

Applications of RSDEs

(1) Rough Stoch. Filtering:

Recall in our system:

$$\mu Y_t = h(X_t, Y_t) \mu t + \mu B_t^\perp. \quad (\text{Observation})$$

$$\mu X_t = b(X_t, Y_t) \mu t + \sigma(X_t, Y_t) \mu B_t(W) + \gamma(X_t, Y_t) \circ \mu Y_t$$

Recall (B, Y) are 2-dim BM. under \mathbb{P}^0 where

$$\mu \mathbb{P}^0 / \mu \mathbb{P} | \mathcal{G}_t^Y = \exp \left(\int_0^t h(X_s, Y_s) \circ \mu Y_s - \frac{1}{2} \int_0^t h^2(X_s, Y_s) \mu s \right)$$

And Kallianpur - Striebel formula hold for

$$\text{filter } \bar{\mathbb{E}}^{\mathbb{P}^0}(\varphi(X_t) | \mathcal{G}_t^Y) = \bar{\mathbb{E}}(\varphi(X_t) \frac{\mu \mathbb{P}^0}{\mu \mathbb{P}} | \mathcal{G}_t^Y)$$

$$=: \langle \mu t, \varphi \rangle. \quad \text{Let } \langle \pi, \varphi \rangle \stackrel{\text{nr.}}{=} \frac{\langle \mu t, \varphi \rangle}{\langle \mu t, 1 \rangle}.$$

Since Y is just observation and we can

freeze it to get $\bar{X} = X^Y | Y = y^{\text{strato}}(w)$ with RSDE

$$X_t^Y - X_0 - \int_0^t b(X_s^Y, Y_s) \mu s - \int_0^t \sigma(X_s^Y, Y_s) \mu B_s(W) =$$

$$\int_0^t (f_s(X_s), (f_s(Df_s) + f_s')(X_s)) \mu Y_s$$

where $f_t(X) = \gamma(X, Y_t)$, $f_t'(X) = D_X \gamma(X, Y_t)$.

Remark: Such procedure is "var-komization". Note

$(Y(w))_{w \in \mathbb{R}}$ is infinite-lim. So we need

to consider its measurability which can be achieved by measurable selection.

Thm. (Robust of filter)

The formula still holds for regular φ :

$$\begin{aligned} \langle \mu_t, \varphi \rangle(\omega) &= \mathbb{E} \left(\varphi(X_t^Y) \exp \left(\int_0^t h(X_s^Y, Y_s) dY_s + \int_0^t c(X_s^Y, Y_s) ds \right) \middle| Y = Y^{\text{Strato}}(\omega) \right) \\ &=: \langle \mu_t^Y, \varphi \rangle \big|_{Y = Y^{\text{Strato}}(\omega)} \quad : -\frac{1}{2} h^2 < \square \end{aligned}$$

And $Y \mapsto \langle \mu_t^Y, \varphi \rangle$ is locally Lip.

Pf: By John-Nirenberg esti. : $\exp(\dots) \in L^1$.

Robust is from def of SRI.

Thm. (Zukai)

$V_t = \mu_t^Y$ is unique sol. to : $V_0 = \text{law}(X_0)$.

$$\begin{aligned} \langle v_t, \varphi \rangle - \langle v_0, \varphi \rangle - \int_0^t \langle v_s, L_s^Y \varphi \rangle ds &= \int_0^t \langle v_s, (\Gamma_s^Y, \Gamma_s'^Y) \varphi \rangle \circ dY_s \\ &\equiv \int_0^t (\langle v_s, \Gamma_s^Y \varphi \rangle, \langle v_t, (\Gamma_t^Y \Gamma_t^Y + \Gamma_t'^Y) \varphi \rangle) \circ dY_s. \end{aligned}$$

Where

$$\begin{aligned} L_t^Y \varphi(x) &= \frac{1}{2} D^2 \varphi(x) : (\sigma \sigma^\dagger)(x, Y_t) + D\varphi(x) b(x, Y_t) + c(x, Y_t) \\ \Gamma_t^Y \varphi(x) &= D\varphi(x) \gamma(x, Y_t) + \varphi(x) h(x, Y_t) \\ \Gamma_t'^Y \varphi(x) &= D\varphi(x) D_y \gamma(x, Y_t) D\varphi + \varphi(x) D_y h(x, Y_t) \end{aligned}$$

for φ regular enough

Pf: Apply rough stock. Ztô formula on

$\varphi(X_t^Y) \exp(\dots)$. And uniqueness is from locality argument.

