Inference and Representation, Fall 2017

Problem Set 5: MCMC.

Due: Wednesday, November 21, 2016 at 3:00 pm (as a PDF document uploaded in Gradescope.)

Important: *See problem set policy on the course web site.*

Hamiltonian Monte-Carlo

This problem will explore Hamiltonian Dynamics as a tool to enhance classic MCMC methods, in the so-called *Hamiltonian Monte-Carlo (HMC)*.

The classical (non-relativistic) Lagrangian Mechanics describing the dynamics of N particles in $\mathbb{R}^3$ with positions $x_1, \dots x_N$ and velocities $v_1, \dots v_N$, $v_i = \dot{x}_i$ is given, in absence of external forces, by

$$\mathcal{L}(\mathbf{v}, \mathbf{x}) = \frac{1}{2}\langle \mathbf{v}, M\mathbf{v}\rangle - U(\mathbf{x}) \ , \ \mathbf{v} = (v_1, \dots, v_N) \in \mathbb{R}^{3N}, \mathbf{x} = (x_1, \dots, x_N) \in \mathbb{R}^{3N} \ , \quad (1)$$

where M is a $3N \times 3N$ diagonal, positive matrix of the form $M = \text{diag}(m_1, m_1, m_1, \dots, m_N, m_N, m_N)$ describing the masses of the particles, and $U(\mathbf{x})$ is a potential energy term, that only depends upon position variables $\mathbf{x}$.

1. Show that, for each fixed $\mathbf{x}$, $\mathcal{L}(\mathbf{v}, \mathbf{x})$ is convex with respect to $\mathbf{v}$.

By using the fact that Lagrangian solutions are stationary points and the fact that $\dot{\mathbf{x}} = \mathbf{v}$, we have that

$$\frac{\mathrm{d}}{\mathrm{d}t}\frac{\partial \mathcal{L}}{\partial \mathbf{v}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}} \ . \quad (2)$$

This is called the *Euler-Lagrange* equation.

The first step to understand HMC is to derive Hamiltonian mechanics from Lagrangian mechanics. For that purpose, we recall the notion of convex or Legendre-Fenchel conjugate: given a convex function $f : \Omega \to \mathbb{R}$ defined on a convex set Ω, it is defined as

$$f^*(p) = \sup_{y \in \Omega} \left(\langle y, p \rangle - f(y) \right) \ . \quad (3)$$

2. Show that f^* is convex. *Hint: think about what happens if you take the maximum of two convex functions.*

3. Using the fact that $\mathcal{L}$ is differentiable, show that the Legendre-Fenchel conjugate of $\mathcal{L}(\mathbf{v}, \mathbf{x})$, for fixed $\mathbf{x}$, has the form

$$\mathcal{H}(\mathbf{p}, \mathbf{x}) = \frac{1}{2}\langle \mathbf{p}, M^{-1}\mathbf{p}\rangle + U(\mathbf{x}) \ , \ \text{with } \mathbf{p} = \frac{\partial \mathcal{L}}{\partial \mathbf{v}} \ . \quad (4)$$

   This is the *Hamiltonian*, and is interpreted as the energy of the system in terms of position $\mathbf{x}$ and momentum $\mathbf{p}$.

The Legendre duality also gives the crucial interpretation of momentum variables $\mathbf{p}$ as the partial derivatives of $\mathcal{L}$ with respect to velocity, and

$$\mathcal{H}(\mathbf{p}, \mathbf{x}) = \langle \mathbf{v}, \mathbf{p} \rangle - \mathcal{L}(\mathbf{v}, \mathbf{x}) \ . \tag{5}$$

