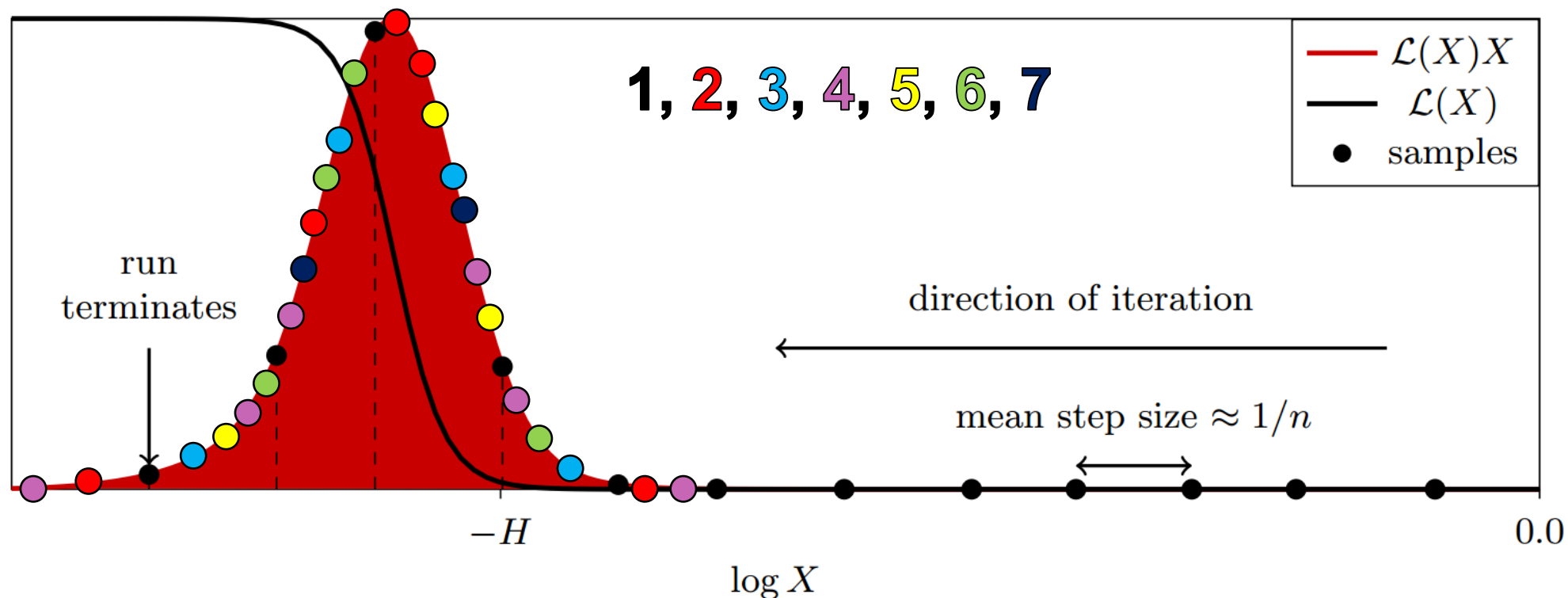
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Dynamic Nested Sampling



