

Convergence of the Markovian iteration for coupled FBSDEs via a differentiation approach

Zhipeng Huang¹ Cornelis W. Oosterlee¹

¹Mathematical Institute, Utrecht University

Thanks Balint Negyesi for fruitful discussions.

The 22nd Winter school on Mathematical Finance,
Soesterberg, The Netherlands.

Outline

- 1 Background
- 2 The Markovian iteration for coupled FBSDEs
- 3 Generalize the Markovian iteration to FBSDEs with Y and Z coupling
- 4 Numerical Examples

Background

Motivations

- FBSDEs have various applications in finance
 - ▶ coupled FBSDE: stochastic control problem depends on the ways of coupling
 - decoupled FBSDE: option pricing, hedging, etc.
 - non-standard FBSDE: mean-field game/control, optimal stopping, etc.
- Difficult to find an analytical solution in general
 - ▶ numerical method is needed

Forward-backward stochastic differential equation

An "almost" fully coupled FBSDE is given by

$$\begin{cases} X_t = x_0 + \int_0^t b(s, X_s, Y_s, Z_s) ds + \int_0^t \sigma(s, X_s, Y_s) dW_s, \\ Y_t = g(X_T) + \int_t^T f(s, X_s, Y_s, Z_s) ds - \int_t^T Z_s dW_s, \end{cases} \quad (1)$$

where the solution is a triple of $(\mathbb{R}^d \times \mathbb{R}^q \times \mathbb{R}^{q \times m})$ valued, \mathcal{F}_t adapted stochastic processes $\{(X_t, Y_t, Z_t)\}_{0 \leq t \leq T}$ solve above almost surely and satisfy natural integrability conditions.

Other classes of FBSDEs:

- Decoupled FBSDE: $b \equiv b(t, X_t)$ and $\sigma \equiv \sigma(t, X_t)$
- Coupled FBSDE through Y : $b \equiv b(t, X_t, Y_t)$ and $\sigma \equiv \sigma(t, X_t, Y_t)$
- Fully coupled FBSDE: $b \equiv b(t, X_t, Y_t, Z_t)$ and $\sigma \equiv \sigma(t, X_t, Y_t, Z_t)$

Connection with PDEs: Feynman-Kac formula

The FBSDE (1) is associated with the following system of quasi-linear parabolic PDEs,

$$\begin{cases} \partial_t u^i + \frac{1}{2} \partial_{xx} u^i : \sigma \sigma^\top(t, x, u) + \partial_x u^i b(t, x, u, \partial_x u \sigma(t, x, u)) \\ \quad + f^i(t, x, u, \partial_x u \sigma(t, x, u)) = 0, \quad \forall i = 1, \dots, q, \\ u(T, x) = g(x). \end{cases}$$

Under suitable regularity assumptions on b , σ , f and g , one can show that the solutions are connected by non-linear Feynman-Kac formula

$$Y_t = u(t, X_t), \quad Z_t = \partial_x u(t, X_t) \sigma(t, X_t, u(t, X_t)) := v(t, X_t)$$

\Rightarrow The functions u and v are called decoupling fields in the context of FBSDE.

The Backward Euler Scheme for BSDE

Consider a decoupled FBSDE case, i.e. $b(t, X_t)$ and $\sigma(t, X_t)$.

The Backward Euler scheme is given by

- ▶ Step 1: Sampling X_i^π for all i in a forward fashion;
- ▶ Step 2: For $i = N$, set $(Y_N^\pi, Z_N^\pi) = (g(X_N^\pi), 0)$
- ▶ Step 3: For $i = N - 1, N - 2, \dots, 0$, compute

$$\begin{cases} Z_i^\pi = E_{t_i} (h^{-1} Y_{i+1}^\pi \Delta W_i) \\ Y_i^\pi = E_{t_i} (Y_{i+1}^\pi + hf(X_i^\pi, Y_{i+1}^\pi, Z_i^\pi)) \end{cases}$$

- To compute the conditional expectations, use L^2 projections properties and set up optimization problems,

$$Z_i^\pi = \arg \min_z E[(h^{-1} Y_{i+1}^\pi \Delta W_i - z)^2]$$

$$Y_i^\pi = \arg \min_y E[(Y_{i+1}^\pi + hf(X_i^\pi, Y_{i+1}^\pi, Z_i^\pi) - y)^2]$$

The Backward Euler Scheme

What if the forward SDE of X couples with Y and Z ?

