

Solving high-dimensional nonlinear partial differential equations and high-dimensional nonlinear backward stochastic differential equations using deep learning

What can data science contribute to stochastic analysis?

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Joint works with

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Introduction

Consider $T > 0$, $d \in \mathbb{N}$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ such that $u(T, x) = g(x)$, $u|_{[0, T) \times \mathbb{R}^d} \in C^{1,2}([0, T) \times \mathbb{R}^d, \mathbb{R})$, and

$$\frac{\partial u}{\partial t}(t, x) + \frac{1}{2}(\Delta_x u)(t, x) + f(u(t, x), (\nabla_x u)(t, x)) = 0. \quad (\text{PDE})$$

for $t \in [0, T)$, $x \in \mathbb{R}^d$. **Goal:** Solve (PDE) approximatively.

Applications: Pricing of financial derivatives,
portfolio optimization, operations research

Approximations methods such as finite element methods, finite differences, sparse grids, regression methods suffer under the curse of dimensionality.

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Deep BSDE solver

Consider probability space $(\Omega, \mathcal{F}, \mathbb{P})$, Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, normal filtration \mathbb{F} generated by W , continuous and adapted $Y: [0, T] \times \Omega \rightarrow \mathbb{R}$ and $Z: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ such that $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, Z_s) ds - \int_t^T \langle Z_s, dW_s \rangle_{\mathbb{R}^d}. \quad (\text{BSDE})$$

Under suitable assumptions (Pardoux & Peng 1990 ...) it holds $\forall t \in [0, T]$ \mathbb{P} -a.s.:

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We suggest that

$$\Lambda_1 \approx u(0, \xi).$$

Consider stochastic gradient descent-type approximations

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Numerical simulations

Implementations in PYTHON using TENSORFLOW
on a MACBOOK PRO 2.9 GHz (INTEL i5, 16 GB RAM)

Numerical simulations

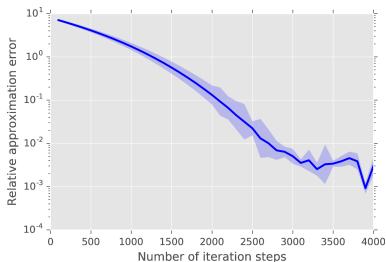
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100-dimensional Allen-Cahn equation

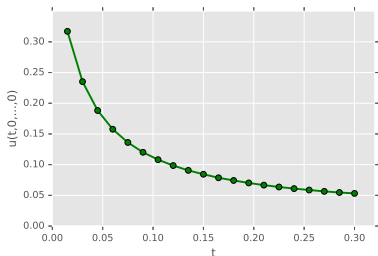
Consider

$$\frac{\partial u}{\partial t}(t, x) = (\Delta_x u)(t, x) + u(t, x) - [u(t, x)]^3 \quad (\text{Allen-Cahn})$$

with $u(0, x) = \frac{1}{(2+0.4\|x\|^2)}$ for $t \in [0, \frac{3}{10}]$, $x \in \mathbb{R}^{100}$.



(a) Relative L^1 -error for $u(\frac{3}{10}, 0) \approx 0.0528$



(b) Approximative plot of $u(t, 0)$, $0 \leq t \leq \frac{3}{10}$

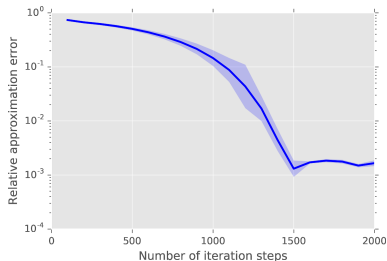
Deep BSDE solver ($N = 20$, $\gamma = \frac{5}{10000}$): L^1 -error: 0.3%, Runtime: 647 seconds.

