Comparing Hamiltonian Monte Carlo and Elliptical Slice Sampling for constrained Gaussian distributions

732A76 Research Project Report

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1 Background

High-dimensional multivariate gaussian distribution is used in various models and applications. In some cases, we need to generate from a certain distribution which applies constraints to a multivariate Gaussian distribution (Gelfand et al. [1992] and Rodríguez-Yam et al. [2004]). Sampling from this distribution is still a challenging issue, particularly because it is not straightforward to compute the normalizing constant for the density function.

The gibbs sampler has proven to be a suitable choices to sample from truncated multivariate Gaussian distributions (Gelfand et al. [1992]). Recently, more sophisticated methods have been developed to generate samples from truncated multivariate Gaussian distributions. In this research project, two methods, namely Exact Hamiltonian Monte Carlo (Pakman and Paninski [2013]) and Analytic Elliptical Slice Sampling (Fagan et al. [2016]), will be compared.

2 Definitions

2.1 Truncated Multivariate Gaussian Distribution

The truncated multivariate Gaussian distribution is a probability distribution obtained from a multivariate Gaussian random variable by bounding it under some linear (or quadratic) constraints.

Let $\mathbf{w}$ be a d-dimensional Gaussian random variable with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. The corresponding truncated multivariate Gaussian distribution can be defined as

$$p(\mathbf{x}) = \frac{\exp\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^\intercal\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\}}{\int_{\mathbf{Fx}+\mathbf{g}\geq 0}\exp\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^\intercal\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\}d\mathbf{x}}\mathbb{1}(\mathbf{Fx}+\mathbf{g}\geq 0) \tag{2.1}$$

where $\mathbf{x}$ is a d-dimensional truncated Gaussian random variable, $\mathbb{1}$ is an indicator function, and $\mathbf{F}$ is an $m \times d$ matrix, which, together with the $m \times 1$ vector of $\mathbf{g}$, defines all m constraints of $p(\mathbf{x})$. We denote this as $\mathbf{x} \sim TN(\boldsymbol{\mu}, \boldsymbol{\Sigma}; \mathbf{F}, \mathbf{g})$.

We can rewrite $p(\mathbf{x})$ as

$$p(\mathbf{x}) = \frac{1}{Z} \exp\left\{ -\frac{1}{2}\mathbf{x}^\intercal \boldsymbol{\Lambda} \mathbf{x} + \boldsymbol{\nu}^\intercal \mathbf{x} \right\} \mathbb{1}(\mathbf{F}\mathbf{x} + \mathbf{g} \geq 0) \tag{2.2}$$

where $\boldsymbol{\Lambda} = \boldsymbol{\Sigma}^{-1}$, $\boldsymbol{\nu} = \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$, and Z is the normalizing constant. Through linear change of variables, (2.2) can be transformed into

$$p(\mathbf{x}) = \frac{1}{Z} \exp\left\{ -\frac{1}{2}\mathbf{x}^\intercal \mathbf{x} \right\} \mathbb{1}(\mathbf{F}^*\mathbf{x} + \mathbf{g}^* \geq 0) \tag{2.3}$$

such that $\mathbf{x} \sim TN(\mathbf{0}, \mathbf{I}_d; \mathbf{F}^*, \mathbf{g}^*)$, for some values of $\mathbf{F}^*$ and $\mathbf{g}^*$.

2.2 Exact Hamiltonian Monte Carlo for Truncated Multivariate Gaussians

Exact Hamiltonian Monte Carlo (HMC) for Truncated Multivariate Gaussians (TMG) (Pakman and Paninski [2013]) considers the exact paths of particle trajectories in a Hamiltonian system

$$H(\mathbf{x}, \mathbf{s}) = U(\mathbf{x}) + K(\mathbf{s}) \tag{2.4}$$

where $U(\mathbf{x})$ is the potential energy term as a function of particle's position ($\mathbf{x}$) and $K(\mathbf{s})$ is the kinetic energy term as a function of particle's momentum ($\mathbf{s}$). Both $\mathbf{x}$ and $\mathbf{s}$ are of d-dimensions. The change of position and momentum over time t can be described by Hamilton's equations

$$\begin{aligned} \frac{\partial x_i}{\partial t} &= \frac{\partial H}{\partial s_i} \\ \frac{\partial s_i}{\partial t} &= -\frac{\partial H}{\partial x_i}, \qquad i = 1, ..., d. \end{aligned} \tag{2.5}$$