The Markovian iteration for coupled FBSDEs

Markovian iteration for FBSDEs with Y coupling

Let m be the number of iterations. Set $u_i^{\pi,0}(\cdot) = 0$, $v_i^{\pi,0}(\cdot) = 0$, and $X_0^{\pi,m} \triangleq x_0$ for all m . Bender et al. 2008 Introduced the following scheme,

$$\left\{ \begin{array}{l} X_{i+1}^{\pi,m} = X_i^{\pi,m} + b(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))h \\ \quad + \sigma(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))\Delta W_i, \\ Y_N^{\pi,m} = g(X_N^{\pi,m}), \\ Z_i^{\pi,m} = h^{-1}E_{t_i}(Y_{i+1}^{\pi,m} \Delta W_i), \quad v_i^{\pi,m}(X_i^{\pi,m}) = Z_i^{\pi,m} \\ Y_i^{\pi,m} = E_{t_i}(Y_{i+1}^{\pi,m} + f(t_i, X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m})h), \quad u_i^{\pi,m}(X_i^{\pi,m}) = Y_i^{\pi,m} \end{array} \right. \quad (2)$$

Markovian iteration for FBSDEs with Y coupling

Let m be the number of iterations. Set $u_i^{\pi,0}(\cdot) = 0$, $v_i^{\pi,0}(\cdot) = 0$, and $X_0^{\pi,m} \triangleq x_0$ for all m . Bender et al. 2008 Introduced the following scheme,

$$\begin{cases} X_{i+1}^{\pi,m} = X_i^{\pi,m} + b(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))h \\ \quad + \sigma(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))\Delta W_i, \\ Y_N^{\pi,m} = g(X_N^{\pi,m}), \\ Z_i^{\pi,m} = h^{-1}E_{t_i}(Y_{i+1}^{\pi,m} \Delta W_i), \quad v_i^{\pi,m}(X_i^{\pi,m}) = Z_i^{\pi,m} \\ Y_i^{\pi,m} = E_{t_i}(Y_{i+1}^{\pi,m} + f(t_i, X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m})h), \quad u_i^{\pi,m}(X_i^{\pi,m}) = Y_i^{\pi,m} \end{cases}$$

- We have the dependency:

$$Z_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}), \quad Y_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m}) \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m})$$

and due to the coupling in the SDE of X ,

$$Y_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m})$$

Markovian iteration for FBSDEs with Y coupling

Let m be the number of iterations. Set $u_i^{\pi,0}(\cdot) = 0$, $v_i^{\pi,0}(\cdot) = 0$, and $X_0^{\pi,m} \triangleq x_0$ for all m . Bender et al. 2008 Introduced the following scheme,

$$\begin{cases} X_{i+1}^{\pi,m} = X_i^{\pi,m} + b(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))h \\ \quad + \sigma(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))\Delta W_i, \\ Y_N^{\pi,m} = g(X_N^{\pi,m}), \\ Z_i^{\pi,m} = h^{-1}E_{t_i}(Y_{i+1}^{\pi,m} \Delta W_i), \quad v_i^{\pi,m}(X_i^{\pi,m}) = Z_i^{\pi,m} \\ Y_i^{\pi,m} = E_{t_i}(Y_{i+1}^{\pi,m} + f(t_i, X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m})h), \quad u_i^{\pi,m}(X_i^{\pi,m}) = Y_i^{\pi,m} \end{cases}$$

- We have the dependency:

$$Z_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}), \quad Y_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m}) \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m})$$

and due to the Y coupling in the SDE of X ,

$$Y_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m})$$

- **Good:** $Y^{\pi,m} \Rightarrow Y^{\pi,m-1} \Rightarrow \dots \Rightarrow Y^{\pi,0}$. Need to control the Lipschitz constant of $u_i^{\pi,m}$ over time steps i and iteration steps m