100-dimensional Hamiltonian-Jacobi-Bellmann equation

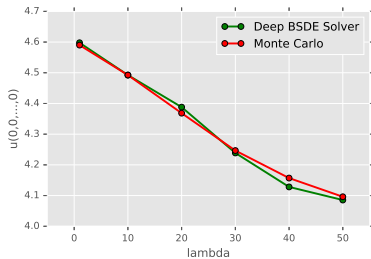
Consider

$$\frac{\partial u}{\partial t}(t, x) + (\Delta u_x)(t, x) - \lambda \|(\nabla_x u)(t, x)\|^2 = 0 \quad (\text{HJB})$$

with $u(1, x) = \frac{2}{(1+\|x\|^2)}$, $\lambda \geq 0$ for $t \in [0, 1]$, $x \in \mathbb{R}^{100}$.



(a) Relative L^1 -error when $\lambda = 1$



(b) Optimal cost against different λ

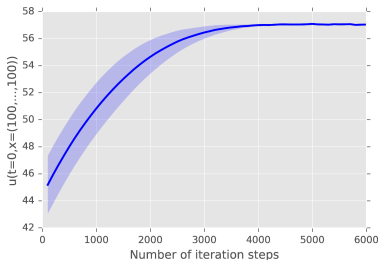
Deep BSDE solver ($N = 20$, $\gamma = \frac{1}{100}$): L^1 -error: 0.17%, Runtime: 330 seconds.

100-dimensional nonlinear derivative pricing model

Duffie, Schroder, & Skiadas 1996 AAP, Bender, Schweizer, & Zhuo 2015 MF:

$$\frac{\partial u}{\partial t}(t, x) + \bar{\mu} \langle x, (\nabla_x u)(t, x) \rangle_{\mathbb{R}^d} + \frac{\bar{\sigma}^2}{2} \sum_{i=1}^d |x_i|^2 \frac{\partial^2 u}{\partial x_i^2}(t, x) - Q(u(t, x)) u(t, x) - Ru(t, x)$$

with $u(1, x) = \min\{x_1, \dots, x_{100}\}$, $\bar{\mu} = 0.02$, $\bar{\sigma} = 0.2$ for $t \in [0, 1]$, $x \in \mathbb{R}^{100}$.



(a) Relative L^1 -error for $u(0, 100, \dots) \approx 57.3$

Deep BSDE solver ($N = 40$, $\gamma = \frac{8}{1000}$): L^1 -error: 0.46%, Runtime: 617 seconds.

Numerics for forward stochastic differential equations

Let $T \in (0, \infty)$, $d \in \{2, 3, 4, \dots\}$, $\xi \in \mathbb{R}^d$, $(a_N)_{N \in \mathbb{N}} \subseteq \mathbb{R}$ satisfy $\lim_{N \rightarrow \infty} a_N = 0$. Then there exist **globally bounded** $\mu, \sigma \in C^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

$$\frac{\partial}{\partial t} X_t = \mu(X_t) + \sigma(X_t) \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi,$$

and every $N \in \mathbb{N}$ we have

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- **Dimension** $d \geq 4$ and **Euler scheme**: Hairer, Hutzenthaler, & J 2015 AOP
- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA (to appear)
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (minor revision))

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Theorem (Heffer & J 2017)

Let $T, \delta, \beta \in (0, \infty)$, $\gamma, \xi \in [0, \infty)$, let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space, let $W: [0, T] \times \Omega \rightarrow \mathbb{R}$ be a Brownian motion, let $X: [0, T] \times \Omega \rightarrow \mathbb{R}$ be a solution of

