

emcee: An Affine-Invariant Sampler

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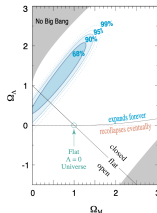
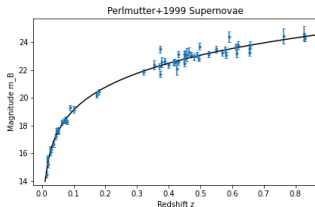
PSI Numerical Methods, 2026-01-23

Borrowing heavily from Dan Foreman-Mackey's slides
<https://speakerdeck.com/dfm/data-analysis-with-mcmc1>
These slides are available at

<https://github.com/dstndstn/MCMC-talk/emcee-slides>

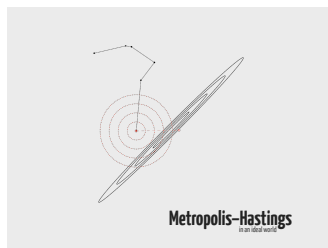
Recap from last lecture (1)

- ▶ Markov Chain Monte Carlo (MCMC) *draws samples from a probability distribution* when you can *numerically evaluate* the probability function (up to a constant)
- ▶ Used extensively in data analysis: *inferring* parameters of models, given observed data
- ▶ *Usually* in a Bayesian context; the probability function we run MCMC on is the *posterior* probability:
$$\text{posterior}(\text{params}|\text{data}) \propto \text{prior}(\text{params}) \times \text{likelihood}(\text{data}|\text{params})$$

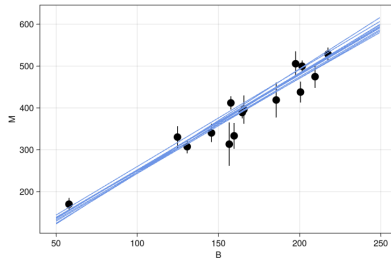
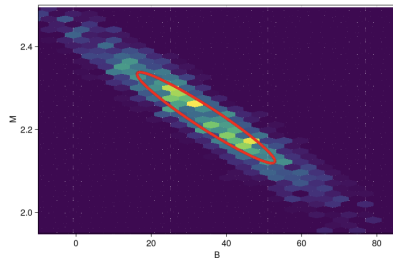
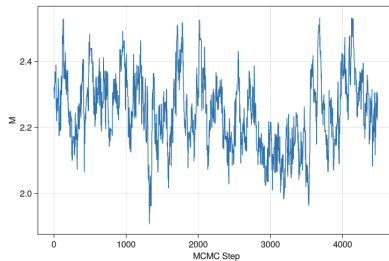
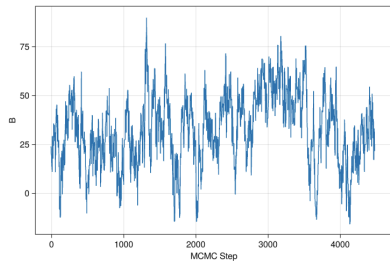


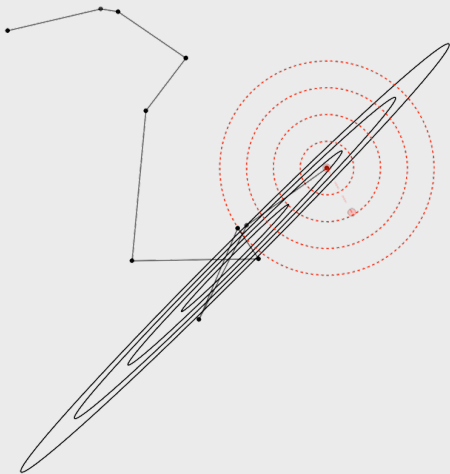
Recap from last lecture (2)

- ▶ The “classic” Markov Chain Monte Carlo algorithm is *Metropolis–Hastings*, which moves a *walker* or *particle* around the *state space* (*model parameter space*)
- ▶ A randomly-drawn *proposed* jump gets *evaluated* (by calling the probability function), and then *accepted*, or not
- ▶ A big difficulty is to *customize* the *proposal distribution* to get the algorithm to work efficiently

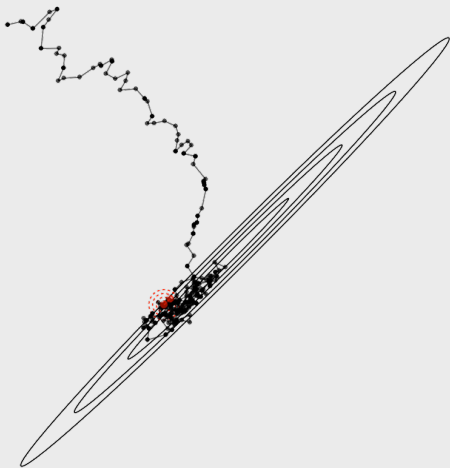


MCMC for model parameter inference



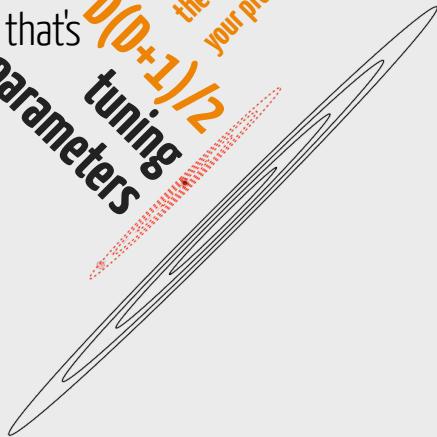


Metropolis-Hastings
in the real world



Metropolis–Hastings
in the real world

that's $D(D+1)/2$ tuning parameters
the dimension of your problem



Metropolis–Hastings
in the real world



Jonathan Goodman



Jonathan Weare

"Ensemble samplers with affine invariance"