Existing convergence results

With the Lipschitz and Holder continuity assumptions, weak and monotonicity conditions, Bender et al. 2008 show that, for sufficiently small h

Theorem (Bender et al. 2008, Thm 5.1 and Thm 6.3)

There is an unique solution u^π to the discretized scheme (2) and there are constants $C > 0$ and $0 < c < 1$ such that

$$\max_{0 \leq i \leq N} |u_i^{\pi, m}(x) - u_i^\pi(x)|^2 \leq C (|x|^2 + m) c^m$$

and, the associated PDE admits a viscosity solution $u(t, x)$ and we have the estimate

$$\max_{0 \leq i \leq N} |u_i^\pi(x) - u(t_i, x)|^2 \leq C (1 + |x|^2) h$$

Existing convergence results

Consequently, an error estimate can be derived,

Theorem (Bender et al. 2008, Thm 6.5)

The continuous FBSDE with Y coupling has a unique solution (X, Y, Z) and there are constants $C > 0$ and $0 < c < 1$ such that, for sufficiently small h ,

$$\sup_{1 \leq i \leq N} E \left\{ \sup_{t \in [t_{i-1}, t_i]} (|X_t - X_{i-1}^{\pi, m}|^2 + |Y_t - Y_{i-1}^{\pi, m}|^2) \right\} + \sum_{i=1}^N E \left\{ \int_{t_{i-1}}^{t_i} |Z_t - Z_{i-1}^{\pi, m}|^2 dt \right\}$$

$$\leq C(1 + |x_0|^2)(mc^m + h)$$

Existing convergence results

Consequently, an error estimate can be derived,

Theorem (Bender et al. 2008, Thm 6.5)

The continuous FBSDE with Y coupling has a unique solution (X, Y, Z) and there are constants $C > 0$ and $0 < c < 1$ such that, for sufficiently small h ,

$$\sup_{1 \leq i \leq N} E \left\{ \sup_{t \in [t_{i-1}, t_i]} (|X_t - X_{i-1}^{\pi, m}|^2 + |Y_t - Y_{i-1}^{\pi, m}|^2) \right\} + \sum_{i=1}^N E \left\{ \int_{t_{i-1}}^{t_i} |Z_t - Z_{i-1}^{\pi, m}|^2 dt \right\}$$

$$\leq C(1 + |x_0|^2)(mc^m + h)$$

What if the forward SDE also couples with Z ?

A similar analysis for Z which is parallel with the Y coupled case?

Challenge: Intertwining of Y and Z

If in addition X also couples with Z ,

$$\left\{ \begin{array}{l} X_{i+1}^{\pi,m} = X_i^{\pi,m} + b(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}), v_i^{\pi,m-1}(X_i^{\pi,m}))h \\ \quad + \sigma(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))\Delta W_i, \\ Y_N^{\pi,m} = g(X_N^{\pi,m}), \\ Z_i^{\pi,m} = h^{-1}E_{t_i}(Y_{i+1}^{\pi,m}\Delta W_i), \quad v_i^{\pi,m}(X_i^{\pi,m}) = Z_i^{\pi,m} \\ Y_i^{\pi,m} = E_{t_i}(Y_{i+1}^{\pi,m} + f(t_i, X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m})h), \quad u_i^{\pi,m}(X_i^{\pi,m}) = Y_i^{\pi,m} \end{array} \right.$$

then through $X_i^{\pi,m}$ we have

$$\begin{aligned} Y_i^{\pi,m} &\Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Z_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m},) \\ Z_i^{\pi,m} &\Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Z_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m}) \end{aligned}$$

- $Y_i^{\pi,m}$ and $Z_i^{\pi,m}$ are intertwined over m and i ;
- Not easy to separate them such that $Y_i^{\pi,m}$ only depends on previous Y and $Z_i^{\pi,m}$ only depends on previous Z .

