

# Sto - Rough Integral

(1) Rough Itô process:

Consider  $(\Omega, \mathcal{F}, (\mathcal{F}_t), \mathbb{P})$  with  $\mathcal{F}_t$ -BM  $B_t$ .

Denote: For  $X: \mathcal{K}^{\geq 0} \rightarrow \mathcal{K}'$ .  $A: \Delta \subset \mathbb{R}^{\geq 0} \times \mathbb{R}^{\geq 0} \rightarrow \mathcal{K}'$ .

$$\delta X_{st} := X_t - X_s. \quad \delta A_{snt} := A_{sn} + A_{nt} - A_{st}$$

Def: Rough Itô process w.r.t.  $Y = (Y, \Upsilon) \in \mathcal{L}^r$

is  $X_t = X_0 + \int_0^t (F_s, F'_s)(\omega) \wedge Y_s + \sigma_s(\omega) \wedge B_s + b_s(\omega) \wedge s$ . Where  $b, \sigma$  and  $(F_s, F'_s)$  are progressive. SRI  $\int_0^t (F_s, F'_s) \wedge Y_s$  is assumed to exist in sense of:

$$\int_0^\cdot (F, F') \wedge Y := \mathbb{P}\text{-limit}_{|\pi| \rightarrow 0} \sum F_s \delta Y_{st} + F'_s \Upsilon_{st}$$

Remark: For  $\alpha > 1/2$ ,  $(F, F') = (m, 0)$  for some  $m \in \mathcal{M}^{loc, c}$ . The SRI can be also well-def (since  $m \in \mathcal{V}^{2+\alpha}$  by Lévy  $\Rightarrow$  Young integral). So it also works for semimart.  $X = m + V$ .

Lemma: For  $\sigma \in L^\infty[0, T]$ , a.s.  $M_t = \int_0^t \sigma_s(\omega) \wedge B_s \in$

$C^r$ . r.s.  $\forall \alpha < 1/2$ . And  $(M, \int M dM) \in$

$C^r$ . r.s.  $\forall \alpha < 1/2$ .

Pf: By DDS represent:  $M_t = B_{\langle M \rangle_t}$

And  $\langle M \rangle = \int \sigma_s^2 ds \in \text{Lip}$ .

Remark: For  $\vec{B}$  is  $k$ -dim. Note  $(M_t, \dots, M_t^k)$  will not have represent  $\vec{B}_{\langle M \rangle}$ . But we can still apply Kolmogorov criterion for RP on it.

Define:  $A \stackrel{Y}{\approx} \bar{A}$  if  $|A_{s,t} - \bar{A}_{s,t}| \lesssim |t-s|^Y$  on  $[0, T]$  uniformly.

e.g.  $(Y, Y) \in C^r \Rightarrow Y \stackrel{r}{\approx} 0, Y \stackrel{2r}{\approx} 0$ .

Lem. (Sewing)

$(\Sigma_{s,t})_{[0,T]}$  satisfies  $(\delta \Sigma)_{s,t} \stackrel{1+\epsilon}{\approx} 0$ . Then

$\exists$  unique conti. path  $I(t)$  s.t.  $I(0) = 0$ .

$|\delta I - \Sigma_{\dots}| \stackrel{1+\epsilon}{\approx} 0, \delta I_{s,t} = \lim_{|z| \rightarrow 0} \Sigma_{\Sigma u, v}$

Def:  $f \in \text{Lip}^r(\mathbb{R}^n, \mathbb{R}^c)$  if  $f \in C^{L_Y}$  and

$D^{L_Y} f \in \text{Lip}^{L_Y}$ .  $D^k f \in \text{Lip}^r, \forall k = L_Y - 1$

RMK: Recall controlled FP is stable  
under  $Lip^2$ .

Next, we define sol. for

$\mathcal{L}X_t = f_t(X_t) \mathcal{L}Y_t$  in sense of

$$X_t = X_0 + \int_0^t (f_s(X_s), (Df_s)f_s + f_s'(X_s)) \mathcal{L}Y_s.$$

RMK: The controlled term is just written

locally:  $f_s'(X_s)$  is  $s$ -derivative and

$$Df_s(X_s) f_s(X_s) \approx Df_s(X_s) X_s \text{ by Ito.}$$

e.g. Let  $f_s(X_s) = A_s X_s$ .  $A_s$  is a linear

transf. To the control part of RZ

$$\text{is } (A_s X_s, (A_s^2 + A_s') X_s)$$

Then the sol. flow is linear operator

$$\text{to itself: } X_t = \Pi_{t \leq 0}^Y X_0, \quad \Pi_{t \leq 0}^Y \in \mathcal{L}(K^d).$$

RMK: For  $\mathcal{L}X = (A, A') X \mathcal{L}Y$  in  $d=1$ .

$$\begin{aligned} \Pi_{t \leq 0}^Y &= \exp \left( \int_0^t (A_s, A_s') \mathcal{L}Y_s \right. \\ &\quad \left. - \frac{1}{2} \int_0^t A_s^2 \mathcal{L}[Y]_s \right) \end{aligned}$$

(2) RSDÉs Preview:

Consider  $(f_{s,w}, \bar{f}_{s,w})$ .  $\sigma_{s,w}$ ,  $b_{s,w}$  are progressive. Any RSD E defined by:

$$\mu X_s = (f_{s,w}, \bar{f}_{s,w})(X_s) \mu Y_s + \sigma_{s,w}(X_s) \mu B_s + b_{s,w}(X_s) \mu s$$

its sol. is defined by:

$$X_t = X_0 + \int_0^t (f_{s,w}, \bar{f}_{s,w})(X_s) \mu Y_s + \sigma_{s,w}(X_s) \mu B_s + b_{s,w}(X_s) \mu s$$

where  $SRI = \mathbb{P}$ -lim  $\sum \{ f_{s,w}(X_s) \delta Y_{s,t} + (f_{s,w} D f_{s,w} + \bar{f}_{s,w})(X_s) Y_{s,t} \}$ .

Ex. i) (Path - indep.)

