High order numerical simulation of the underdamped Langevin diffusion

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Introduction

The underdamped Langevin diffusion is given by the following SDE:

$$dQ_t = P_t dt, (1)$$

$$dP_t = -\nabla U(Q_t) dt - \nu P_t dt + \sqrt{\frac{2\nu}{\beta}} dW_t, \qquad (2)$$

where $Q, P \in \mathbb{R}^d$ will represent the position and velocity of a particle moving in a potential $U : \mathbb{R}^d \to \mathbb{R}$ under the influence of a frictional force (with coefficient v > 0) along with a stochastic force given by a d-dimensional Brownian motion W (and inverse temperature β).

The underdamped Langevin equation can be viewed as an extension of Newton's second law and is a key model in statistical mechanics. ([1] is a detailed textbook that surveys these scientific applications)

Introduction

Recently this equation has been applied to computational statistics as, under mild conditions on the potential (see [2] for more details), the process admits a stationary measure with the following density:

$$\varphi(q, p) \propto \exp\left(-\beta \left(U(q) + \frac{1}{2} \|p\|^2\right)\right).$$

Hence by setting U equal to the log density of a target distribution, it is possible to generate samples by simulating a Langevin diffusion.

In practice, (1) can not be solved exactly and must be approximated.

Introduction

One strategy for discretizing the underdamped Langevin equation is

- 1. Replace the Brownian motion W by a piecewise linear path \widehat{W} .
- 2. Along each piece of \widehat{W} we can approximate (1) using the ODE:

$$d\widehat{Q}_t = \widehat{P}_t \, dt, \tag{3}$$

$$d\widehat{P}_t = f(\widehat{Q}_t) dt - \nu \widehat{P}_t dt + \sigma d\widehat{W}_t, \tag{4}$$

where $f := -\nabla U$ and $\sigma := \sqrt{\frac{2\nu}{\beta}}$.

3. In each step, discretize (3) and (4) with a suitable ODE solver.

To construct the path \widehat{W} , we shall use the below theorem from [3].

Theorem (Brownian motion as a cubic with independent noise)

Consider a standard Brownian motion W over the unit interval [0,1]. Let \widetilde{W} be the (unique) cubic polynomial with a root at 0 such that

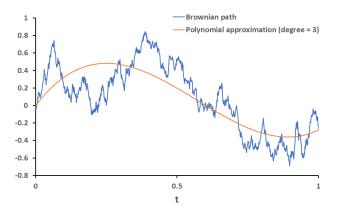
$$\int_0^1 u^k d\widetilde{W}_u = \int_0^1 u^k dW_u, \text{ for } k = 0, 1, 2.$$

Then

$$W = \widetilde{W} + Z$$

where Z is a centred Gaussian process independent of the cubic \widetilde{W} .

Therefore, the cubic polynomial \widetilde{W} is an unbiased estimator for W.



The piecewise linear path \widehat{W} will be designed to resemble this cubic.

Theorem (Pathwise approximation of the cubic polynomial \widehat{W})

There exists a piecewise linear path \widehat{W} on [0,1] and a>0 such that:

- 1. $\widehat{W}_0 = 0$.
- 2. \widehat{W} has three pieces which connect at $\frac{1}{2}(1\pm a)$.
- 3. $\int_0^1 u^k d\widehat{W}_u = \int_0^1 u^k d\widetilde{W}_u$, for k = 0, 1, 2, 3.

Proof.

Note that for any fixed $a \in (0,1)$, the first three integral conditions and \widehat{W}_0 are enough to uniquely determine the piecewise linear path.

Hence, the idea of the proof is to derive a necessary condition for a.

Proof. (continued)

Using the orthogonality of the Legendre polynomials, it follows that

$$\int_0^1 (20u^3 - 30u^2 + 12u - 1) d\widehat{W}_u$$

$$= \int_0^1 (20u^3 - 30u^2 + 12u - 1) d\widetilde{W}_u$$

$$= \int_0^1 (20u^3 - 30u^2 + 12u - 1) (\widetilde{W}_u)' du$$

$$= 0.$$

On the other hand, the above integral can be explicitly computed as

$$\int_0^1 (20u^3 - 30u^2 + 12u - 1) d\widehat{W}_u$$

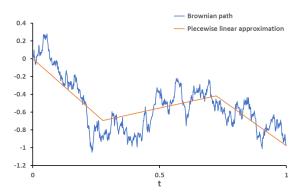
$$= \frac{1}{8} (5a^3 + 5a^2 - a - 1) (\widehat{W}_1 - \widehat{W}_{\frac{1}{2}(1+a)} - \widehat{W}_{\frac{1}{2}(1-a)}).$$

