

第五次分享
一些前置知识

Hilbert space.
FEM.
Spectral theory

1. Hilbert space $L^2(D)$

Thm 1.1 For \forall domain D , $L^2(D)$ is a real Hilbert space, with inner product $\langle u, v \rangle_{L^2(D)} = \int_D u(x)v(x)dx$

Thm 1.2 Let (X, \mathcal{F}, μ) be a measure space and H be a Hilbert space with inner product $\langle \cdot, \cdot \rangle_{L^2(X, H)}$. Then $L^2(X, H)$ is a Hilbert space with

$$\langle u, v \rangle_{L^2(X, H)} = \int_X \langle u(x), v(x) \rangle d\mu(x)$$

Fig. 1.3. We have complex Hilbert space $L^2(\mathbb{R}^d, \mathbb{C})$ with inner product $\langle u, v \rangle_{L^2(\mathbb{R}, \mathbb{C})} = \int_{\mathbb{R}^d} u(x)\overline{v(x)} dx$. For SPDE, we have measure space (Ω, \mathcal{F}, P) . Note the square integrable functions $u(x, w)$ on $D \times \Omega$ space as $L^2(\Omega, L^2(D))$ s.t.

$u(\cdot, w) \in L^2(D)$ for almost $\forall w \in \Omega$:

$$\langle u, v \rangle_{L^2(\Omega, L^2(D))} = \iint_{\Omega \times D} u(x, w)v(x, w) dx dP(w)$$

Since we have inner product, then we define orthonormal projections and bases. Consider H as Hilbert space, then G be a subspace of H

Def 1.4 (Orthogonal component).

$$G^\perp = \{u \in H : \langle u, v \rangle = 0, \forall v \in G\}$$

$$\Rightarrow G^\perp \cap G = \{0\}$$

Thm 1.5 If G is a closed subspace of a Hilbert space H .

$\forall u \in H$ can be uniquely written as $u = p^* + q$ ($p^* \in G$, $q \in G^\perp$)
and $\|u - p^*\| = \inf_{p \in G} \|u - p\|$

Def 1.5 (Orthogonal projection) $P: H \rightarrow G$ is defined by

$$P_u = p^* \Rightarrow P^2 = P.$$

Def 1.6 (Orthonormal basis) Let H be a Hilbert space. $\{\phi_j : j \in \mathbb{N}\}$

is orthonormal if $\langle \phi_i, \phi_j \rangle = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} = \delta_{ij}$

If $\text{span}\{\phi_i\}$ is additionally dense in H , then we have a complete orthonormal set, call $\{\phi_i\}$ orthonormal basis

$$\Rightarrow u = \sum_{j=1}^{\infty} \langle u, \phi_j \rangle \phi_j. \quad \forall u \in H.$$

$$\|u\|^2 = \sum_{j=1}^{\infty} |\langle u, \phi_j \rangle|^2 = \sum_{j=1}^{\infty} |\langle \phi_j, u \rangle|^2$$

Thm 1.7 Consider a separable Hilbert space H with orthonormal

basis $\{\phi_j : j \in \mathbb{N}\}$. Let $G_n = \text{span}\{\phi_1, \dots, \phi_n\}$. Denote the projection from H to G_n by P_n , then $P_n u = \sum_{j=1}^n \langle u, \phi_j \rangle \phi_j$.

Def 1.8 (Weak derivative) Let \mathbb{Y} be a Banach space. We say a measurable function $D^\alpha u: D \rightarrow \mathbb{R}$ is α th weak derivative if

$$\int_D D^\alpha u(x) \phi(x) dx = (-1)^{|\alpha|} \int_D u(x) D^\alpha \phi(x) dx \quad \forall \phi \in C_c^\infty(D)$$

Def 1.9 (Sobolev space) Let D be domain, \mathbb{Y} be Banach space & $p \geq 1$. Sobolev space $W^{r,p}(D, \mathbb{Y})$ is the set of functions whose weak derivatives up to $r \in \mathbb{N}$ are in $L^p(D, \mathbb{Y})$. That is

$$W^{r,p}(D, \mathbb{Y}) = \{u: D^{\alpha} u \in L^p(D, \mathbb{Y}) \text{ if } |\alpha| \leq r\}$$

where $p=2$, then \mathbb{Y} is a Hilbert space H .

