

Lecture Notes

(First introduce my work interest)

Theme: Numerical methods for Ito SODEs.

Notice the differences between different integral methods, like Ito, Stratonovich, etc.

Part I. Review.

Generally. SODE

$$du = f(u, t) dt + G(u, t) dW(t)$$

where $f: \mathbb{R}^d \times \mathbb{R} \rightarrow \mathbb{R}$ $G: \mathbb{R}^d \times \mathbb{R} \rightarrow \mathbb{R}^{d \times m}$.

We can write SODE as the form: 自左之右

$$du = f(u) dt + G(u) dW(t) \quad u(0) = u_0$$

where $u_0 \in \mathbb{R}^d$, $u \in \mathbb{R}^d$ $W(t) = [W_i(t)]_{i=1}^m \in \mathbb{R}^m$. ($W_i(t)$ is i.i.d B.M.). So $G: \mathbb{R}^d \rightarrow \mathbb{R}^{d \times m}: u \mapsto G(u)$

Rmk. $u(t) = \begin{pmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_d(t) \end{pmatrix} \quad W(t) = \begin{pmatrix} W_1(t) \\ W_2(t) \\ \vdots \\ W_m(t) \end{pmatrix} \quad W_i(t) \text{ i.i.d.}$

$$G(u) = \begin{pmatrix} g_{11}(u) & \cdots & g_{1m}(u) \\ g_{21}(u) & \cdots & g_{2m}(u) \\ \vdots & \ddots & \vdots \\ g_{d1}(u) & \cdots & g_{dm}(u) \end{pmatrix}$$

1.1. Classical Model

E.g.1. (Ornstein - Uhlenbeck process)

$$dP(t) = -\frac{\gamma P(t) dt}{\text{dispersive}} + \frac{\sigma dW}{\text{fluctuating}}$$

Particle movement
 $P(0) = P_0$

E.g.2. (Geometric Brownian Motion)

$$du = r u dt + \sigma u dW(t) \quad u(0) = u_0$$

$$\Rightarrow \frac{du}{dt} = (r + \sigma^2/2) u dt$$

1.2. Itô Integral

$$\int_0^t X(s) dW(s) = \lim_{N \rightarrow \infty} S_N^X(t)$$

(Martingale property)

$$E\left[\int_0^t X(s) dW(s) \mid \mathcal{F}_r\right] = \int_0^r X(s) dW(s)$$

$$\text{in particular, } E\left[\int_0^t X(s) dW(s)\right] = \int_0^t X(s) dW(s) = 0$$

(Itô isometry)

$$E\left[\left|\int_0^t X(s) dW(s)\right|^2\right] = \int_0^t E\left[\|X(s)\|_2^2\right] dt.$$

Part 2. Numerical methods

Here we will discuss.

$$\text{Since } u(t_{n+1}) = u_0 + \int_0^{t_{n+1}} f(u(s)) ds + \int_0^{t_{n+1}} G(u(s)) dW(s)$$

$$u(t_n) = u_0 + \int_0^{t_n} f(u(s)) ds + \int_0^{t_n} G(u(s)) dW(s)$$

$$\Rightarrow u(t_{n+1}) - u(t_n) = \int_{t_n}^{t_{n+1}} f(u(s)) ds + \int_{t_n}^{t_{n+1}} G(u(s)) dW(s)$$

$$\approx f(u(t_n)) \Delta t + \underbrace{G(u(t_n))}_{\Delta W_n} \Delta W_n$$

$$(\Delta t = \int_{t_n}^{t_{n+1}} dt, \quad \Delta W_n = \int_{t_n}^{t_{n+1}} dW(t))$$

Since we talk about Ito SODE, the $G(u(t))$ is chosen as $G(u(t_n))$, instead of $G(u(t))$ $t \in (t_n, t_{n+1}]$.

To obtain high-order numerical method, we identify the remainder term. Split $f(u)$ and $G(u)$ by Taylor Expansion.