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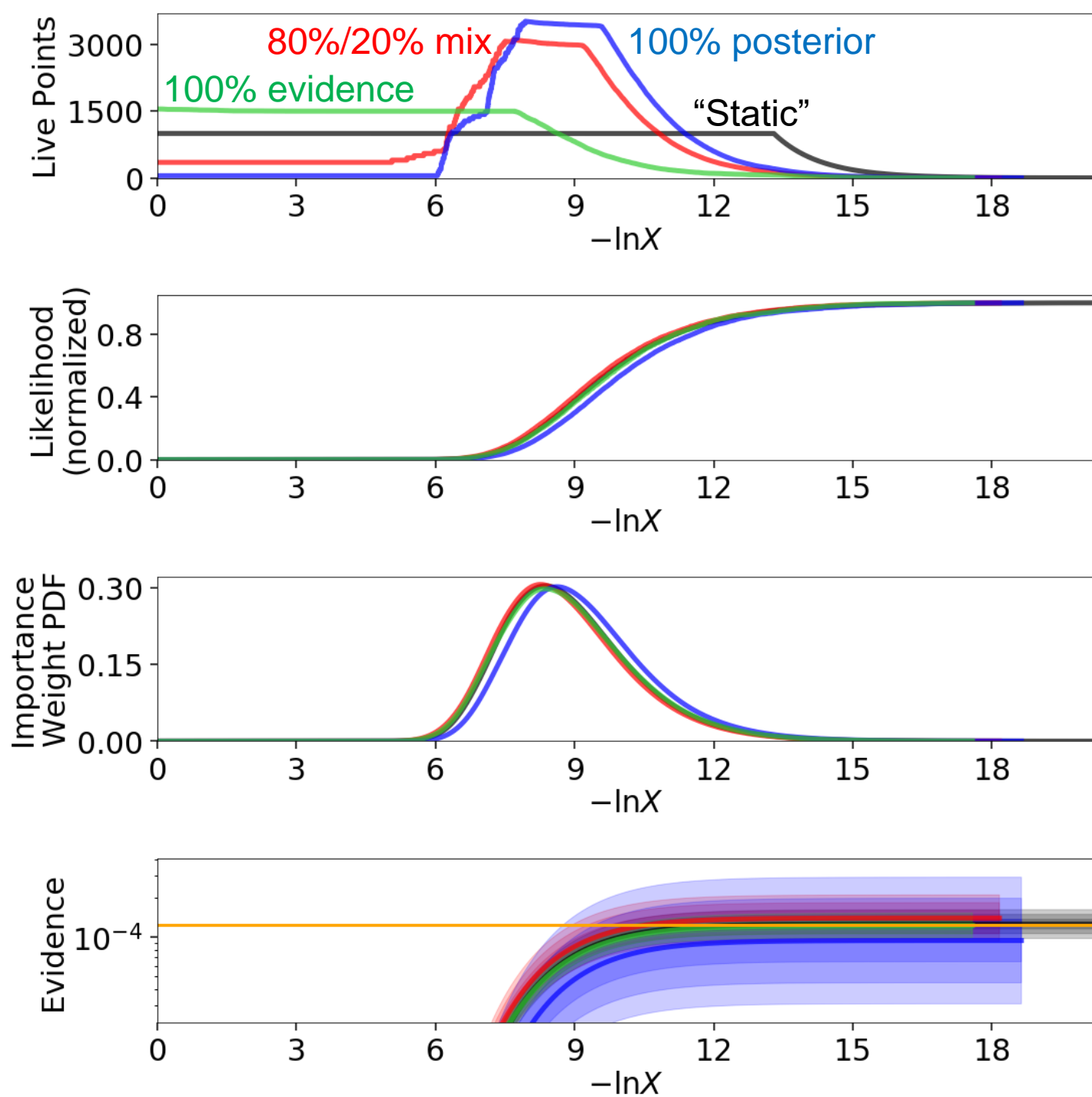
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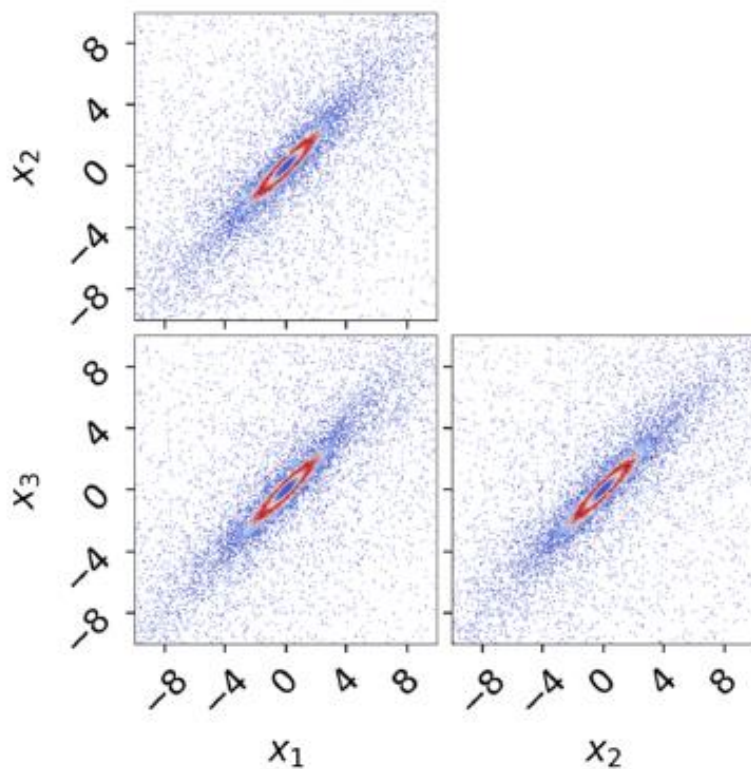
Comparisons

