

Backward stochastic dynamics on a filtered probability space

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Backward stochastic differential equation (BSDE) revisited: Pardoux and Peng (1990)

- On a complete filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$:

$$\begin{cases} dY_t = -f(t, Y_t, Z_t)dt + Z_t dW_t, \\ Y_T = \xi \in \mathcal{F}_T. \end{cases} \quad (1)$$

- $\{\mathcal{F}_t\}_{t \geq 0}$ is generated by a Brownian motion W .
 - Constraint: Y is adapted to $\{\mathcal{F}_t\}_{t \geq 0}$.
 - A solution is a pair (Y, Z) .
- If $f(t, y, z)$ is Lipschitz continuous w.r.t. y and z , there exists a unique square-integrable solution pair $(Y, Z) \in \mathcal{S}([0, T]; R) \times \mathcal{H}^2([0, T]; R)$.
 - $\mathcal{S}([0, T]; R)$: the space of \mathcal{F}_t -adapted processes with the norm:

$$\|Y\|_{\mathcal{C}[0, T]} = \sqrt{E \sup_{t \in [0, T]} |Y_t|^2}$$

- $\mathcal{H}^2([0, T]; R)$: the space of predictable processes with the norm:

$$\|Z\|_{\mathcal{H}^2_{[0, T]}} = \sqrt{E \int_0^T |Z_s|^2 ds}$$



BSDE revisited: Pardoux and Peng (1990)

- (Y, Z) is a solution to BSDE (1) if

$$Y_t = \xi + \int_t^T f(s, Y_s, Z_s) ds - \int_t^T Z_s dW_s$$

- Idea of the proof:

- For any fixed $(Y(1), Z(1)) \in \mathcal{S}([0, T]; R) \times \mathcal{H}^2([0, T]; R)$, by the martingale representation,

$$Y_t = \xi + \int_t^T f(s, Y_s(1), Z_s(1)) ds - \int_t^T Z_s dW_s \quad (2)$$

admits a unique solution pair $(Y(2), Z(2))$.

- Define a mapping \mathbb{L} on $\mathcal{S}([0, T]; R) \times \mathcal{H}^2([0, T]; R)$ by the linear BSDE (2). \mathbb{L} is a contraction mapping.
- Martingale representation + contraction mapping. (they are coupled together.)



Potential method for nonlinear PDE

- On an open bounded subset Ω of R^d ,

$$\begin{cases} -\Delta u = f(u) & \text{in } \Omega, \\ u = g & \text{on } \partial\Omega. \end{cases} \quad (3)$$

- Potential method:

- For any fixed u in some appropriate space,

$$\begin{cases} -\Delta v = f(u) & \text{in } \Omega, \\ v = g & \text{on } \partial\Omega. \end{cases} \quad (4)$$

- The Green's representation:

$$\begin{aligned} v(x) &= \int_{\Omega} f(u(y))G_{\Omega}(x, y)dy - \int_{\partial\Omega} g(y)\frac{\partial G_{\Omega}}{\partial \vec{n}}(x, y)dS_y \\ &= G_{\Omega}\nu(x) + \int_{\partial\Omega} g(y)\mu_{\Omega}(x, dy) \end{aligned}$$

where $G_{\Omega}\nu$ is the potential of ν with $d\nu = f(u)dy$, and $\mu_{\Omega}(x, \cdot)$ is the harmonic measure relative to x with $\mu_{\Omega}(x, A) = -\int_A \frac{\partial G_{\Omega}}{\partial \vec{n}}(x, y)dS_y$.

- Define a mapping \mathbb{L} by the Poisson equation (4). \mathbb{L} is a contraction mapping.



Potential method for BSDE

- An analogy between superharmonic function and semimartingale:
 - Riesz decomposition:

$$\text{superharmonic function} = \text{potential} + \text{harmonic function}$$

- Doob-Meyer decomposition:

$$\text{semimartingale} = \text{finite variation process} + \text{martingale}$$

- **Lemma 1.** *If Y is a semimartingale on $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$, which satisfies the usual conditions, with a decomposition:*

$$Y_t = M_t - V_t \quad t \in [0, T]$$

where M is an \mathcal{F}_t -adapted martingale, and V is a continuous and \mathcal{F}_t -adapted finite variation process, then

$$M_t = E(Y_T + V_T | \mathcal{F}_t)$$

and

$$Y_t = E(Y_T + V_T | \mathcal{F}_t) - V_t.$$



Potential method for BSDE

- Given the terminal data $Y_T = \xi$ and the finite variation part V , there is an one-to-one correspondence:

$$(\xi, V) \rightarrow Y(\xi, V); \quad (\xi, V) \rightarrow M(\xi, V)$$

- If $\{\mathcal{F}_t\}_{t \geq 0}$ is generated by a Brownian motion W , by the martingale representation, there exists a density process $Z \in \mathcal{H}^2([0, T]; R)$ such that

