Monte-carlo methods

- Agenda 1. Administrative
 - 2. MAP/ML
 - 3. MCMC
 - 4. Hamiltonian MC
 - 5. What can go wrong
 - 6. Hands on: Convergence in brms and lme4

Worksheet 4

Forthcoming!Hopefully later today

Maximizing probability



Recall: simple binomial model 5 trials; 4 'successes'
$$4 \sim \mathrm{Binom}(5,p) \ p \sim \mathrm{Beta}(1,1)$$

This is the same as an intercept-only logistic distribution with a logit-transformed uniform for the prior on lpha

Bayes' rule
$$\Pr(p|n=5,k=4) = rac{\Pr(k=4|n=5,p)\Pr(p|n=5)}{\Pr(k=4|n=5)}$$

EXPLORING THE POSTERIOR

Recall: simple binomial model 5 trials; 4 'successes'
$$\begin{array}{c|c} \textbf{Recall: simple binomial model} & 4 \sim \text{Binom}(5,p) \\ p \sim \text{Beta}(1,1) \end{array}$$

This is the same as an intercept-only logistic distribution with a logit-transformed uniform for the prior on α

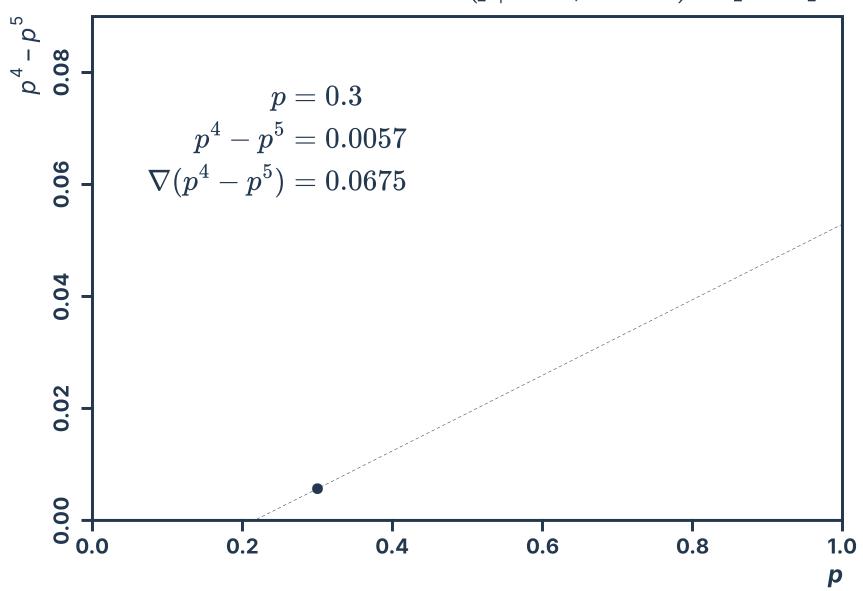
this

Bayes' rule
$$\Pr(p|n=5,k=4) = \frac{\Pr(k=4|n=5,p)\Pr(p|n=5)}{\Pr(k=4|n=5)}$$

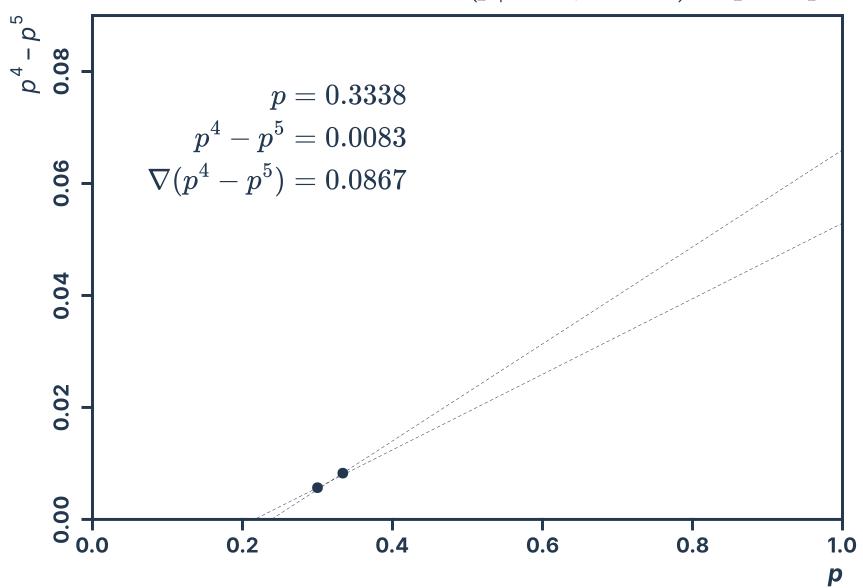
$$\propto \Pr(k=4|n=5,p)\Pr(p|n=5)$$

$$= \binom{5}{4}p^4(1-p)^1 \times 1$$

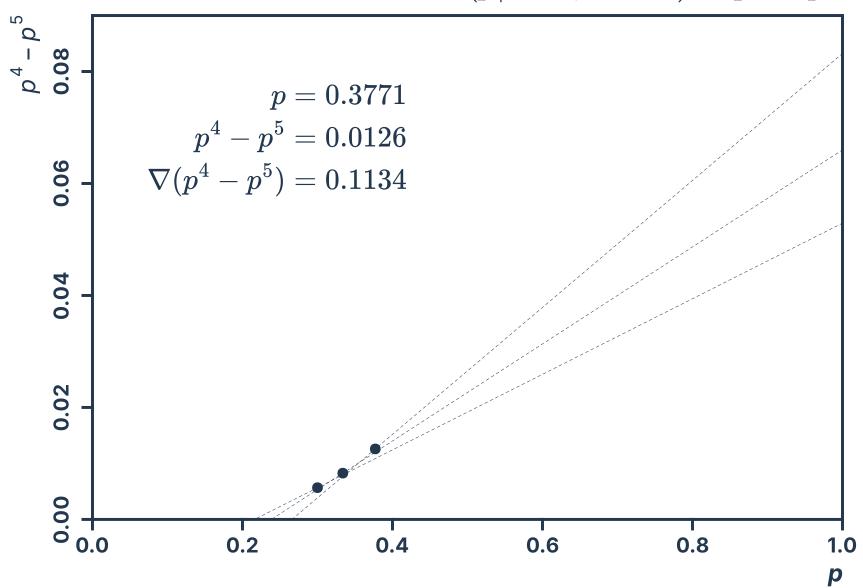
$$= p^4 - p^5$$
 the posterior distribution of p is proportional to



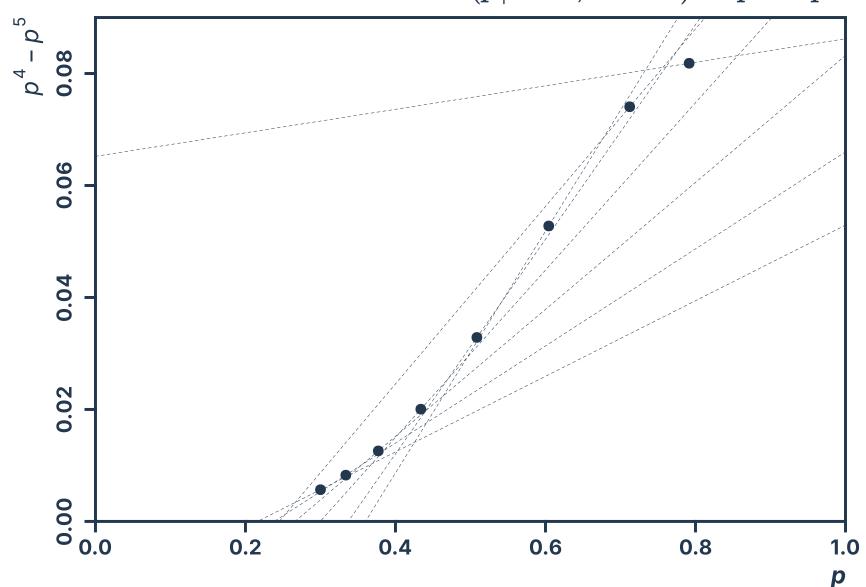
HILL CLIMBING (MAP/ML)