(Taylor Expansion) If $u \in C^{n+1}(\mathbb{R}^d, \mathbb{R}^m)$, then

$$u(x+h) = u(x) + Du(x)h + \dots + \frac{1}{n!} D^{(n)}u(x) h^{(n)} + R_n.$$

$$(D^{(n)}u(x)) \in \underbrace{\{(R^d \times \dots \times R^d, \mathbb{R}^m)\}_n, \quad h \in \mathbb{R}^d, \quad h^{(n)} = [\underbrace{h, h, \dots, h}_n]}$$

We have Integral Remainder:

$$R_n = \frac{1}{n!} \int_0^1 (1-s)^n D^{(n+1)}u(x+sh) h^{(n+1)} ds$$

Then we apply T.E. to f and G .

For drift term $f \in C^2(\mathbb{R}^d, \mathbb{R}^d)$ 余项

$$\begin{aligned} f(u(r)) &= f(u(s)) + \underbrace{Df(u(s))(u(r) - u(s))}_{+ \int_0^1 (1-h) D^2 f(u(s) + h(u(r) - u(s))) (u(r) - u(s))^2 dh}. \end{aligned} \quad (1)$$

$$\text{Note } R_f(r, s; u(s)) = f(u(r)) - f(u(s)) = \uparrow$$

For diffusion $G \in C^2(\mathbb{R}^d, \mathbb{R}^{d \times m})$

$$G(u(r)) = G(u(s)) + DG(u(s))(u(r) - u(s)) + R_G(r, s; u(s)) \quad (2)$$

$$R_G(r, s; u(s)) = \int_0^1 (1-h) D^2 G(u(s) + h(u(r) - u(s))) (u(r) - u(s))^2 dh$$

$$\text{Hence } u(t) = u(s) + \underbrace{\int_s^t f(u(r)) dr}_{\int_s^t G(u(r)) dW(r)} + R_E(t, s, u(s)) \quad (*)$$

$$= u(s) + f(u(s))(t-s) + G(u(s)) \int_s^t dW(r) + R_E(t, s, u(s)) \quad (3)$$

$$\text{where } R_E(t, s, u(s)) = \int_s^t R_f(r, s, u(r)) dr + \int_s^t R_G(r, s, u(r)) dW(r) \\ + \int_s^t DG(u(r))(u(r) - u(s)) dW(r) \quad (4)$$

~~RM~~ Why we only expand $f \rightarrow O(\Delta t)$? (Later).

2.1 Euler-Maruyama method

EM Method is found by dropping $R_E(t, s, u(s))$.

$$\Rightarrow u(t_{n+1}) = u(t_n) + f(u(t_n)) \Delta t + G(u(t_n)) \Delta W_n$$

2.2 Milstein method. . (Add $\frac{1}{2} \Delta t$ term in (4))

Rewrite (3) as:

$$u(t) = u(s) + \underbrace{G(u(s)) \int_s^t dW(r)}_{\text{where } R_1(t, s, u(s)) = f(u(s))(t-s) + R_E(t, s, u(s))} + \underbrace{R_1(t, s, u(s))}_{\text{Hence } G(u(r)) = G(u(s)) + DG(u(s)) \underbrace{(u(r) - u(s))}_{= G(u(s)) + DG(u(s)) \int_s^r dW(p)} + DG(u(s)) R_1(r, s, u(s)) + R_G(r, s, u(s))}$$

$$\begin{aligned} & \text{Hence } G(u(r)) = G(u(s)) + DG(u(s)) \underbrace{(u(r) - u(s))}_{= G(u(s)) + DG(u(s)) \int_s^r dW(p)} + DG(u(s)) R_1(r, s, u(s)) + R_G(r, s, u(s)) \\ & \qquad \qquad \qquad + DG(u(s)) R_1(r, s, u(s)) + R_G(r, s, u(s)) \end{aligned}$$

Apply $G(u(r))$ here and $f(u(r)) \rightarrow (\ast)$

$$\begin{aligned} u(t) &= u(s) + f(u(s))(t-s) + G(u(s)) \int_s^t dW(r) \quad (\ast\ast) \\ &+ \int_s^t DG(u(s)) \cdot G(u(s)) \left(\int_s^r dW(p) \right) dW(r) + R_M(t, s, u(s)) \end{aligned}$$

$$\begin{aligned} \text{Where } R_M(t, s, u(s)) &= \int_s^t DG(u(s)) R_1(r, s, u(s)) dW(r) + \int_s^t R_G dW(r) \\ &+ \int_s^t R_f(r, s, u(s)) dr. \end{aligned}$$

Then Milstein Method is found by dropping R_m .