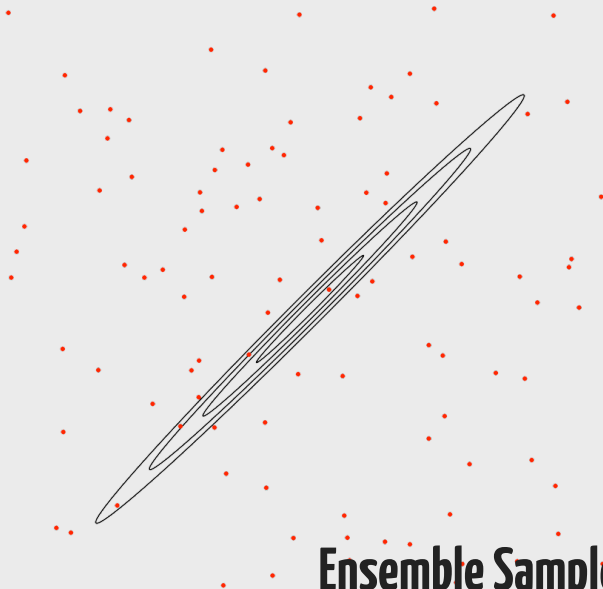
(dfm.io/mcmc-gw10)



introducing **emcee** the MCMC Hammer

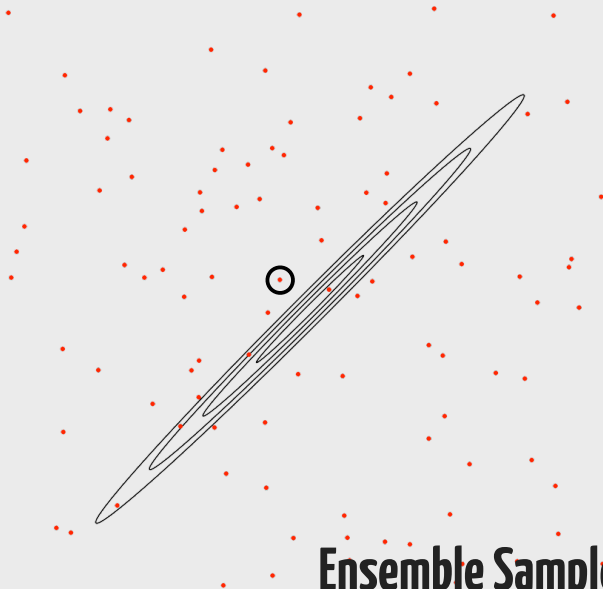
arxiv.org/abs/1202.3665

dan.iel.fm/emcee

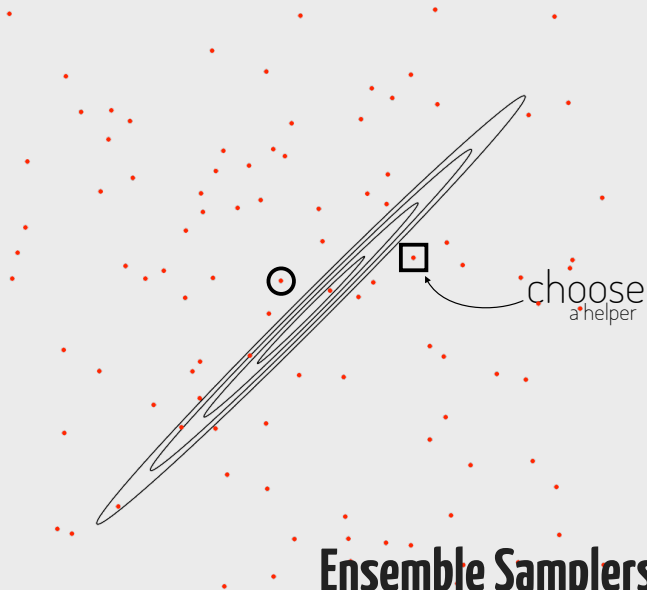


Ensemble Samplers

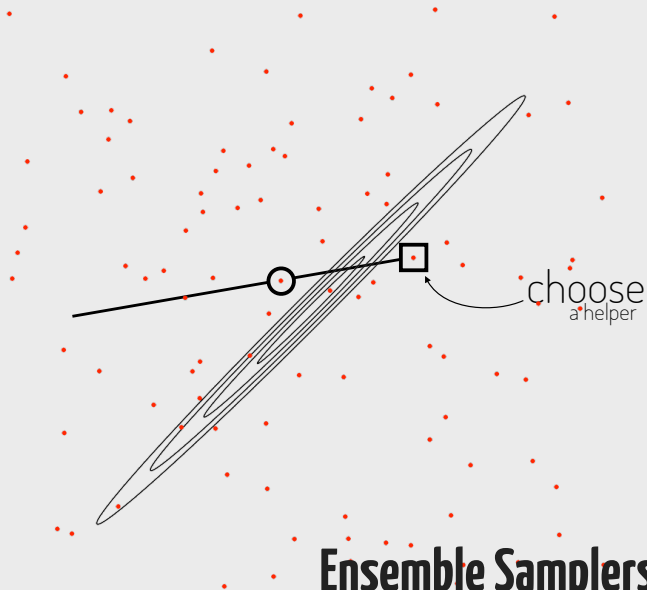
in the real world



Ensemble Samplers
in the *real* world

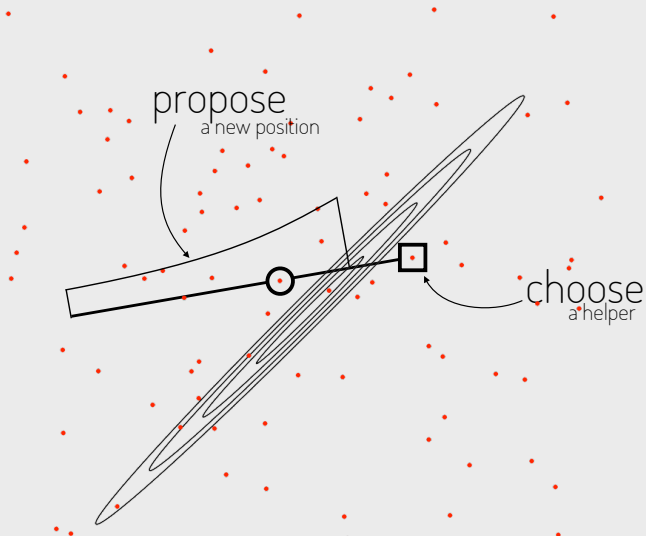


Ensemble Samplers
in the real world



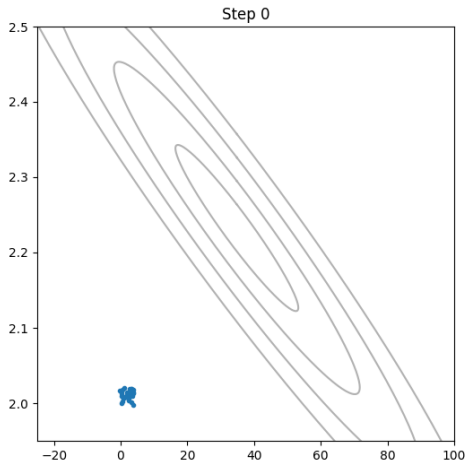
Ensemble Samplers

in the real world

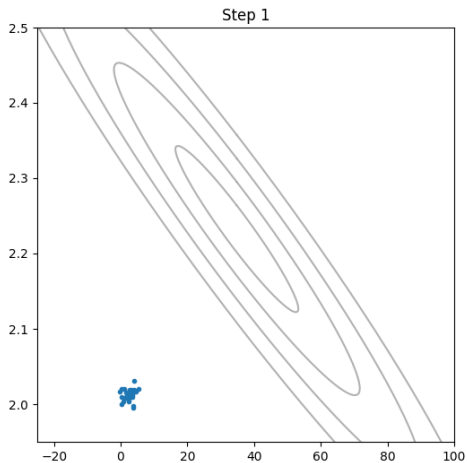


Ensemble Samplers
in the real world

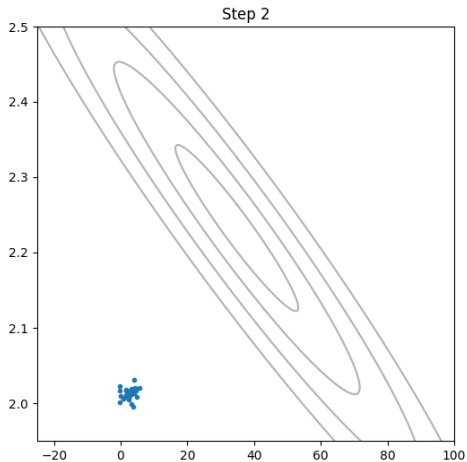
Emcee demo



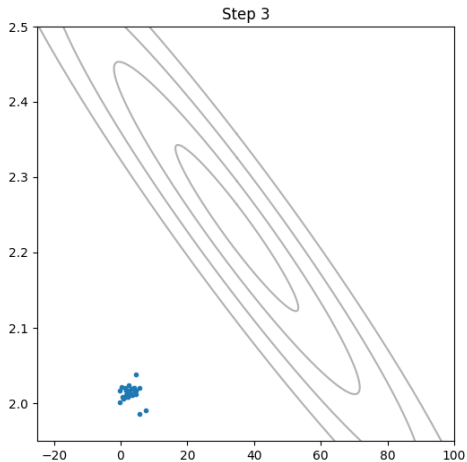
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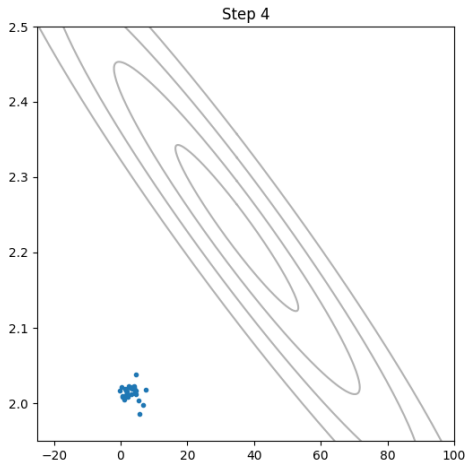
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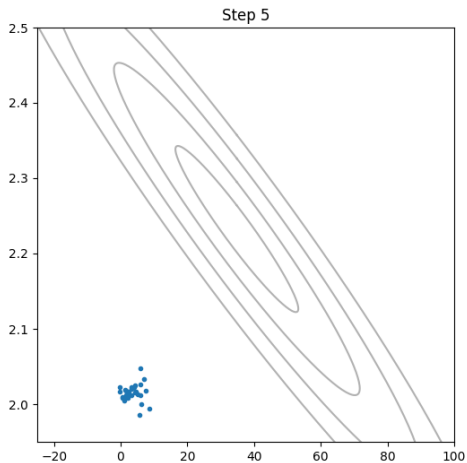