<u>HILL CLIMBING (MAP/ML)</u>

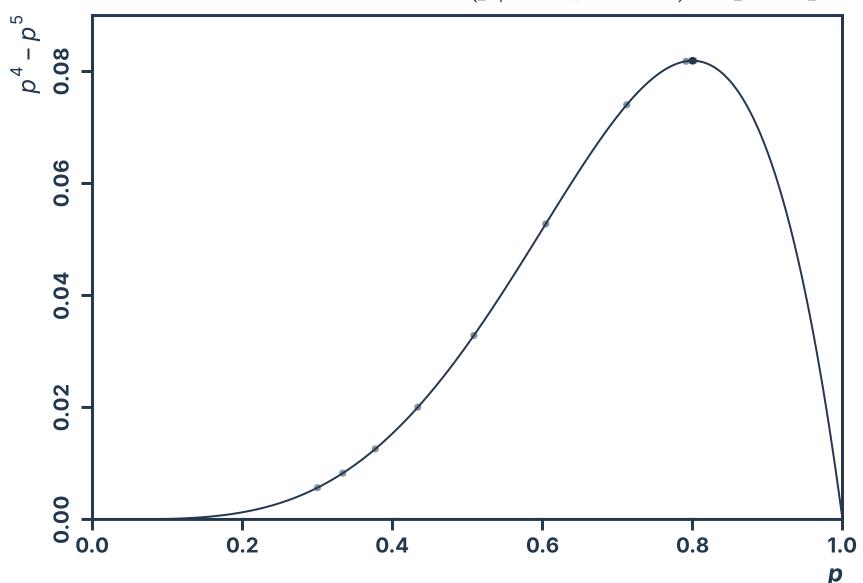




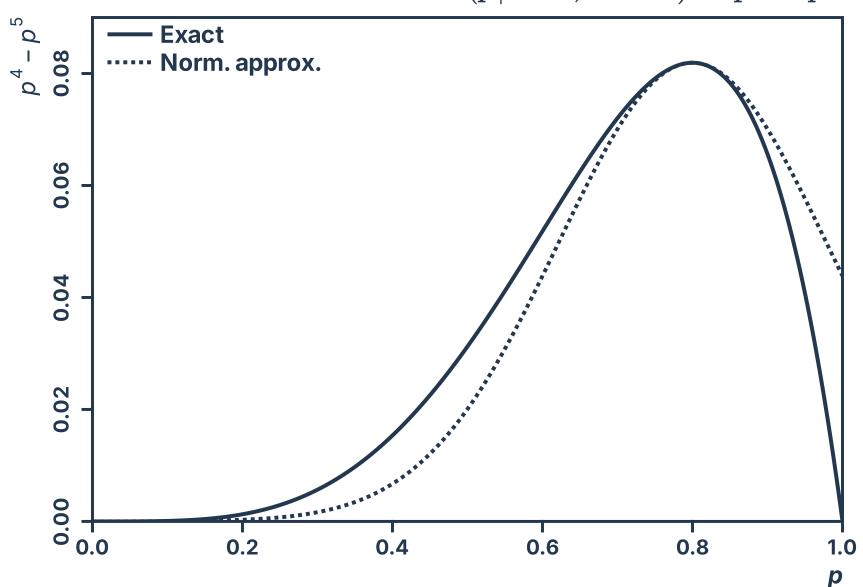


<u>HILL CLIMBING (MAP/ML)</u>





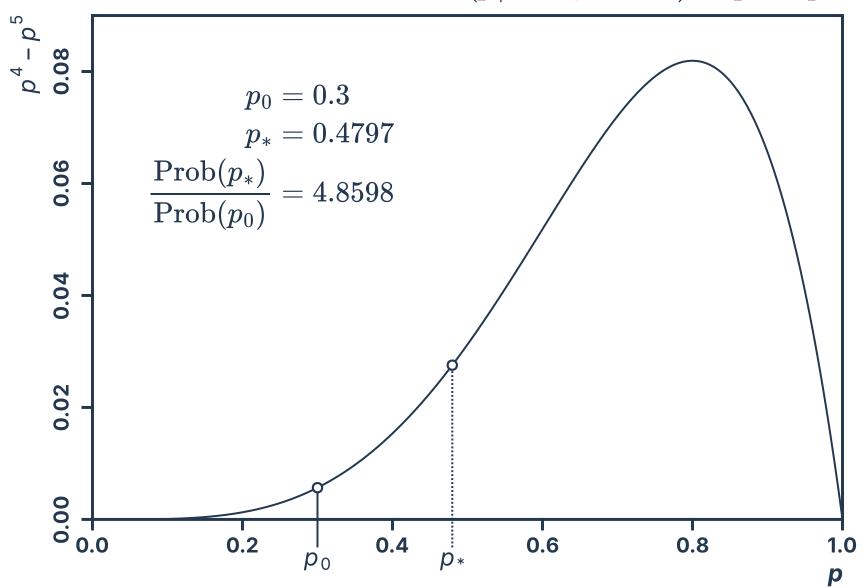
<u>HILL CLIMBING (MAP/ML)</u>