Proof. (continued)

So in order for \widehat{W} to exist, the constant a must satisfy the equation

$$5a^3 + 5a^2 - a - 1 = 0.$$

Therefore by setting $a = \frac{\sqrt{5}}{5}$, we can construct the desired path. \square



In practice, \widehat{W} can be generated on [s,t] using the random variables

$$\begin{split} W_{s,t} &:= W_t - W_s, \\ H_{s,t} &:= \frac{1}{h} \int_s^t W_{s,u} - \frac{u - s}{h} W_{s,t} \, du, \\ K_{s,t} &:= \frac{1}{h^2} \int_s^t \left(W_{s,u} - \frac{u - s}{h} W_{s,t} \right) \left(\frac{1}{2} h - (u - s) \right) du, \end{split}$$

where h = t - s.

It is straightforward to prove that $(W_{s,t}, H_{s,t}, K_{s,t})$ are independent and uniquely determine the cubic polynomial \widetilde{W} (see [3] for details).

Furthermore $W_{s,t} \sim N(0,h)$, $H_{s,t} \sim N(0,\frac{1}{12}h)$ and $K_{s,t} \sim N(0,\frac{1}{720}h)$.

Theorem (Pathwise approximation of the Brownian motion W)

Let \widehat{W} be the piecewise linear path on [s,t] with three pieces which connect the points (s,W_s) , (s+Ah,B), (t-Ah,C), (t,W_t) given by

$$A = \frac{1}{2} - \frac{1}{2\sqrt{5}},$$

$$\frac{1}{2}(B+C) = W_s + \frac{1}{2}W_{s,t} + \frac{1}{1-A}H_{s,t},$$

$$\frac{1}{2}(B-C) = \frac{6}{1-A}K_{s,t} - \frac{1}{2}(1-2A)W_{s,t}.$$

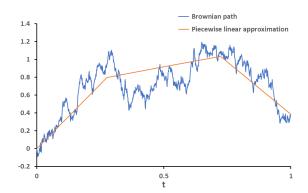
Then \widehat{W} matches the increment $W_{s,t}$, the time areas $(H_{s,t},K_{s,t})$ and

$$\int_s^t (u-s)^2 \, \widehat{W}_{s,u} \, du = \mathbb{E}\left[\left. \int_s^t (u-s)^2 \, W_{s,u} \, du \, \right| W_{s,t}, H_{s,t}, K_{s,t} \, \right].$$

Proof.

The result is a direct consequence of the previous two theorems.

When approximating the underdamped Langevin diffusion on [0, T], we shall generate \widehat{W} on the uniform grid \triangle_N with mesh size $h = \frac{T}{N}$.



Recall that the underdamped Langevin equation is the SDE given by

$$dQ_t = P_t dt, (5)$$

$$dP_t = f(Q_t) dt - vP_t dt + \sigma dW_t.$$
 (6)

Provided that f is twice differentiable, we have the Taylor expansion

$$\begin{pmatrix} Q_t \\ P_t \end{pmatrix} = \begin{pmatrix} Q_s \\ P_s \end{pmatrix} + (\cdots)h + (\cdots)W_{s,t} + (\cdots)\int_s^t W_{s,u} du + (\cdots)h^2 + (\cdots)h^3
+ (\cdots)\int_s^t \int_s^u W_{s,v} dv du + (\cdots)\int_s^t \int_s^u \int_s^v W_{s,r} dr dv du
+ (\cdots)\int_s^t \int_s^u \int_s^v (r-s) dW_r dv du + O(h^4),$$

where (\cdots) are terms involving the vector fields and their derivatives.

Similarly, $(\widehat{Q},\widehat{P})$ will also have this expansion but with \widehat{W} integrals.