- Same 2-D Gaussian example as before with **fixed number of samples**.
- Only change is in overall Dynamic Nested Sampling **strategy**.

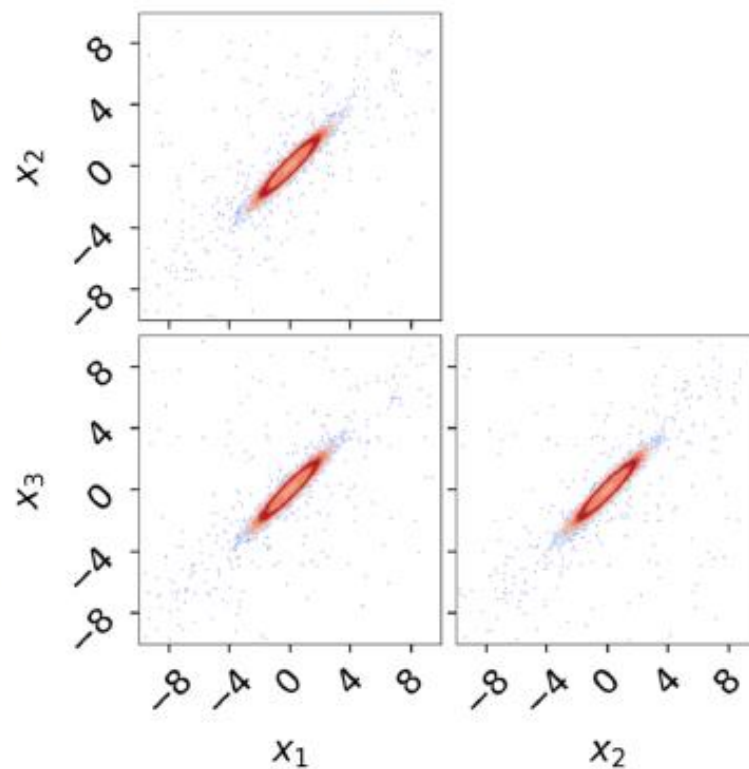


Comparisons

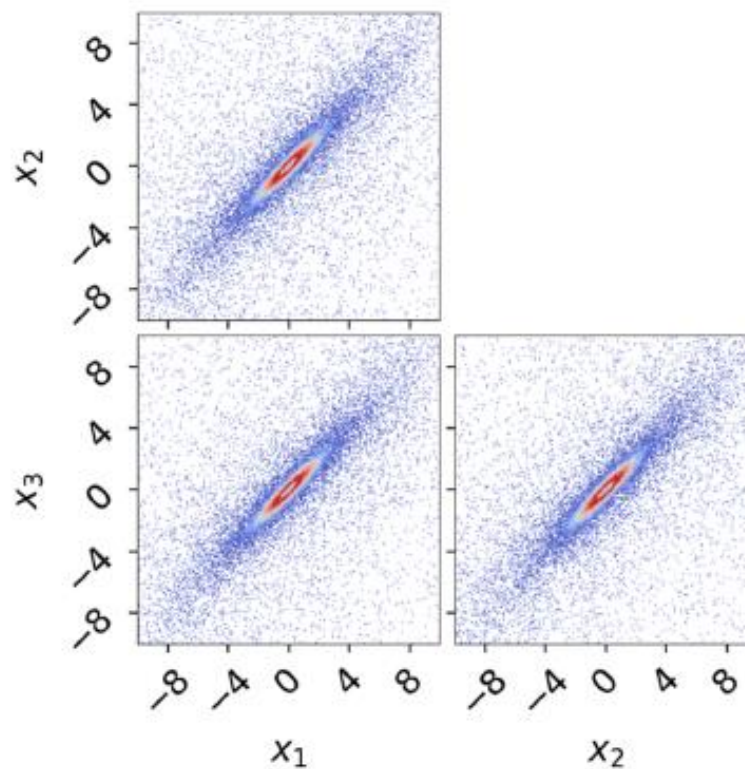