For  $(f_{s,w}, \bar{f}_{s,w}) = (F, F') \in \mathcal{D}_Y^{2r}$ , a.s.

$$\text{Let } Z_t \stackrel{\Delta}{=} X_0 + \int_0^t (F, F') \mu Y_s$$

$$\Rightarrow X_t = Z_t + \int_0^t \sigma_{s,w}(X_s) \mu B_s + b_{s,w}(X_s) \mu s$$

i.e. Z's reduced to SDE case.

ii) (linear deterministic.)

For  $(f_{s,w}, \bar{f}_{s,w})(x) = (A_s, A'_s)(x) \in \mathcal{D}_Y^{2r}$ .

Z's sol. satisfies SVE:

$$X_t \stackrel{(*)}{=} \prod_{s \leftarrow 0}^Y X_0 + \int_0^t \prod_{s \leftarrow s}^Y (\sigma_{s,w}(X_s) \mu B_s + b_{s,w}(X_s) \mu s)$$

Remark:  $\forall (A_s, A'_s) \stackrel{\text{a.s.}}{\in} \mathcal{D}_Y^{2r}$  & progressive

Then:  $\pi_{t \leq s}^Y \in \mathcal{F}_t$ . And it's not easy  
to write  $\pi_{t \leq s}^Y (\square \mu_B + \square \mu_S)$   
 $= \square \mu_B + \square \mu_S$  i.e.

Itô formulation. ( $\pi_{t \leq s}^Y$  involve random)

Set  $\tilde{X}_t = \pi_{1 \leq t}^Y X_t \Rightarrow$  it transfers

RISDE (\*) to SDE:

$$\tilde{X}_t = X_0 + \int_0^t \pi_{0 \leq s}^Y \left\{ \sigma_{s,w} (\pi_{0 \leq s}^Y \tilde{X}_s) \mu_B + b_{s,w} (\pi_{0 \leq s}^Y \tilde{X}_s) \mu_S \right\}$$

$\Rightarrow$  We solve RISDE (\*) by recovering

$X_t$  from  $\tilde{X}_t : X_t = \pi_{t \leq 0}^Y \tilde{X}_t$  (It's called  
flow transformation technique.

iii) (Joint Rough Path approach)

$$\text{For } X_t = X_0 + \int_0^t f(X_s) \mu_Y + \int_0^t \sigma(X_s) \mu_B + \int_0^t b(X_s) \mu_S.$$

Although rough integral and Itô's  
integral use different integration sys-  
tem. They're still consistent in the  
case of Bm.

So we can consider joint rough lift

$$(Y, B) =: J$$

$$\Rightarrow dX_t = x_0 + \int_0^t g(x_s) dJ_s + \int_0^t f(x_s) ds$$

where  $g = (f, \sigma)$ . become stoch. PDE.

(3) Stochastic Rough integral:

① Stochastic Sewing:

Define: i)  $\mathbb{E}_s(\cdot) := \mathbb{E}(\cdot | \mathcal{F}_s)$ . For  $A = \Delta \rightarrow \mathbb{R}^d$ , set

$$\|A_{st}\|_{m,n} := \| \|A_{st} | \mathcal{F}_s\|_{m,n} \|_n$$

$$\underline{\text{Prop:}} \quad \|A_{st}\|_{m,n} = \|A_{st}\|_m.$$

$$A_{st} \in \mathcal{F}_s \Rightarrow \|A_{st}\|_{m,n} = \|A_{st}\|_m.$$

$$\text{ii) } (\mathbb{E}_s(A))_{st} = \mathbb{E}_s(A_{st}).$$

$$(\mathbb{E}_s(B))_{snt} = \mathbb{E}_s(B_{snt})$$

Lem'. (Doob comp.)

$(X_k)_0^N \in L^1(\mathcal{N}; \mathbb{R}^d)$ , adapted to  $\mathcal{F}_k \Rightarrow$

There exists unique  $(\eta_k), (Z_k)$  st.  $\eta_k$

is  $\mathbb{R}^d$ -mart. with  $\eta_0 = X_0$  and  $Z_k :=$

$$\sum_{j=1}^k \overline{\mathbb{E}}_{j-1}(\delta X_j) \in \mathcal{F}_{k-1} \text{ pred.}$$

Lem<sup>2</sup> (condition BDL)

$(X_k)_0^N$  is  $\kappa$ -dim  $L^m$ ,  $\mathcal{F}_k$ -mart. st.

$1 \leq m < \infty$ . For  $g \in \mathcal{G}_0$ , we have:

$$\|S_{X_N} |g|\|_m \stackrel{i)}{\leq} \|M_{X_N} |g|\|_m \stackrel{ii)}{\leq} \|S_{X_N} |g|\|_m \text{ for}$$

$$S_{X_N} := \left( |x_0|^2 + \sum_1^N |dX_k|^2 \right)^{1/2}, \quad M_{X_N} = \max_{0 \leq k \leq N} |x_k|$$

Pf: i) is trivial. As for ii): we only

consider  $m=1$ , i.e. Doob's inequality.

For  $\kappa=1$ : Note we have:  $\forall (f_k) \subset \mathcal{R}$ .

$$M_{f_N} \leq b S_{f_N} + \sum_0^{N-1} h_k (f_{k+1} - f_k) \text{ where}$$

$$h_k := f_k / \left[ (S_{f_k})^2 + (M_{f_k})^2 \right]^{1/2}.$$

Remark: It's kind of superhedging.

Let  $f_k = X_k$  since the second term of RHS is martingale transform.