By the previous theorem, these integrals are approximated optimally using \widehat{W} (in an $L^2(\mathbb{P})$ sense) and should give the local error estimate

Conjecture (Local error estimate for the approximation on [s,t])

Suppose that f and its first two derivatives are Lipschitz continuous and let $(\widehat{Q},\widehat{P})$ be defined from time s with the initial value (Q_s,P_s) . Then provided P and f(Q) satisfy a global $L^2(\mathbb{P})$ bound, there exist universal constants $C_1,C_2>0$ (independent of P_s and Q_s) such that

$$\left\| \left(Q, P \right)_t - \left(\widehat{Q}, \widehat{P} \right)_t \right\|_{L^2(\mathbb{P})} \le C_1 h^{\frac{7}{2}}, \tag{7}$$

$$\left\| \mathbb{E}_{s} \left[(Q, P)_{t} - (\widehat{Q}, \widehat{P})_{t} \right] \right\| \leq C_{2} h^{4}, \tag{8}$$

for sufficiently small h = t - s.

Remark

The required global L^2 bound on P and f(Q) is satisfied if $f = -\nabla U$ where U is a strongly convex potential.

Directly applying the exponential contractivity of the underdamped Langevin diffusion [2, 4] yields the following global error estimate:

Conjecture (Third order strong convergence rate for the ODE)

Let $\alpha>0$ be an exponential contraction rate for the diffusion (Q,P) started from $(Q_0,P_0)\sim\pi$, with π denoting the invariant distribution. Then there exists a constant C>0 such that for all $k\geq 0$, we have

$$\left\| \begin{pmatrix} Q_{kh} \\ P_{kh} \end{pmatrix} - \begin{pmatrix} \widehat{Q}_{kh} \\ \widehat{P}_{kh} \end{pmatrix} \right\|_{L^2(\mathbb{P})}^2 \le 3e^{-\frac{1}{2}\alpha kh} \left\| \begin{pmatrix} Q_0 \\ P_0 \end{pmatrix} - \begin{pmatrix} \widehat{Q}_0 \\ \widehat{P}_0 \end{pmatrix} \right\|_{L^2(\mathbb{P})}^2 + Ch^6,$$

provided the step size h is sufficiently small.

Question

Are there cheaper ODE methods that can achieve this convergence?

Definition (An "adjusted" ODE approximation of the diffusion)

Given $(\widetilde{Q}_s,\widetilde{P}_s)$, we can define an approximation $(\widetilde{Q}_t,\widetilde{P}_t)$ at time t by

$$\widetilde{Q}_t := \overline{Q}_1 - 2\sigma K_{s,t} h,$$

$$\widetilde{P}_t := \overline{P}_1 - \sigma \big(H_{s,t} + 2 \big(1 - vh \big) K_{s,t} \big),$$

and $(ar{Q}, ar{P})$ satisfy the ODE driven by the linear path $\{uW_{s,t}\}_{u \in [0,1]}$,

$$\frac{d\overline{Q}}{du} = \overline{P}_u h, \quad \frac{d\overline{P}}{du} = f(\overline{Q}_u) h - v \overline{P}_u h + \sigma W_{s,t},$$

with initial conditions

$$\begin{split} \widetilde{Q}_0 &:= \widetilde{Q}_s, \\ \widetilde{P}_0 &:= \widetilde{P}_s + \sigma \big(H_{s,t} + 2K_{s,t} \big). \end{split}$$

Remark

By setting $K_{s,t} = 0$, it is straightforward to show that this numerical scheme reduces to the high order log-ODE method discussed in [3].

We expect the small adjustments to have a profound impact on the Taylor expansion of the ODE driven by the linearized Brownian path.

In particular, we anticipate the above approximation will achieve the same third order convergence rate whilst being roughly 3x cheaper.

On the other hand, the non-adjusted method may be easier to apply to diffusions on manifolds. This is likely to be a topic for the future.

Discretization of the underdamped Langevin ODE

Since the ODE driven by \widehat{W} is a third order approximation, it should be discretized using a numerical method that is at least third order.

Due to the structure of (3, 4), we can apply Runge-Kutta-Nyström (RKN) methods, which are explicitly designed for ODEs of the form

$$y'' = F(t, y),$$
 (9)
 $y(0) = y_0, \quad y'(0) = y'_0,$

In addition, we wish for the RKN method to be symplectic since the underdamped Langevin equation is a stochastic Hamiltonian system.

Fortunately, the RKN method proposed by [5] has these properties.

