

# Stochastic (Backward) Differential Equation with constraint in law

(aka Mean-Reflected (B)SDEs)

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joint works with {Briand, Guillin, Labart} & {Briand, Cardaliaguet, **Hu**}

⌘ A Stochastic Backward Excursion with Ying Hu ⌘



## MR-SDE: financial introduction

Consider on  $[0, T]$ ,  $T > 0$  the system:

$$dX_t = b(X_t)dt + \sigma(X_t)dB_t \quad X_0 = x_0,$$

- stochastic dynamics for the value of a portfolio  $X$  through the time  $X_t$  until a given date  $T > 0$

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Consider on  $[0, T]$ ,  $T > 0$  for some  $H : \mathcal{P}_2(\mathbf{R}^d) \rightarrow \mathbf{R}$ , the system:

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- constrains to remain acceptable  $\rightsquigarrow$  Apply the rule up to an event  $\beta > 0$  ( $\beta$  small)  
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- Introduced by Briand, Elie, Hu (Backward system), Considered in the same time by Jabir (forward) with different motivations/approach/results, Extension in the backward case by Djehiche, Elie, Hamadène.

## ⌚ The Skorohod problem (61)

For  $y$  a continuous path, find a continuous  $(x, k)$  s.t.

- (i)  $x_t = x_0 + y_t + k_t, \quad x_0 \geq 0$
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• Solution ?

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### • Randomness ?

Works for any continuous path,  $y$  may be a B.M.



Find a continuous  $(X, K)$ ,  $K$  deterministic s.t.

- (i)  $X_t = x_0 + \int_0^t \beta - \alpha X_s ds + \sigma B_t + K_t, \quad x_0 \geq p$
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- Set  $Y_t = x_0 + \int_0^t \beta - \alpha Y_s ds + \sigma B_t \rightsquigarrow \mathbf{E}[Y_t] = e^{-\alpha t} x_0 + \frac{\beta}{\alpha} (1 - e^{-\alpha t})$

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- Solution is  $K_t = \int_0^t e^{-\alpha s} d\nu_s, \quad \nu_s := \sup_{r \leq s} \max(0, -e^{\alpha r}(\mathbf{E}[Y_r] - p))$

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- Smooth coefficients, let  $\varphi$  be a test function,

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$$\partial_t \mu_t - \frac{1}{2} \partial^2 (\sigma^2 \mu_t) - \operatorname{div}(\mu_t b) - \operatorname{div}(\mu_t) dK_t = 0, \quad \mu_0 = \delta_{x_0}$$

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↳ MR-SDE  $\leadsto$  Skorokhod problem on Fokker-Planck PDE !

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where  $B$  is a Brownian motion define on some filtered probability space  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  with  $K$  deterministic

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- $h$  bi-Lipschitz  $\rightsquigarrow G_0^+ : \mathcal{P}(\mathbf{R}) \ni \mu \mapsto G_0^+(\mu)$  Lipschitz for the Wasserstein distance !



## MR-SDE scalar case: Mean field counterpart ( $\mu_0 = \delta_{x_0}$ )

$$\left\{ \begin{array}{l} X_t = x_0 + \int_0^t b(X_s) ds + \int_0^t \sigma(X_s) dB_s + K_t \\ E[h(X_t)] \geq 0, \quad \int_0^t \mathbf{E}[h(X_s)] dK_s = 0 \end{array} \right.$$

- Mean reflection  $\leftrightarrow$  non linear reflection (McKean-Vlasov sense)  
↳ Interacting reflected particles system with oblique reflection ?



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- Existence and uniqueness of a solution with
  - $h$  concave (Tanaka, 89)



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  - $h$  concave (Tanaka, 89)
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- Chaos propagation ?



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- Existence and uniqueness of a solution with
  - $h$  concave (Tanaka, 89)
  - $K_t^N = \sup_{s \leq t} G_0^+(\hat{\mu}_s^N)$
- Chaos propagation  $N \rightarrow +\infty : \hat{\mu}_t^N \rightarrow \mu_t$  (LLN) and  $K_t^N \rightarrow K_t$  ?



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## Q Constrained in law SDE : a more general setting

Consider on  $[0, T]$ ,  $T > 0$  the system:

$$X_t = X_0 + \int_0^t b(X_s)ds + \int_0^t \sigma(X_s)dB_s + \int_0^t dK_s$$
$$\forall t \in [0, T] : \mathbf{E}h(X_t) \geq 0 \quad \int_0^t \mathbf{E}[h(X_s)]dK_s = 0$$

At the PDE level: (in distribution sense)

$$\partial_t \mu_t - \frac{1}{2} \partial^2 (\sigma^2 \mu_t) + \operatorname{div}(\mu_t b) + \operatorname{div}(\mu_t) dK_t = 0, \quad \mu_0 = \delta_x$$