$$\int_0^t Z(\xi, V)_s dW_s = E(\xi + V_T | \mathcal{F}_t) - E(\xi + V_T)$$

- Translate BSDE (1) into a functional differential equation:

$$V_t = \int_0^t f(s, Y(\xi, V)_s, Z(\xi, V)_s) ds \quad (5)$$

- Y is determined by $Y(\xi, V)_t = E(\xi + V_T | \mathcal{F}_t) - V_t$.
- Z is determined by

$$\int_0^t Z(\xi, V)_s dW_s = E(\xi + V_T | \mathcal{F}_t) - E(\xi + V_T).$$



Potential method for BSDE

- By the contraction mapping, the functional differential equation (5) admits a unique solution $V \in \mathcal{C}([0, T]; R)$.
 - $\mathcal{C}([0, T]; R)$: the space of continuous and \mathcal{F}_t -adapted finite variation processes with the norm:

$$\|V\|_{\mathcal{C}[0,T]} = \sqrt{E \sup_{t \in [0, T]} |V_t|^2}$$

- (Y, Z) satisfies BSDE (1):

$$Y_t = E(\xi + V_T | \mathcal{F}_t) - \int_0^t f(s, Y_s, Z_s) ds$$

i.e.

$$\begin{aligned} Y_t &= \xi + E(\xi + V_T | \mathcal{F}_t) - (\xi + V_T) + \int_t^T f(s, Y_s, Z_s) ds \\ &= \xi - \int_t^T Z_s dW_s + \int_t^T f(s, Y_s, Z_s) ds \end{aligned}$$

- Contraction mapping and martingale representation are decoupled. Brownian filtration and martingale representation are not essential.



Backward stochastic dynamics

- On a filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$, which satisfies the usual conditions,

$$\begin{cases} dY_t = -f(t, Y_t, L(M)_t)dt + dM_t, \\ Y_T = \xi \in \mathcal{F}_T. \end{cases} \quad (6)$$

- M is a square-integrable martingale, and Y is adapted to $\{\mathcal{F}_t\}_{t \geq 0}$.
- A solution is a pair (Y, M) .
- A solution to the backward stochastic dynamics (6) is a pair (Y, M) satisfying

$$Y_t = \xi + \int_t^T f(s, Y_s, L(M)_s)ds + M_t - M_T$$

- Let Y be a semimartingale, and M be a square-integrable martingale. For any $\tau \in [0, T]$, a pair (Y, M) is called a **strict solution** to the backward stochastic dynamics (6) on $[\tau, T]$, if $V = M - Y \in \mathcal{C}([\tau, T]; R)$ such that
 - $V_\tau = 0$ and $M_t = E(\xi + V_T | \mathcal{F}_t)$.
 - V is a fixed point of \mathbb{L} on $\mathcal{C}([\tau, T]; R)$ where

$$\mathbb{L}(V)_t = \int_\tau^t f(s, Y(\xi, V)_s, L(M(\xi, V))_s)ds.$$

Admissible operator L

- $\mathcal{M}^2([0, T]; R)$: the space of square-integrable martingales with the norm:

$$\|M\|_{\mathcal{C}[0, T]} = \sqrt{E \sup_{t \in [0, T]} |M_t|^2}$$

- An operator $L : \mathcal{M}^2([0, T]; R) \rightarrow \mathcal{H}^2([0, T]; R)$ (resp. $\mathcal{C}([0, T]; R)$) is called **admissible** if
 - L satisfies the **restriction property**.
 - $L : \mathcal{M}^2([0, T]; R) \rightarrow \mathcal{H}^2([0, T]; R)$ (resp. $\mathcal{C}([0, T]; R)$) is bounded and Lipschitz continuous by a constant C_1 .
- Examples of L :
 - $L(M)_t = \sqrt{\langle M, M \rangle_t}$, where $\langle M, M \rangle$ is the continuous part of the quadratic variation process $[M, M]$.
 - Suppose $\{\mathcal{F}_t\}_{t \geq 0}$ is generated by a Brownian motion W . $L(M)_t = Z_t$, where Z is the density representation of M .



Local existence on $[\tau, T]$

- **Lemma 2.** *If there is a constant C_2 such that*

$$|f(t, y, z)| \leq C_2(1 + t + |y| + |z|)$$

and

$$|f(t, y, z) - f(t, y', z')| \leq C_2(|y - y'| + |z - z'|),$$

then \mathbb{L} on $\mathcal{C}([\tau, T]; \mathbb{R})$ admits a unique fixed point provided that

$$T - \tau = l \leq \left(\frac{1}{4C_2(3 + 3\sqrt{3} + 2C_1)} \right)^2 \wedge 1.$$

That is, the functional differential equation $V = \mathbb{L}(V)$ admits a unique solution in $\mathcal{C}([\tau, T]; \mathbb{R})$.