then note $W^{r,2}(D, H)$ as $H^r(D, H)$

(Consider the Sobolev space cause the good properties)

Thm 1.10.(1) $W^{r,p}(D, \mathbb{Y})$ is a Banach Space with norm

$$\|u\|_{W^{r,p}(D, \mathbb{Y})} = \left(\sum_{0 \leq |\alpha| \leq r} \|D^\alpha u\|_{L^p(D, \mathbb{Y})}^p \right)^{\frac{1}{p}}$$

(2) $H^r(D, H)$ is a Hilbert space with inner product.

$$\langle u, v \rangle_{H^r(D, H)} = \sum_{0 \leq |\alpha| \leq r} \langle D^\alpha u, D^\alpha v \rangle_{L^2(D, H)}$$

\Rightarrow the norm is

$$\|u\|_{H^r(D)} = \left(\sum_{0 \leq |\alpha| \leq r} \|D^\alpha u\|_{L^2(D)}^2 \right)^{\frac{1}{2}}$$

Also we can define semi-norm: $|u|_{H^r(D)} = \left(\sum_{|\alpha|=r} \|D^\alpha u\|_{L^2(D)}^2 \right)^{\frac{1}{2}}$

2. Linear operator and spectral theory.

Def 2.1 (Linear operator) Let X, Y be two vector spaces on \mathbb{F} . A function $L: X \rightarrow Y$ is said to be linear operator if $\forall u, v \in X$ and any scalar $a \in \mathbb{F}$: $L(u+v) = L(u) + L(v)$.

Def 2.2. (Bounded linear operator) $(X, \| \cdot \|_X)$, $(Y, \| \cdot \|_Y)$ be Banach Space.

Linear operator $L: X \rightarrow Y$ is bounded if $\exists K > 0$ s.t.

$$\|L\|_Y \leq K \|u\|_X. \quad \forall u \in X.$$

Note $\mathcal{L}(X, Y)$: bounded linear operators: $L: X \rightarrow Y$.

If $X = Y \Rightarrow \mathcal{L}(X) = \mathcal{L}(X, X)$.

Then we have the norm: $\|L\|_{\mathcal{L}(X, Y)} = \sup_{u \neq 0} \frac{\|L\|_Y}{\|u\|_X}$.

Def 2.3. (Bounded Linear functional): a member of $\mathcal{L}(X, \mathbb{R})$.

\Rightarrow If X is banach, the set of B.L.F on X is called dual sp.

and itself is a Banach space with norm $\| \cdot \|_{\mathcal{L}(X, \mathbb{R})}$

Thm 2.4 (Riesz Representation). H (Hilbert space with inner product $\langle \cdot, \cdot \rangle$)

Let ℓ be bounded linear functional on H . There exists a unique

$u_\ell \in H$ s.t. $\langle u_\ell, x \rangle = \ell(x) \quad \forall x \in H$.

Thm 2.5. (Lax-Milgram).

We consider Hilbert-Schmidt operators.

Def 2.6. Let H, U be separable Hilbert Spaces with norms $\|\cdot\|_H$, $\|\cdot\|_U$ respectively. $\{\phi_j\}$ orthonormal basis of U . Define

$$\text{Hilbert-Schmidt norm } \|L\|_{HS(U,H)} := \left(\sum_{j=1}^{\infty} \|L\phi_j\|_U^2 \right)^{\frac{1}{2}}$$

$HS(U,H) = \{L \in \mathcal{L}(U,H) : \|L\|_{HS(U,H)} < \infty\}$ is Banach.

$L \in HS(U,H)$ is a Hilbert-Schmidt operator.

If $U=H$, then $\|L\|_{HS} = \|L\|_{HS(H,H)}$

Eg. 2.7. $\mathbb{R}^{d \times d}$ Matrix. : $\mathbb{R}^d \rightarrow \mathbb{R}^d$.

$$\|A\|_{HS} = \left(\sum_{i,j}^d a_{ij}^2 \right)^{\frac{1}{2}} \text{ which is Frobenius norm.}$$

Eg. 2.8 $L \in \mathcal{L}(L^2(0,1))$ defined by $(Lu)(x) = \int_0^x u(y) dy \quad u \in L^2(0,1)$.