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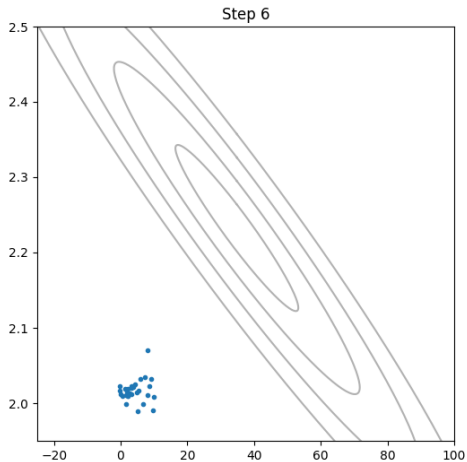
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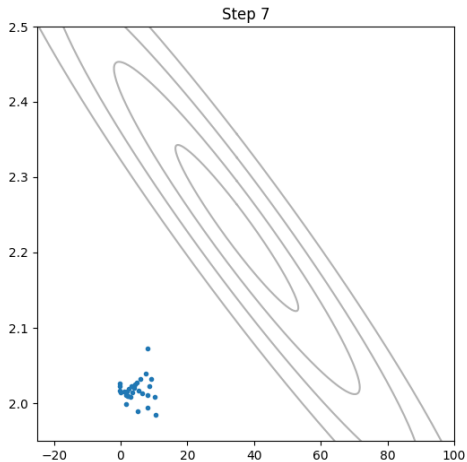
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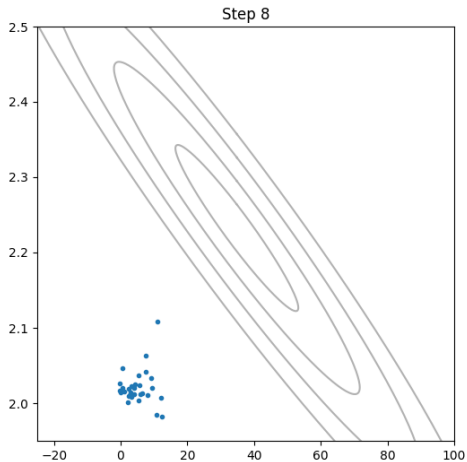
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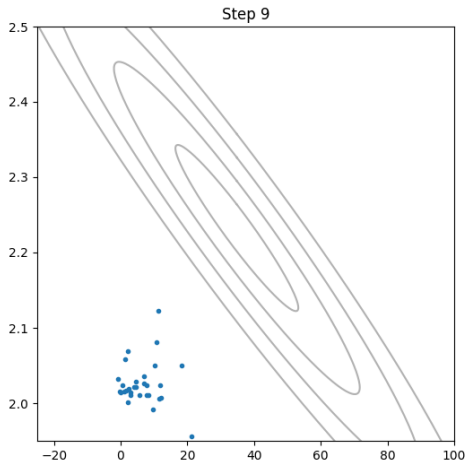
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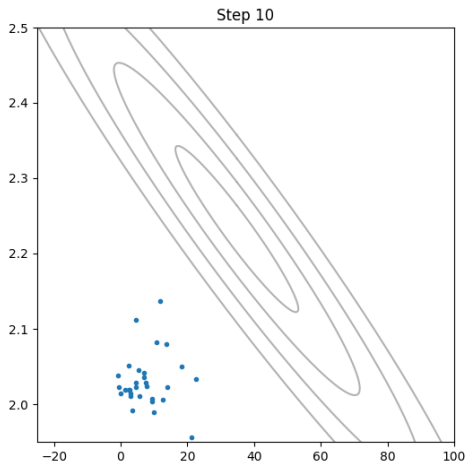
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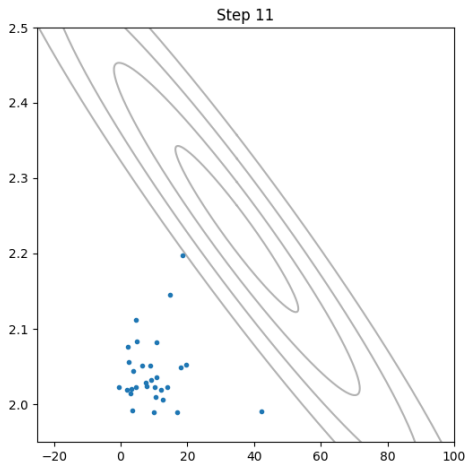
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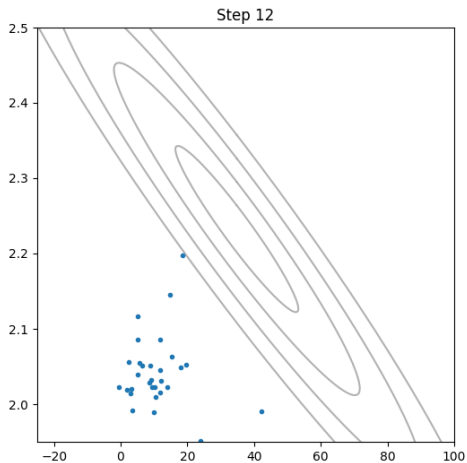
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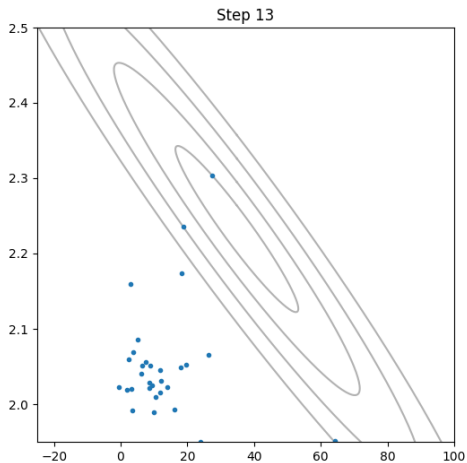
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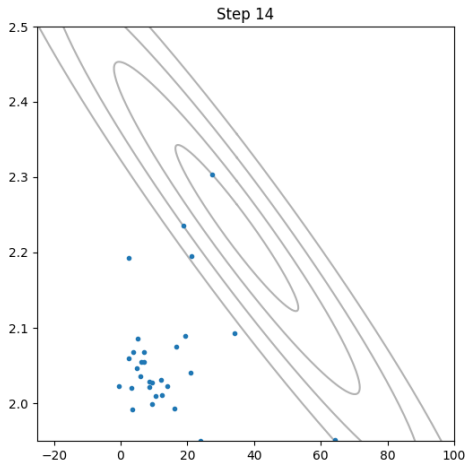
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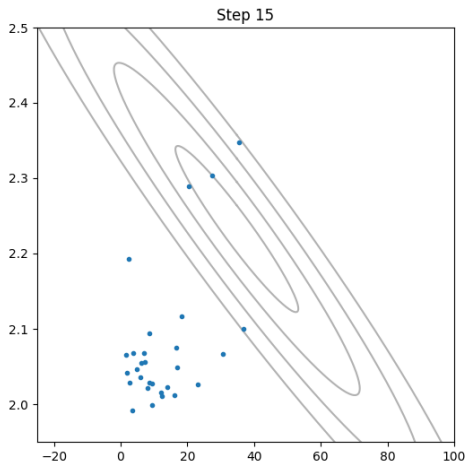
