

On deep learning based approximation algorithms for partial differential equations

Arnulf Jentzen (ETH Zurich, Switzerland)

Joint works with

Weinan E (Beijing Institute of Big Data Research, China,
Princeton University, USA, & Beijing University, China),

Máté Gerencér (IST Austria, Austria),

Jiequn Han (Princeton University, USA),

Martin Hairer (University of Warwick, UK),

Mario Hefter (University of Kaiserslautern, Germany),

Martin Hutzenthaler (University of Duisburg-Essen, Germany),

Thomas Kruse (University of Duisburg-Essen, Germany),

Thomas Müller-Gronbach (University of Passau, Germany),

Diyora Saliomva (ETH Zurich, Switzerland), and

Larisa Yaroslavtseva (University of Passau, Germany)

5th NUS-USPC Workshop on Machine Learning and FinTech, AmphiBuffon,
University Paris Diderot, France, Buffon Lecture Hall, 15 rue Hélène Brion, 75013 Paris

November 30, 2017

Introduction

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Consider

$$\frac{\partial u}{\partial t}(t, x) + f(x, u(t, x), (\nabla_x u)(t, x), (\text{Hess}_x u)(t, x)) = 0 \quad (\text{PDE})$$

and $u(T, x) = g(x)$ for $t \in [0, T]$, $x \in \mathbb{R}^d$ where $T > 0$, $d \in \mathbb{N}$,
 $f: \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $u \in C([0, T] \times \mathbb{R}^d, \mathbb{R})$ satisfies
 $u|_{[0, T] \times \mathbb{R}^d} \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$. **Goal:** Solve (PDE) approximatively.

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

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

Linear PDEs

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist **globally bounded** $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist **globally bounded** $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(Euler-Maruyama approximations), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ 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

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

Theorem (Hairer, Hutzenthaler, & J 2015 AOP)

Let $T \in (0, \infty)$, $d \in \{4, 5, \dots\}$, $\xi \in \mathbb{R}^d$. Then there exist *globally bounded* $\mu, \sigma \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ such that for every probability space $(\Omega, \mathcal{F}, \mathbb{P})$, every Brownian motion $W: [0, T] \times \Omega \rightarrow \mathbb{R}$, every solution $X: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ of

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

every $Y^N: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$, $N \in \mathbb{N}$, with $\forall N \in \mathbb{N}, n \in \{0, 1, \dots, N-1\}: Y_0^N = X_0$ and

$$Y_{n+1}^N = Y_n^N + \mu(Y_n^N) \frac{T}{N} + \sigma(Y_n^N) (W_{\frac{(n+1)T}{N}} - W_{\frac{nT}{N}})$$

(*Euler-Maruyama approximations*), and every $\alpha \in [0, \infty)$ we have

$$\lim_{N \rightarrow \infty} (N^\alpha \|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|) = \begin{cases} 0 & : \alpha = 0 \\ \infty & : \alpha > 0 \end{cases}.$$

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension $d \geq 4$:** J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and $d \geq 4$:** Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and $d \geq 4$:** Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and $d \geq 7$:** Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- Dimension $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- Weak convergence and $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- Adaptive approximations and $d \geq 4$: Yaroslavtseva 2016 JoC
- At most polynomially growing derivatives and $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\left\| X_T - u(W_{s_1}, \dots, W_{s_N}) \right\| \right] \geq a_N.$$

- **Dimension $d \geq 4$:** J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and $d \geq 4$:** Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and $d \geq 4$:** Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and $d \geq 7$:** Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

Theorem (Gerencsér, J, & Salimova 2017 PRSL A (to appear))

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

$$\inf_{s_1, \dots, s_N \in [0, T]} \inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R}^d \\ \text{measurable}}} \mathbb{E} \left[\|X_T - u(W_{s_1}, \dots, W_{s_N})\| \right] \geq a_N.$$

- **Dimension** $d \geq 4$: J, Müller-Gronbach & Yaroslavtseva 2016 CMS
- **Weak convergence and** $d \geq 4$: Müller-Gronbach & Yaroslavtseva 2016 SAA
- **Adaptive approximations and** $d \geq 4$: Yaroslavtseva 2016 JoC
- **At most polynomially growing derivatives and** $d \geq 7$: Müller-Gronbach & Yaroslavtseva 2017