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↳ consider “normal” reflection

## 🏆 Constrained in law SDE with normal reflection

Consider on  $[0, T]$ ,  $T > 0$  the system:

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- Coefficients Lispchitz +  $H$  is “bi-Lipschitz” : there exist  $0 < m \leq M$  such that

$$\forall \mu \in \mathcal{P}^2(\mathbf{R}^d) \quad m^2 \leq \int_{\mathbf{R}^d} |\partial_\mu H(\mu)|^2(x) \mu(dx) \leq M^2,$$

- +  $H$  has “Lispchitz” derivative : there exists  $C \geq 0$  such that

$$\forall X \in L^2(\Omega), \quad \mathbf{E} \left[ |\partial_\mu H([X])(X) - \partial_\mu H([Y])(Y)|^2 \right] \leq C \mathbf{E} \left[ |X - Y|^2 \right],$$

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AND

- the coefficient  $\sigma$  is uniformly bounded
- OR  $H$  is  $L$ -concave:  $H(\nu) - H(\mu) - \mathbf{E} [\partial_\mu H([X])(X) \cdot (Y - X)] \leq 0$ .  
(Carmona-Delarue / Jabir ) “curve is below the tangent”

**Result:** The normally reflected SDE admits a unique solution  $(X, K)$



## Constrained in law SDE with normal reflection: penalization

Consider on  $[0, T]$ ,  $T > 0$  the system:

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Define the **penalized approximation**:

$$X_t^k = X_0 + \int_0^t b(X_s^k) ds + \int_0^t \sigma(X_s^k) dB_s + \int_0^t \partial_\mu H(\mu_s)(X_s^k) \psi_k(s, H(\mu_s)) ds, \quad t \geq 0,$$

where

$$\psi_k(t, x) = r(t) \text{ if } x \leq -1/k, \quad \psi_k(t, x) = -kr(t)x, \text{ if } -1/k \leq x \leq 0, \quad \psi_k(t, x) = 0, \text{ if } x > 0$$



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- $(X^k, K^k)_{k \geq 0}$  is a Cauchy sequence -> **main step**

$$\text{Find } r(\cdot) \text{ so that } \forall k, \forall s \in [0, T] : H(\mu_s^k) \geq -1/k$$

↳ relies on “bi-Lipschitz” property + partial  $C^2$  regularity of  $H$

+ control of the second order term in Itô - measure expansion

(Chassagneux-Crisan-Delarue)  $\leadsto$  **concavity of  $H$  OR boundedness of  $\sigma$**

## Constrained in law SDE with normal reflection: PDE (2<sup>nd</sup>)

Consider on  $[0, T]$ ,  $T > 0$  the system:

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$$\begin{cases} (\partial_t + \mathcal{A})u(t, \mu) = 0 \\ u(T, \mu) = \phi(\mu) \end{cases}$$

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$$\mathcal{A}\varphi = \int b(z)\partial_\mu\varphi(\mu)(z)d\mu(z) + \frac{1}{2} \int \sigma^2(z)\partial_z\partial_\mu\varphi(\mu)(z)d\mu(z)$$

- Non linear process

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constrained  $\rightarrow$  Neumann condition

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- Let  $\phi : \mathcal{P}_2(\mathbf{R})$  (smooth) and  $u(t, \mu) := \phi(\mu_T)$
- u* is A viscosity solution of**

$$\begin{cases} (\partial_t + \mathcal{A})u(t, \mu) = 0 \text{ if } H(\mu) > 0, \\ + \int \partial_\mu H(\mu)(z) \partial_\mu u(t, \mu)(z) d\mu(z) = 0 \text{ if } H(\mu) = 0, \\ u(T, \mu) = \phi(\mu) \end{cases}$$

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- Non linear process
- non-linear constrained  $\rightarrow$  Neumann condition on the L-derivative

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- “natural” MF counterpart: Interacting particles system **reflected in mean field**

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$\hookrightarrow$  Transport initial conditions along the normal up to set of constraint

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- MF system converges:  $\mathbf{E} X_0^4 < +\infty + (H \text{ concave OR } \sigma \text{ bounded}) \rightsquigarrow W_2(\mu_{X_0^i(r)}^N, \mu_0) \rightarrow 0$  and coupling works.

 Constrained in law SDE : generalization

- Back to PDE pb: Skorokhod problem on deterministic fokker-planck

$$\partial_t \mu_t = \frac{1}{2} \partial^2 ([\sigma \sigma^*] \mu_t) + \operatorname{div}(\mu_t b) + \operatorname{div}(\partial_\mu H(\mu_t) \mu_t) dK_t$$

$$H(\mu_t) \geq 0 \quad \int_0^t H(\mu_s) dK_s = 0, \quad t \geq 0$$

 Constrained in law SDE : generalization

- Back to PDE pb: Skorokhod problem on stochastic fokker-planck

$$\partial_t \mu_t = \frac{1}{2} \partial^2 ([\sigma \sigma^* + \sigma_1 \sigma_1^*] \mu_t) + \text{div}(\mu_t b) + \text{div}(\partial_\mu H(\mu_t) \mu_t) dK_t \\ + \text{div}(\mu_t \sigma_1 dW_t)$$

$$H(\mu_t) \geq 0 \quad \int_0^t H(\mu_s) dK_s = 0, \quad t \geq 0$$

- $K$  is no longer deterministic.