The target distribution is related to the current energy state of the particle through canonical distribution:

$$p(\mathbf{x}) \propto \exp\{-E(\mathbf{x})\} \tag{2.6}$$

where the target distribution, $p(\mathbf{x})$, depends on the value of energy function $E(\mathbf{x})$. In a Hamiltonian system, we have $H(\mathbf{x}, \mathbf{s})$ as our energy function, which results in the canonical distribution:

$$\begin{aligned} p(\mathbf{x}, \mathbf{s}) &\propto \exp\{-H(\mathbf{x}, \mathbf{s})\} \\ &\propto \exp\{-U(\mathbf{x})\} \exp\{-K(\mathbf{s})\} \\ &\propto p(\mathbf{x})p(\mathbf{s}). \end{aligned} \tag{2.7}$$

Hence, $\mathbf{x}$ and $\mathbf{s}$ are independent. To sample from the target distribution $p(\mathbf{x})$, we can sample from the joint distribution $p(\mathbf{x}, \mathbf{s})$ and ignore the variable $\mathbf{s}$.

Suppose our target distribution $p(\mathbf{x})$ is a truncated multivariate Gaussian distribution as in (2.3). We can set our momenta to be normally distributed, that is $\mathbf{s} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_d)$. Therefore, the Hamiltonian system can be described as:

$$H = U(\mathbf{x}) + K(\mathbf{s}) = \frac{1}{2}\mathbf{x}^\intercal \mathbf{x} + \frac{1}{2}\mathbf{s}^\intercal \mathbf{s} \tag{2.8}$$

subject to:

$$\mathbf{F}\mathbf{x} + \mathbf{g} \geq 0. \tag{2.9}$$

for some values of $\mathbf{F}$ and $\mathbf{g}$.

The equations of motion for the Hamiltonian system in (2.8) are:

$$\begin{aligned} \frac{\partial x_i}{\partial t} &= \frac{\partial H}{\partial s_i} = s_i \\ \frac{\partial s_i}{\partial t} &= -\frac{\partial H}{\partial x_i} - x_i, \qquad i = 1, ..., d. \end{aligned} \tag{2.10}$$

In this sense, we want the particles in Hamiltonian system to only move around inside the constrained space. The exact trajectory of a particle using the equations above is:

$$x_i(t) = s_i(0)\sin(t) + x_i(0)\cos(t). \tag{2.11}$$

A particle will follow the trajectory above until it hits a wall, or in other words, until $\mathbf{F}\mathbf{x} + \mathbf{g} = 0$. Let t_h be the time when the particle hits wall h, or when $\mathbf{F}_h \cdot \mathbf{x}(t_h) + \mathrm{g}_h = 0$. It will hit the wall with velocity $\dot{\mathbf{x}}(t_h)$ which can be decomposed into:

$$\dot{\mathbf{x}}(t_h) = proj_{\mathbf{n}}\dot{\mathbf{x}}(t_h) + proj_{\mathbf{F}_h}\dot{\mathbf{x}}(t_h) \tag{2.12}$$

where $proj_{\mathbf{n}}\dot{\mathbf{x}}(t_h)$ is the projection of $\dot{\mathbf{x}}(t_h)$ on the normal vector $\mathbf{n}$ perpendicular to $\mathbf{F}_h$ and

$$\begin{aligned} proj_{\mathbf{F}_h}\dot{\mathbf{x}}(t_h) &= \frac{\mathbf{F}_h \cdot \dot{\mathbf{x}}(t_h)}{||\mathbf{F}_h||}\frac{\mathbf{F}_h}{||\mathbf{F}_h||} \\ &= \frac{\mathbf{F}_h \cdot \dot{\mathbf{x}}(t_h)}{||\mathbf{F}_h||^2}\mathbf{F}_h \\ &= \alpha_h \mathbf{F}_h. \end{aligned} \tag{2.13}$$

By inverting the direction of $proj_{\mathbf{n}}\dot{\mathbf{x}}(t_h)$, we can obtain the reflected velocity as

$$\begin{aligned} \dot{\mathbf{x}}_R(t_h) &= -proj_{\mathbf{n}}\dot{\mathbf{x}}(t_h) + proj_{\mathbf{F}_h}\dot{\mathbf{x}}(t_h) \\ &= -\dot{\mathbf{x}}(t_h) + 2\alpha_h \mathbf{F}_h \end{aligned} \tag{2.14}$$

which can be used as the new initial velocity in (2.11) for the particle to continue its path.

References

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