Take  $\mathbb{E}(\cdot | \mathcal{G})$  on both sides  $\Rightarrow$  ii)

To obtain  $\kappa > 1$  case:

$$\text{Note: } M_{f_k} \leq \sum_1^k M_{f_k}^i, \quad \sum_1^k S_{f_k}^i \stackrel{\text{Cauchy}}{\leq} \sqrt{\kappa} S_{f_k}.$$

Remark: To extend to  $m > 1$ . We can

use Harsia-Neveu Lem.:

$$\mu^p = p(p-1) \int_0^\infty \lambda^{p-2} (\mu - \lambda) + \lambda \lambda.$$

to reduce  $m > 1$  to  $m = 1$  (Davis)

Thm. (Stochastic Sewing in mixed moment)

For  $2 \leq m \leq n \leq \infty$ ,  $m < \infty$ ,  $A_{\cdot, \cdot}(w) = \mu \times \Delta$

$\rightarrow \mathbb{R}^{\mu A}$  is sto. two para. func. st.  $A_{s,s} = 0$ .  $A_{s,t} \in \mathcal{F}_t \forall (s,t) \in \Delta$ . If uniformly on  $[0, T]$ , we have:

$$\| \mathbb{E}_0 \langle \delta A_{\cdot, \cdot, \cdot} \rangle \|_n^{1+\varepsilon} = 0 \quad \| \delta A_{\cdot, \cdot, \cdot} \|_{m,n}^{\frac{1+\varepsilon}{2}} = 0.$$

Then for  $\forall$  partition  $\pi = (t_i)$  of  $[s, t]$ .

$$A_{s,t}^\pi := \sum_0^{n-1} A_{t_i, t_{i+1}} \quad J_{s,t}^\pi := A_{s,t}^\pi - A_{s,t}.$$

i)  $J_{s,t}^\pi$  is  $L^m$ -Cauchy  $\xrightarrow{L^m} J_{s,t} \in L^m$

ii)  $J_{s,t} = (\delta A)_{s,t} - A_{s,t}$ . Where  $A_t :=$

$\lim_{|\pi| \rightarrow 0} A_{0,t}^\pi$  in pr. is  $\mathcal{F}_t$ -adapted.

$$\text{iii) } \| \mathbb{E}_0 \langle \delta A - A \rangle \|_n^{1+\varepsilon} = 0 \quad \| \delta A - A \|_{m,n}^{\frac{1+\varepsilon}{2}} = 0.$$

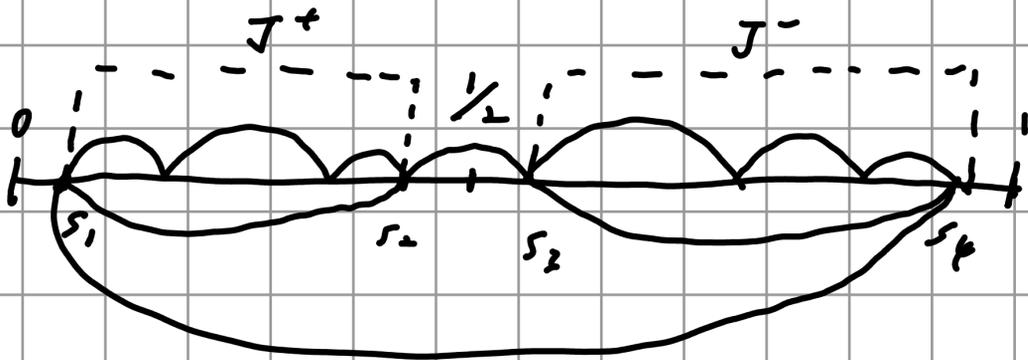
Lemma (Dynamic Allocation)

Set  $R_i^\pi := s + \frac{i}{2^n} (t-s)$ . We have:  $J_{s,t}^\pi$

$$= \sum_{k=0}^{\infty} \sum_{i=0}^{2^{k-1}} R_i^\pi. \text{ Where } R_i^\pi = 0. \forall i \text{ for } k \geq \pi(n)$$

for some  $T(n)$ . and  $\exists (s_i)_i^+ \subset \Pi \cap [d_n^{i+1}, d_n^i]$ .  
 st.  $R_i = \delta A_{s_1, s_2} + \delta A_{s_3, s_4}$

Pf. WLOG.  $[s, t] = [0, 1]$ . For  $n=0$ :



Assume the upper arcs =  $\Sigma A_{t_i t_{i+1}}$   
 there's one arc containing  $\frac{1}{2}$  with  
 arcs in  $J_{s_1, s_2}^+ \subset [0, \frac{1}{2}]$  and arcs in  
 $J_{s_3, s_4}^- \subset [\frac{1}{2}, 1]$  in  $\Sigma A_{t_i t_{i+1}} = A_{0,1}^\pi$ . So:

$$J_{s_1, s_4} + A_{s_1, s_4} = A_{0,1}^\pi = (J_{s_1, s_2}^+ + A_{s_1, s_2}) + A_{s_2, s_3} + (J_{s_3, s_4}^- + A_{s_3, s_4})$$

$$\Rightarrow J_{s_1, s_4} = J_{s_1, s_2}^+ + J_{s_3, s_4}^- + R.$$

where  $R = \delta A_{s_1, s_2, s_3} + \delta A_{s_3, s_4} = R_0^0$

$\Rightarrow$  We can recursively repeat it  
 inside  $J^+ \subset [0, \frac{1}{2}]$  and  $J^- \subset [\frac{1}{2}, 1]$ .

Lem<sup>+</sup> (Doob/BDH estimate for random sum)

For  $\infty > m \geq 2$ .  $\infty \geq n \geq 2$ .  $(y_k)_{k \geq 0} \subset L^m$

is  $\mathcal{F}_k$ -adapted. Fix  $g \in \mathcal{G}$ . Denote

$\|\cdot\|_{m,n,g} := \|\cdot\|_{\mathcal{G}} \|\cdot\|_{m,n}$ . Then:

$$\left\| \sum_0^N \eta_k \right\|_{m,n,g} \lesssim \sum_1^N \|\mathbb{E}_{k-1}(\eta_k)\|_{m,n,g} + \left( \sum_0^N \|\eta_k\|_{m,n,g}^2 \right)^{\frac{1}{2}}$$

Pf: Set  $f_k = g_0 + \sum_1^k \eta_i - \mathbb{E}_{i-1}(\eta_i)$

$\Rightarrow f_k$  is  $L^m$ -mart w.r.t.  $\mathcal{F}_k$ .