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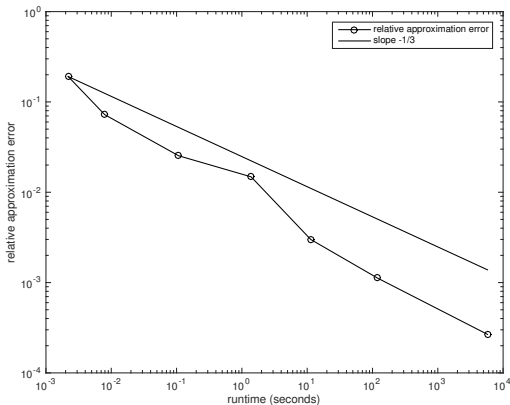
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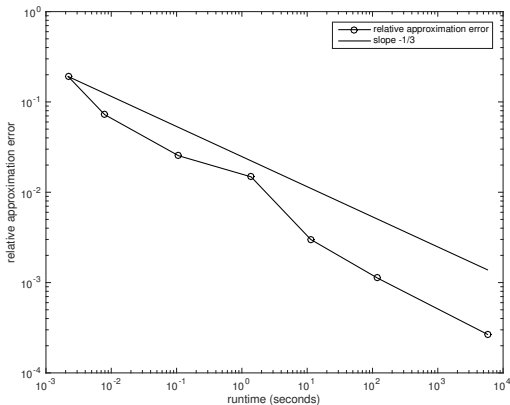
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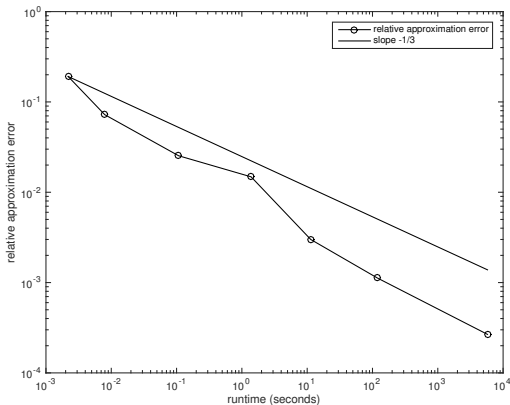
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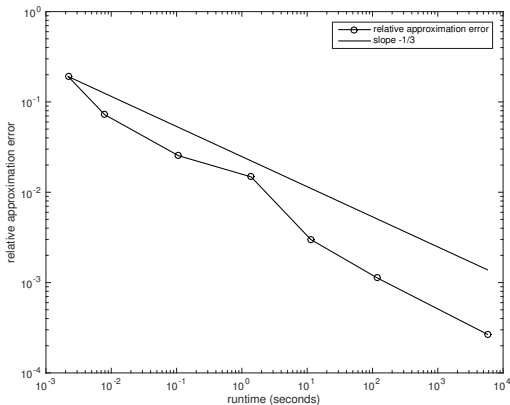
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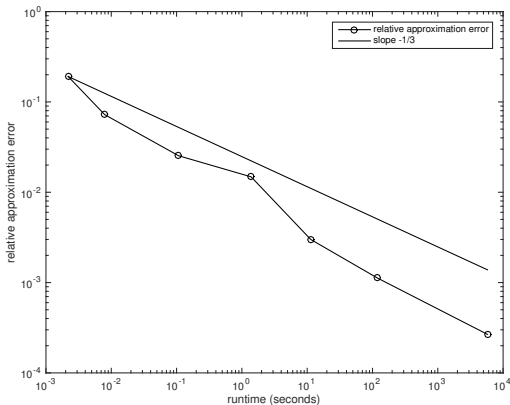
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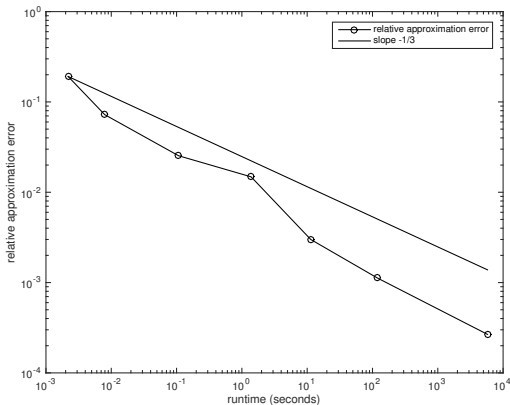
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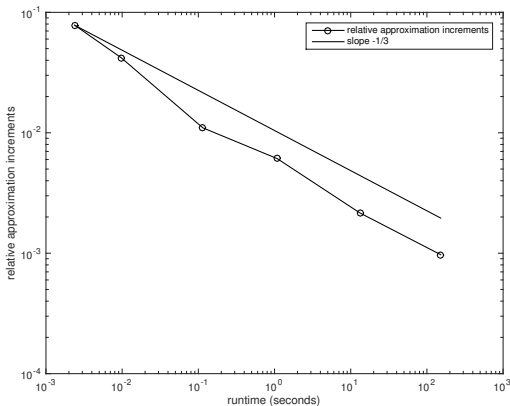
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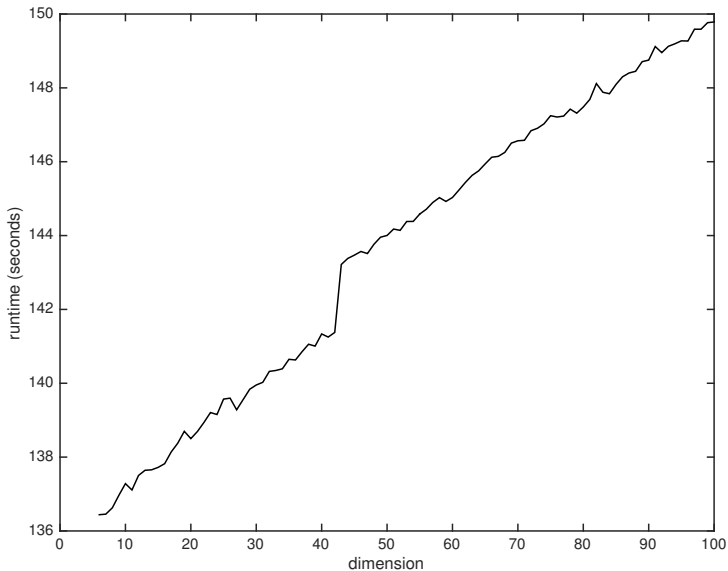
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for $(t, x) \in [0, T) \times \mathbb{R}^d$. $\left[\frac{1}{10} \sum_{i=1}^{10} |u_{\rho+1, \rho+1}^i(0, \xi) - u_{\rho, \rho}^i(0, \xi)| \right] / \left[\frac{1}{10} \sum_{i=1}^{10} u_{7,7}^i(0, \xi) \right]$ for $\rho \in \{1, 2, \dots, 6\}$ against runtime; $u(0, \xi) \approx 58.113$.