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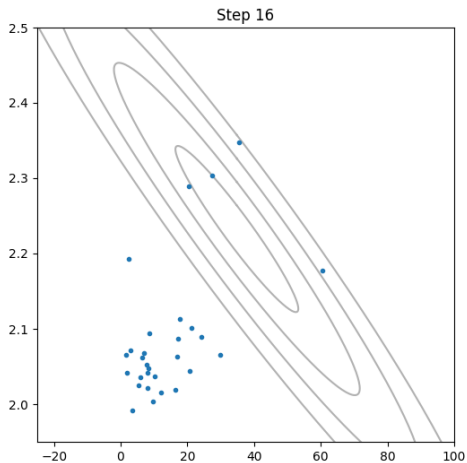
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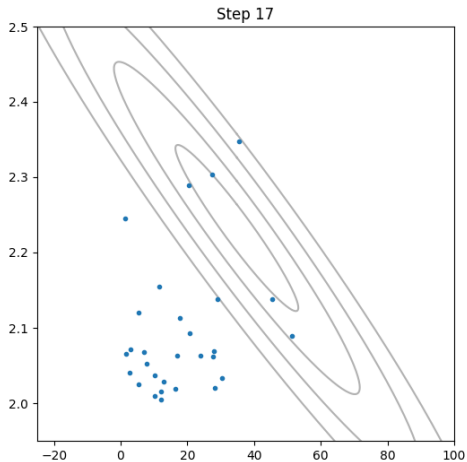
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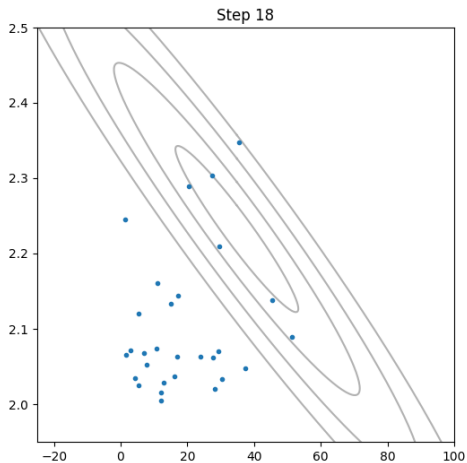
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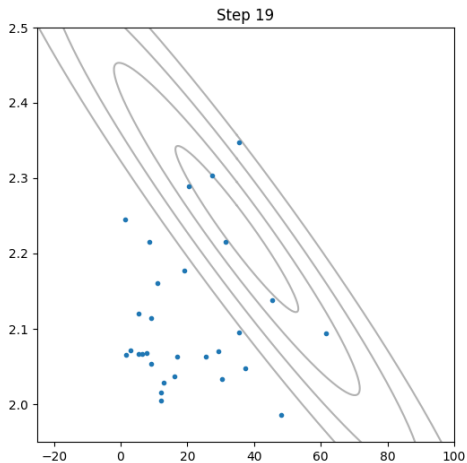
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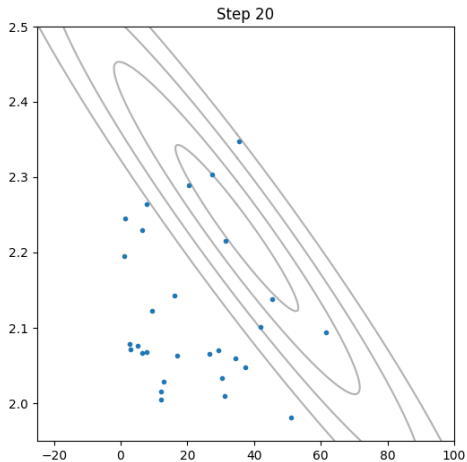
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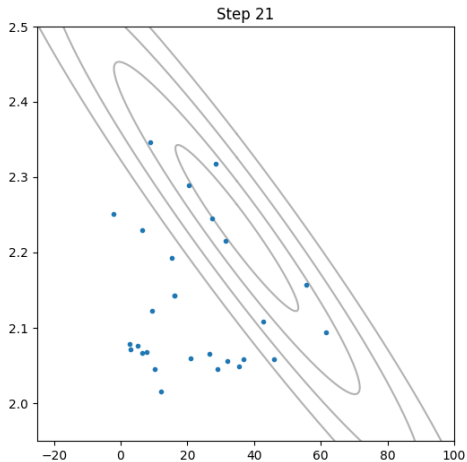
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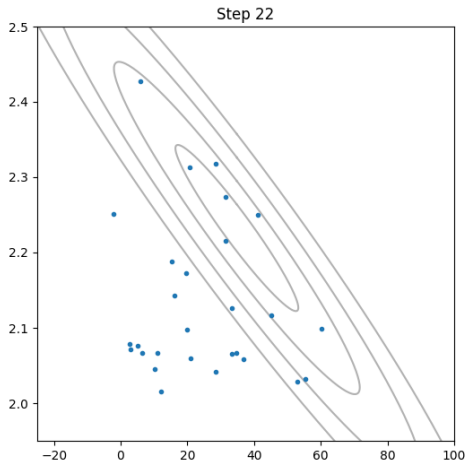
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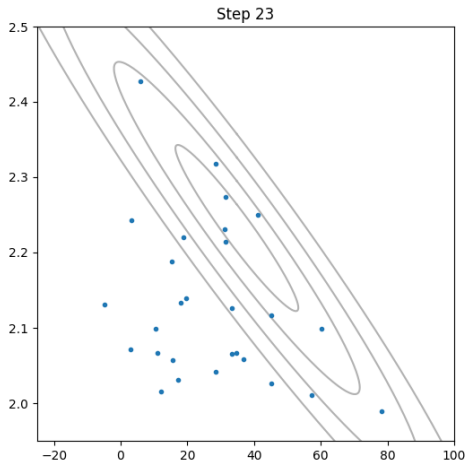
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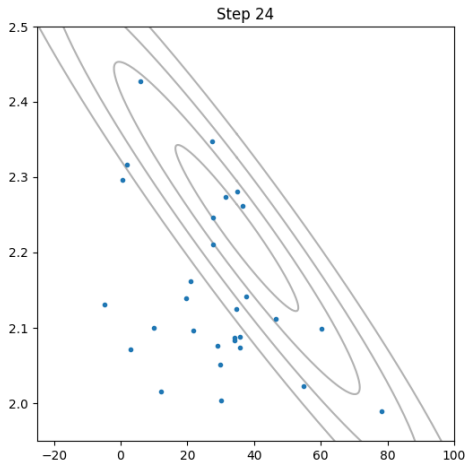