$$LHS \lesssim \left\| \sum_1^N \mathbb{E}_{k-1}(\eta_k) \right\|_{m,n,g} + \|f_N\|_{m,n,g}$$

and BPH

$$\lesssim \sum \|\mathbb{E}_{k-1}(\eta_k)\|_{m,n,g} + \left\| \left( \sum_0^N |\delta f_k|^2 \right)^{\frac{1}{2}} \right\|_{m,n,g}$$

Minkov.

$$\lesssim \square + \left( \sum \|\delta f_k\|_{\frac{m}{2}, \frac{n}{2}, g}^2 \right)^{\frac{1}{2}}$$

With  $\|\delta f_k\|_{\frac{m}{2}, \frac{n}{2}, g}^2 = \|\delta f_k\|_{m,n,g}^2$

$$\leq 2 \|\eta_k\|_{m,n,g}.$$

Lem<sup>5</sup> (Uniform estimate)

Under assumpt of Sto-sew. We have:

$$\|\mathbb{E}_{\cdot} \circ J^{\pi}\|_{n} \stackrel{1+\varepsilon}{=} 0, \quad \|J^{\pi}\|_{m,n} \stackrel{1+\varepsilon}{=} 0.$$

$$\text{Pf: } J^{\pi} = \sum_{r=0}^N \sum_{i=0}^{2^r-1} R_i = \sum \sum (\delta A_{s_1^{N,i}}^{N,i} s_2^{N,i} s_3^{N,i} + \delta A_{\square})$$

$$\text{And } \max_{j_1, j_2} |s_{j_1}^{N,i} - s_{j_2}^{N,i}| \leq |t-s|/2^N.$$

$$\text{Let } \mathcal{G}_i^N := \mathcal{F}_{s_1^{N,i}} \Rightarrow R_i \in \mathcal{G}_{i+1}^N$$

By assumpt of Sto-sew:

$$\|E(R_i | \mathcal{G}_i^N)\|_n \lesssim \left(\frac{|t-s|}{2^N}\right)^{1+\varepsilon}$$

$$\|R_i^N\|_{n,m} \lesssim \left(\frac{|t-s|}{2^N}\right)^{\frac{1+\varepsilon}{2}}$$

$$\text{AMM} \quad \left\| \sum_0^{2^N-1} R_i^N \right\|_{m,n, \mathcal{F}_{t_0}} \lesssim \sum_0^{2^N-1} \|E(R_i^N | \mathcal{G}_i^N)\|_{m,n, \mathcal{F}_{t_0}} + \left(\sum \|R_i^N\|_{m,n, \mathcal{F}_{t_0}}\right)^{\frac{1}{2}}$$

$$\lesssim \sum \|E(R_i^N | \mathcal{G}_i^N)\|_n + \left(\sum \|R_i^N\|_{m,n, \mathcal{F}_{t_0}}^2\right)^{\frac{1}{2}}$$

from Jensen inequality and contraction property of conditional expectation.

$$\text{So: } \left\| \sum_0^{2^N-1} R_i^N \right\|_{m,n, \mathcal{F}_{t_0}} \lesssim \sum |k_{i+1}^N - k_i^N| + \left(\sum |k_{i+1}^N - k_i^N|^{1+\varepsilon}\right)^{\frac{1}{2}}$$

$$\lesssim |t-s|^{\frac{1+\varepsilon}{2}} 2^{-N\varepsilon/2}$$

$$\Rightarrow \|J^N\|_{m,n, \mathcal{F}_{t_0}} \stackrel{1+\varepsilon}{=} 0.$$

$$\text{AMM} \quad \|E_{t_0}(J^N)\|_n \leq \sum \sum \|E(R_i^N | \mathcal{F}_{t_0})\|_n$$

$$\stackrel{\text{Contract}}{\leq} \sum \sum \|E(R_i^N | \mathcal{G}_i^N)\|_n \lesssim |t-s|^{1+\varepsilon}$$

Next, we can return proof of  $\Gamma_{t_0-s}$ :

i) For  $\pi = (t_i)_0^N$ ,  $\pi' = (s_i)_0^{N'}$  partitions of

$[0, t]$ . Set  $\pi'' = \pi \cup \pi' = (u_i)_0^{N''}$ .  $N'' \leq N + N'$ .

$$\Rightarrow A_{0t}^{\pi} - A_{0t}^{\pi'} = \sum_{i=0}^{N-1} Z_i. \quad Z_i = \sum_{j: t_i \leq t_j < t_{i+1}} A_{t_j} - A_{t_{i+1}}$$

By Doob / BDH estimate:

$$\begin{aligned} \|A_{0t}^{\pi''} - A_{0t}^{\pi}\|_m &\lesssim \sum_0^{N-1} \|\mathbb{E}_{t_i} (Z_i)\|_m + \left( \sum_0^{N-1} \|Z_i\|_m \right)^{\frac{1}{2}} \\ &\stackrel{\text{Lem}^5}{\lesssim} \sum A_{t_i}^{1+\varepsilon} + \left( \sum A_{t_i}^{1+\varepsilon} \right)^{\frac{1}{2}} \\ &\lesssim t^{\frac{\varepsilon}{2}} |\pi|^{2/\varepsilon} \vee t |\pi|^{\varepsilon} \end{aligned}$$

Similarly, we have:  $\|A_{0t}^{\pi} - A_{0t}^{\pi'}\|_m \lesssim |\pi|^{\frac{\varepsilon}{2}} \vee |\pi'|^{\frac{\varepsilon}{2}}$

$J_0: J_{0t}^{\pi} = A_{0t}^{\pi} - A_{0t}$  is  $L^m$ -bounded  $\rightarrow J_{0t}$ .

ii) Since  $A_0 := \lim A_{0t}^{\pi} = J_{0t} + A_{0t}$  from i).

Repeat construct on  $[0, s], [s, t]$ .

