Reduction of variance in the numerical solution of BSDEs

Réduction de variance pour la solution numérique des BSDEs

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Numerical methods based on time discretization and estimation of conditional expectations for solving backward stochastic differential equations (BSDEs) have been the object of considerable research, particularly in view of the applications to finance. We introduce and implement a simple control variate technique to reduce the simulation error of the conditional expectation estimates in BSDE methods. These modifications increase the accuracy of the existing algorithms without additional computational cost.

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1. Introduction

Several approaches for solving backward stochastic differential equations (BSDEs) have been considered in the literature (see for instance [5,7] and references therein). One type of numerical scheme is based on time discretization and estimating conditional expectations (see e.g. [8,6,2–4]). Since these conditional expectations cannot be evaluated explicitly, methods such as Least Squares Monte-Carlo or kernel regression are used. We suggest here a simple modification to these methods in order to reduce the simulation error of the conditional expectation estimates.

The main idea is captured in the following elementary observation. Let \( W_t \) be a standard Brownian motion and \( f \) a sufficiently smooth function satisfying, e.g., a polynomial growth condition. Integration by parts with dominated convergence theorem then shows that:

\[
f'(x) = \lim_{\Delta t \to 0} \mathbb{E} \left[ f(x + W_{\Delta t}) \frac{W_{\Delta t}}{\Delta t} \right],
\]

(1)
\[ f''(x) = \lim_{\Delta t \to 0} \mathbb{E} \left[ f(x + W_{\Delta t}) \frac{W_{\Delta t}^2 - \Delta t}{\Delta t^2} \right]. \] (2)

These formulas suggest an approach for estimating derivatives by Monte-Carlo. Unfortunately, replacing expectations by empirical averages leads to poor convergence when \( \Delta t \) is small. A simple Taylor expansion argument shows that the sample variances are \( f(x)^2 \Delta t^{-1} + \mathcal{O}(1) \) in (1) and \( 2f(x)^2 \Delta t^{-2} + \mathcal{O}(\Delta t^{-1}) \) in (2) which blow up as \( \Delta t \to 0 \), thus leading to a large standard error in the estimates. This problem can be avoided by using estimators based on the equivalent formulas:

\[ f'(x) = \lim_{\Delta t \to 0} \mathbb{E} \left[ (f(x + W_{\Delta t}) - f(x)) \frac{W_{\Delta t}}{\Delta t} \right], \] (1*)

\[ f''(x) = \lim_{\Delta t \to 0} \mathbb{E} \left[ (f(x + W_{\Delta t}) - f(x) - f'(x) W_{\Delta t}) \frac{W_{\Delta t}^2 - \Delta t}{\Delta t^2} \right] \] (2*)

obtained by subtracting the first-order Taylor terms from \( f(x + W_{\Delta t}) \) in order to make the numerator and the denominator of the same order in \( \Delta t \) while keeping the expectation unchanged. This leads to sample variances \( 2f'(x)^2 + \mathcal{O}(\Delta t) \) and \( \frac{2}{\Delta t} f''(x)^2 + \mathcal{O}(\Delta t) \) which, to the leading order, do not depend on \( \Delta t \) and thus allow much smaller values of \( \Delta t \) to be used.

2. Application to the numerical solution of BSDEs

To keep the notation simple, we consider the one-dimensional case; the ideas extend readily to multiple dimensions. Suppose that we are given a fully non-linear parabolic PDE in \([0, T] \times \mathbb{R}^n\):

\[ u_t + Lu = f(t, x, u, u_x, u_{xx}), \quad u(x, T) = g(x) \] (3)

where \( L \) is the generator of a diffusion \( dX_t = b(t, X_t) dt + \sigma(t, X_t) dW_t \) with a fixed initial value \( X_0 = x \). If the PDE has a sufficiently smooth solution, then it follows by Ito’s Lemma that the four processes \( Y_t = u(X_t, t), Z_t = u_x(X_t, t), \Gamma_t = u_{xx}(X_t, t), \) \( A_t = (u_{xx} + Lu)_t(X_t, t) \) satisfy the second-order BSDE

\[ dY_t = (f(t, X_t, Y_t, Z_t, \Gamma_t) dt + \sigma(t, X_t) Z_t dW_t, \quad dZ_t = A_t dt + \sigma(t, X_t) \Gamma_t dW_t \] (4)

with the terminal condition \( Y_T = g(X_T) \). Conversely, if we can solve for \( Y_0 \) via the BSDE approach, we can find the numerical solution of the PDE (3) at a given point \((x, 0)\).