Static



100% posterior

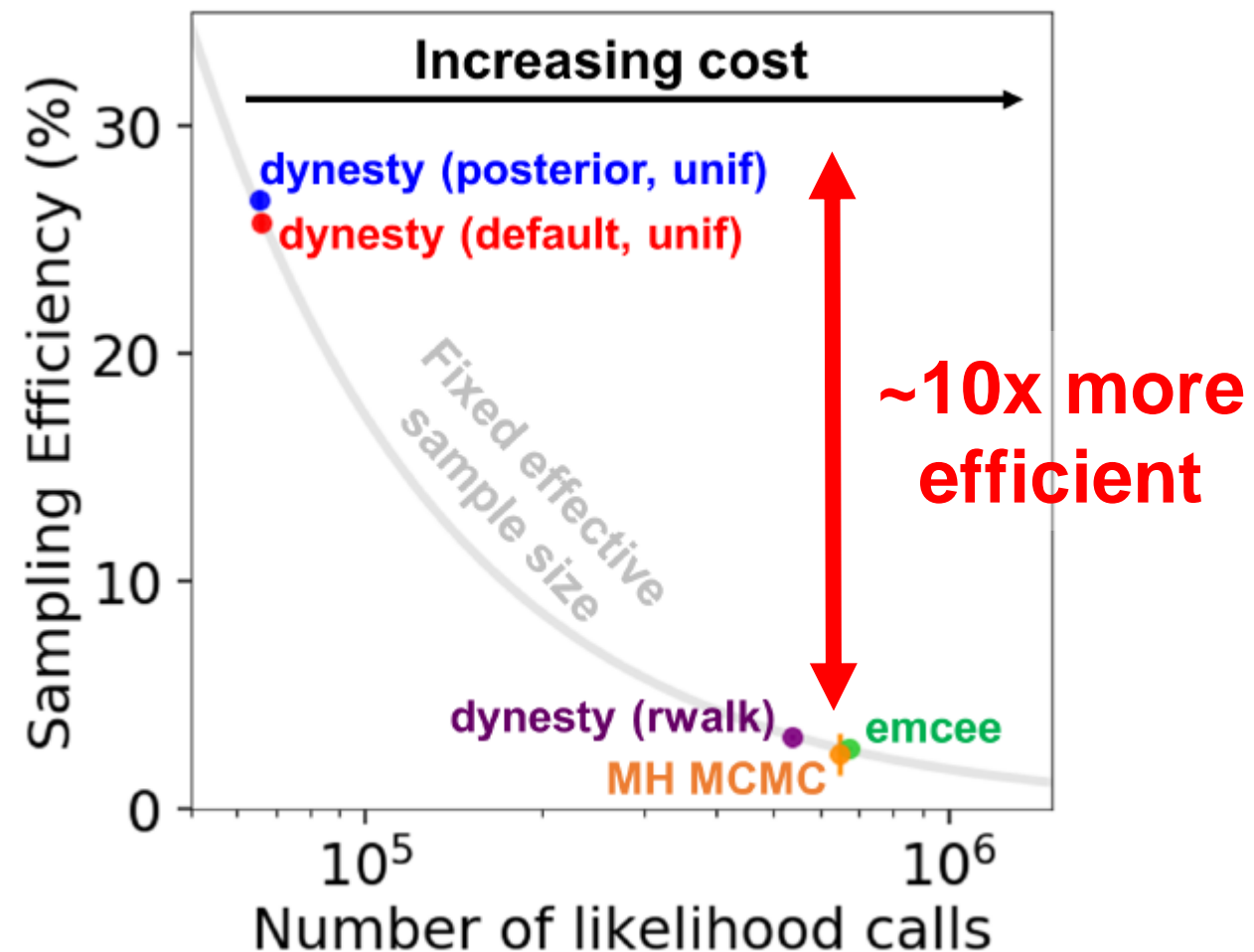
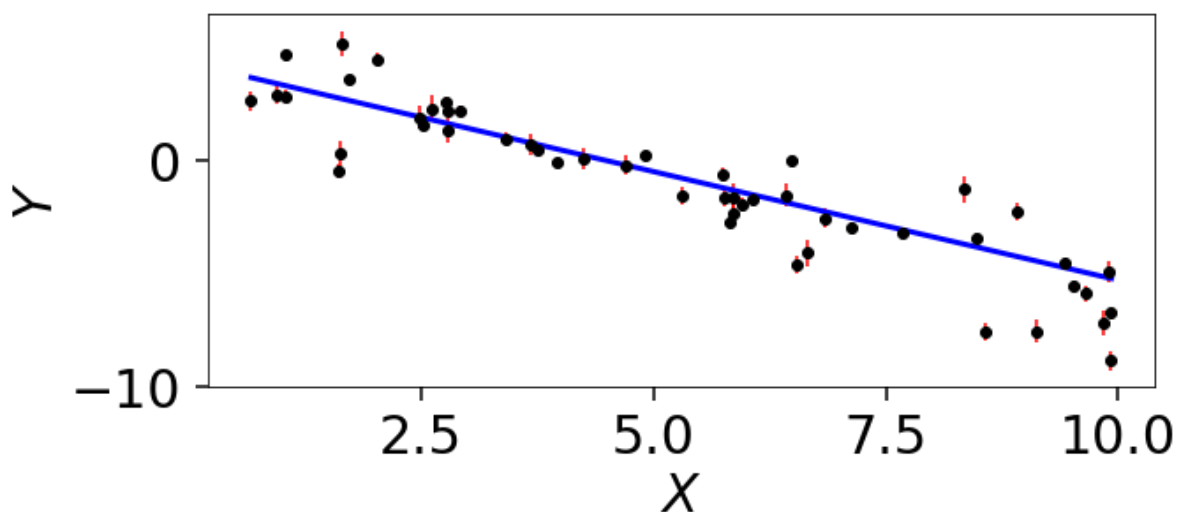