(Note it converges on arbitrary mesh, we

can set  $\pi \cap [0, t] = \pi' \cap [0, s] \cup \pi'' \cap [s, t], |\pi| \rightarrow 0$ )

$$J_{st} + A_{st} = \lim A_{st}^{\pi''} = \lim A_{0t}^{\pi} - A_{0s}^{\pi'} = A_t - A_s$$

iii) Using Fatou's Lem (lim case) and  $J_{st}^{\pi}$

$$\xrightarrow{L^m} J_{st} = \delta A_{st} - A_{st} \Rightarrow \exists \pi' \text{ subseq of } \pi, st.$$

$\mathbb{E} \in J_{st}^{\pi'} | \mathcal{F}_s \rightarrow \mathbb{E} \in J_{st} | \mathcal{F}_s$ . Apply Lem<sup>5</sup>:

$$\text{So } 0 = \lim |\pi'|^{1+\varepsilon} \geq \lim \| \mathbb{E} \in A_{st}^{\pi'} - A_{st} \|_m$$

$$\geq \| \lim \mathbb{E} \in A_{st}^{\pi'} - A_{st} \|_m = \square$$

Also since  $\|A - A^T\|_m \rightarrow 0$ , so  $\|A - A^T\|_{\mathcal{G}, \|m\|} \rightarrow 0$ .

Then apply Frobenius to get another one.

RMK: i) It can also work for Banach space with norm type  $p$ .

ii)  $m = \infty$  is a strong assumption so we drop it. Since BDh doesn't work in  $L^\infty$  ( $m = \infty$  even excludes BM case)

② Stochastic Control Rough path:

Def:  $(A_t \in \mathcal{L}(W))_{t \in [0, T]} \in C_2^k L_{m,n}$  if  $\|A\|_{k,m,n} :=$

$$\sup_{0 \leq s, t \leq T} \|A_t - A_s\|_{\mathcal{L}(W)} / |t - s|^k < \infty \text{ and we}$$

denote it by  $A^{k,m,n} = 0$ .

RMK: For path  $(X_t \in W) \in C^k L_{m,n}$  if

$\delta X \in C_2^k L_{m,n}$ . Denote:

$$[[X]]_{k,m,n}^A = \|\delta X\|_{k,m,n}$$

$$\|X\|_{k,m,n} = [[X]]_{k,m,n} + \sup_{[0, T]} \|X_t\|_m$$

Prop. For  $1 \leq m \leq n < \infty$  and  $k > 0$ . Then:

i)  $C_2^k L_{m,n}$  is Banach for  $\forall k > 0$ .

ii)  $C_2^k L_{m,n} \hookrightarrow C_2^k L_{m',n'}$   $\forall m \geq m', n \geq n'$ .

ii)  $\forall A^k \rightarrow A$  in  $C^k L_m$ . Then:

$$\lim_k \|A^k\|_{k,m,\infty} \geq \|A\|_{k,m,\infty}$$

Thm. (John - Nirenberg)

$X$  is conti.  $\mathcal{F}_t$ -adapted. s.t.  $\delta X \in C^k L_{1,\infty}$

$$\Rightarrow \forall \lambda > 0. \log \mathbb{E} e^{\lambda \sup_{0 \leq t \leq T} |\delta X_{st}|} \leq CT (\lambda \|\delta X\|_{k,1,\infty})^{k'} / \lambda$$

where  $C$  is indep't of  $\lambda, Y, T$ .

Def.  $(z, z') \in D_Y^{2\alpha} L_{m,n}$  is  $\mathcal{F}_t$ -controlled RP

if i)  $(z, z')$  is progressive.

ii)  $\delta z \in C^{\alpha} L_{m,n}$

iii)  $\mathbb{E}(R^z) \in C^{\alpha} L_n$

iv)  $z' \in C^{\alpha} L_{m,n}$ .  $\sup_t \|z'_t\|_n < \infty$ .

Denote  $\|(z, z')\|_{D_Y^{2\alpha} L_{m,n}} = \|\delta z\|_{\alpha,m,n} + \|\delta z'\|_{\alpha,m,n}$

+  $\sup_t \|z'_t\|_n + \|\mathbb{E}(R^z)\|_{\alpha,n}$  seminorm on it.

Remark:  $(z, z') \in D_Y^{2\alpha} L_{m,n}$  can imply:

i)  $\mathbb{E}(R^z) \stackrel{\alpha,n}{=} 0$ .    ii)  $\mathbb{E}(\delta z') \stackrel{\alpha,n}{=} 0$ .

iii)  $R^z \stackrel{\alpha,m,n}{=} 0$ .    iv)  $z' \stackrel{\alpha,n}{=} 0$ .

Note for iii):  $(n > m)$

$$\|R^z\|_{m,n,\infty} \leq \sup_t \|z_t\|_n |\delta Y|_r + \|\delta z\|_{m,n,\infty}$$

Lemma. Def iv)  $\Rightarrow$  Rank ii)

Def iii)  $\Rightarrow$  Rank i)

Pf: By Hölder and Jensen inequality.

Thm. If  $(z, z') \in D_Y^{2\alpha} L_{m,n}$ ,  $Y \in \mathcal{L}^r$ ,  $\alpha \in (\frac{1}{2}, \frac{1}{2}]$

$2 \leq m \leq n \leq \infty$ ,  $m < \infty$ . Then: SPI exists

$$I_t := \int_0^t (z, z') \cdot Y = \lim_{|\pi| \rightarrow 0} \sum (z \delta Y + z' \delta Y)$$

Pf: Apply Itô-Stratonovich Thm on  $A :=$

$$z \delta Y + z' \delta Y \Rightarrow \delta A = R^z \delta Y + \delta z' \delta Y$$

$CZ_t$  also works for  $\varepsilon_1, \varepsilon_2 > 0$  in

$1 + \varepsilon_1$  and  $1 + \varepsilon_2/2$ ,  $3\tau = 1 + \varepsilon_1$ ,  $2\tau = 1 + \varepsilon_2/2$ )

Combined with Rank above.

