Stan

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1 Introduction

- We will talk about Stan and implement a few simple models in it.
- Stan uses HMC(Hamiltonian Monte Carlo) for generating Monte Carlo steps.
- HMC is more effective for large samples.
- Stan is written in C++. It offers more programming flexibility.

2 HMC Sampling

- Problems with Gaussian distributions: They will always be centered around the current position(for both univariate and multivariate distributions). This can cause problems for data that have large tails.
- HMC used proposal distribution that changes depending on current position.
- HMC wraps posterior distribution around **gradient**.
- Metropolis algorithm would produce proposal jumps such that anything above or below the current position is equally probable.
- HMC generates distribution based on negative log of posterior density(called **potential**).

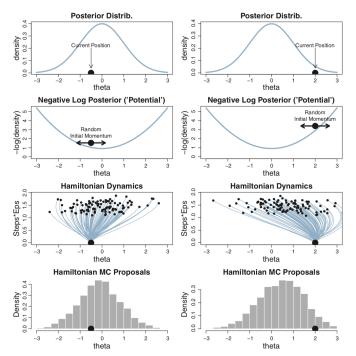


Figure 14.1 Examples of a Hamiltonian Monte Carlo proposal distributions. Two columns show two different current parameter values, marked by the large dots. First row shows posterior distribution. Second row shows the potential energy, with a random impulse given to the dot. Third row shows trajectories, which are the theta value (*x*-axis) as a function of time (*y*-axis marked Steps*Eps). Fourth row shows histograms of the proposals.

Figure 1: HMC proposal distributions

- ullet Posterior tall \Longrightarrow Potential low and vice versa.
- Large dot represents the current position.
- Proposed position generated by flicking marble in random direction and letting it roll for some duration.
- \bullet Magnitude of flick is sampled from ${\bf zero}$ ${\bf mean}$ ${\bf Gaussian}$ distribution.
- Flick gives **momentum** to the ball. When time is up, the new position of the ball is the new proposed jump.
- Ball will be near the lower part of the curve i.e it will be in regions of higher posterior probability (because the curve is inverted posteior probability).
- Potential is similar to physics concept of potential energy.
- Third row in figure shows many trajectories taken by the ball from it's initial position and allowed to roll for random times.(impluses is called **Steps*Eps**. Trajectories show theta value as a function of time as the ball rolls after it receives the random initial push.
- Bottom row shows histogram of all proposed positions. Proposal distribution is **not** centered around initial position.

- Proposal distribution has moved towards the **mode** of the posterior distribution.
- Metropolis decision rule: Used to accept or reject proposal. ϕ is used to denote the momentum.
- In ideal system, all potential energy will be converted to kintetic energy when the marble is moving and vice versa when the marble is stable i.e lossless system.
- For ideal system, sum of potential $(-log(p(\theta|D)))$ and kinetic $(-log(p(\phi)))$ will be constant, and proposal will always be rejected.
- **However**, because there is always some loss in energy(due to friction) in real world scenarios, proposals will not always be accepted.

$$p_{accept} = min \bigg(\frac{p\theta_{proposed}|D)p(\phi_{proposed})}{p(\theta_{current}|D)p(\phi_{current})}, 1 \bigg).$$

- Proposal distribution can be "tuned" by:
 - 1. adjusting step size called **epsilon(or eps)**
 - 2. adjusting number of steps taken.
- Step size \implies Time taken to make a step. Hence, it is called **Steps*Eps**
- General acceptance rate is 62%.
- Acceptance rate low \implies Epsilon reduced
- Acceptance rate high \implies Epsilon increased **and** changes in number of steps to maintain trajectory duration.
- Step size controls smoothness or jaggedness of trajectory.
- Duration(Steps*Eps) controls how far proposed steps are from the current position.
- Duration is important because we want proposed position closer to mode of posterior distribution.

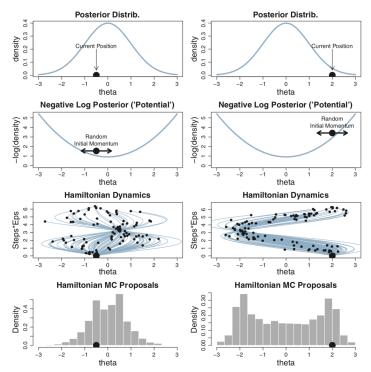


Figure 14.2 Examples of a Hamiltonian Monte Carlo proposal distributions for two different current parameter values, marked by the large dots, in the two columns. For this figure, a large range of random trajectory lengths (Steps*Eps) is sampled. Compare with Figure 14.1.

Figure 2: HMC proposal distributions for different trajectory lengths