We consider two well-known numerical schemes for solving second-order BSDEs:

- Cheridito et al. [3]:

\[
\begin{align*}
Y_n &= g(X_n), \\
Z_n &= g'(X_n), \\
Y_{n-1} &= \mathbb{E}_{n-1}[Y_n] - f(t_{n-1}, X_{n-1}, Y_{n-1}, Z_{n-1}, \Gamma_{n-1}) \Delta t, \\
Z_{n-1} &= \frac{1}{\sigma_{n-1}} \mathbb{E}_{n-1} \left[ Y_n \frac{\Delta W_{n-1}}{\Delta t} \right], \quad 1 \leq n \leq N, \\
\Gamma_{n-1} &= \frac{1}{\sigma_{n-1}} \mathbb{E}_{n-1} \left[ Z_n \frac{\Delta W_{n-1}}{\Delta t} \right].
\end{align*}
\] (5)

- Fahim et al. [4]:

\[
\begin{align*}
Y_n &= g(X_n), \\
Y_{n-1} &= \mathbb{E}_{n-1}[Y_n] - f(t_{n-1}, X_{n-1}, Y_{n-1}, Z_{n-1}, \Gamma_{n-1}) \Delta t, \\
Z_{n-1} &= \frac{1}{\sigma_{n-1}} \mathbb{E}_{n-1} \left[ Y_n \frac{\Delta W_{n-1}}{\Delta t} \right], \quad 1 \leq n \leq N, \\
\Gamma_{n-1} &= \frac{1}{\sigma_{n-1}^2} \mathbb{E}_{n-1} \left[ Y_n \frac{(\Delta W_{n-1})^2 - \Delta t}{\Delta t^2} \right].
\end{align*}
\] (6)

Subscripts indicate evaluations at time \( t_n = n \Delta t \), \( \mathbb{E}_n[\cdot] = \mathbb{E}[\cdot | X_n] \), \( \Delta W_{n-1} = W_n - W_{n-1} \) and \( \sigma_n = \sigma(t_n, X_n) \). Since \( Z_n \) and \( \Gamma_n \) are approximations to \( u_x(X_n, t_n) \) and \( u_{xx}(X_n, t_n) \), we see that the expressions of \( Z_{n-1} \) and \( \Gamma_{n-1} \) are essentially the formulas (1) and (2). These formulas produce poor results for small time steps (see [7]). We suggest the following modifications based on the formulas (1*) and (2*):
errors of the new estimates do not to depend on

Example 1

modifications do not add any significant computational cost.

The naive estimators of (1) and (2) with their leading order standard errors are

\[ \hat{f}(x) = \frac{1}{N\sqrt{\Delta t}} \sum_{n=1}^{N} Z_{n} f(x + \sqrt{\Delta t} Z_{n}), \quad \text{std} \approx \frac{|f(x)|}{\sqrt{\Delta t} \sqrt{N}}, \]

\[ \hat{f}''(x) = \frac{1}{N\Delta t} \sum_{n=1}^{N} (Z_{n}^2 - 1) f(x + \sqrt{\Delta t} Z_{n}), \quad \text{std} \approx \frac{\sqrt{2}|f(x)|}{\Delta t \sqrt{N}}, \]

where \( Z_{n} \) are independent standard normal random variables. Respectively, for \((1)^*\) and \((2)^*\) we have

\[ \hat{f}^*(x) = \frac{1}{N\sqrt{\Delta t}} \sum_{n=1}^{N} Z_{n} (f(x + \sqrt{\Delta t} Z_{n}) - f(x)), \quad \text{std} \approx \frac{\sqrt{2}|f'(x)|}{\sqrt{N}}, \]

\[ \hat{f}''^*(x) = \frac{1}{N\Delta t} \sum_{n=1}^{N} (Z_{n}^2 - 1)(f(x + \sqrt{\Delta t} Z_{n}) - f(x) - \sqrt{\Delta t} Z_{n} f'(x)), \quad \text{std} \approx \frac{\sqrt{27}|f''(x)|}{2 \sqrt{N}}. \]

These differ from the original ones only in the way that we have subtracted approximations of the first-order Taylor expansion terms in the expressions of \( Z_{n-1} \) and \( I_{n-1} \). Note that the correction terms are already computed at each step so the modifications do not add any significant computational cost.