100% evidence



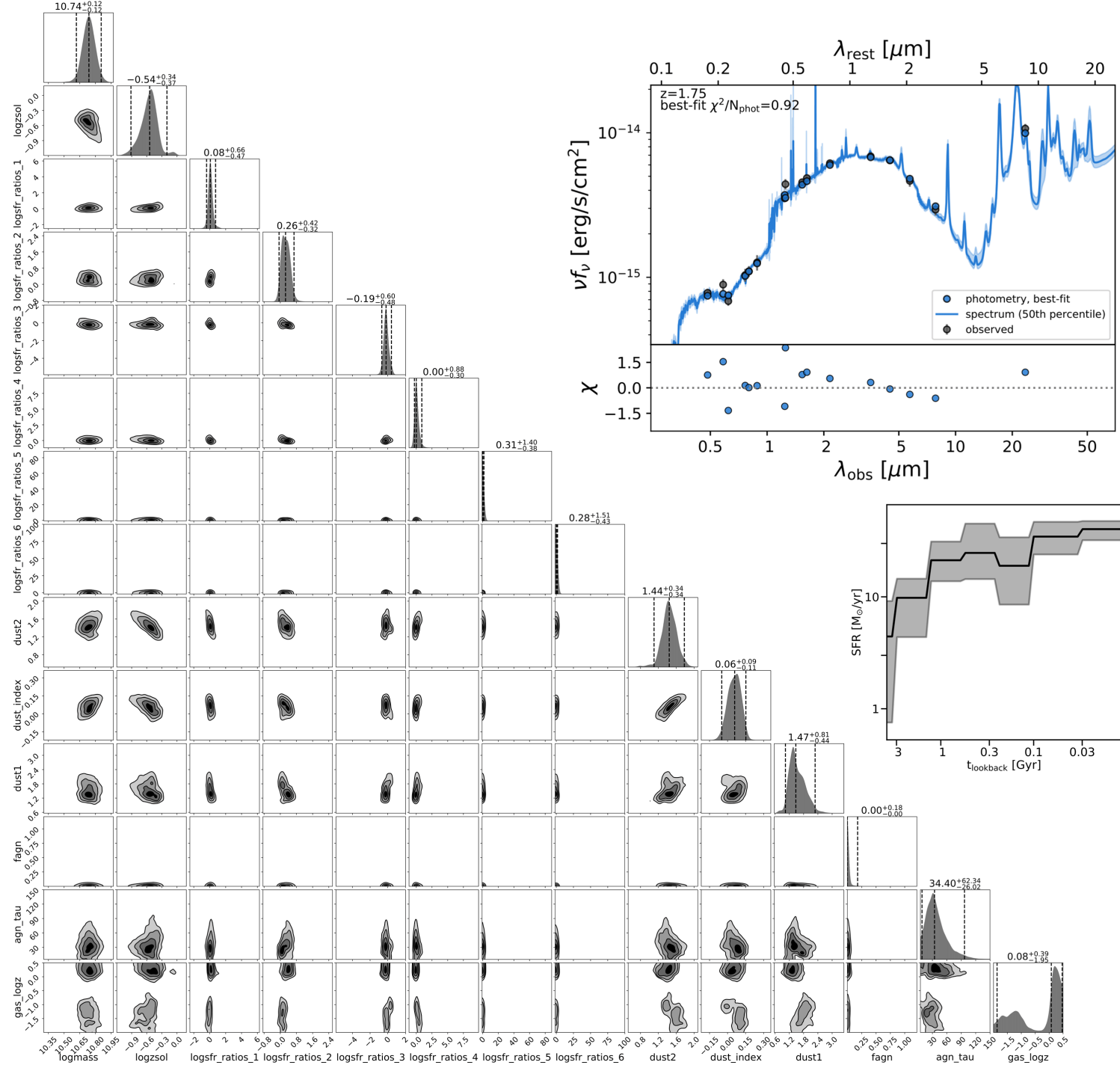
Comparisons with emcee

- Simple 3-parameter linear regression problem with reasonable prior constraints.