Thm.  $(z, z') \in D_Y^{2\alpha} L_{m,n}$ . If  $\|z\|_{n,\infty} < \infty$ . Then:

$(\int z \cdot Y, z) \in D_Y^{2\alpha} L_{m,n}$  with estimate

$$\|(\int z \cdot Y, z)\|_{D_Y^{2\alpha} L_{m,n}}$$

$$\leq C_\alpha \| (z, z') \|_{D_Y^{2\alpha} L_{m,n}} + \|z\|_{n,\infty}$$

Pf:  $\|(\int z \cdot Y, z)\|_{D_Y^{2\alpha} L_{m,n}} = \sup_{|\pi|} \|z_t\|_n + \|\delta z\|_{m,n,\infty}$

$$\|E. (\int z \cdot Y - z \delta Y)\|_{m,n} + \|\int z \cdot Y\|_{m,n}$$

$$\text{Note } \|E. ( \int z \wedge Y - z \delta Y - z' Y ) \|_{n, \infty}^{3\tau} = 0.$$

$$\| \int z \wedge Y - z \delta Y - z' Y \|_{m, n}^{2\tau} = 0.$$

(const. consists of  $\| \square \|_{q, m, n}, \| \square \|_{2r, n, \dots}$ )

$$J_0: KNS \leq \|z\|_{n, \infty} + \|E. (z' Y)\|_{2r, n} +$$

$$\|z \delta Y + z' Y\|_{q, m, n} + \|\delta z\|_{q, m, n}$$

$$\leq \|z\|_{n, \infty} + \|z'\|_{n, \infty} \|Y\|_{2r} (1 + T^\alpha) +$$

$$T^\alpha \|R^z\|_{2r, m, n} + \|\delta z\|_{q, m, n} + \|\delta z\|_{q, m, n}$$

$$\text{With } \|R^z\|_{2r, m, n}^{(n \geq m)} \leq \|E. (R^z)\|_{2r, n}$$

Cor. (Stability)

For  $(\bar{z}, \bar{z}') \in D_{\bar{Y}}^{2r} L_{m, n}, \bar{Y} \in \mathcal{L}^r$  and

$\|\bar{z}\|_{n, \infty} < \infty$ . Then:

$$\|C \int z \wedge Y, z; \int \bar{z} \wedge \bar{Y}, \bar{z}\|_{Y, \bar{Y}, 2r, m, n} \lesssim$$

$$\|\delta C Y - \bar{Y}\|_{r} + \|\delta C Y - \bar{Y}\|_{2r} + \|z - \bar{z}\|_{n, \infty} +$$

$$\|\delta C z - \bar{z}\|_{q, m, n} + T^\alpha \|z, z'; \bar{z}, \bar{z}'\|_{Y, \bar{Y}, 2r, m, n}$$

③ Composition with Regular func.:

For  $(x, x') \in D_Y^{2r} L_{m, n}, g \in \text{Lip}^2$ . We consider

the composition  $Cz, z' := (g(x), Dg(x)x')$

Remark: i) If  $g$  is linear, obviously  $(z, z') \in$

$D_Y^{2\tau} L_{m,n}$  still.

ii) If  $f = f(t, X)$ . We will consider  $Z'$   
 $= f'(t, X) + Df(t, X) X'$ .

$$\Rightarrow R_{st}^Z = f_t(X_t) - f_s(X_s) - f'_s(X_s) \delta Y_{st} \\ + f_s(X_t) - f_s(X_s) - Df_s(X_s) X'_s \delta Y_{st}$$

The following prop. also holds for  $(f_t,$

$f'_t) \in D_Y^{F,P'} L_{m,n} C_b^\nu$ . sto. contr. Vec. field.

prop. For  $f \in Lip^2$ ,  $(X, X') \in D_Y^{2\tau} L_{m,n}$ ,  $2 \leq m \leq n$   
for  $m < \infty$ . Then:  $(Z, Z') = (f(X), Df(X) X')$   
 $\in D_Y^{2\tau} L_{m, \frac{n}{2}}$ . Besides.

$$\|(Z, Z')\|_{D_Y^{2\tau} L_{m, \frac{n}{2}}} \leq C \|f\|_{Lip^2} (1 + \|(X, X')\|_{D_Y^{2\tau} L_{m,n}})$$

rank: Note that  $n$  is half. It's the  
reason that we consider  $D_Y^{2\tau} L_{m,n}$   
space in the following.

Pf:  $\|\delta Z\|_{q,m,n}$ ,  $\|\delta Z'\|_{q,m,n}$ ,  $\|Z'\|_{0,n}$  are b.f.d  
from  $X \in D_Y^{2\tau} L_{m,n}$ ,  $f \in Lip^2$ .

$$\text{As for } R^Z = \delta f(X) - Df(X) X' \delta Y \\ = \delta f(X) - Df(X) \delta X + Df(X) R^X$$

$$\begin{aligned} \text{Let } Lg(x_s, x_t) &:= g(x_t) - g(x_s) - Dg(x_s) \delta x_{st} \\ &= \int_0^1 (Dg(x_s + \theta \delta x_{st}) - Dg(x_s)) \delta x_{st} \\ &\leq C_g |\delta x_{s,t}|^2 \quad (\Rightarrow \text{cancel halving of } n) \end{aligned}$$

$$\| \mathbb{E} \cdot |\delta x_{s,t}|^2 \|_{\frac{n}{2}} = \| \delta x_{st} \|_{2,n}^2 \stackrel{X \in D}{\lesssim} |t-s|^{2\alpha}$$

$$\begin{aligned} \| Dg(x_s) \mathbb{E} \cdot \langle R_{st}^x \rangle \|_{\frac{n}{2}} &\leq \| Dg \|_{\infty} \| \mathbb{E} \cdot \langle R^x \rangle \|_n \\ &\lesssim |t-s|^{2\alpha} \end{aligned}$$

$$\Rightarrow \| \mathbb{E} \cdot \langle R^z \rangle \|_{2\alpha, \frac{n}{2}} \leq C_{\text{Lip}} ( \| \delta X \|_{\alpha, m, n}^2 + \| \mathbb{E} \cdot \langle R^x \rangle \|_{2\alpha, n} )$$

prop. (Stability of composition)

Let  $g \in \text{Lip}^2$ .  $(X, X')$ ,  $(\bar{X}, \bar{X}')$  bounded in  $D_{\gamma}^{2\alpha} L_{m,\infty}$ .  $2 \leq m < \infty$ . Then:

$$\begin{aligned} \| (z, z') - (\bar{z}, \bar{z}') \|_{\gamma, 2\alpha, m} &\lesssim \| |X_0 - \bar{X}_0| \wedge 1 \|_m \\ &\quad + CR \| (X, X') - (\bar{X}, \bar{X}') \|_{\gamma, 2\alpha, m} \end{aligned}$$

where  $\| (X, X') \|_{\gamma, 2\alpha, m, \infty} \vee \| (\bar{X}, \bar{X}') \|_{\gamma, 2\alpha, m, \infty} \leq R$ .