Remark: Compared to BSPDE locality method

there's no Sobolev embedding. So it avoids requirement on regular coefficients when λ is large.

c²) Rough Stoch. Control:

For $X = X^{\omega}$ solves controlled RSDP: $Y \in \mathcal{L}^{\alpha}$.

$$\lambda X_t = f(X_t) \lambda Y_t + \sigma(X_t, \eta_t(\omega)) \lambda B_t(\omega) + b(X_t, \eta_t(\omega)) \lambda t$$

Define: $V(s, y; Y) = \inf_{\eta(\cdot)} \mathbb{E}^{s, y} [g(X_T) + \int_s^T \ell(t, X_t; \eta_t(\omega)) \lambda t]$
Value func.

Thm. (Regularity of V)

For $(f, \sigma, b, g, \ell), (\bar{f}, \bar{\sigma}, \bar{b}, \bar{g}, \bar{\ell})$ bdd. Lip.

$$\text{Then: } |\bar{V}(t, \bar{y}; \bar{Y}) - V(t, y; Y)| \lesssim |(\bar{g} - g)_+|_{\infty} + |T - t|^\alpha \{(1) + (2) + (3)\}$$

where

$$(1) = |(b, \sigma, \ell) - (\bar{b}, \bar{\sigma}, \bar{\ell})|_{\infty} + |f - \bar{f}|_{C_b^{\alpha+}}$$

$$(2) = \|Y - \bar{Y}\|_{\alpha} + \|\bar{Y} - Y\|_{2\alpha}$$

$$(3) = |t - \bar{t}|^{\alpha} + |y - \bar{y}|$$

Thm. (Rough DPP)

$$V(s, x; Y) = \inf_{\eta(\cdot)} \mathbb{E}^{s, x} \left(V(s+h, X_{s+h}; Y) + \int_s^{s+h} \ell(t, X_t; \eta_t) dt \right)$$

Pf: WLOG. Let $Y \in \mathcal{L}_T^{\alpha, 0}$. So $\exists Y^{\varepsilon}$ smooth
 $\xrightarrow{C^{\alpha}} Y$. Then use conti. of $Y \mapsto V$ and
result is from classical DPP for $V^{Y^{\varepsilon}}$.

Cor. If $(Y^\varepsilon, \int \delta Y^\varepsilon \wedge Y^\varepsilon) \xrightarrow{\mathcal{L}^r} Y$. Then: s.l. to

$$-\partial_s V^\varepsilon = H(s, x, DV^\varepsilon(x), D^2V^\varepsilon) + (f(x) \cdot DV^\varepsilon) \dot{Y}_s^\varepsilon, \quad V^\varepsilon(T, \cdot) \equiv g$$

converges uniformly to $V(\cdot, \cdot; Y)$

Remark: It gives a limit meaning to

rough HJB equation:

$$d_s V = H(s, x, DV, D^2V) dt + (f(x) \cdot DV) dY_t$$

Let $\mathcal{L} = 0$. We can compare with classical stock control problems:

$$V(s, x; Y) \equiv \inf_{\eta(\cdot)} \mathbb{E}^{s, y}(g(X_T^Y, \eta)) \rightsquigarrow V(t, x; W) \equiv \text{ess inf}_{\nu(\cdot)} \mathbb{E}^{t, x}(g(X_T^W) | \mathcal{F}_T^W)$$

Thm. $V(s, x; Y) |_{Y=W(\omega)} = V(t, x; W)$ a.s. for admissible choice $V(\cdot, \cdot)$. where W is Br.