## Constrained in conditional law SDE : generalization

- Back to PDE pb: Skorokhod problem on stochastic fokker-planck

$$\partial_t \mu_t = \frac{1}{2} \partial^2 ([\sigma \sigma^* + \sigma_1 \sigma_1^*] \mu_t) + \text{div}(\mu_t b) + \text{div}(\partial_\mu H(\mu_t) \mu_t) dK_t \\ + \text{div}(\mu_t \sigma_1 dW_t)$$

$$H(\mu_t) \geq 0 \quad \int_0^t H(\mu_s) dK_s = 0, \quad t \geq 0$$

- $K$  is no longer deterministic. Associated SDE:

$$X_t = X_0 + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dB_s + \int_0^t \sigma_1(s, X_s) dW_s \\ + \int_0^t \partial_\mu H([X_s | W])(X_s) dK_s,$$

$$H([X_t | W]) \geq 0, \quad \int_0^t H([X_s | W]) dK_s = 0, \quad t \geq 0.$$



## Constrained in conditional law SDE with common noise

- Back to PDE pb: Skorokhod problem on stochastic fokker-planck

$$\partial_t \mu_t = \frac{1}{2} \partial^2 ([\sigma \sigma^* + \sigma_1 \sigma_1^*] \mu_t) + \operatorname{div}(\mu_t b) + \operatorname{div}(\partial_\mu H(\mu_t) \mu_t) dK_t$$

$+ \operatorname{div}(\mu_t \sigma_1 dW_t)$

$$H(\mu_t) \geq 0 \quad \int_0^t H(\mu_s) dK_s = 0, \quad t \geq 0$$

- $K$  is no longer deterministic. Associated SDE:

$$X_t = X_0 + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dB_s + \int_0^t \sigma_1(s, X_s) dW_s$$
$$+ \int_0^t \partial_\mu H([X_s | W]) (X_s) dK_s,$$
$$H([X_t | W]) \geq 0, \quad \int_0^t H([X_s | W]) dK_s = 0, \quad t \geq 0.$$

- Associated MF system:

$$X_t^i = X_0^i + \int_0^t b(s, X_s^i) ds + \int_0^t \sigma(s, X_s^i) dB_s^i + \int_0^t \sigma_1(s, X_s^i) dW_s + \int_0^t \partial_\mu H(\mu_s^N) (X_s^i) dK_s^N,$$
$$\mu_t^N = \frac{1}{N} \sum_{i=1}^N \delta_{X_t^i}, \quad H(\mu_t^N) \geq 0, \quad \int_0^t H(\mu_s^N) dK_s^N = 0, \quad t \geq 0.$$



## Constrained in law SDE: resume

- measurable in time and Lipschitz in space coefficients (could be Wasserstein w.r.t. a law argument)
- constraints of the form  $H(\mu) \geq 0 + H$  "bi-Lipschitz" (locally)  
↳ one dimensional case and constraint of scalar type ( $\exists!$ ) and MF counterpart ( $\exists!$  +convergence  $\rightsquigarrow$  numerical scheme)
- +  $H$  partially  $C^2$  +  $H$  is concave OR  $\sigma$  is bounded  
↳ normal reflection, any dimension ( $\exists!$ ) and MF counterpart ( $\exists!$  +convergence  $\rightsquigarrow$  numerical scheme) + Neumann PDE on Wasserstein space ( $\exists$  in viscosity sense + Feynman-Kak formulae)
- +  $H$  is fully  $C^2$   
↳ reflection in conditional law ( $\exists!$ ) and MF counterpart with common noise + Stochastic Neumann PDE (Feynman-Kak formulae)

What about constrained in law **backward** SDE ?

- "same assumptions give same results" (up to common noise)  
↳ **Warning:** works for  $H$  concave + fully  $C^2$  ( $\sigma$  bounded  $\rightsquigarrow Z$  bounded )  
↳ **Warning:** convergence of MF counterpart requires  $Z$  bounded in  $\mathbb{L}_p$ ,  $p > 4 \rightsquigarrow$  requires regularity  
↳ **Warning:** Associated PDE is not Neumann: driver independent of  $Z \rightsquigarrow \exists$  viscosity solution to obstacle problem on Wasserstein space + Feynman-Kak formulae for decoupling field

**Thank you!**