Pf: Similarly as above, we focus on  $\mathbb{R}^D$ .

$$\begin{aligned} \mathbb{R}^z - \mathbb{R}^{\bar{z}} &= Lg(x_s, x_t) - Lg(\bar{x}_s, \bar{x}_t) + \\ &\quad Dg(x_s) \delta x_{st} - Dg(\bar{x}_s) \delta \bar{x}_{st}. \end{aligned}$$

$$\text{Set } X^{\theta} = \theta X + (1-\theta) \bar{X}. \quad \tilde{X} = X - \bar{X}.$$

$$\begin{aligned}
&\Rightarrow \mathcal{L}g(x_s, x_t) - \mathcal{L}g(\bar{x}_s, \bar{x}_t) \\
&= \int_0^1 \frac{\kappa}{\kappa\theta} (\mathcal{L}g(x_s^\theta, x_t^\theta)) \kappa\theta \\
&= \int_0^1 (Dg(x_t^\theta) \tilde{x}_t - Dg(x_s^\theta) \bar{x}_s - Dg(x_s^\theta) \delta \tilde{x}_{st} \\
&\quad - D^2g(x_s^\theta) \langle \tilde{x}_s, \delta x_{st}^\theta \rangle) \kappa\theta \\
&= \int_0^1 A + B \kappa\theta
\end{aligned}$$

$$\begin{aligned}
|A| &= |Dg(x_t^\theta) \tilde{x}_s - Dg(x_s^\theta) \bar{x}_s \\
&\quad - D^2g(x_s^\theta) \langle \tilde{x}_s, \delta x_{st}^\theta \rangle|
\end{aligned}$$

$$\leq |\tilde{x}_s| |g|_{\text{Lip}^2} |\delta x_{st}^\theta|^2$$

$$\begin{aligned}
|B| &= |Dg(x_t^\theta) \delta \tilde{x}_{st} - Dg(x_s^\theta) \delta \tilde{x}_{st}| \\
&\leq |g|_{\text{Lip}^2} |\delta x_{st}^\theta| |\delta \tilde{x}_{st}|
\end{aligned}$$

$$|\delta x_{st}^\theta| \leq |\delta x_{st}| + |\delta \bar{x}_{st}| =: M_{st}$$

$$\text{So } |\mathcal{L}g(x_s, x_t) - \mathcal{L}g(\bar{x}_s, \bar{x}_t)| \leq M_{st}^2 |\tilde{x}_s| + M_{st} |\delta \tilde{x}_{st}|$$

$$\begin{aligned}
&\text{With } |\mathcal{L}g(x_s, x_t) - \mathcal{L}g(\bar{x}_s, \bar{x}_t)| \\
&\leq |\delta x_{st}|^2 + |\delta \bar{x}_{st}|^2 \lesssim M_{st}^2 \text{ from above.}
\end{aligned}$$

$$\begin{aligned}
&\Rightarrow \mathbb{E}_s (|\mathcal{L}g(x_s, x_t) - \mathcal{L}g(\bar{x}_s, \bar{x}_t)|) \leq \\
&\quad (|\tilde{x}_s| \wedge 1) \mathbb{E}_s (M_{st}^2) + \mathbb{E}_s (M_{st} |\delta \tilde{x}_{st}|)
\end{aligned}$$

$$\text{Since } \mathbb{E}_s (M_{st}^2) \leq \|M\|_{2,\infty}^2 \leq \|M\|_{\infty,2,\infty}^2 |t-s|^{2\tau}$$

$$\text{with } \|\tilde{x}_s\|_n \leq \|\tilde{x}_0\|_n + \|\delta \tilde{x}\|_{n,\tau} T^\tau$$

LEM.  $\|AB\|_{p,2} \leq \|A\|_{p,2} \cdot \|B\|_{p',2}$  for  $\frac{1}{p} \leq \frac{1}{p'} + \frac{1}{p''}$  and  $\frac{1}{2} \leq \frac{1}{2} + \frac{1}{2}$

Pf: Use Hölder inequality twice.

$$\Rightarrow \|E_s \circ M_{st}(\delta \tilde{X}_{st})\|_n \leq \|M_{st}(\delta \tilde{X}_{st})\|_n$$

$$\stackrel{\text{LEM.}}{\leq} \|M_{st}\|_{2,\infty} \|\delta \tilde{X}_{st}\|_{n,\infty}$$

$$\leq \|M\|_{2,\infty} \cdot \|\delta \tilde{X}_{st}\|_{n,\infty} |t-s|^{2\alpha}$$

$B$  can also be estimated by above.

By the cond.  $\Rightarrow n=m$  is best.