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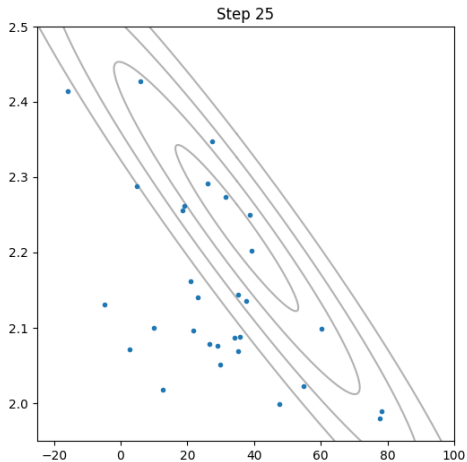
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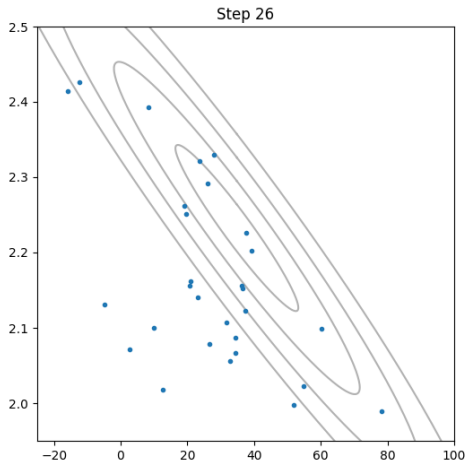
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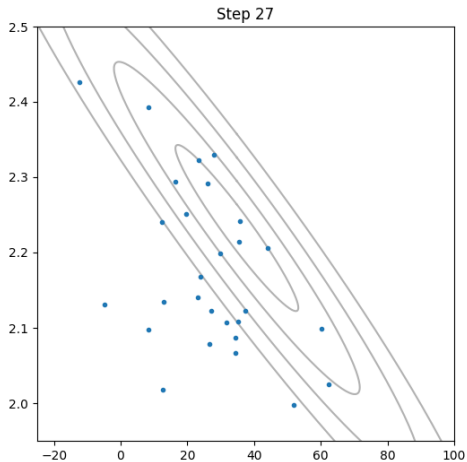
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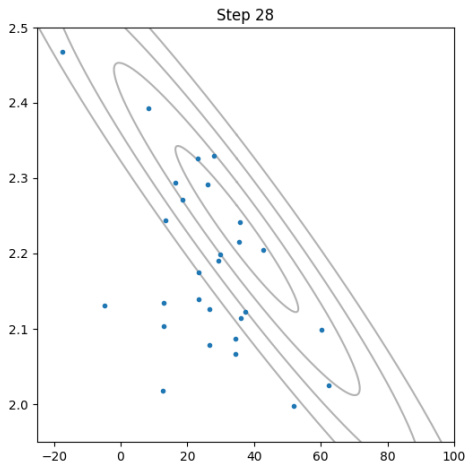
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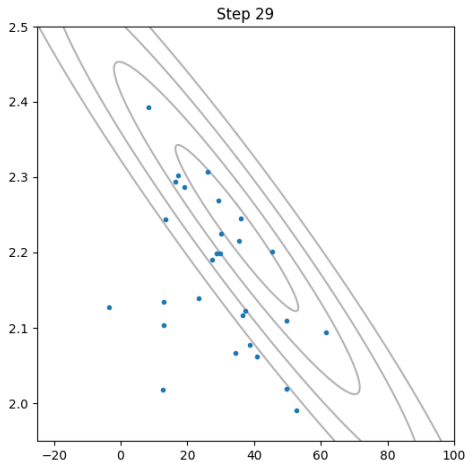
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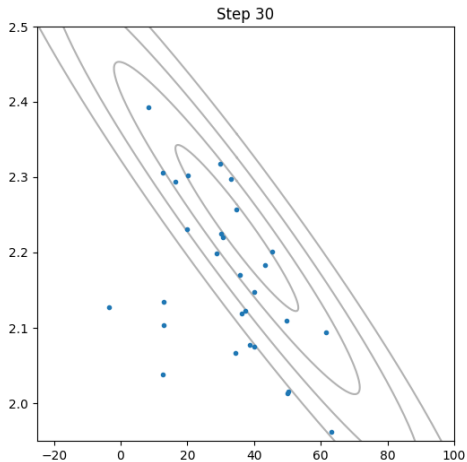
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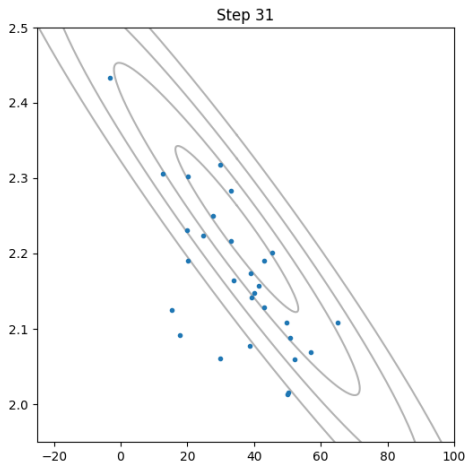
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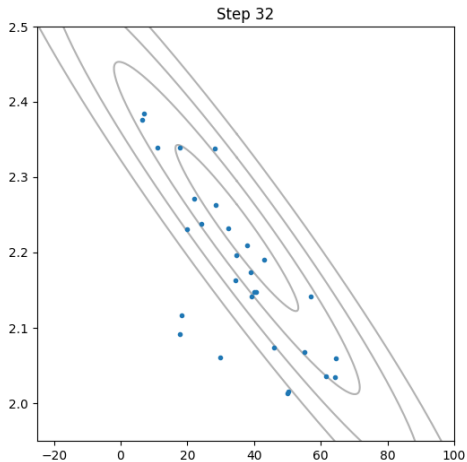
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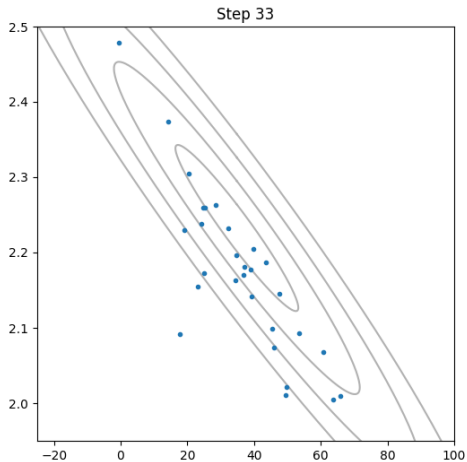
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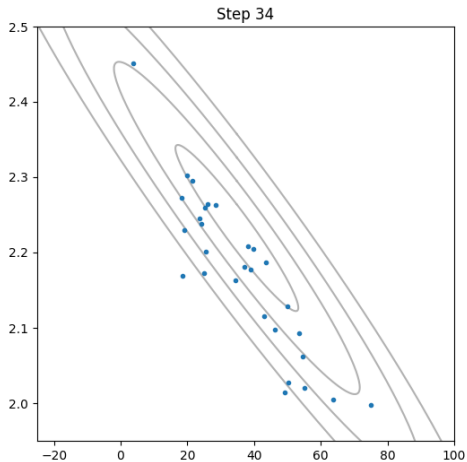