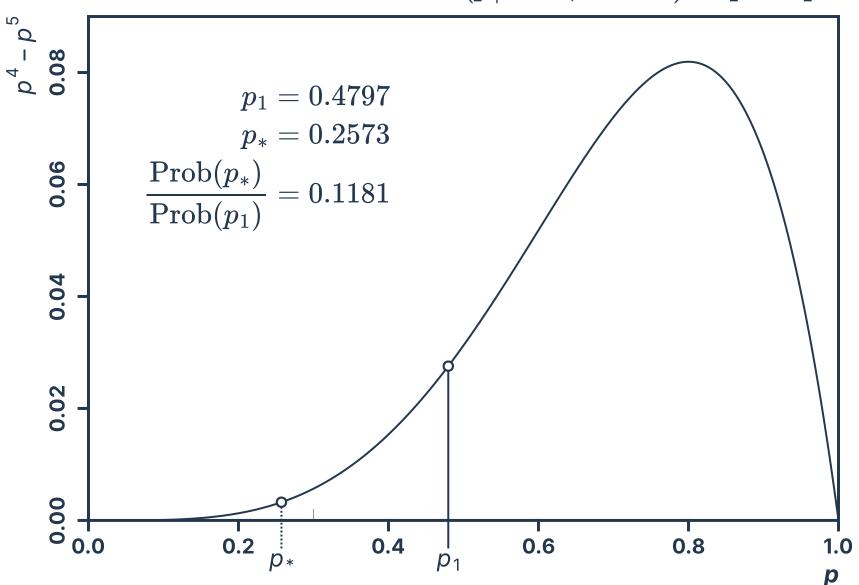


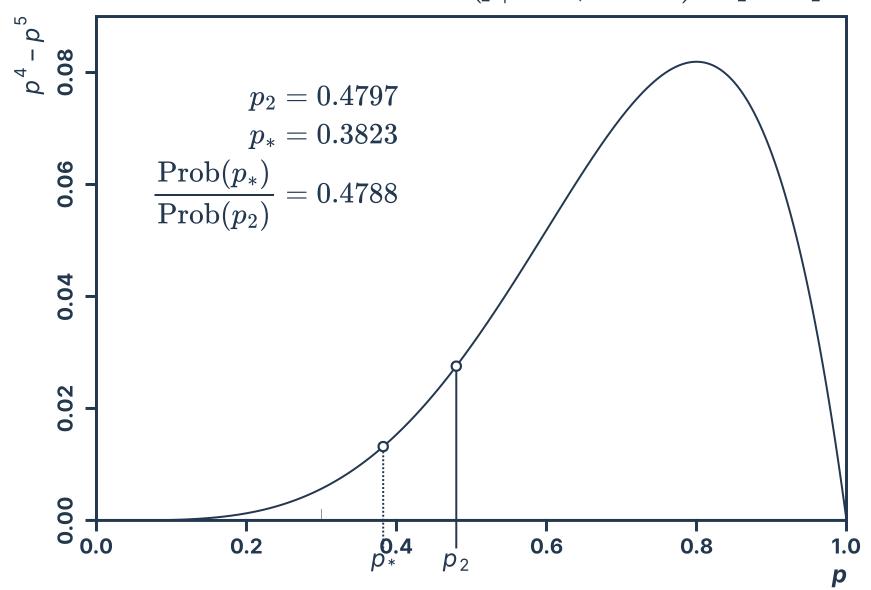
Markov chain Monte Carlo

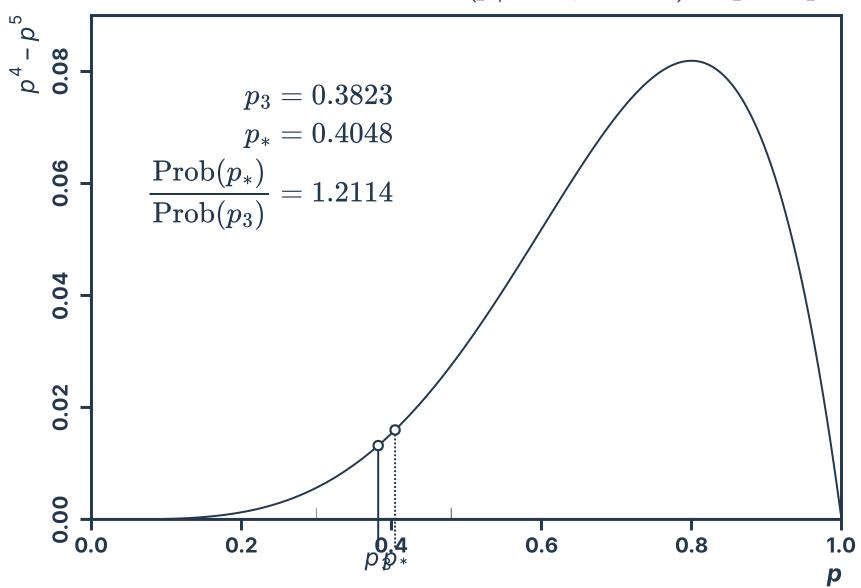






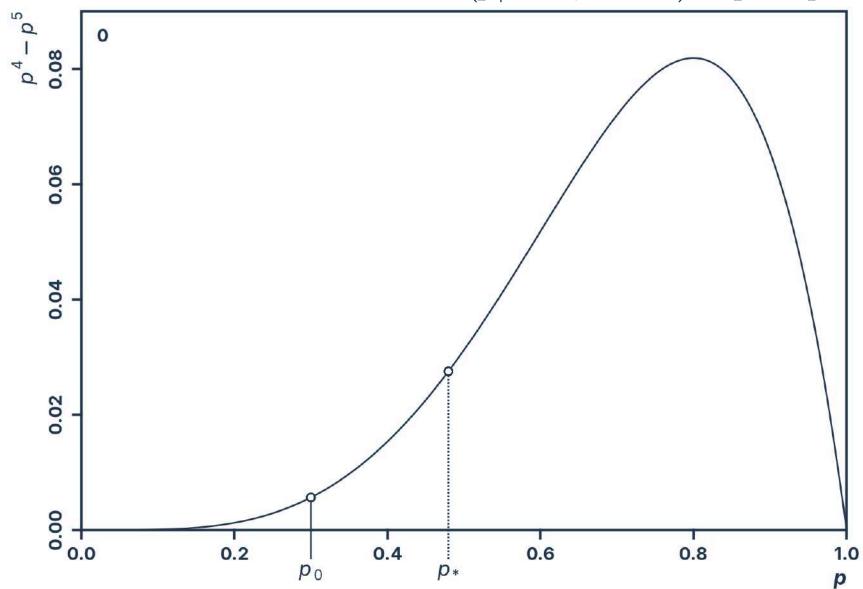