Consider the orthonormal basis $\phi_j(x) = \sqrt{2} \sin(j\pi x)$.

$$\Rightarrow (L\phi_j)(x) = \sqrt{2} (1 - \cos(j\pi x)) \frac{1}{j\pi} \Rightarrow \|L\phi_j\|_{L^2(0,1)} \leq \frac{2\sqrt{2}}{j\pi}.$$

$$\Rightarrow \|L\|_{HS}^2 = \sum \|L\phi_j\|_{L^2(0,1)}^2 \leq \sum_{j=1}^{\infty} \frac{8}{j^2\pi^2} < \infty.$$

$\Rightarrow L$ is a valid HS operator.

We focus on integral operators and relationship with HS operator on $L^2(D)$.

Def 2.9. (Integral operator with kernel G). For a domain D, and $G \in L^2(D \times D)$, the integral operator L on $L^2(D)$ with kernel G is defined by

$$(Lu)(x) := \int_D G(x, y) u(y) dy \quad x \in D, u \in L^2(D). \quad (\star)$$

Thm 2.10. Any integral operator with kernel $G \in L^2(D \times D)$ is a HS operator on $L^2(D)$.

Conversely, any HS operator L on $L^2(D)$ can be written as (\star) , and $\|L\|_{HS} = \|G\|_{L^2(D \times D)}$

Def 2.11 Symmetric operator $L \in L(H)$ is symmetric on Hilbert H if $\langle Lu, v \rangle = \langle u, Lv \rangle$ for $\forall u, v \in H$.

Thm 2.12. The integral operator L with kernel G is symmetric.

Thm 2.13. (HS spectral). Let H be countably infinite-dim Hilbert space and $L \in L(H)$ be symmetric and compact, with Eigenvalue $|\lambda_j| > |\lambda_{j+1}|$ with corresponding eigenfunction $\phi_j \in H$. Then (i) $\forall \lambda_j \in \mathbb{R}$ and $\lambda_j \rightarrow 0$ as $j \rightarrow \infty$.

(ii) ϕ_j can be chosen $\xrightarrow{\text{to form an orthonormal basis for } L}$

(iii) $\forall u \in H, Lu = \sum_{j=1}^{\infty} \lambda_j \langle u, \phi_j \rangle \phi_j$

Def 2.14 (Non-negative definite operators).

Prepare .

Section 1. Semigroups of linear operators.

The space \mathbb{R}^d where $u(t)$ exists called the phase space
 $S(t) : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is a family of operators on the phase space \mathbb{R}^d .

↗ phase space.

Def 1.1 (Semigroup) Let X be a vector space. $S(t) : X \rightarrow X$

is a semigroup if 1) $S(0) = I$ (The identity operator)

$$2) S(t+s) = S(t)S(s) \text{ for } s, t \geq 0.$$

Specially, if $S(t)$ is linear, then $S(t)$ is a semigroup of linear operators.

Def 1.2. (Infinitesimal generator) Let $S(t)$ be a semigroup of linear operators on Banach space X .

The infinitesimal generator $-A$ is defined by

$$(-A)u := \lim_{h \rightarrow 0} \frac{S(h)u - u}{h}.$$

The domain of A is denoted by $D(A) \subset X$ (the set of $u \in X$ where the limit exists).

E.g. 1.3. (linear ODE). $\frac{du}{dt} = -\lambda u$. $u_0 \in \mathbb{R}$ $\lambda > 0$.

\Rightarrow Phase space is \mathbb{R} and $S(t)u_0 := u(t) = e^{-\lambda t}u_0$.

$\Rightarrow S(t) = e^{-\lambda t} \Rightarrow$ generator is $-\lambda$

$-\lambda$ is said to generate the semigroup.

Rmk 1.4. $u(t, x)$ is interpreted as functions $u(t) : t \rightarrow X$.

X is a function space like $L^2(D)$. Then PDE can be written as ODEs.