Here we find the term $\int_s^t \int_s^r dW_i(p) dW_j(r)$. $W(t) \in \mathbb{R}^m$.

Note $I_{ij}(s,t) := \int_s^t dW_i(p) dW_j(r)$, then we have some properties:-

~~Prop 1.~~

$$\text{prop 1. } \int_s^t \int_s^r dW_i(p) dW_j(r) + \int_s^t \int_s^r dW_j(p) dW_i(r) = I_{ij}(s,t) I_{ji}(s,t)$$

Pf: Since W_i, W_j is independent, then.

$$\begin{aligned} LHS &= \int_s^t (W_i(r) - W_i(s)) dW_j(r) + \int_s^t (W_j(r) - W_j(s)) dW_i(r) \\ &= \int_s^t W_i(r) dW_j(r) + \int_s^t W_j(r) dW_i(r) - W_i(s) \int_s^t dW_j(r) - W_j(s) \int_s^t dW_i(r) \\ &= \int_s^t d(W_i(r) W_j(r)) - W_i(s)(W_j(t) - W_j(s)) - W_j(s)(W_i(t) - W_i(s)) \\ &= W_i(t) W_j(t) - W_i(s) W_j(s) - W_i(s) W_j(t) + W_i(s) W_j(s) \\ &\quad - W_j(s) W_i(t) + W_j(s) W_i(s) \\ &= [W_i(t) - W_i(s)][W_j(t) - W_j(s)] = \int_s^t dW_i(r) \cdot \int_s^t dW_j(r) = RHS. \quad \square \end{aligned}$$

$$\text{prop 2. } \int_s^t \int_s^r dW_i(p) dW_i(r) = \frac{1}{2} (I_{ii}(s,t)^2 - (t-s))$$

$$LHS = \int_s^t (W_i(r) - W_i(s)) dW_i(r) = \int_s^t W_i(r) dW_i(r) - W_i(s) \int_s^t dW_i(r)$$

$$\begin{aligned} \text{Since } \int_s^t W_i(r) dW_i(r) &= \frac{1}{2} \int_s^t d(W_i^2(r)) - \frac{1}{2} \int_s^t dt \\ &= \frac{1}{2} (W_i^2(t) - W_i^2(s)) - \frac{1}{2}(t-s). \end{aligned}$$

$$\begin{aligned} \text{Hence } LHS &= \frac{1}{2} (W_i^2(t) - W_i^2(s)) - \frac{1}{2}(t-s) - W_i(s) W_i(t) + W_i^2(s) \\ &= \frac{1}{2} ([W_i(t) - W_i(s)]^2) - \frac{1}{2}(t-s) \\ &= \frac{1}{2} \left(\int_s^t dW_i(r) \right)^2 - \frac{1}{2}(t-s) = \frac{1}{2} (I_{ii}(s,t)^2 - (t-s)) = RHS \quad \square \end{aligned}$$

$$\text{Define } A_{ij} \text{ (s.t.)} := \int_s^t \int_s^r dW_i(p) dW_j(r) - \int_s^t \int_s^t dW_j(p) dW_i(r)$$

$$\text{then } I_i I_j + A_{ij} = 2 \int_s^t \int_s^r dW_i(p) dW_j(r)$$

$$I_i I_j - A_{ij} = 2 \int_s^t \int_s^r dW_j(p) dW_i(r)$$

$$\underline{\mathbb{R}^d} \mapsto \underline{\mathbb{R}^{dm}}$$

$$G = [g_{ij}] \quad g_{ij}: \mathbb{R}^d \rightarrow \mathbb{R}$$

$$\text{Consider the term } \underbrace{\int_s^t DG(u(s)) \left[G(u(s)) \left(\int_s^r dW(p) \right) \right] dW(r)}_{[\mathbf{d}, \mathbf{m}, \mathbf{d}]} \quad [\mathbf{d}, \mathbf{m}] \quad [\mathbf{m}, \mathbf{1}] \quad \mathbb{R}^m.$$

$$DG(u(s)) = \left[\begin{array}{c} \left[\frac{\partial g_{11}}{\partial u_1}, \dots, \frac{\partial g_{1n}}{\partial u_n} \right], \left[\quad \right], \dots, \left[\quad \right] \\ \vdots \qquad \vdots \\ \left[\quad \right], \left[\quad \right], \dots, \left[\quad \right] \end{array} \right]. \quad [d, m, d].$$