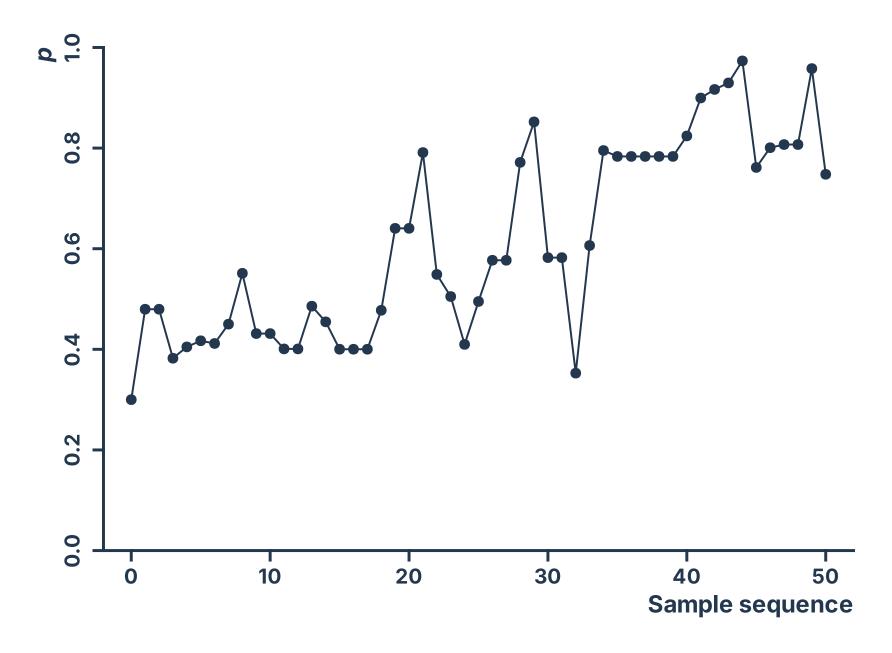


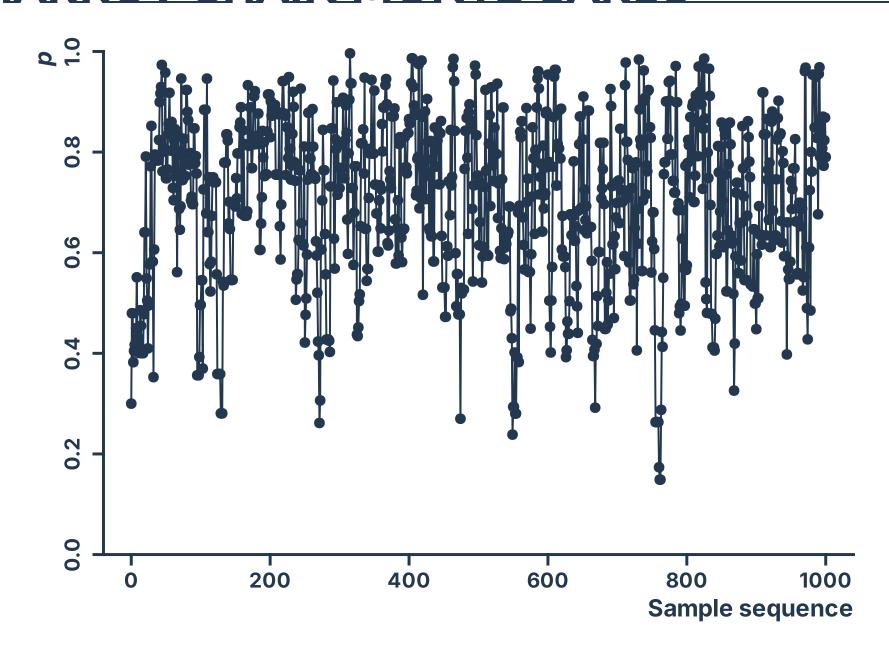


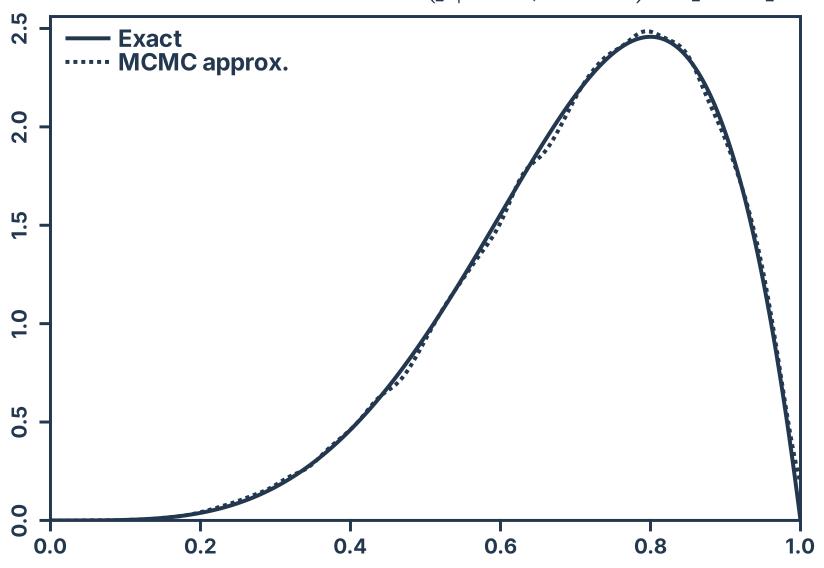
<u>MARKOV CHAIN MONTE CARLO</u>











Density based on 50,000 posterior observations