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

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

$$\frac{\partial}{\partial t} X_t = (\delta - \gamma X_t) + \beta \sqrt{X_t} \frac{\partial}{\partial t} W_t, \quad t \in [0, T], \quad X_0 = \xi.$$

Then there exists a $c \in (0, \infty)$ such that for all $N \in \mathbb{N}$ we have

$$\inf_{\substack{u: \mathbb{R}^N \rightarrow \mathbb{R} \\ \text{measurable}}} \mathbb{E} \left[\left| X_T - u \left(W_{\frac{T}{N}}, W_{\frac{2T}{N}}, \dots, W_T \right) \right| \right] \geq c \cdot N^{-\min\{1, \frac{2\delta}{\beta^2}\}}.$$

Nonlinear PDEs: Deep (2)BSDE method

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T] \mathbb{P}$ -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T] \mathbb{P}$ -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T] \mathbb{P}$ -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

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.:

$$Y_t = u(t, \xi + W_t) \in \mathbb{R} \quad \text{and} \quad Z_t = (\nabla_x u)(t, \xi + W_t) \in \mathbb{R}^d.$$

Hence, $\forall t \in [0, T]$ \mathbb{P} -a.s.:

$$Y_t = g(\xi + W_T) + \int_t^T f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds - \int_t^T \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

In particular, $\forall t_1, t_2 \in [0, T]$ with $t_1 \leq t_2$ it holds \mathbb{P} -a.s. that

$$Y_{t_2} = Y_{t_1} - \int_{t_1}^{t_2} f(Y_s, (\nabla_x u)(s, \xi + W_s)) ds + \int_{t_1}^{t_2} \langle (\nabla_x u)(s, \xi + W_s), dW_s \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta, v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta, v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta, 1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta, 1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta, 1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{Y}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{Y}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{Y}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{Y}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{Y}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{Y}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{Y}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{Y}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{Y}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{Y}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{Y}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{Y}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $N \in \mathbb{N}$ and $0 = t_0 < t_1 < \dots < t_N = T$ and observe that

$$Y_{t_{n+1}} \approx$$

$$Y_{t_n} - f(Y_{t_n}, (\nabla_x u)(t_n, \xi + W_{t_n})) (t_{n+1} - t_n) + \langle (\nabla_x u)(t_n, \xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

Consider $\rho = 1 + 3Nd(d+1)$, let $\mathcal{R}: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy $\forall x = (x_1, \dots, x_d)$:

$$\mathcal{R}(x) = (\max\{x_1, 0\}, \dots, \max\{x_d, 0\}),$$

$\forall \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$, $v \in \mathbb{N}_0$, $k, l \in \mathbb{N}$ with $v + k(l+1) \leq \rho$ let

$A_{k,l}^{\theta,v}: \mathbb{R}^l \rightarrow \mathbb{R}^k$ satisfy $\forall x = (x_1, \dots, x_l)$:

$$A_{k,l}^{\theta,v}(x) = \begin{pmatrix} \theta_{v+1} & \theta_{v+2} & \dots & \theta_{v+l} \\ \theta_{v+l+1} & \theta_{v+l+2} & \dots & \theta_{v+2l} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{v+(k-1)l+1} & \theta_{v+(k-1)l+2} & \dots & \theta_{v+kl} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{pmatrix} + \begin{pmatrix} \theta_{v+kl+1} \\ \theta_{v+kl+2} \\ \vdots \\ \theta_{v+kl+k} \end{pmatrix},$$

$\forall \theta \in \mathbb{R}^\rho$, $n \in \{0, 1, \dots, N\}$ let $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$ satisfy

$$\mathcal{V}_n^\theta = A_{d,d}^{\theta,1+3nd(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+1)d(d+1)} \circ \mathcal{R} \circ A_{d,d}^{\theta,1+(3n+2)d(d+1)}$$

and $\forall \theta \in \mathbb{R}^\rho$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

$\forall \theta \in \mathbb{R}^p$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

We suggest to minimize

$$\mathbb{R}^p \ni \theta \mapsto \mathbb{E}[|\mathcal{Y}_N^\theta - g(\xi + W_T)|^2] \in [0, \infty]. \quad (\text{Optimization problem})$$