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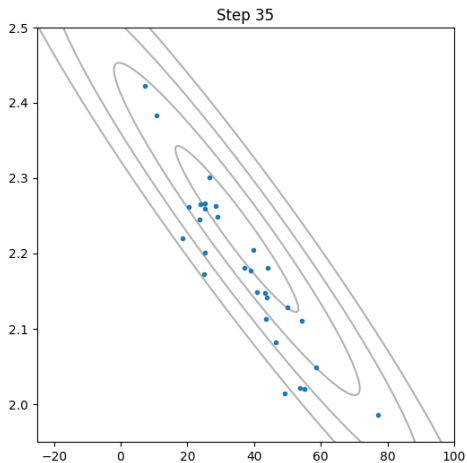
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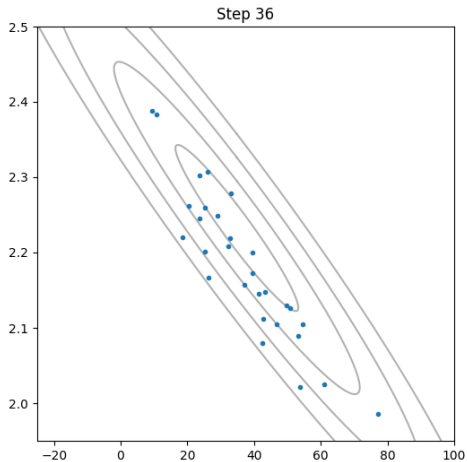
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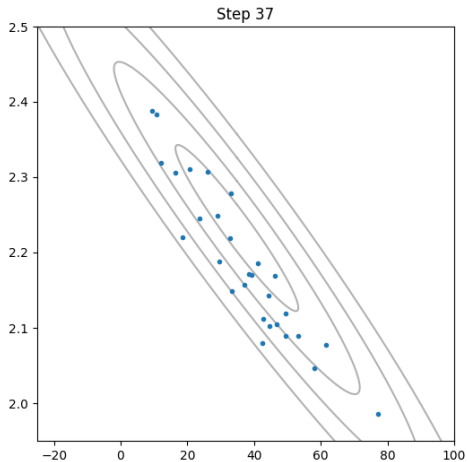
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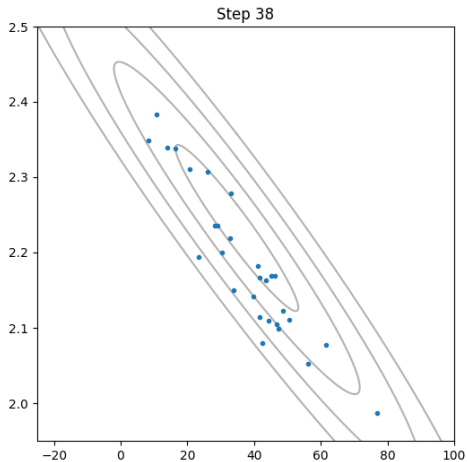
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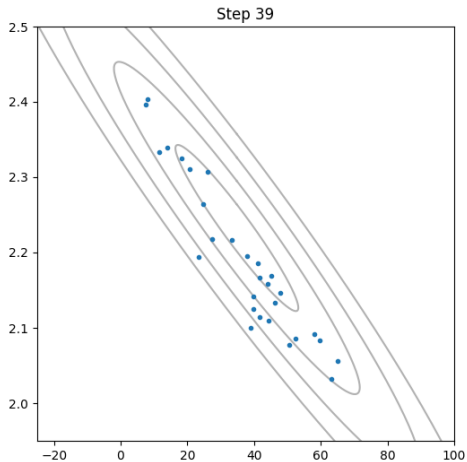
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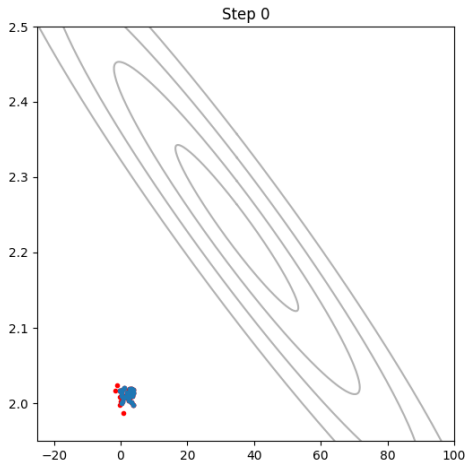
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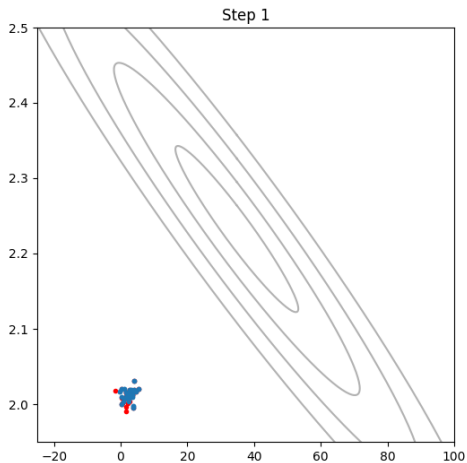
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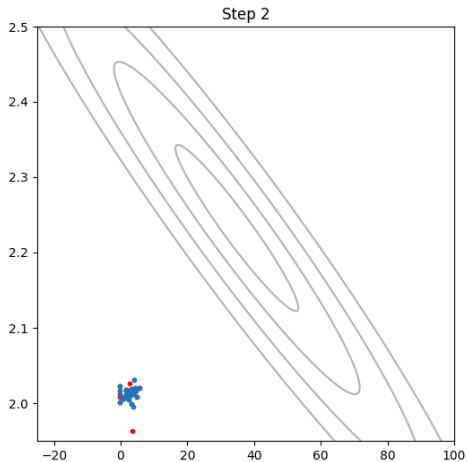
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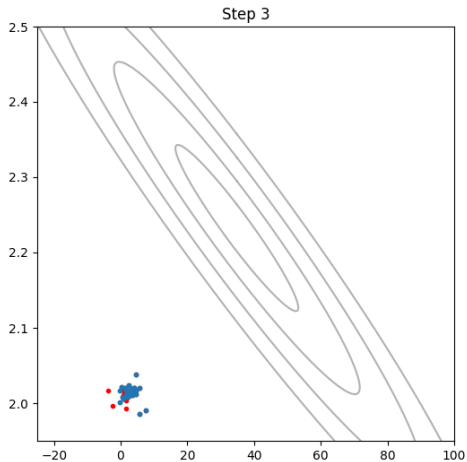