(Note  $\|\cdot\|_{2\alpha, \gamma, m, m} = \|\cdot\|_{2\alpha, \gamma, m}$ )

④ Controlled spatial  $\text{Lip}_x^2$  func.:

Def: i)  $f: \mathbb{R}^{d_1} \rightarrow \mathbb{R}^{d_2}$  is  $\gamma$ -Lip,  $\gamma \in (0,1]$  if  $\exists C$

$$|f(x_1) - f(x_2)| \leq C |x_1 - x_2|^\gamma, \forall x_1, x_2 \in \mathbb{R}^{d_1}.$$

$$\text{Set } [f]_\gamma := \min\{C > 0 \mid \square\}. \|f\|_\gamma = \|f\|_\infty + [f]_\gamma.$$

$$\text{Inductively } [f]_{k+\gamma} := \|Df\|_{k-1+\gamma}, \|f\|_{k+\gamma} =$$

$$[f]_{k+\gamma} + \|f\|_\infty.$$

ii) Consider norm  $\|x, t\|_\gamma := |x| \vee |t|^\gamma, \delta f$

$$(x, \bar{x}) = f(x) - f(\bar{x}) \text{ for } \bar{x} = (x, t). \text{ We say}$$

$$(f, f', \partial f) \in \mathcal{D}_\gamma^2 \text{Lip}_{x,loc} \text{ if } \delta f = f' \delta \gamma + \partial f \delta x.$$

$$\bar{\delta} f' \stackrel{!}{=} 0, \quad \bar{\delta} \partial f \stackrel{!}{=} 0.$$

$$\text{And } \mathcal{D}_Y^{2\alpha} \text{Lip}_x^2 = \{f \in \mathcal{D}_Y^{2\alpha} \text{Lip}_x^2 \mid \|f\|_\infty \vee \|f'\|_\infty \vee \|\partial f\|_\infty < \infty\}.$$

Remark: i) Note that fix  $t$  of  $f$ . Then:

$f$  is  $x$ -diff. and  $\partial f = Df$ . So:

for convention, see  $(f, f') \in \mathcal{D}_Y^{2\alpha} \text{Lip}_x^2$ .

ii) Fix  $x$ . we see  $(f, f')(x, \cdot) \in \mathcal{D}_Y^{2\alpha}$

and fix  $t$ ,  $f(\cdot, t) \in \text{Lip}_x^2$  but

$\mathcal{D}_Y^{2\alpha} \text{Lip}_x^2$  can't be understood as

crp.  $\mathcal{D}_Y^{2\alpha} \text{C}^0; U$  with  $U = \text{Lip}_x^2$ , i.e.

$$\sup_{t_0, t_1} \frac{\|f(\cdot, t_1) - f(\cdot, t_0) - f'(\cdot, t_0) \delta Y_{t_0, t_1}\|_{\text{Lip}_x^2}}{|t_1 - t_0|^{2\alpha}} = \infty$$

may hold since  $f(\cdot, t) \in \text{Lip}_x^2$

only work for pointwise  $t$ ).

**Lemma 1.** Set  $[(f, f')]_2 := c_{1.1} + c_{1.2} + c'_{1.1} + c'_{1.2}$  where

$$c_{1.1} = \sup_t |Df_t|_\infty, \quad c_{1.2} = \sup_t [Df_t]_1, \quad c'_{1.1} = \sup_t |f'_t|_\infty, \quad c'_{1.2} = \sup_t [f'_t]_1$$

and also  $[f, f']_{Y; 2\alpha} := c_{2.1} + c_{2.2} + c'_{2.2} + c_{2.3}$  where

$$|f_t - f_s|_\infty \leq c_{2.1} |t - s|^\alpha, \quad |Df_t - Df_s|_\infty \leq c_{2.2} |t - s|^\alpha, \quad |f'_t - f'_s|_\infty \leq c'_{2.2} |t - s|^\alpha, \quad |R_{s,t}^f|_\infty \leq c_{2.3} |t - s|^{2\alpha}.$$

Then:  $(f, f'; Df) \in \mathcal{D}_Y^{2\alpha} \text{Lip}_x^2$  with estimate:

$$|Df|_{\infty} = c_{1.1}, \quad |f'|_{\infty} = c'_{1.1},$$

and with  $(\star) = (|x_1 - x_0| \vee |t_1 - t_0|^\alpha)$ ,  $C_2 = c_{1.2} + c_{2.2}$ ,  $C_1 = c_{1.2} + c_{2.1}$ ,  $C'_1 = c'_{1.2} + c'_{2.1}$ ,

$$|\bar{\delta}f(\bar{x}_0, \bar{x}_1) - f'(\bar{x}_0)\delta Y_{t_0 t_1} - \partial f(\bar{x}_0)(x_1 - x_0)| \leq C_2(\star)^2, \quad |\bar{\delta}f'(\bar{x}_0, \bar{x}_1)| \leq C'_1(\star), \quad |\bar{\delta}\partial f(\bar{x}_0, \bar{x}_1)| \leq C_1(\star),$$

Remark: It gives criterion for  $(f, f', Df) \in D_Y^{2\sigma} \text{Lip}_X^2$ .

Pf: Note that  $g(x_1, t_1) - g(x_0, t_0) = (g(x_1, t_1) - g(x_0, t_1)) + (g(x_0, t_1) - g(x_0, t_0))$ .

Let  $g = Df$  and  $f'$  then use assumptions.

prop. (composition of crp and  $(f)$ )

Let  $X \in D_Y^{2\sigma}$ ,  $(f, f') \in D_Y^{2\sigma} \text{Lip}_X^2$ . Then:  $(z, z')$

$$z' = (f(x), Df(x)X' + f'(x)) \in D_Y^{2\sigma}.$$

Pf:  $\delta z(t_0, t_1) = \bar{\delta}f((X_{t_0, t_1}), (X_{t_1, t_1}))$

$$\stackrel{z}{=} f'(X_{t_1, t_1})\delta Y_{t_0, t_1} + Df(X_{t_1, t_1})\delta X_{t_0, t_1}$$

$$\stackrel{z'}{=} (f' + Df \cdot X') (X_{t_1, t_1}) \delta Y_{t_0, t_1}$$

Similarly we have  $\delta z' = 0$  by using

definition of  $D_Y^{2\sigma} \text{Lip}_X^2$ .

Remark: For  $(f, f') \in D_Y^{2\sigma} \text{Lip}_X^2$ :

$$\delta z = \delta f((f(x), Pf(x) + f(x) + f'(x))) \mathcal{L}Y$$

$\Rightarrow (f, f')$  is control. Vector field

as in ODE  $\mathcal{L}X = f(x) \mathcal{L}Y$ .