3. Numerical examples

Example 1 (Simple estimator). We estimate the expectations described in the first section using the average of \( N \) samples. The naive estimators of (1) and (2) with their leading order standard errors are

\[ \hat{f}(x) = \frac{1}{N\sqrt{\Delta t}} \sum_{n=1}^{N} Z_{n} f(x + \sqrt{\Delta t} Z_{n}), \quad \text{std} \approx \frac{|f(x)|}{\sqrt{\Delta t} \sqrt{N}}, \]

\[ \hat{f}''(x) = \frac{1}{N\Delta t} \sum_{n=1}^{N} (Z_{n}^2 - 1) f(x + \sqrt{\Delta t} Z_{n}), \quad \text{std} \approx \frac{\sqrt{2}|f(x)|}{\Delta t \sqrt{N}}, \]

where \( Z_{n} \) are independent standard normal random variables. Respectively, for \((1)^*\) and \((2)^*\) we have

\[ \hat{f}^*(x) = \frac{1}{N\sqrt{\Delta t}} \sum_{n=1}^{N} Z_{n} (f(x + \sqrt{\Delta t} Z_{n}) - f(x)), \quad \text{std} \approx \frac{\sqrt{2}|f'(x)|}{\sqrt{N}}, \]

\[ \hat{f}''^*(x) = \frac{1}{N\Delta t} \sum_{n=1}^{N} (Z_{n}^2 - 1)(f(x + \sqrt{\Delta t} Z_{n}) - f(x) - \sqrt{\Delta t} Z_{n} f'(x)), \quad \text{std} \approx \frac{\sqrt{27}|f''(x)|}{2 \sqrt{N}}. \]

In particular, if \( N \) is held constant and the time step \( \Delta t \) gets smaller, the naive estimates diverge whereas the standard errors of the new estimates do not to depend on \( \Delta t \). For example, if we chose \( \Delta t = 0.01 \) we would need 10 000 times more samples to get the same standard error for the naive estimate of \( f'' \), than what we would get by just using the new estimate. See Table 1.

Example 2 (Non-linear PDE). We used the four different BSDE schemes to solve the PDE

\[ u_t + \frac{1}{2} \Sigma^2 (u_{xx})^2 u_{xx} = 0, \quad u(x, T) = (x - 90)^+ - (x - 110)^+ \]

where \( \Sigma(x) = \sigma_{\min} 1_{x<0}(x) + \sigma_{\max} 1_{x\geq0}(x) \). The value \( u(100,0) \) corresponds to the maximum value of the call spread \( C_{09} - C_{110} \) in the uncertain volatility model (see [1,7]) with spot price 100, zero interest rate, 1 year time to maturity and volatility band \([\sigma_{\min}, \sigma_{\max}] = [0.1, 0.2] \).
Table 2
The results given by different methods with different time steps. The correct price is 11.20 and the asterisk means that the computation diverged.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Time step Δt</th>
<th>1/10</th>
<th>1/20</th>
<th>1/40</th>
<th>1/80</th>
<th>1/160</th>
<th>1/320</th>
<th>1/640</th>
</tr>
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<tr>
<td>Cheridito et al.</td>
<td>10.98</td>
<td>11.13</td>
<td>11.26</td>
<td>32.53</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td></td>
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<tr>
<td>Fahim et al.</td>
<td>10.98</td>
<td>11.18</td>
<td>11.68</td>
<td>18.48</td>
<td>41.12</td>
<td>*</td>
<td>*</td>
<td></td>
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<tr>
<td>Modified Cheridito et al.</td>
<td>10.97</td>
<td>11.07</td>
<td>11.18</td>
<td>11.22</td>
<td>11.21</td>
<td>11.21</td>
<td>11.27</td>
<td></td>
</tr>
<tr>
<td>Modified Fahim et al.</td>
<td>10.99</td>
<td>11.14</td>
<td>11.18</td>
<td>11.21</td>
<td>11.26</td>
<td>11.29</td>
<td>11.65</td>
<td></td>
</tr>
</tbody>
</table>

We generated 100,000 paths of the forward diffusion (geometric Brownian motion with zero drift and volatility 0.15). Conditional expectations were estimated using basis projections on 20 exponentials $e^{-x^2/100}$ centered equidistantly between the minimum and maximum values of the sample paths $X_{t_n}$ at each $t_n = nΔt$. The experiments were repeated with different time steps $Δt = (10 \cdot 2^i)^{-1}$, $i = 0, 1, \ldots, 6$.

The results are shown in Table 2. The original schemes only give sensible answers for large values of $Δt$ and diverge as $Δt$ gets smaller. This is to be expected since the variances of the sample points used in the estimation of the conditional expectations blow up as $Δt \to 0$. The modified versions behave much better for smaller time steps although eventually show divergence for small enough $Δt$. A larger number of sample paths would probably allow even smaller time steps to be used.

References