(3) McKean-Vlasov RSD E:

Consider n particles system with common noise $W_t \perp B_t^i, \forall i, \mu_t^n := n^{-1} \sum_{k=1}^n \delta_{X_t^{n,k}(\omega)} \in \mathcal{P}(\mathbb{R}^d)$

$$dX_t^{n,i} = f(X_t^{n,i}, \mu_t^n) dW_t + \sigma(X_t^{n,i}, \mu_t^n) dB_t^i + b(X_t^{n,i}, \mu_t^n) dt$$

Denote empirical mean $\bar{m}_t^n(\omega) = \frac{1}{n} \sum_{k=1}^n X_t^{n,k}(\omega)$

Next, we replace W by rough common noise:

$$dX_t^{n,i} = (f_t^\wedge, f_t^\wedge')(X_t^{n,i}) dY_t + \sigma(X_t^{n,i}, \mu_t^\wedge) dB_t^i + b(\dots) dt$$

with $f_t^\wedge(x) := f(x, \mu_t^\wedge), Y_t \in \mathcal{L}^q$ deterministic.

Let $n \rightarrow \infty$. We expect it converges to
 MKU-RSDE: $dX_t = (f_t, f_t^i)(X_t) dY_t + \sigma(X_t, \mu_t) dB_t +$
 $b(X_t, \mu_t) dt$. where $X_t \sim \mu_t$.

e.g. Consider $dX_t^{n,i} = dY_t + dB_t^i + \alpha (m_t^n - X_t^{n,i}) dt$
 $X_0^{n,i} = \xi^i \in L$. i.i.d. (s.o. $m_0^n \xrightarrow{w.p.} E(\xi)$). And
 Y_t is deterministic func.

Note $m_t^n = m_0^n + Y_t + \frac{1}{n} \sum_{i=1}^n B_t^i + \alpha \int_0^t (m_s^n - m_s^i) ds$
 $\xrightarrow{p.s.} E(\xi) + Y_t$ by LLN.

By basic limit theorem for MKU:

We have: $X^{n,i} \Rightarrow X^i$. where X^i satisfies

$$X_t^i = \xi^i + Y_t + B_t^i + \alpha \int_0^t (E(\xi) + Y_s - X_s^i) ds$$

$$\Rightarrow A_t := E(X_t^i - \xi^i) - Y_t = \alpha \int_0^t A_s ds$$

s.o. $A_t = 0$. i.e. $E(X_t^i) = E(\xi) + Y_t$. Then:

$$X_t^i = \xi^i + Y_t + B_t^i + \alpha \int_0^t (E(X_s^i) - X_s^i) ds$$

Note if Y is replaced by W_t . SBM.

Repeat the argument above, then we can

still get the same result in $E(\cdot | \mathcal{F}_t^w)$:

$$i.e. X_t = \xi + W_t(w) + B_t(w) + \alpha \int_0^t (E(X_s | \mathcal{F}_s^w) - X_s) ds$$

Remark: Let $Y = W$ is kind of randomization

So we can't directly get the result.

Sometimes, there's problem:

e.g. If $Y \in C[0, T]$ deterministic and

W is SBM . Then:

$$\langle Y, W \rangle = \lim \sum \delta Y \delta W = 0.$$

Since $|\sum \delta Y \delta W| \leq \|Y\|_{\infty} \cdot \sum_i |\Delta W_i| \xrightarrow{a.s.} 0$

$$\text{But } \langle Y, W \rangle|_{Y=W} = t \neq 0.$$

Recall in the RIDE case, we require measurable selection.

① For $dX_t^v = (f_t, f_t')(X_t^v) dY + \sigma(X_t^v, \nu_t) dB_t + b(\dots) dt$

Next, we assume $Y \in \mathcal{L}_T^1$. apply rough stock

Itô formula, we have: $\mu_t = \text{Law}(X_t^v)$ satisfy

$$d\langle \mu_t, \varphi \rangle = \langle \mu_t, (\Gamma_t, \Gamma_t') \varphi \rangle \circ dY_t + \langle \mu_t, (L_t^v \varphi) \rangle dt \Leftrightarrow d\mu_t = (\Gamma_t, \Gamma_t')^* \mu_t \circ dY_t + (L_t^v)^* \mu_t dt;$$