$g_{kj} \quad \Delta_{xi} \quad W_j$

the kth component:

$$\sum_{j=1}^m \int_s^t \sum_{l=1}^m \frac{d}{du_l} \frac{\partial g_{kj}}{\partial u_l} \sum_{i=1}^m g_{ei} \int_s^r dW_i(p) dW_j(p)$$

$$\text{If } j=i, \sum_{l=1}^m \int_s^t \sum_{e=1}^m \frac{d}{du_e} \frac{\partial g_{ki}}{\partial u_e} g_{ei} \int_s^r dW_i(p) dW_i(p)$$

$$= \frac{1}{2} \sum_{i=1}^m \sum_{e=1}^m \frac{d}{du_e} \frac{\partial g_{ki}}{\partial u_e} g_{ei} (I_i^2 - (t-s))$$

$$\text{if } j \neq i, \sum_{j=1}^m \int_s^t \sum_{l=1}^m \frac{d}{du_l} \frac{\partial g_{kj}}{\partial u_l} \sum_{i=1}^m g_{ei} \int_s^r dW_i(p) dW_j(p)$$

$$= \sum_{j=1}^m \int_s^t \sum_{l=1}^m \frac{d}{du_l} \frac{\partial g_{kj}}{\partial u_l} \left[\sum_{i < j} g_{ei} \int_s^r dW_i(p) dW_j(p) + \sum_{i > j} g_{ei} \int_s^r dW_i(p) dW_j(p) \right]$$

$$\text{for } i < j \sum_{j=1}^m \int_s^t \frac{d}{d u_\ell} \frac{\partial g_{kj}}{\partial u_\ell} \sum_{i < j} g_{\ell i} \int_s^r dW_i(p) dW_j(p)$$

$$= \sum_{j=1}^m \sum_{i < j} \sum_{\ell=1}^d \frac{\partial g_{kj}}{\partial u_\ell} g_{\ell i} \int_s^t \int_s^r dW_i(p) dW_j(p)$$

$$= \frac{1}{2} \sum_{j=1}^m \sum_{i < j} \sum_{\ell=1}^d \frac{\partial g_{kj}}{\partial u_\ell} g_{\ell i} (I_{ij} I_{\bar{j}} + A_{ij})$$

$$\text{for } i > j \sum_{j=1}^m \sum_{i > j} \sum_{\ell=1}^d \frac{\partial g_{ki}}{\partial u_\ell} g_{\ell i} \int_s^t \int_s^r dW_i(p) dW_j(p)$$

$$= \sum_{j=1}^m \sum_{i < j} \sum_{\ell=1}^d \frac{\partial g_{ki}}{\partial u_\ell} g_{\ell j} \int_s^t \int_s^r dW_j(p) dW_i(p)$$

$$= \sum_{j=1}^m \sum_{i < j} \sum_{\ell=1}^d \frac{\partial g_{ki}}{\partial u_\ell} g_{\ell j} (I_{ij} I_{\bar{j}} - A_{ij})$$

$$\text{Hence } \frac{1}{2} \sum_{i=1}^m \sum_{\ell=1}^d \frac{\partial g_{ki}}{\partial u_\ell} \cdot g_{\ell i} (I_i^2 - (t-s))$$

$$+ \frac{1}{2} \sum_{j=1}^m \left[\sum_{i < j} \sum_{\ell=1}^d \left(\frac{\partial g_{kj}}{\partial u_\ell} g_{\ell i} + \frac{\partial g_{ki}}{\partial u_\ell} g_{\ell j} \right) I_{ij} I_{\bar{j}} \right]$$

$$- \sum_{i < j} \sum_{\ell=1}^d \left(\frac{\partial g_{kj}}{\partial u_\ell} g_{\ell i} - \frac{\partial g_{ki}}{\partial u_\ell} g_{\ell j} \right) A_{ij} \right] = R$$

$$\Rightarrow u_{k,n+1} = u_{k,n} + f_k(u_n) \Delta t + \sum_{j=1}^m g_{kj}(u_n) \Delta W_j + R \quad \square$$

Rmk 1.