Consider stochastic gradient descent-type approximations

$$\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^p$$

associated to (Optimization problem). We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that

$$\Theta_m^{(1)} \approx u(0, \xi). \quad (\text{Deep BSDE method})$$

$\forall \theta \in \mathbb{R}^p$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

We suggest to minimize

$$\mathbb{R}^p \ni \theta \mapsto \mathbb{E}[|\mathcal{Y}_N^\theta - g(\xi + W_T)|^2] \in [0, \infty]. \quad (\text{Optimization problem})$$

Consider stochastic gradient descent-type approximations

$$\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^p$$

associated to (Optimization problem). We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that

$$\Theta_m^{(1)} \approx u(0, \xi). \quad (\text{Deep BSDE method})$$

$\forall \theta \in \mathbb{R}^p$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

We suggest to minimize

$$\mathbb{R}^p \ni \theta \mapsto \mathbb{E}[|\mathcal{Y}_N^\theta - g(\xi + W_T)|^2] \in [0, \infty]. \quad (\text{Optimization problem})$$

Consider stochastic gradient descent-type approximations

$$\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^p$$

associated to (Optimization problem). We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that

$$\Theta_m^{(1)} \approx u(0, \xi). \quad (\text{Deep BSDE method})$$

$\forall \theta \in \mathbb{R}^p$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

We suggest to minimize

$$\mathbb{R}^p \ni \theta \mapsto \mathbb{E}[|\mathcal{Y}_N^\theta - g(\xi + W_T)|^2] \in [0, \infty]. \quad (\text{Optimization problem})$$

Consider stochastic gradient descent-type approximations

$$\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^p$$

associated to (Optimization problem). We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that

$$\Theta_m^{(1)} \approx u(0, \xi). \quad (\text{Deep BSDE method})$$

$\forall \theta \in \mathbb{R}^p$ let $\mathcal{Y}^\theta: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}$ satisfy $\mathcal{Y}_0^\theta = \theta_1$ and

$$\mathcal{Y}_{n+1}^\theta = \mathcal{Y}_n^\theta - f(\mathcal{Y}_n^\theta, \mathcal{V}_n^\theta(\xi + W_{t_n})) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}), W_{t_{n+1}} - W_{t_n} \rangle_{\mathbb{R}^d}.$$

We suggest to minimize

$$\mathbb{R}^p \ni \theta \mapsto \mathbb{E}[|\mathcal{Y}_N^\theta - g(\xi + W_T)|^2] \in [0, \infty]. \quad (\text{Optimization problem})$$

Consider stochastic gradient descent-type approximations

$$\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^p$$

associated to (Optimization problem). We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that

$$\Theta_m^{(1)} \approx u(0, \xi). \quad (\text{Deep BSDE method})$$

Consider $T, \gamma > 0, d, \rho, N \in \mathbb{N}, \xi \in \mathbb{R}^d, f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}, g: \mathbb{R}^d \rightarrow \mathbb{R}, 0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d, m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d, \theta \in \mathbb{R}^\rho, 0 \leq n \leq N$, for every $m \in \mathbb{N}_0, \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0, d, \rho, N \in \mathbb{N}, \xi \in \mathbb{R}^d, f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}, g: \mathbb{R}^d \rightarrow \mathbb{R}, 0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d, m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d, \theta \in \mathbb{R}^\rho, 0 \leq n \leq N$, for every $m \in \mathbb{N}_0, \theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$, $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$, $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$, $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$, $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
 motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Consider $T, \gamma > 0$, $d, \rho, N \in \mathbb{N}$, $\xi \in \mathbb{R}^d$, $f: \mathbb{R} \times \mathbb{R}^d \rightarrow \mathbb{R}$, $g: \mathbb{R}^d \rightarrow \mathbb{R}$,
 $0 = t_0 < t_1 < \dots < t_N = T$, probability space $(\Omega, \mathcal{F}, \mathbb{P})$, independent Brownian
motions $W^m: [0, T] \times \Omega \rightarrow \mathbb{R}^d$, $m \in \mathbb{N}_0$, functions $\mathcal{V}_n^\theta: \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\theta \in \mathbb{R}^\rho$,
 $0 \leq n \leq N$, for every $m \in \mathbb{N}_0$, $\theta = (\theta_1, \dots, \theta_\rho) \in \mathbb{R}^\rho$ a function
 $\mathcal{Y}^{\theta, m}: \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^k$ satisfying $\mathcal{Y}_0^{\theta, m} = \theta_1$ and $\forall n = 0, 1, \dots, N-1$:

$$\mathcal{Y}_{n+1}^{\theta, m} = \mathcal{Y}_n^{\theta, m} - f(\mathcal{Y}_n^{\theta, m}, \mathcal{V}_n^\theta(\xi + W_{t_n}^m)) (t_{n+1} - t_n) + \langle \mathcal{V}_n^\theta(\xi + W_{t_n}^m), W_{t_{n+1}}^m - W_{t_n}^m \rangle_{\mathbb{R}^d},$$

for every $m \in \mathbb{N}_0$ a function $\phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}$ satisfying

$$\forall \theta \in \mathbb{R}^\rho: \quad \phi^m(\theta) = |\mathcal{Y}_N^{\theta, m} - g(\xi + W_T^m)|^2,$$

for every $m \in \mathbb{N}_0$ a function $\Phi^m: \mathbb{R}^\rho \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall \theta \in \mathbb{R}^\rho, \omega \in \Omega: \quad \Phi^m(\theta, \omega) = (\nabla_\theta \phi^m)(\theta, \omega),$$

and $\Theta = (\Theta^{(1)}, \dots, \Theta^{(\rho)}): \mathbb{N}_0 \times \Omega \rightarrow \mathbb{R}^\rho$ satisfying

$$\forall m \in \mathbb{N}: \quad \Theta_m = \Theta_{m-1} - \gamma \cdot \Phi^m(\Theta_{m-1}).$$

We suggest for sufficiently large $N, \rho, m \in \mathbb{N}$ that $\Theta_m^{(1)} \approx u(0, \xi)$.

Numerical simulations

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

Numerical simulations

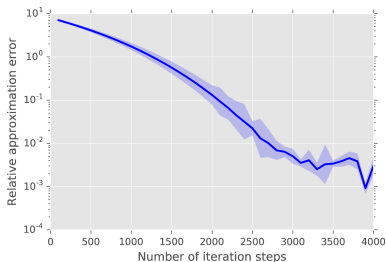
Implementations in PYTHON using TENSORFLOW
on a MACBOOK PRO 2.9 GHz (INTEL i5, 16 GB RAM)

100-dimensional Allen-Cahn equation

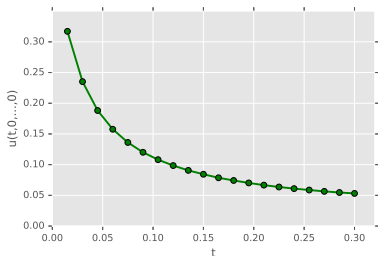
Consider

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

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 $u(t, 0)$, $0 \leq t \leq \frac{3}{10}$

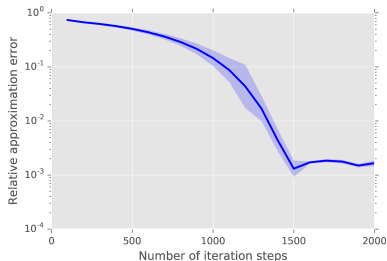
Deep BSDE method ($N = 20$, $\gamma = \frac{5}{10000}$): L^1 -error: 0.3%, Runtime: 647 seconds.

100-dimensional Hamiltonian-Jacobi-Bellman equation

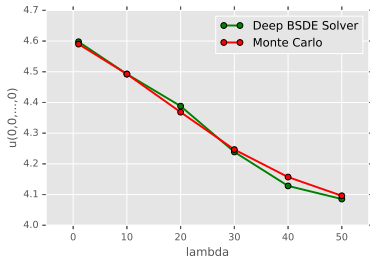
Consider

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

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

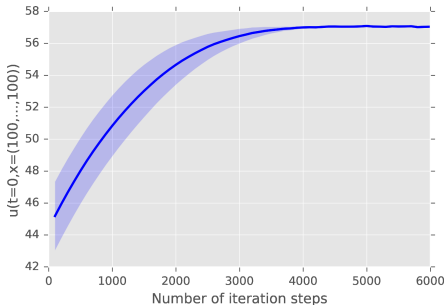
Deep BSDE method ($N = 20$, $\gamma = \frac{1}{100}$): L^1 -error: 0.17%, Runtime: 330 seconds.