$$L_t^v \varphi(x) = D\varphi(x) b(x, \nu_t) dt + \frac{1}{2} D^2 \varphi(x) : (\sigma \sigma^\dagger)(x, \nu_t), \Gamma_t \varphi(x) := D\varphi(x) f_t(x), \Gamma_t' \varphi(x) := D\varphi(x) f_t'(x).$$

where $\langle \mu_t, \varphi \rangle = \mathbb{E}(\varphi(X_t^v))$

From limit view: if $\varphi \in \text{Lip}_x^3$, we have:

$$\begin{aligned} d\varphi(X_t^{n,i}) &= D\varphi(X_t^{n,i}) f_t(X_t^{n,i}) dY_t \\ &+ D\varphi(X_t^{n,i}) \sigma(X_t^{n,i}, \mu_t^n) dB_t^i \\ &+ \{D\varphi(X_t^{n,i}) b(X_t^{n,i}, \mu_t^n) dt + \frac{1}{2} D^2 \varphi(X_t^{n,i}) : (\sigma \sigma^\dagger)(X_t^{n,i}, \mu_t^n)\} dt \\ &\equiv (\Gamma_t \varphi, \Gamma_t' \varphi)(X_t^{n,i}) dY_t + dM_t^{n,i} + (L^{\mu_t^n} \varphi)(X_t^{n,i}) dt \end{aligned}$$

where $M_t^{n,i} = \int_0^t \sigma \sigma^\dagger dB_s^i$. Let $M_t^n = \frac{1}{n} \sum_i M_t^{n,i}$.

Average $i=1, \dots, n$ as before, we have:

$$\mathcal{L} \langle \mu_t^n, \varphi \rangle = \langle \mu_t^n, (\Gamma_t, \Gamma_t') \varphi \rangle \circ dY_t + \mathcal{L} M_t^n + \langle \mu_t^n, L^{\mu_t^n} \varphi \rangle \mathcal{L} t$$

For P.C. σ b.m. $\Rightarrow \mu_t^n$ is mart. s.t. $\langle \mu_t^n \rangle \sim \frac{1}{n}$

Let $n \rightarrow \infty$. We have:

$$\mathcal{L} \langle \mu_t, \varphi \rangle = \langle \mu_t, (\Gamma_t, \Gamma_t') \varphi \rangle \circ dY_t + \langle \mu_t, L^{\mu_t} \varphi \rangle \mathcal{L} t.$$

Uniqueness of sol. is from duality argument

Proof: Similarly for $V(t, X) \in D_T^{3,2} Lip_x^3$ s.t.

$$-V' = \Gamma_t V_t, \quad -V'' = \Gamma_t' V_t - \Gamma_t^2 V_t$$

$$\Rightarrow \mathcal{L} V_t = (\Gamma_t, \Gamma_t') V_t \circ dY_t + \mathcal{L} V_t \mathcal{L} t.$$

And $V(t, X_t^Y)$ is mart. $V(t, X) = E^{z, X} (V(T, X_T))$

② If we consider the rough term depends on measure as well, i.e.

$$\mathcal{L} X_t^Y = (f, \tilde{f}) (X_t^Y, V_t) \circ dY_t + \sigma (X_t^Y, V_t) \mathcal{L} B_t + b(\dots) \mathcal{L} t$$

It causes a harder problem.

WLOG, we consider $\mathcal{L} X_t = (f_t, \tilde{f}_t) (X_t^Y, V_t) \circ dY_t$

i) For n particles system: $\mu_t^n = \frac{1}{n} \sum_i \delta_{X_t^i}$

$$\mathcal{L} X_t^i = (f_t, \tilde{f}_t) (X_t^i, \mu_t^n) \circ dY_t. \quad X_0^i = \xi^i(\omega) \sim \xi \in L^0.$$

We need to understand $\tilde{f}_t(x, \mu)$, it can be done by Lions lifts:

Denote $\vec{X}_t = (X_t^1, \dots, X_t^n)$ w.e.n. We have,
 $f_t(x; \mu_t^n) = \hat{g}(x, \vec{X}_t)$. Assume $\hat{g} \in \text{Lip}^3$ for the
 well-posedness of the system, $X^i \in L^2$.