Challenge: Intertwining of Y and Z

If in addition X also couples with Z ,

$$\begin{cases} X_{i+1}^{\pi,m} = X_i^{\pi,m} + b(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}), v_i^{\pi,m-1}(X_i^{\pi,m}))h \\ \quad + \sigma(t_i, X_i^{\pi,m}, u_i^{\pi,m-1}(X_i^{\pi,m}))\Delta W_i, \\ Y_N^{\pi,m} = g(X_N^{\pi,m}), \\ Z_i^{\pi,m} = h^{-1}E_{t_i}(Y_{i+1}^{\pi,m}\Delta W_i), \quad v_i^{\pi,m}(X_i^{\pi,m}) = Z_i^{\pi,m} \\ Y_i^{\pi,m} = E_{t_i}(Y_{i+1}^{\pi,m} + f(t_i, X_i^{\pi,m}, Y_{i+1}^{\pi,m}, Z_i^{\pi,m})h), \quad u_i^{\pi,m}(X_i^{\pi,m}) = Y_i^{\pi,m} \end{cases}$$

then through $X_i^{\pi,m}$ we have

$$Y_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Z_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m},)$$

$$Z_i^{\pi,m} \Rightarrow (X_i^{\pi,m}, Y_{i+1}^{\pi,m}) \Rightarrow (X_{i-1}^{\pi,m}, Y_{i-1}^{\pi,m-1}, Z_{i-1}^{\pi,m-1}, Y_{i+1}^{\pi,m})$$

- $Y_i^{\pi,m}$ and $Z_i^{\pi,m}$ are intertwined over m and i ;
- Not easy to separate them such that $Y_i^{\pi,m}$ only depends on previous Y and $Z_i^{\pi,m}$ only depends on previous Z .

Why not combine them?

Generalize the Markovian iteration to FBSDEs with Y and Z coupling

Combining Y and Z : a differentiation approach

Construct $u_i^{\pi,m}$ as in Bender et al. 2008 and denote $L(u_i^{\pi,m})$ the Lipschitz constant.

Inspired by the Feynman-Kac formulas, we simply construct $v_i^{\pi,m}$ by

$$v_i^{\pi,m}(x) = \partial_x u_i^{\pi,m}(x) \sigma(t, x, u_i^{\pi,m}(x))$$

With this setting, we can show that, for some $C > 0$

$$|v_i^{\pi,m}(x_1) - v_i^{\pi,m}(x_2)|^2 \leq CL(u_i^{\pi,m})|x_1 - x_2|^2$$

- Obtain $v_i^{\pi,m}$ by direct computation;
- Controlling two "independent" and intertwined Lipschitz constants reduces to controlling one object.
- Convergence of $u_i^{\pi,m}$ leads to convergence of $v_i^{\pi,m}$

Convergence result: FBSDEs with Y and Z coupling

Let $b := b(t, X_t, Y_t, Z_t)$ and $\sigma := \sigma(t, X_t, Y_t)$, we can show that

Theorem 1 (Convergence for FBSDEs coupled with Y and Z)

In addition to the assumptions in Bender et al. 2008, if $u \in C_b^2$ and σ is bounded, with our differentiation setting there exist constants $C > 0$ and $0 < c < 1$ such that for sufficiently small h

$$\sup_{1 \leq i \leq N} E \left\{ \sup_{t \in [t_{i-1}, t_i]} (|X_t - X_{i-1}^{\pi, m}|^2 + |Y_t - Y_{i-1}^{\pi, m}|^2) \right\} + \sum_{i=1}^N E \left\{ \int_{t_{i-1}}^{t_i} |Z_t - Z_{i-1}^{\pi, m}|^2 dt \right\}$$

$$\leq C(1 + |x_0|^2)(mc^m + h)$$

- Proofs are based on a fixed-point argument, which naturally gives algorithm and the well-posedness of the discretized FBSDE
- Z -coupling \Rightarrow can treat FBSDEs formulated via dynamic programming

Combining Y and Z : a differentiation approach

Finally, recall that we still want to have the relations

$$\begin{cases} Z_i^\pi = E_{t_i} (h^{-1} Y_{i+1}^\pi \Delta W_i) \\ Y_i^\pi = E_{t_i} (Y_{i+1}^\pi + hf(X_i^\pi, Y_{i+1}^\pi, Z_i^\pi)) \end{cases}$$