When the noise is additive, G is independent of u , then

$\frac{\partial g_{kj}}{\partial u_\ell} \equiv 0 \Leftrightarrow$ EM & Milstein are equivalent.

(Additive : G is independent of u)

Rmk 2.

When G is diagonal, then $g_{ij} = 0$ ($i \neq j$), Hence .

Milstein reduced to :

$$u_{k,n+1} = u_{kn} + f_k(u_n) \Delta t + g_{kk}(u_n) \Delta W_{kn}$$

$$+ \frac{1}{2} \frac{\partial g_{kk}}{\partial u_k}(u_n) g_{kk}(u_n) (W_{kn}^2 - \Delta t) . *$$

Back to question mentioned, we have:

If we expand f to $O(\Delta t)$ as well, then

$$\int f(u(r)) = f(u(s)) + Df(u(s))(u(r) - u(s)) + R_f$$

$$\text{with } G(u(r)) = G(u(s)) + DG(u(s))(u(r) - u(s)) + R_G$$

$$\Rightarrow u(t) = u(s) + f(u(s)) \int_s^t dr + \underbrace{Df(u(s)) \int_s^t (u(r) - u(s)) dr}_{(*)}$$

$$+ G(u(s)) \int_s^t dW(r) + DG(u(s)) \int_s^t (u(r) - u(s)) dW(r) \quad (**)$$

$$+ \int_s^t R_f dr + \int_s^t R_G dW(r)$$

$$\text{If } u(r) - u(s) = f(u(s))(r-s) + G(u(s)) \int_s^r dW(p)$$

$$\text{then } (*) = Df(u(s)) \int_s^t \left[f(u(s))(r-s) + G(u(s)) \int_s^r dW(p) \right] dr$$

$$= Df(u(s)) \left[f(u(s)) \int_s^t \int_s^r \underbrace{dp dr}_{0} + G(u(s)) \int_s^t \int_s^r \underbrace{dW(p) dr}_{0} \right] .$$

$$(**) = DG(u(s)) \left[f(u(s)) \underbrace{\int_s^t \int_s^r dp dW(r)}_0 + G(u(s)) \underbrace{\int_s^t \int_s^r dW(p) dW(r)}_0 \right]$$

So, expand f to $O(1)$ is enough for Milstein Method. \square

看實驗，與例 1.3n/2 .

Part 3. (Implicit method)

3.1 Stability.

However, the time step needs to be controlled for the stability of system.

E.g. Geometric B.M.

$$du = r u dt + \sigma u dW(t) \quad u(0) = u_0$$

We have the exact solution: $u = u_0 e^{(r - \frac{\sigma^2}{2})t + \sigma W(t)}$

$$\text{then } E[u^2(t)] = u_0^2 e^{(2r + \sigma^2)t}$$

EM. method: $u_{n+1} = u_n + r u_n \Delta t + \sigma u_n \Delta W_n$

$$\Rightarrow u_n = \prod_{j=0}^{n-1} (1 + r \Delta t + \sigma \Delta W_j) u_0$$

$$\Rightarrow E[u_n^2] = \prod_{j=0}^{n-1} E[(1 + r \Delta t + \sigma \Delta W_j)^2] u_0^2$$

$$= \prod_{j=0}^{n-1} \left[(1 + r \Delta t)^2 + \sigma^2 \Delta t \right] u_0^2$$

$$\Rightarrow \left| (1 + r \Delta t)^2 + \sigma^2 \Delta t \right| = 1 + 2\Delta t \left(r + \frac{\sigma^2}{2} + \frac{\Delta t \cdot r^2}{2} \right) < 1$$

$$\text{So } r + \frac{\sigma^2}{2} + \frac{\Delta t \cdot r^2}{2} < 0 \Rightarrow 0 < \Delta t < -\frac{2(r + \frac{\sigma^2}{2})}{r^2}$$