100-dimensional pricing model incorporating default risk

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

$$\frac{\partial u}{\partial t}(t, x) + \bar{\mu} \langle x, (\nabla_x u)(t, x) \rangle_{\mathbb{R}^d} + \frac{\bar{\sigma}^2}{2} \sum_{i=1}^d |x_i|^2 \frac{\partial^2 u}{\partial x_i^2}(t, x) - Q(u(t, x)) u(t, x) - R u(t, x) = 0$$

with $u(1, x) = \min_{1 \leq j \leq 100} x_j$, $\bar{\mu} = R = 2\%$, $\bar{\sigma} = 20\%$ for $t \in [0, 1]$, $x \in \mathbb{R}^{100}$.



Approximations for $u(0, 100, \dots, 100) \approx 57.3$ (default risk excluded: ≈ 60.8)

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

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

Thanks for your attention!

Fully-nonlinear PDEs:

- A 100-dimensional Black-Scholes-Barenblatt equation
- Nonlinear expectations of G -Brownian motions in 1 and 100 space-dimensions

All source codes available on GITHUB or ARXIV:

- E, Han, & J, *Deep learning-based numerical methods for high-dimensional parabolic partial differential equations and backward stochastic differential equations*. arXiv 2017. *Comm. Math. Stat.* (2017)
- Han, J, & E, *Overcoming the curse of dimensionality: Solving high-dimensional partial differential equations using deep learning*. arXiv 2017.
- Beck, E, & J, *Machine learning approximation algorithms for high-dimensional fully nonlinear partial differential equations and second-order backward stochastic differential equations*. arXiv 2017.

Outlook: Other PDEs and Proofs!

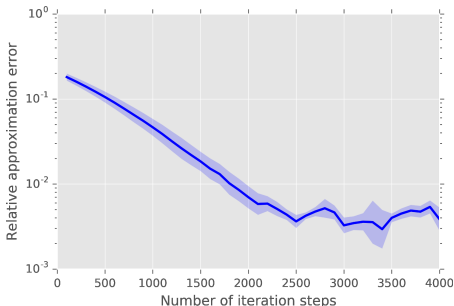
Thanks for your attention!

100-dimensional pricing model with different interest rates (Bergman 1995)

Consider $\bar{\sigma} = 20\%$, $R^l = 4\%$, $R^b = 6\%$ and for $t \in [0, 1/2]$, $x \in \mathbb{R}^{100}$:

$$\frac{\partial u}{\partial t} + \frac{\bar{\sigma}^2}{2} \sum_{i=1}^d |x_i|^2 \frac{\partial^2 u}{\partial x_i^2} - \min \left\{ R^b \left(u - \sum_{i=1}^d x_i \frac{\partial u}{\partial x_i} \right), R^l \left(u - \sum_{i=1}^d x_i \frac{\partial u}{\partial x_i} \right) \right\} = 0$$

with $u(1/2, x) = \max\{[\max_i x_i] - 120, 0\} - 2 \max\{[\max_i x_i] - 150, 0\}$.



Relative L^1 -error for $u(0, 100, \dots, 100) \approx 21.299$

Deep BSDE method ($N = 20$, $\gamma = \frac{1}{200}$): L^1 -error: 0.39%, Runtime: 566 seconds.

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

Consider $\delta = \frac{2}{3}$, $\gamma^h = \frac{2}{10}$, $\gamma^l = \frac{2}{100}$, $v^h, v^l \in (0, \infty)$ satisfying $v^h < v^l$ and

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

- Bender et al. consider $v^h = 54$, $v^l = 90$ in the case $d = 5$.
- We consider $v^h = 50$, $v^l = 70$ in the case $d = 100$.

Plot of $\|\mathbb{E}[X_T] - \mathbb{E}[Y_N^N]\|$ for $T = 2$ and $N \in \{2^1, 2^2, \dots, 2^{30}\}$.