\Rightarrow Reformulating the two regression problems into one, i.e. we solve

$$(Y_i^{\pi,m}, Z_i^{\pi,m}) = \arg \min_{y,z} E \left(|Y_{i+1}^{\pi,m} - (y - hf(X_i^{\pi,m}, Y_{i+1}^{\pi,m}, z) + z \Delta W_i)|^2 \right)$$

- Price to pay: a more complicated optimization problem
- Similar to the one used in Huré et al. 2020 for decoupled case, but we consider coupled FBSDEs and set f explicit in Y .

Numerical Examples

Implementation setting

- We approximate $u_i^{\pi,m}$ by basis functions and obtain $v_i^{\pi,m}$ by direct computation, i.e.

$$u_i^{\pi,m}(x) = \sum_k w_k \beta_k(x), \quad v_i^{\pi,m}(x) = \sum_k w_k \partial_x \beta_k(x) \sigma(t_i, x, u_i^{\pi,m}(x))$$

⇒ Could also use other function approximators, e.g. neural networks.

- Hyper-parameters: Basis functions, batch size, optimizer.
- The errors corresponding to the discretized equation are defined as:

$$\text{error}(X) := \max_{0 \leq n \leq N} E \left[\|X_{t_n}^{\pi} - X_{t_n}\|^2 \right], \quad \text{error}(Y) := \max_{0 \leq n \leq N} E \left[\|Y_{t_n}^{\pi} - Y_{t_n}\|^2 \right],$$

$$\text{error}(Z) := T/N \sum_{n=0}^{N-1} E \left[\|Z_{t_n}^{\pi} - Z_{t_n}\|^2 \right], \quad \text{total} = \text{error}(X) + \text{error}(Y) + \text{error}(Z).$$

Example 1: FBSDEs with Z coupling only

We adopt and modify a one-dimensional FBSDE example with a time-dependent solution from Ruijter et al. 2015,

$$b(t, x, y, z) = \kappa_z z + \kappa_b,$$

$$\sigma(t, x, y) = 1,$$

$$f(t, x, y, z) = yz - z + 2.5y - \sin(x + t) \cos(x + t) - 2 \sin(x + t) \\ - \cos(x + t) \kappa_z z - \cos(x + t) \kappa_b,$$

$$g(x) = \sin(x + T),$$

and the solution is given by

$$Y_t = \sin(X_t + t), \quad Z_t = \cos(X_t + t)$$

- ▶ FBSDE with Z coupling but no Y coupling in the forward SDE, which doesn't fall in the framework of Bender et al. 2008;
- ▶ But it falls in our analysis framework;

Example 1: FBSDEs with Z coupling only

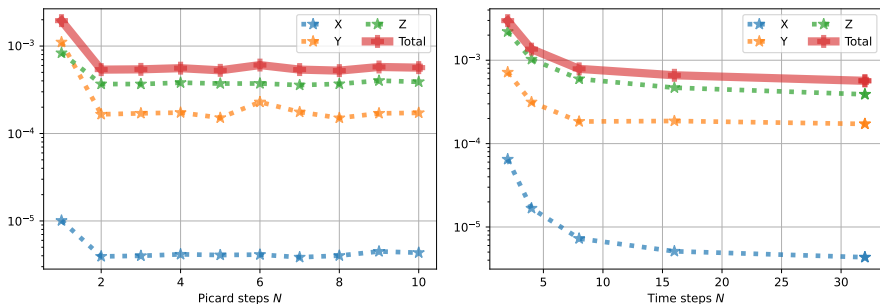


Figure: Example 1. **Left:** Errors versus Iteration steps. **Right:** Errors versus time steps. $T = 0.25, X_0 = 1$.