Discretization of the underdamped Langevin ODE

To propagate the numerical solution over [s, t], we use the variables

$$\begin{pmatrix} y_u \\ x_u \end{pmatrix} := \begin{pmatrix} e^{\frac{1}{2}\nu(u-s)} \widehat{Q}_u \\ e^{\nu(u-s)} \widehat{P}_u \end{pmatrix}, \quad \forall u \in [s,t],$$

to represent the system (3, 4) using the following second order ODE

$$\frac{d^{2}y}{du^{2}} = \frac{1}{4}v^{2}y + e^{\frac{1}{2}v(u-s)} \left(f\left(e^{-\frac{1}{2}v(u-s)}y\right) + \sigma \frac{d\widehat{W}}{du} \right), \qquad (10)$$

$$y_{s} = \widehat{Q}_{s}, \quad y'_{s} = \widehat{P}_{s} + \frac{1}{2}v\widehat{Q}_{s}.$$

We can apply RKN methods on the intervals where $\frac{d\widehat{W}}{du}$ is constant.

Discretization of the underdamped Langevin ODE

For the numerical example, we will use the below numerical method.

Definition (A third order three-stage symplectic RKN method)

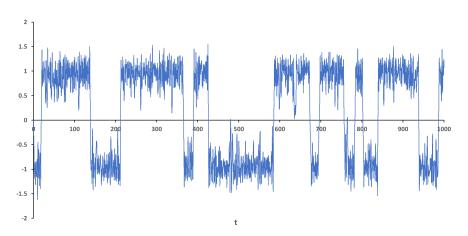
This method is presented in [5] and defined by the Butcher tableau:

0			
0.630847693	0.164217030		
0.536704894	0.139710559	-0.103005664	
	0.260311692	0.4039053382	-0.164217030
	0.260311692	1.094142798	-0.354454490

For the numerical experiment, we shall consider a scalar double-well potential with the same parameters used in the first example of [6]:

$$U(q) = (q^2 - 1)^2,$$
 $v = 1, \quad \beta = 3, \quad (Q_0, P_0) = 0.$

A sample path of the Langevin diffusion obtained by discretizing (3)



Let \widehat{Q}_T be the approximate position at time T computed with $h=\frac{T}{N}$.

We examine the strong and weak convergence using the estimators:

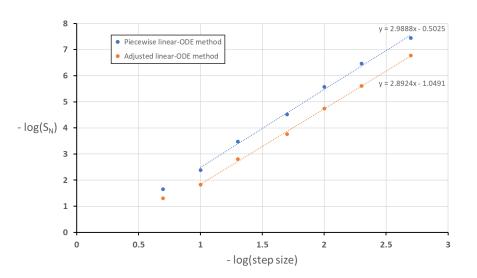
$$S_N := \sqrt{\mathbb{E}\left[\left(\widehat{Q}_T - Q_T^{\text{fine}}\right)^2\right]},\tag{11}$$

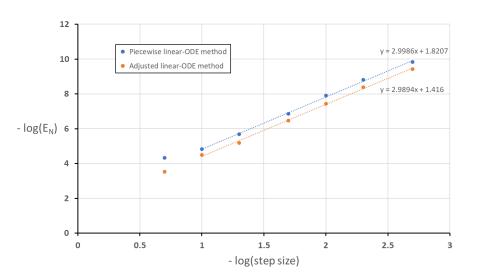
$$E_N := \left| \mathbb{E} \left[\hat{Q}_T^2 \right] - \mathbb{E} \left[\left(Q_T^{\text{fine}} \right)^2 \right] \right|, \tag{12}$$

where the expectations are approximated by Monte-Carlo simulation and $Q_T^{\rm fine}$ denotes the numerical solution of (1) obtained at time T using the proposed method with a "fine" step size of $\min\left(\frac{h}{10}, \frac{T}{50000}\right)$.

We will compute both \widehat{Q}_T and Q_T^{fine} using the same Brownian paths.

For the numerical experiment, we shall use a time horizon of T = 10.





Future work

- Are the methods useful for problems within Bayesian statistics?
- ▶ What are best ODE solvers for discretizing the system (3), (4)?
- Can these methodologies be improved using variable step sizes?
- ► How might the methods be applied to diffusions on manifolds?
- Are these numerical methods applicable if the noise is Cauchy?

Thank you for your attention!

References 1

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