Then we consider (θ -Euler-Maruyama Method). It is an implicit method.

$$\Rightarrow u_{n+1} = u_n + [c(1-\theta)f(u_n) + \theta f(u_{n+1})] \Delta t + G(u_n) \Delta W_n$$

Similarly for G.B.M.

$$U_{n+1} = U_n + r[(1-\theta)U_n + \theta U_{n+1}] \Delta t + \delta U_n \Delta W_n$$

$$(1-r\theta \Delta t)U_{n+1} = [(r(1-\theta)\Delta t + 1) + \delta \Delta W_n] U_n.$$

$$\Rightarrow U_n = \prod_{j=0}^{n-1} [(r(1-\theta)\Delta t + 1) + \delta \Delta W_j] / (1-r\theta \Delta t)^n U_0.$$

$$E[U_n^2] = \prod_{j=0}^{n-1} [(r(1-\theta)\Delta t + 1)^2 + \delta^2 \Delta t] / (1-r\theta \Delta t)^{2n} U_0^2.$$

$$\Rightarrow 1 + 2r(1-\theta)\Delta t + (r(1-\theta)\Delta t)^2 + \delta^2 \Delta t < 1 - 2r\theta \Delta t + r^2 \theta^2 \Delta t^2$$

$$\Rightarrow 2r\Delta t + [r^2(1-\theta)^2 - r^2\theta^2] \Delta t^2 + \delta^2 \Delta t < 0$$

$$\Rightarrow \Delta t [2r + \delta^2 + r^2(1-2\theta)\Delta t] < 0$$

$$\Rightarrow r + \frac{\delta^2}{2} + \Delta t \cdot \frac{1-2\theta}{2} < 0$$

So when $1-2\theta=0$, i.e. $\theta=\frac{1}{2}$, the stability condition is independent of time step size.

Part 4. Strong approximation .

the approximation about the sample path, i.e. for $\forall w \in \Omega$

$$U_n(\cdot, w) \rightarrow U(\cdot, w) \quad (n \rightarrow \infty).$$

$$\text{Define } \|\cdot\|_{L^2(\Omega, \mathbb{R}^d)} = E[\|\cdot\|_2^2]^{\frac{1}{2}},$$

$$\text{So we care about } \sup_{0 \leq t_n \leq T} \|U(t_n) - u_n\|_{L^2(\Omega, \mathbb{R}^d)}$$

$$= \sup_{0 \leq t_n \leq T} E[\|U(t_n) - u_n\|_2^2]^{\frac{1}{2}}$$

We try to prove the strong convergence of EM M. and Milstein

are $O(\Delta t^{\frac{1}{2}})$ and $O(\Delta t)$ respectively. $\sup_{0 \leq t_n \leq T} \|u(t_n) - u_n\|_{L^2(\Omega)} \leq k \Delta t$

Review the last lecture. When we prove the existence and uniqueness of solution u .

We need ① the linear growth condition:

$$\begin{cases} \|f(u)\|_2^2 \leq L(1 + \|u\|_2^2) & \forall u \in \mathbb{R}^d \\ \|G(u)\|_F^2 \leq L(1 + \|u\|_2^2) \end{cases}$$

② global Lipschitz condition:

$$\begin{cases} \|f(u_1) - f(u_2)\|_2 \leq L\|u_1 - u_2\| & \forall u_1, u_2 \in \mathbb{R}^d \\ \|G(u_1) - G(u_2)\|_F \leq L\|u_1 - u_2\| \end{cases}$$

Thm.