$$\Rightarrow f_t(x, \mu_t^n) = \sum_{j=1}^n D_{x^j} \hat{g}(x, \vec{X}_t) \langle X_t^j \rangle'$$

$$= \langle \vec{D} \hat{g}(x, \vec{X}_t), \hat{g}(x^j, \vec{X}_t) \rangle$$

$$\text{So: } \mu X_t^j = \langle \hat{g}(x^j, \vec{X}_t), ((D_x \hat{g}) \hat{g}(x^j, \vec{X}_t) + \langle \vec{D} \hat{g}(x^j, \vec{X}_t), \hat{g}(x^j, \vec{X}_t) \rangle) \rangle \circ \mu_t.$$

ii) Let $n \rightarrow \infty$, go back to our McKV-RSDE
 similarly as above. We can consider Lions
 lift $\tilde{g}(x, z) = g(x, \mu)$ defined on $\mathbb{R}^d \times$
 $L^2(\mu)$ for $z \sim \mu$. (Assume $g(x, \cdot)$ on W^2)

Remark: Notice that most func $g(\cdot)$ defined
 on W^2 doesn't have regularity. e.g.

$$g(\mu) = \int \sin(x) \mu(dx), \quad \tilde{g}(z) = \mathbb{E}(\sin(z))$$

For $H, \tilde{H} \in L^2$. We have:

$$\langle D \tilde{g}(z), H \rangle = \mathbb{E}(\cos(z) H)$$

$$\langle D^2 \tilde{g}(z), (H, \tilde{H}) \rangle = \mathbb{E}(-\sin(z) H \tilde{H})$$

$$\|D^2 \tilde{g}(z) - D^2 \tilde{g}(\tilde{z})\| =$$

$$\sup \{ | \bar{E} [(\sin(z) - \sin(\tilde{z})) H \tilde{H}] | : \|H\|, \|\tilde{H}\| \leq 1 \}$$

$$= \| \sin(z) - \sin(\tilde{z}) \|_\infty$$

(By Hölder: $LHS \leq \| \sin(z) - \sin(\tilde{z}) \|_\infty$. And

We can let $H = H' = I_{A_\varepsilon} / P(A_\varepsilon)^{\frac{1}{2}}$. Where

$$A_\varepsilon = \{ \omega \mid |f(\omega)| \geq \|f\|_\infty - \varepsilon \}. \text{ Let } \varepsilon \rightarrow 0$$

It doesn't converge to 0 for $n \rightarrow \infty$ if

$$P(\tilde{z}^n = \frac{z}{2}) = \frac{1}{2} = 1 - P(\tilde{z}^n = 0) \text{ and } z = 0.$$

Remark: We see the problem arises cause

$HH' \in L^1$ only. If we assume $H,$

$H' \in L^r, z_n \xrightarrow{L^r} z, r > 4$. Then $D\hat{f}(z)$

can be conti.

But we can naturally require regularity on its Lions derivative $\partial_\mu f(\mu)(z)$

Remark: Note $\langle D\hat{f}(z), H \rangle = \bar{E}(\cos(z) H) z$ is r.v. while $\partial_\mu f(\mu)(z) = z z, z \in \mathcal{P}^L$ in the last example.

iii) Solving McKV-RSDE: We can just consider

$f(x, \mu) = \hat{f}(x, X_t)$ and apply the Picard iteration to solve it in moment space.

Now it's controlled in sense:

$$\delta g(X_t; X_t) \stackrel{29}{=} D_x g(\dots) \delta X_{st} + D_z g(\dots) \delta X_{st}.$$

Alternatively, we can also freeze $g(X_t, \mu_t^x)$

and replace μ_t^x by another serp. (z, z') .

(like replace $\text{Law}(X_t)$ by $\mu \in \mathcal{P}(\mathbb{C}[0, T])$)

Then consider $\tilde{f}(X_t; (z, z'))$ as Gubinelli

vari. of $X^{(z, z')}$. We find the fix pt of

$$(z, z') \mapsto (X^{(z, z')}, \tilde{f}(X_t; (z, z'))).$$