Example 2: An "almost" fully coupled FBSDE

We modify a coupled FBSDE originating from Bender et al. 2008, and obtain an "almost" fully coupled FBSDE:

$$b(t, x, y, z) = \kappa_y \bar{\sigma} y \mathbf{1}_d + \kappa_z z^\top, \quad \sigma(t, x, y) = \bar{\sigma} y \mathbf{1}_d, \quad g(x) = \sum_{i=1}^d \sin(x_i),$$

$$f(t, x, y, z) = -ry + 1/2 e^{-3r(T-t)} \bar{\sigma}^2 \left(\sum_{i=1}^d \sin(x_i) \right)^3 \\ - \kappa_y \sum_{i=1}^d z_i - \kappa_z \bar{\sigma} e^{-3r(T-t)} \sum_{i=1}^d \sin(x_i) \sum_{i=1}^d \cos^2(x_i),$$

with dimensions $q = 1, d = m = 4$. The solution to the BSDE is given by

$$y(t, x) = e^{-r(T-t)} \sum_{i=1}^d \sin(x_i), \quad z_i(t, x) = e^{-2r(T-t)} \bar{\sigma} \left(\sum_{j=1}^d \sin(x_j) \right) \cos(x_i).$$

- ▶ FBSDE with fully coupled drift and partial coupled diffusion;
- ▶ it satisfies the assumptions we need;

Example 2: An "almost" fully coupled FBSDE

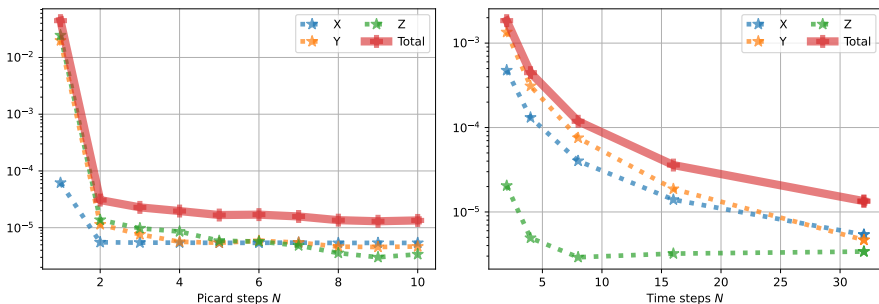


Figure: Example 2. **Left:** Errors versus Iteration steps. **Right:** Errors versus time steps. $T = 0.25, X_0 = (\pi/4, \dots, \pi/4)$.

Summary and conclusion

- We generalize the Markovian iteration by Bender et al. 2008 to FBSDEs with both Y and Z coupling via a differentiation setting.
- Convergence results are based on a fixed-point argument for the discretized scheme, which naturally gives the well-posedness and an algorithm.
- Enable the treatment of FBSDEs formulated via the dynamic programming.
- The numerical results have verified our theoretical findings.

End

Thanks for your attention!

This talk is based on a working paper (coming soon!):

[Zhipeng Huang, and Cornelis W. Oosterlee \(2024\)](#). Convergence of the Markovian iteration for coupled FBSDEs via a differentiation approach.

References

-  Bender, Christian and Jianfeng Zhang (Feb. 2008). “Time discretization and Markovian iteration for coupled FBSDEs”. In: *The Annals of Applied Probability* 18.1, pp. 143–177.
-  Huré, Côme, Huyên Pham, and Xavier Warin (2020). “Deep backward schemes for high-dimensional nonlinear PDEs”. In: *Mathematics of Computation* 89.324, pp. 1547–1579.
-  Ruijter, Marjon J and Cornelis W Oosterlee (2015). “A Fourier cosine method for an efficient computation of solutions to BSDEs”. In: *SIAM Journal on Scientific Computing* 37.2, A859–A889.
-  Negyesi, Balint, Zhipeng Huang, and Cornelis W. Oosterlee (2024). *Generalized convergence of the deep BSDE method: a step towards fully-coupled FBSDEs and applications in stochastic control*. arXiv: 2403.18552.
-  Reisinger, Christoph, Wolfgang Stockinger, and Yufei Zhang (Sept. 2023). “A posteriori error estimates for fully coupled McKean–Vlasov forward-backward SDEs”. In: *IMA Journal of Numerical Analysis*, drad060.