Assume ①② holds, $W(t)$ is an F_t -adapted B.M. on $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P})$

For $\forall T > 0$, $u_0 \in \mathbb{R}^d$, then $\exists! u \in H_{2,T}$ s.t. $t \in [0, T]$

$$u(t) = u_0 + \int_0^t f(u(s)) ds + \int_0^t G(u(s)) dW(s).$$

($H_{2,T}$ is $\{u(t); t \in [0, T]\}$ s.t. $\|u\|_{H_{2,T}} := \sup_{t \in [0, T]} E[\|u(t)\|_2^2]^{\frac{1}{2}} < \infty$)

Recall that.

$$\begin{aligned} R_m(t, s, u(s)) &= \int_s^t D G(u(r)) R_r(r, s, u(r)) dW(r) + \int_s^t R_G dW(r) \\ &\quad + \int_s^t R_f(r, s, u(r)) dr. \end{aligned}$$

We prove that $E\left[\left\|\sum_{t_j < t} R_m(t_{j+1} \wedge t; t_j; u(t_j))\right\|_2^2\right] \leq k \delta t^2$

Pf:

$$\text{LHS} \leq 3 E\left[\left\|\sum_{t_j < t} \int_{t_j}^{t_{j+1}} R_f(r, t_j, u(t_j)) dr\right\|_2^2\right]$$

$$+ 3 E\left[\left\|\sum_{t_j < t} \int_{t_j}^{t_{j+1}} DG(u(t_j)) R_i(r, t_j, u(t_j)) dW(r)\right\|_2^2\right]$$

$$+ 3 E\left[\left\|\sum_{t_j < t} \int_{t_j}^{t_{j+1}} R_G dW(r)\right\|_2^2\right]$$

It's some way

$$\leq 3 E\left[\left\|\sum_{t_j < t} \int_{t_j}^{t_{j+1}} R_f dr\right\|_2^2\right]$$

$$+ 3 \sum_{t_j < t} \int_{t_j}^{t_{j+1}} \left(E\left[\left\|DG(u(t_j)) R_i(r, t_j, u(t_j))\right\|_F^2\right] + E\left[\left\|R_G(r, t_j, u(t_j))\right\|_F^2\right] \right) dr$$

provided $E\left[\left\|R_i(t, s, u(s))\right\|_2^2\right] \leq k(t-s)^2$

$$E\left[\left\|R_G(t, s, u(s))\right\|_2^2\right] \leq k(t-s)^2$$

$$\sim \leq K \Delta t^2$$

□

Part 5. Weak approximation.

$$\lim_{\Delta t \rightarrow 0} E[\phi(u_n(t))] = E[\phi(u(t))]$$

We consider the approximation of $E[\psi(u(T))]$ ($\psi: \mathbb{R}^d \rightarrow \mathbb{R}$)

E.g. We want to know the average quantities $E[\psi(u(T))]$

then we generate M independent sample paths, then

$$M_M = \frac{1}{M} \sum_{j=1}^M \psi(u_N^j)$$

Then

$$E[\psi(u(T))] - M_M = \underbrace{(E[\psi(u(T))] - E[\psi(u_N)])}_{\text{discretization error}} + \underbrace{(E[\psi(u_N)] - M_M)}_{\text{MC error}}$$

Stratonovich Integrals and SODE.

Define $W'(t) = \frac{dW(t)}{dt}$ by K-L Expansion.

$$W(t) = \sum_{j=0}^{\infty} \frac{\sqrt{2}}{(j+\frac{1}{2})\pi} \xi_j \sin((j+\frac{1}{2})\pi t) \quad \xi_j \sim N(0, 1) \text{ i.i.d.}$$

then we can have the truncated form:

$$W_J(t) = \sum_{j=0}^J \frac{\sqrt{2}}{(j+\frac{1}{2})\pi} \xi_j \sin((j+\frac{1}{2})\pi t)$$

$$\text{then we have } W_J'(t) = \sum_{j=0}^J \sqrt{2} \xi_j \cos((j+\frac{1}{2})\pi t)$$

$$\text{E.g. } \int_0^t W(s) W'(s) ds \rightarrow \frac{1}{2} W(t)^2 \text{ as } J \rightarrow \infty.$$

Thm (Wong - Zakai)

$$V_J(t) \text{ s.t. } \frac{dV_J}{dt} = f(V_J) + g(V_J) W_J'(t)$$

$$V(t) \text{ s.t. } dV = \tilde{f}(V) dt + g(V) dW(t)$$

where the modified drift $\tilde{f}(v) = f(v) + \frac{1}{2} g(v) g'(v)$.

$$\text{Then } \sup_{0 \leq t \leq T} |V(t) - V_J(t)| \rightarrow 0 \quad \text{as } J \rightarrow \infty.$$