4. Using the previous results, take the differential of $\mathcal{H}(\mathbf{p}, \mathbf{x})$ with respect to time

$$\frac{\mathrm{d}\mathcal{H}}{\mathrm{d}t} = \langle \frac{\partial \mathcal{H}}{\partial \mathbf{p}}, \dot{\mathbf{p}} \rangle + \langle \frac{\partial \mathcal{H}}{\partial \mathbf{x}}, \dot{\mathbf{x}} \rangle$$

and use the Euler-Lagrange equation to derive the *Hamiltonian equations*:

$$\frac{\partial \mathcal{H}}{\partial \mathbf{p}} = \dot{\mathbf{x}} = \mathbf{v} \ , \ \frac{\partial \mathcal{H}}{\partial \mathbf{x}} = -\dot{\mathbf{p}} \ . \tag{6}$$

Now that we have derived the Hamiltonian Dynamics, we need an algorithm to implement them in a computer. A popular strategy is the so-called *Leap Frog* method. Given a stepsize $\delta > 0$, it consists in the following steps:

- Take a half-step to update the momentum variable:

$$\mathbf{p}(t + \delta/2) = \mathbf{p}(t) - \frac{\delta}{2} \nabla_{\mathbf{x}} \mathcal{H}(\mathbf{p}(t), \mathbf{x}(t)) \ .$$

- Take a full-step to update the position variable:

$$\mathbf{x}(t + \delta) = \mathbf{x}(t) + \delta \nabla_{\mathbf{p}} \mathcal{H}(\mathbf{p}(t + \delta/2), \mathbf{x}(t)) \ .$$

- Take the remaining half-step to update momentum:

$$\mathbf{p}(t + \delta) = \mathbf{p}(t + \delta/2) - \frac{\delta}{2} \nabla_{\mathbf{x}} \mathcal{H}(\mathbf{p}(t + \delta/2), \mathbf{x}(t + \delta)) \ .$$

The goal of Hamiltonian Monte-Carlo is to use Hamiltonian Dynamics to approximate expectations on a given model of the form

$$p(\mathbf{x}) = \frac{\tilde{p}(\mathbf{x})}{Z} \ , \tag{7}$$

where Z is the partition function. By denoting $U(\mathbf{x}) = -\log p(\mathbf{x})$, this is interpreted as the *canonical* distribution of the system with energy $U(\mathbf{x})$.

5. If $U(\mathbf{x})$ in (7) denotes the potential energy of the system, derive the canonical distribution in terms of $\mathbf{x}$ and $\mathbf{p}$ using the Hamiltonian, and conclude that the joint canonical distribution $p(\mathbf{x}, \mathbf{p})$ is separable in $\mathbf{x}$ and $\mathbf{p}$, that is, $\mathbf{x}$ and $\mathbf{p}$ are independent: $p(\mathbf{x}, \mathbf{p}) = p(\mathbf{x})p(\mathbf{p})$. Explain how this property justifies using $\mathbf{p}$ as auxiliary variables to sample from $p(\mathbf{x})$.

6. Using (4), show that the marginal $p(\mathbf{p})$ is a Normal distribution with zero mean.

7. Show that the leap-frog algorithm does not require knowledge of Z.

8. Finally, let us consider the following proposal distribution. Given $\mathbf{x}^{(0)}$, we draw $\mathbf{p}^{(0)} \sim p(\mathbf{p})$ and run 1 step of the Leapfrog algorithm with step δ, to obtain $(\mathbf{x}^*, \mathbf{p}^*)$. Denote by

$$q(\mathbf{x}^*, \mathbf{p}^* \mid \mathbf{x}^{(0)}, \mathbf{p}^{(0)}) \tag{8}$$

the resulting distribution. Show that the Metropolis-Hastings algorithm using this proposal distribution produces samples from $p(\mathbf{x})$ when marginalizing over position variables.

9. (HMC Example) Implement a Python code to sample from a bivariate Gaussian with correlation 0.988 using the Hamiltonian Monte Carlo method. Starting from the initial state, plot the resulting trajectories. Please submit your source code together with the plots. For background information and format of the plots, see Chap. 30 of MacKay's Information Theory, Inference, and Learning Algorithms, which is freely available online: `http://www.inference.phy.cam.ac.uk/mackay/itila/`.