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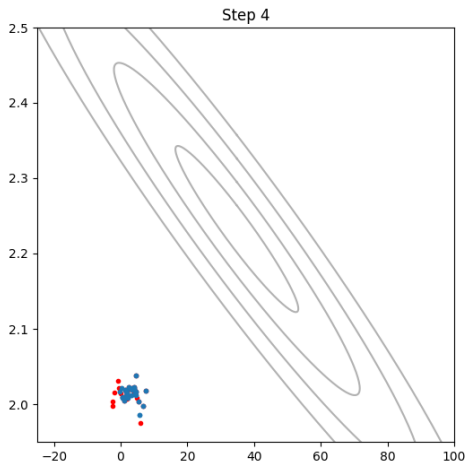
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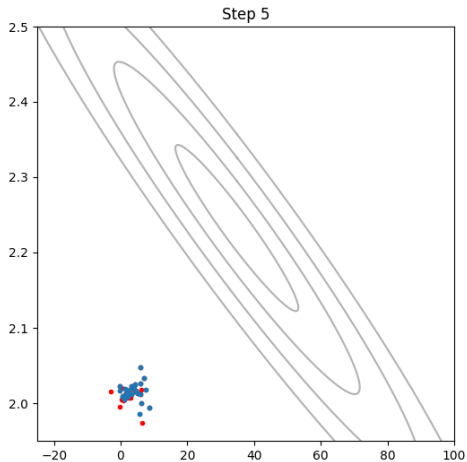
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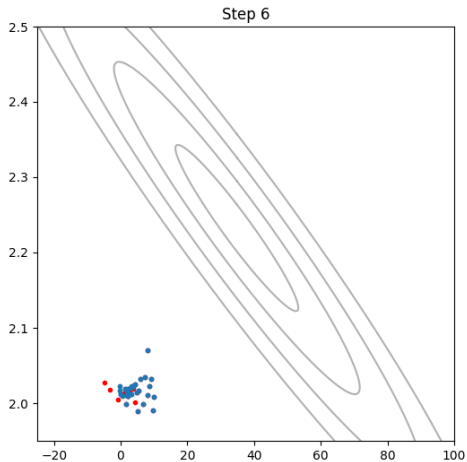
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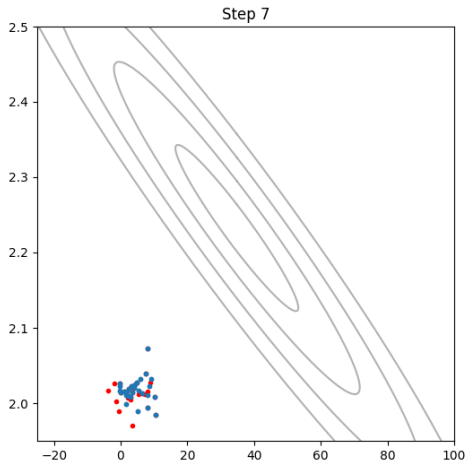
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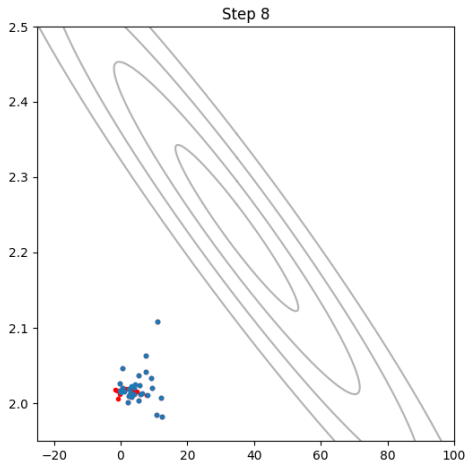
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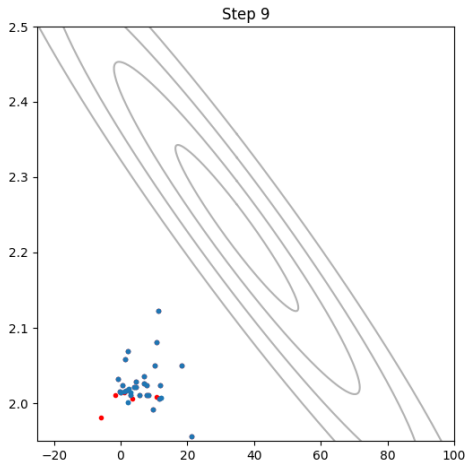
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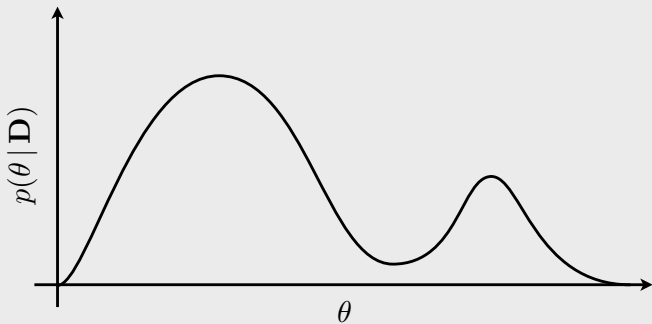
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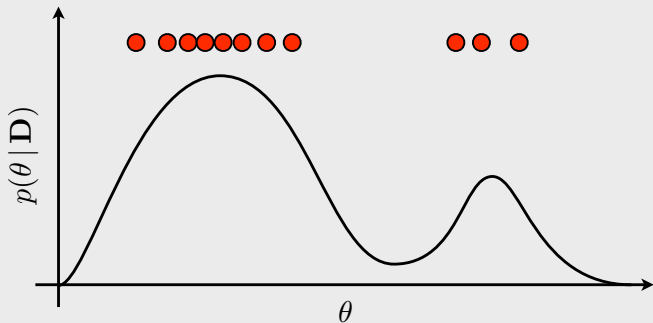
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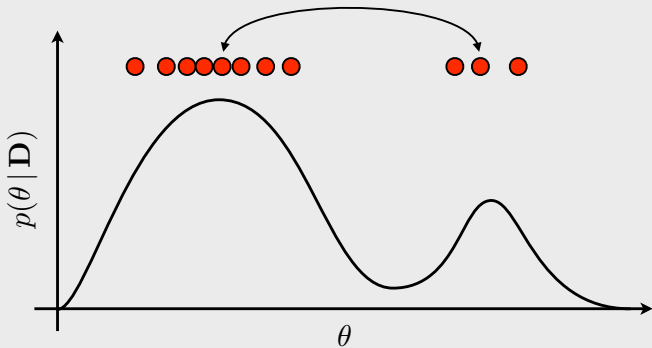
what about **multimodal densities?**