Hamiltonian Monte Carlo



physical system

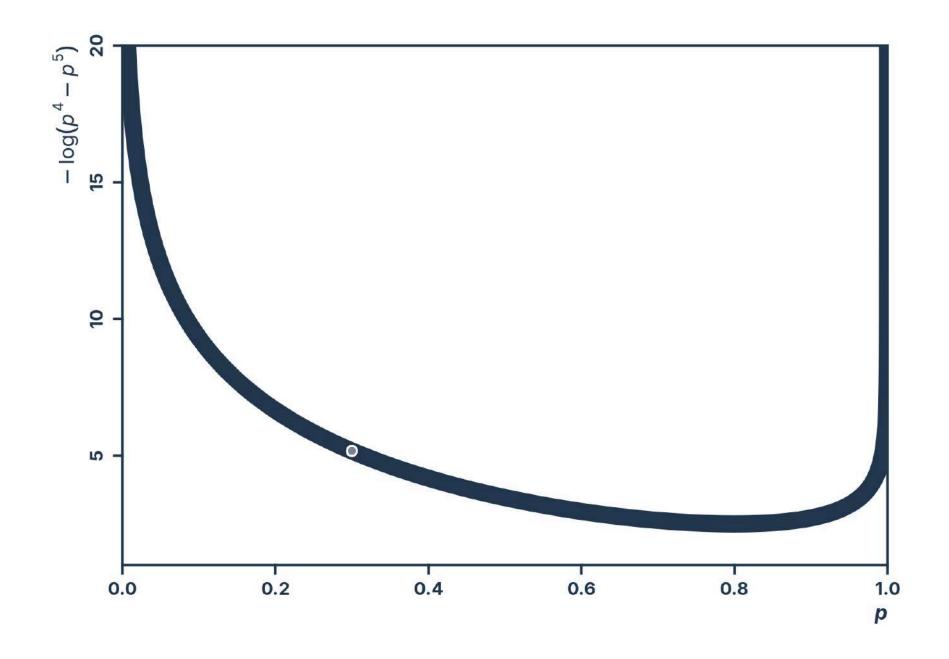
Simulate a "Energy" at any point in the parameter cal system space is proportional to the negative log posterior probability:

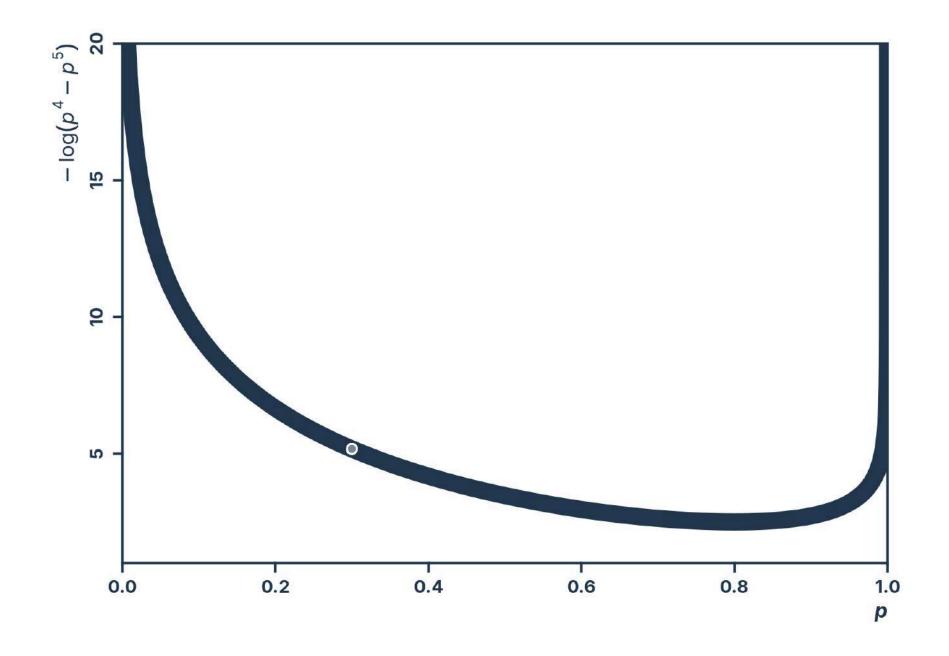
$$U_{ heta} \propto -\log\left(\operatorname{Prob}(\theta|\operatorname{data, model})\right)$$

by 'perturbing' a particle in that field

Get random draws Place a particle in that system, give it a push by 'perturbing' a in a random direction, and use Hamiltonian dynamics to simulate its motion.

> Wherever the particle ends up after a fixed amount of time is the next candidate draw from the posterior.





Takes advantage of gradient (slope) information helps HMC adjust to the shape of the posterior.

Reduces autocorrelation HMC tends to explore the plausible areas of the parameter space much more quickly than 'standard' MCMC like Metropolis—Hastings. It is not likely to spend too much time in one small area.

"No-U-Turn sampler" (NUTS) A version of HMC that automatically optimizes some of the meta-parameters of the algorithm.

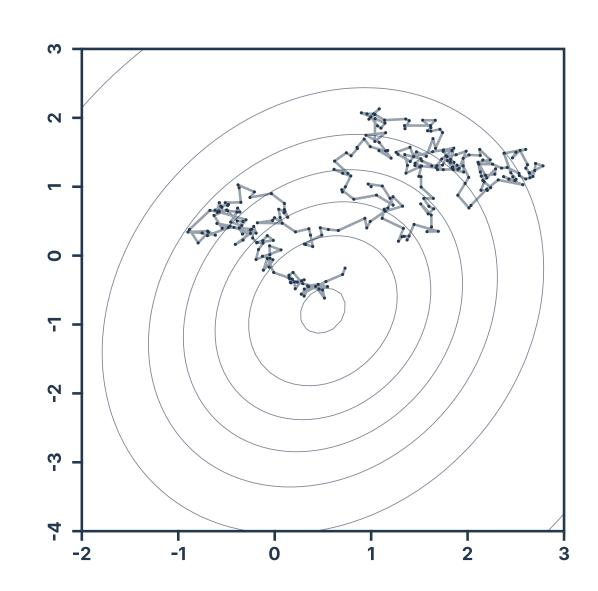
What can possibly go wrong?