Pricing with default risk Runtime for one realization
of $\mathbf{U}_{6.6}^1(0, \xi)$ against dimension $d \in \{5, 6, \dots, 100\}$.



Pricing with default risk (Duffie, Schroder, & Skiadas 1996 AAP, Bender, Schweizer, & Zhuo 2015 MF)

Consider $\delta = \frac{2}{3}$, $R = \frac{2}{100}$, $\gamma^h = \frac{2}{10}$, $\gamma^l = \frac{2}{100}$, $\bar{\mu} = \frac{2}{100}$, $\bar{\sigma} = \frac{2}{10}$, $v^h, v^l \in (0, \infty)$ satisfy $v^h < v^l$, and assume for all $x \in \mathbb{R}^d$, $y \in \mathbb{R}$ that

$$\mu(x) = \bar{\mu}x, \quad \sigma(x) = \bar{\sigma} \text{diag}(x),$$

and

$$f(x, y) = -(1 - \delta) y \left[\gamma^h \mathbb{1}_{(-\infty, v^h)}(y) + \gamma^l \mathbb{1}_{[v^l, \infty)}(y) \right. \\ \left. + \left[\frac{(\gamma^h - \gamma^l)}{(v^h - v^l)} (y - v^h) + \gamma^h \right] \mathbb{1}_{[v^h, v^l)}(y) \right] - Ry.$$

- We consider $v^h = 50$, $v^l = 120$ in the case $d = 1$.
- Bender et al. consider $v^h = 54$, $v^l = 90$ in the case $d = 5$.
- We consider $v^h = 47$, $v^l = 65$ in the case $d = 100$.