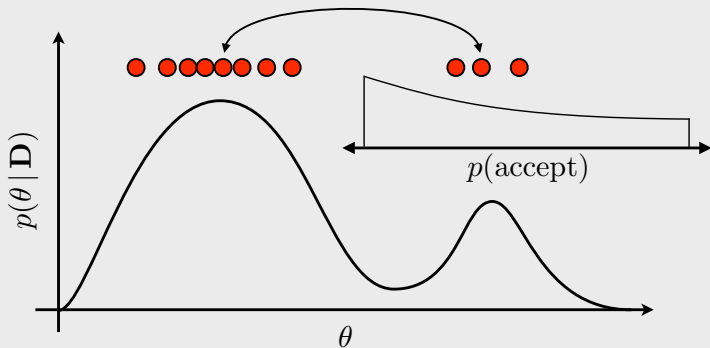
what about **multimodal densities?**



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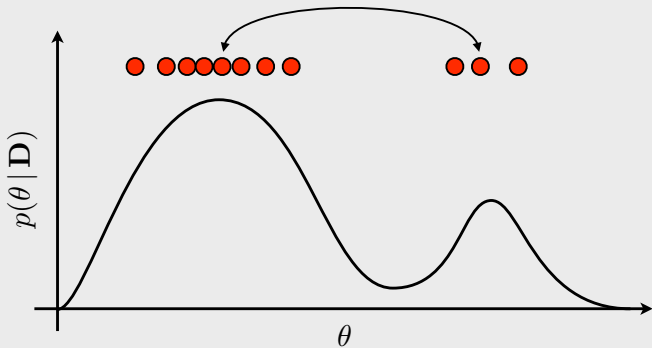
what about **multimodal densities?**



Differential Evolution move

- ▶ **emcee** allows us to use different *move* types (different *proposal* functions)
- ▶ The **Differential Evolution** (DE) move can improve the sampling for multi-modal distributions
- ▶ DE move: randomly select *two* “helpers”
- ▶ Propose moving by their **vector difference**
- ▶ (If they are from different modes, this proposes *jumping between modes*)
- ▶ Mixing in a fraction of DE moves with the regular “Stretch” move works well!

what about **multimodal densities?**



Summary

- ▶ Traditional Metropolis–Hastings MCMC suffers from a *lack of affine invariance* – requires *tuning parameters* that change for each specific probability function
- ▶ *Ensemble samplers* like **emcee** use the *distribution of the walkers* to achieve *affine invariance*
- ▶ → much easier to use, and faster sampling
- ▶ (Huge side effect: parallelizable!)
- ▶ Multi-modal distributions still hard, but *DE Move* can help