<u>WHAT CAN GO WRONG?</u>

Autocorrelation

- Because each posterior sample depends on the previous sample, HMC usually displays some autocorrelation
- A sample of 1,000 autocorrelated samples will have less information than a sample of 1,000 independent samples
- Relevant quantity: effective sample size (ESS)



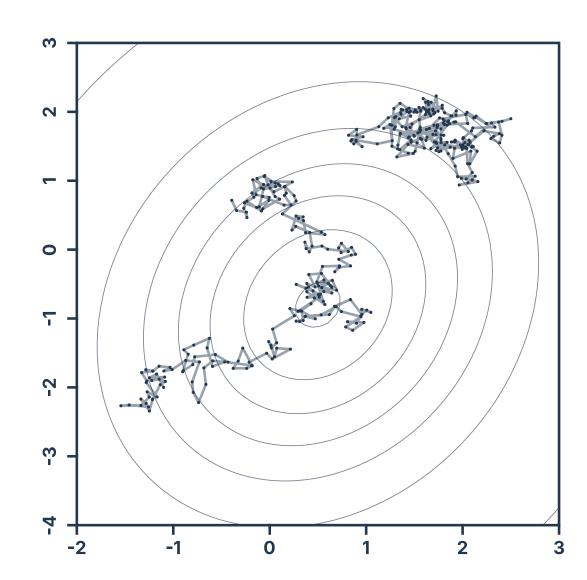
<u>WHAT CAN GO WRONG?</u>

Non-convergence

- Sampling may have trouble "converging" (properly representing the posterior)
- Many possible causes

Bad model specification Insufficient iterations Badly tuned sampler

Diagnose with R ("Rhat") on multiple chains to check agreement between multiple chains



<u>WHAT CAN GO WRONG?</u>

Divergent transistions

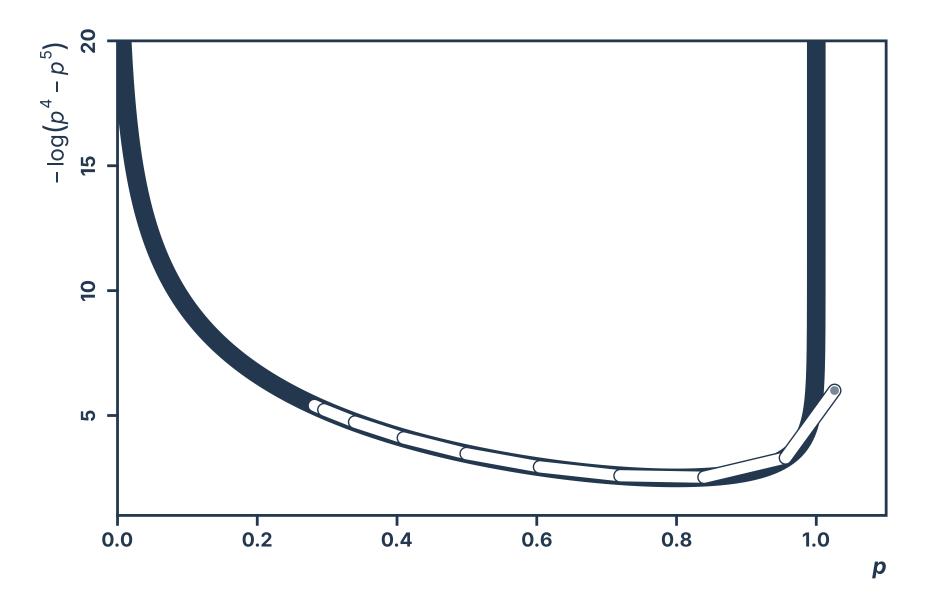


Image credit



Figures by Peter McMahan (<u>source</u> <u>code</u>)



Still from <u>The Legend</u> of the Drunken Master (1994)



Still from <u>Batman</u> (1966)



Clip from <u>Gleaming the</u> <u>Cube (1989)</u>



Clip from <u>Raiders of the Lost Ark (1981)</u>