(*)
Assumption 1.5. Suppose H is a Hilbert space with inner product $\langle \cdot, \cdot \rangle$ and the linear operator $-A : D(A) \subset H \rightarrow H$ has a complete orthonormal set of eigenfunctions $\{\phi_j : j \in \mathbb{N}\}$ and eigenvalue $\lambda_j > 0$ ($\lambda_{j+1} > \lambda_j$)

Def 1.6. If Assumption 1.5 is satisfied.

$$e^{-tA} u = \sum_{j=1}^{\infty} e^{-\lambda_j t} \langle u, \phi_j \rangle \phi_j$$

We can prove that e^{-tA} is a semigroup of linear operators on H . with generator $-A$

Then we talk about semilinear evolution equations,

Many PDEs have semilinear structure like reaction-diffusion eqn.

Def 1.7 (semilinear ODEs).

$$\frac{du}{dt} = -Mu + f(u) \quad u(0) = u_0 \in \mathbb{R}^d.$$

where M needs to be positive-definite.

$$\Rightarrow u(t) = e^{-tM} u_0 + \int_0^t e^{-(t-s)M} f(u(s)) ds.$$

Ex 1.8. For $f: \mathbb{R} \rightarrow \mathbb{R}$, consider $u_t = \Delta u + f(u)$. $x \in D$, $t \in [0, \infty)$.

with homogeneous boundary conditions; the initial condition $u_0(x) = u(0, x)$

The solution $u(t, x)$, by semigroup theory, can be interpreted as a function $u: [0, \infty) \rightarrow L^2(D)$

$$\Rightarrow \frac{du}{dt} = -Au + f(u)$$

where $A = -\Delta$ with $D(A) = H^2(D) \cap H_0'(D)$.

$-A$ is the generator of semigroup $S(t)$ on $L^2(D)$

Rmk: We find that the boundary conditions are incorporated into A .

Def. 1.9. (Semilinear evolution equation)

A

a Semilinear evolution equation on Hilbert space H :

$$\frac{du}{dt} = -Au + f(u) \quad u(0) = u_0 \in H.$$

where A needs to satisfy Assumption (x). $f: H \rightarrow H$.

\Rightarrow variation of constant formula.

$$u(t) = e^{-tA} \underbrace{u_0}_{\text{the variation of } u_0} + \int_0^t e^{-(t-s)A} \underbrace{f(u(s))}_{\text{the accumulation of source term } f} ds.$$

the variation of u_0 the accumulation of source term f .

Def. 1.10. (Mild solution) A mild solution of semilinear evolution equation on $[0, T]$ is a function $u \in C([0, T], H)$ s.t. variation of constant formula holds.

Then just as ODE, we need some conditions to construct the existence and uniqueness of mild solution.

1.11 First

Assumption: Assumption (F) holds, then let $u_0 \in H$. $f: H \rightarrow H$. s.t.

$$\|f(u)\| \leq L(1 + \|u\|)$$

$$\|f(u_1) - f(u_2)\| \leq L\|u_1 - u_2\|.$$

$\Rightarrow \exists!$ mild solution $u(t)$. And $\exists K_T > 0$. s.t. $\forall u_0 \in H$

$$\|u(t)\| \leq K_T (1 + \|u_0\|) \quad 0 \leq t \leq T.$$

Thm 1.12. Let Assumption 1.11 holds, then $u(t)$ be mild solution then $u(t) \in D(A^{\frac{1}{2}})$ $\frac{du}{dt}(t) \in D(A^{-\frac{1}{2}})$. $\forall t > 0$.

Then we develop the weak solution.

$$\Rightarrow \begin{cases} \left\langle \frac{du}{dt}, v \right\rangle = \left\langle A^{-\frac{1}{2}} \frac{du}{dt}, A^{\frac{1}{2}} v \right\rangle \\ \left\langle Au, v \right\rangle = \left\langle A^{\frac{1}{2}} u, A^{\frac{1}{2}} v \right\rangle \end{cases} \text{ for } v \in D(A^{\frac{1}{2}}), u \in D(A) \quad \frac{du}{dt} \in H.$$

Def. 1.13. Let $V = D(A^{\frac{1}{2}})$ $V^* = D(A^{-\frac{1}{2}})$. $u: [0, T] \rightarrow V$ is a weak solution of $\frac{du}{dt} = -Au + f(u)$. If almost all $s \in [0, T]$.