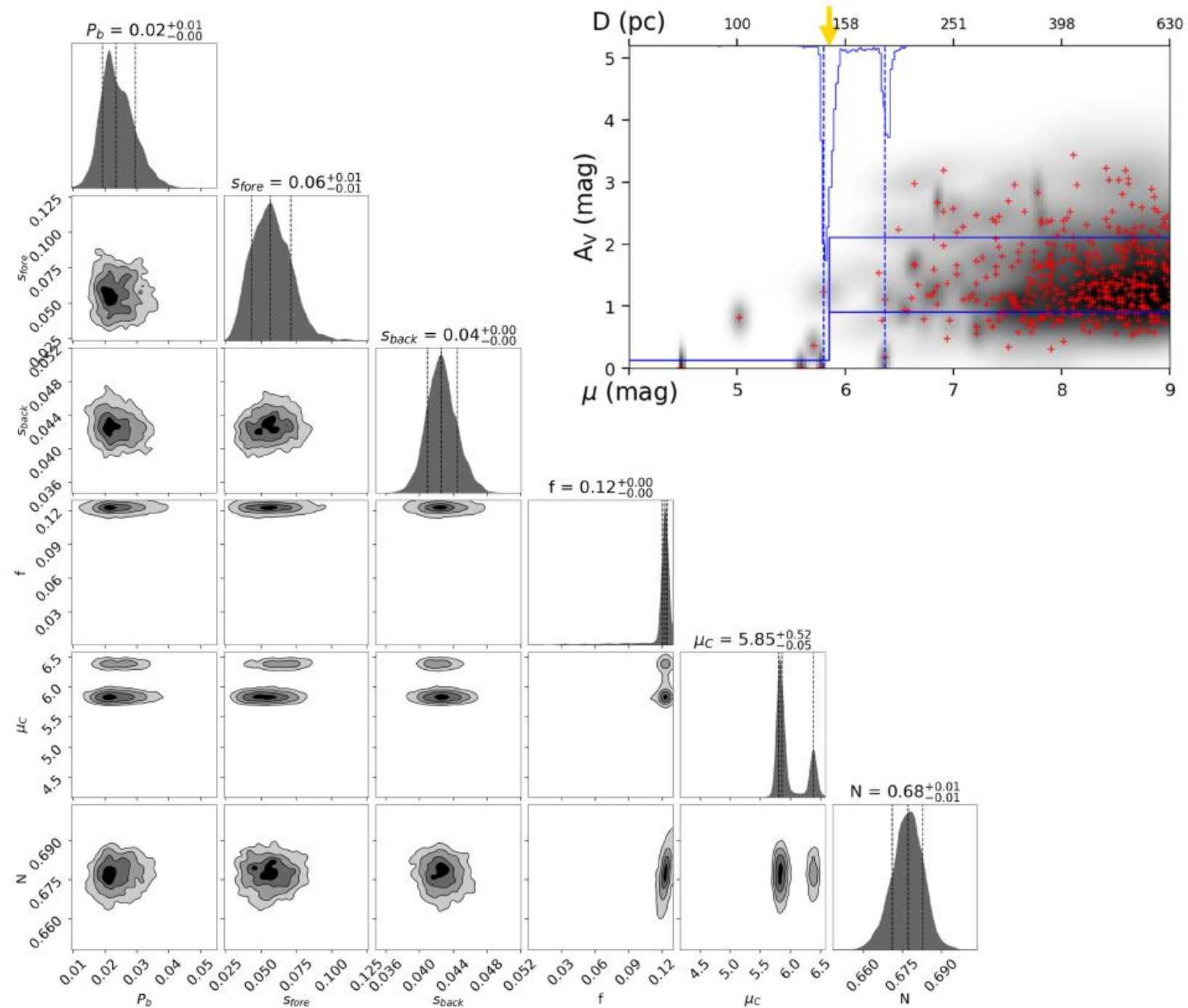
Applications

- Galaxy SED modeling with *Prospector* (Leja et al. 2019, Johnson et al. in prep.).



Applications

- 3-D dust mapping (Zucker & Speagle et al. 2019)



Advantages and Disadvantages

Advantages to Nested Sampling:

1. Can characterize complex uncertainties in real-time.
2. Can allocate samples much more efficiently in some cases.
3. Possesses well-motivated stopping criteria (Skilling 2006; Speagle 2020).

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Advantages to Nested Sampling:

1. Can characterize complex uncertainties in real-time.
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Disadvantages to Nested Sampling:

1. Implementations require a prior transform.
2. Runtime sensitive to size of prior.
3. Overall approach can sometimes miss certain types of solutions.
4. Sampling is more involved.

dynesty

Inspired by *emcee* (Foreman-Mackey et al. 2013)

- **Public, open source Python package** designed to make (Dynamic) Nested Sampling easy to use but also easy to customize.
- Designed to be **highly modular** and can mix-and-match methods.
- Includes **built-in plotting utilities** and post-processing tools.



Speagle (2020)

<https://dynesty.readthedocs.io>