- Idea of the proof: standard use of the fixed point theorem to \mathbb{L} .
- The strict solution to (6) on $[\tau, T]$ is:

$$M_t = E(\xi + V_T | \mathcal{F}_t) \quad \text{and} \quad Y_t = M_t - V_t$$

Global existence on $[0, T]$

- Choose the finite partition:

$$\Lambda : T \equiv T_0 > T_1 > \dots > T_k \equiv 0$$

such that the mesh $|\Lambda| = \max_{1 \leq j \leq k} |T_{j-1} - T_j| \leq l$.

- For $t \in [T_j, T_{j-1}]$, $1 \leq j \leq k$, define $Y_0(V(0))_{T_0} = \xi$,

$$(\mathbb{L}_j V)_t = \int_{T_j}^t f_0(s, Y_j(V)_s, L(M_j(V))_s) ds$$

where

$$\begin{aligned} M_j(V)_t &= E [Y_{j-1}(V(j-1))_{T_{j-1}} + V_{T_{j-1}} | \mathcal{F}_t], \\ Y_j(V)_t &= M_j(V)_t - V_t \end{aligned}$$

- Note that at the partition points T_{j-1} for $2 \leq j \leq k$,
 - $Y_{j-1}(V(j-1))_{T_{j-1}} = Y_j(V(j))_{T_{j-1}}$
 - $V(j-1)_{T_{j-1}} \neq V(j)_{T_{j-1}}$



Existence and uniqueness theorem

- For $1 \leq j \leq k$, construct (Y, M) as

$$Y_t = Y(j)_t \quad \text{if } t \in [T_j, T_{j-1}]$$

and define V by shifting it at the partition points:

$$V_t = \begin{cases} V(k)_t & \text{if } t \in [0, T_{k-1}], \\ V(k-1)_t + V(k)_{T_{k-1}} & \text{if } t \in [T_{k-1}, T_{k-2}], \\ \dots & \\ V(1)_t + \sum_{l=2}^k V(l)_{T_{l-1}} & \text{if } t \in [T_1, T]. \end{cases}$$

Then, it is easy to see that $V \in \mathcal{C}([0, T]; R)$. Finally we define

$$M_t = Y_t - V_t \quad \text{for } t \in [0, T].$$

- **Theorem 1.** *There exists a unique $V \in \mathcal{C}([0, T]; R)$ such that*

$$V_t = \int_0^t f(s, Y_s, L(M)_s) ds$$

where $M_t = E(\xi + V_T | \mathcal{F}_t)$ and $Y_t = M_t - V_t$. Moreover (Y, M) satisfies:

$$Y_t = \xi + \int_t^T f(s, Y_s, L(M)_s) ds + M_t - M_T$$



Examples of backward stochastic dynamics

- Suppose $\{\mathcal{F}_t\}_{t \geq 0}$ is generated by a Brownian motion W . By the martingale representation, there exists a density process $Z \in \mathcal{H}^2([0, T]; R)$ such that

$$M_t = E(M_0) + \int_0^t Z_s dW_s.$$

- Define

$$L(M)_t = \sqrt{\langle M, M \rangle_t} = \int_0^t |Z_s|^2 ds$$

then the backward stochastic dynamics (6) becomes

$$\begin{cases} dY_t = -f\left(t, Y_t, \int_0^t |Z_s|^2 ds\right) dt + Z_t dW_t, \\ Y_T = \xi. \end{cases} \quad (7)$$

- Define

$$L(M)_t = Z_t$$

then the backward stochastic dynamics (6) becomes

$$\begin{cases} dY_t = -f(t, Y_t, Z_t) dt + Z_t dW_t, \\ Y_T = \xi. \end{cases} \quad (8)$$



Comments

- Backward stochastic dynamics is a generic extension of a class of nonlinear PDE into infinite dimensional path space. some nonlinear PDE is a pathwise version of backward stochastic dynamics.
- Backward dynamics under other constraints (not adaptiveness constraints):

$$(\xi, V) \rightarrow Y(\xi, V); \quad (\xi, V) \rightarrow M(\xi, V)$$

are general projections (not conditional expectations).

- Extensions to more general case:

$$\left\{ \begin{array}{l} dY_t = -f_0(t, Y_t, L(M)_t)dt - \sum_{i=1}^N f_i(t, Y_t)dW_t^i \\ \quad - \int_{R \setminus \{0\}} f_{N+1}(t-, Y_{t-}, z)(N(t, dz) - t\nu(dz)) + dM_t, \\ Y_T = \xi \in \mathcal{F}_T. \end{array} \right. \quad (9)$$



Thank you!



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