we have $\frac{du(s)}{dt} \in V^*$ and

$$\left\langle \frac{du(s)}{dt}, v \right\rangle = -\alpha(u(s), v) + \langle f(u(s)), v \rangle \quad \forall v \in V.$$

where $\alpha(u(s), v) = \langle A^\frac{1}{2}u, A^\frac{1}{2}v \rangle$

If take $\tilde{V} = \text{span}\{\psi_1, \dots, \psi_j\} \subset V$. seek $\tilde{u} = \sum \hat{u}_j(t) \psi_j$.

$$\Rightarrow \left\langle \frac{d\tilde{u}}{dt}, v \right\rangle = -\alpha(\tilde{u}, v) + \langle f(\tilde{u}), v \rangle \quad \forall v \in \tilde{V}.$$

That is $\left\langle \frac{d\tilde{u}}{dt}, \psi_j \right\rangle = -\alpha(\tilde{u}, \psi_j) + \langle f(\tilde{u}), \psi_j \rangle$ for $\forall j$.

Section 2. Normal numerical method.

Spectral Galerkin Approximation.

Assume A satisfy Assumption (*), then we have $\{\phi_j\}$ for H .

\Rightarrow we can define $\tilde{V} = V_J = \text{span}\{\phi_1, \dots, \phi_J\}$. Note $P_J: H \rightarrow V_J$
 $P_J u = \sum_{j=1}^J \hat{u}_j(t) \phi_j$ where $\hat{u}_j = \frac{1}{\|u\|_H^2} \langle u, \phi_j \rangle$

$$\Rightarrow \frac{du_J}{dt} = -A_J u_J + P_J f(u_J) \quad u_J(0) = P_J(u_0)$$

$$\Rightarrow \text{For } j=1, \dots, J. \quad \frac{d\hat{u}_j(t)}{dt} = -\lambda_j \hat{u}_j(t) + \hat{f}_j(u_J) \quad \hat{u}_j(0) = \hat{u}_{0,j}$$

$$\text{Let } \hat{u}_J(t) = [\hat{u}_1(t), \dots, \hat{u}_J(t)]^T \quad \hat{f}_J(u_J) = [\hat{f}_1(u_J), \dots, \hat{f}_J(u_J)]^T$$

$$\text{we have } \frac{d\hat{u}_J(t)}{dt} = -M \hat{u}_J(t) + \hat{f}_J(u_J) \quad (M = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_J \end{pmatrix}).$$

Then How to compute? We need to approximate $\hat{u}_J(t)$.

$$\text{Note } \hat{u}_J(t_n) \rightarrow \hat{u}_J(t)$$

where $\hat{u}_j(t_n) = [\hat{u}_1(t_n) \dots \hat{u}_J(t_n)]^T$

$$\Rightarrow u_{j,n} = \sum_j \hat{u}_{j,n} \phi_j$$

\Rightarrow Semi-implicit Euler method.

$$\frac{u_{j,n+1} - u_{j,n}}{\Delta t} = -A_J u_{j,n+1} + P_J f(u_{j,n})$$

$$\Rightarrow \frac{\hat{u}_{j,n+1} - \hat{u}_{j,n}}{\Delta t} = -M \hat{u}_{j,n+1} + \hat{f}_j(\hat{u}_{j,n})$$

$$\Rightarrow (I + \Delta t M) \hat{u}_{j,n+1} = \hat{u}_{j,n} + \Delta t \cdot \hat{f}_j(\hat{u}_{j,n})$$

$$\text{that is } (I + \Delta t \lambda_j^-) \hat{u}_{j,n+1} = \hat{u}_{j,n} + \Delta t \cdot \hat{f}_j(u_{j,n}) \quad \square$$

Galerkin Finite elements Method.

