

Hybrid Monte Carlo

Radford M. Neal. An improved acceptance procedure for the hybrid monte carlo algorithm. *J. Comput. Phys.*, 111(1):194–203, 1994

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13 Feb 2009

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- 1 The Dynamical Method
 - Motivation
 - Solution
- 2 Hybrid Monte Carlo
 - Motivation
 - How does it work?
 - Analysis
 - Applications
 - Improvement

Current Section

1 The Dynamical Method

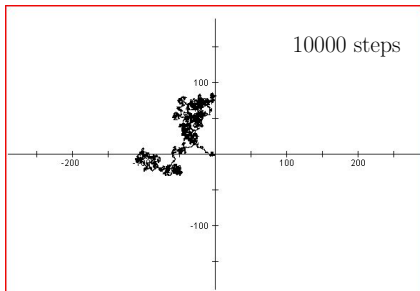
- Motivation
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2 Hybrid Monte Carlo

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Problem with Naive Metropolis-Hastings

- Random Walks travel expected distance of $O(\sqrt{n})$ after n steps



What to do?

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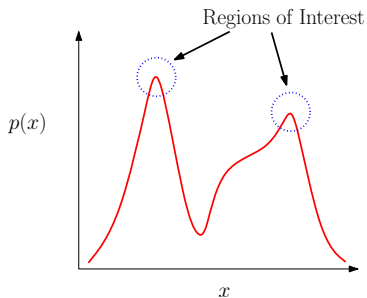
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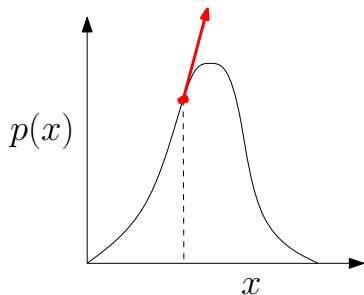
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Observation

- When a ball is on an incline, the angle of incline dictates the force with which it rolls down



Characterization for a physical system

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- The gradient of $E(x)$ dictates the change in momentum

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$P(x)$ and $P(u)$ are independent

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- And Then?

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- Modify using above equations to get a new sample

Leapfrog Discretization

$$u(\tau + \frac{\epsilon}{2}) = u(\tau) - \frac{\epsilon}{2} \nabla E(x(\tau))$$

$$x(\tau + \epsilon) = x(\tau) + \epsilon u(\tau + \frac{\epsilon}{2})$$

$$u(\tau + \epsilon) = u(\tau + \frac{\epsilon}{2}) - \frac{\epsilon}{2} \nabla E(x(\tau + \epsilon))$$

Time Reversible and Volume Preserving

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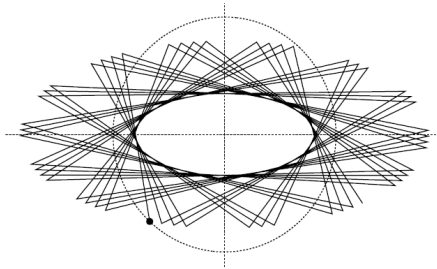
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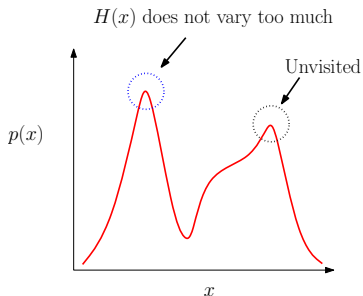
Discretization errors



Two problems with the dynamical method

Energy Well

We might be stuck in an energy well (intuitively, a local maxima)



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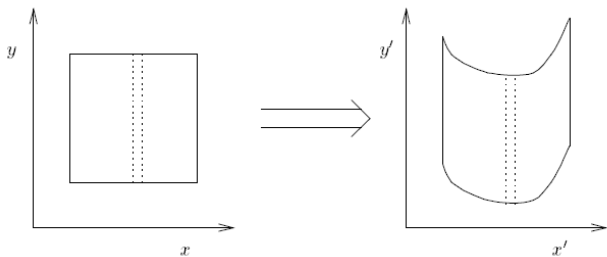
- Replace all values of momentum u with values picked from their distribution
- Why can we do this?
 - $P(u)$ is independent of $P(x)$
- What does this get us?
 - We can move to regions of different energies H
 - Usually enough to ensure ergodicity

Accept/Reject Step

- Similar to MH
- The Acceptance Probability is a function of the difference in energies

$$a(\Delta H) = \min(1, \exp(-\Delta H))$$

Detailed Balance



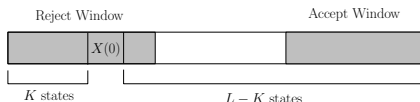
Speed of Computation

- Tunable Parameters - L and ϵ
- Tradeoff between computation time and quality
 - Generally works better for non-local variables (higher dimensions?)

Applications

- Simulation of Physical Systems
- Optimization
- Sampling

Acceptance Procedure using Windows



- Select window to move to
- Select state within window to move to
- Free Energy

$$F(W) = -\log \sum_{X \in W} \exp(-H(X))$$

- Acceptance Probability is $a(\Delta F)$

Questions?