$$\frac{du}{dt} = -Au + f(u). \quad -A = \varepsilon \frac{d^2}{dx^2}$$

We formulate PDE as ODE on $H = L^2(0,a)$. with $-A = \varepsilon \frac{d^2}{dx^2}$

with $D(A) = H^2(0,a) \cap H_0^1(0,a)$

$$\Rightarrow \left\langle \frac{du_h}{dt}, v \right\rangle_H = -a(u_h, v) + \langle f(u_h), v \rangle_H,$$

$$u_h(t,x) = \sum_{j=1}^J u_j(t) \phi_j(x)$$

Let $u_h(t) = [u_1(t) \dots u_J(t)]^T$. This satisfies ODEs:

$$M \frac{du_h(t)}{dt} = -K u_h + f(u_h).$$

where $f(u_h) \in \mathbb{R}^J$. $\hat{f}_j(u_h) = \langle f(u_h), \phi_j \rangle_H$

$$(M)_{ij} = \langle \phi_i, \phi_j \rangle_H \quad K_{ij} = a(\phi_i, \phi_j)$$

$$\Rightarrow \frac{du_h}{dt} = -M^{-1} K u_h + M^{-1} f(u_h).$$

$$dW(t,x)$$

Review. Random Fields.

FEM

$$u_t = -\Delta u + \xi(t, x)$$

w^某

$\int dW(t, x)$

Itô

We mainly talk about Elliptic PDEs and semilinear SPDEs.

Elliptic PDEs with Random Data.

E.g.

$$\begin{cases} -\nabla \cdot (a(x, w) \nabla u(x)) = f(x, w) & x \in D \\ u(x, w) = g(x) & x \in \partial D \end{cases}$$

where $\{a(x)\}$ and $\{f(x)\}$ are second-order random fields.

$\Rightarrow u(x)$ is a random field.

$X(t)$ sample path $X(t, w)$

$v(\cdot, w)$ $\in L^2(D)$ $u(x)$. realization

Hence we work with real-valued random fields $\{v(x): x \in D\}$

that are $L^2(D)$ -valued random variables. i.e. $v: D \times \Omega \rightarrow \mathbb{R}$

$v \in L^2(\Omega, \mathcal{F}, L^2(D))$ st.

Ω $\boxed{\{w\}}$

$$\|v\|_{L^2(\Omega, L^2(D))}^2 = \underbrace{\int_{\Omega} \int_D v^2(x, w) dx dP(w)}_{\sim} = E[\|v\|_{L^2(D)}^2] < \infty.$$

For simplicity. We take $f \in L^2(D)$, instead of $L^2(\Omega, L^2(D))$, $g=0$

Variational formulation on D .

Problem setting: Given realization of $a(\cdot, w)$. Consider the random field $u(x)$ with realizations $u(\cdot, w) \in V := H_0^1(D)$ st.

$$\int_D a(x, w) \nabla u(x, w) \cdot \nabla v(x) dx = \int_D f(x) v(x) dx \quad \forall v \in V.$$

(The well-posedness of $u(\cdot, w)$ is the same as FEM).

Here we use FEM to approximate $u(\cdot, w) \Rightarrow u_h(\cdot, w) \in V^h$

where $V^h \subset H_0^1(D)$.

$$\int_D a(x, w) \nabla u_h(x, w) \cdot \nabla v(x) dx = \int_D f(x) v(x) dx \quad \forall v \in V$$

Suppose we only have the realization $\tilde{a}(\cdot, w)$ of an approximation $\tilde{a}(x)$ to $a(x)$.

We just need to consider the approximation $\tilde{u}_h(x) \in V^h$ s.t.

$$\int_D \tilde{a}(x, w) \cdot \nabla \tilde{u}_h(x, w) \cdot \nabla v(x) dx = \int_D f(x) v(x) dx \quad \forall v \in V^h$$

If we want to estimate $E[\tilde{u}_h]$, the basic idea is MC.

Monte Carlo Method.

Given i.i.d samples $\tilde{a}_r = \tilde{a}(\cdot, w_r)$, $r=1 \dots Q$.

We can get Q variational problems to get $\tilde{u}_h^r(x) = \tilde{u}_h(x, w_r)$ with Galerkin Matrix $A \in \mathbb{R}^{N \times N}$, $b \in \mathbb{R}^N$.

$$\begin{cases} a_{ij} = \int_D \tilde{a}_r(x) \nabla \phi_i(x) \cdot \nabla \phi_j(x) dx \\ b_i = \int_D f(x) \phi_i(x) dx \end{cases}$$

So once we get $\tilde{u}_h^r(x)$. then $E[\tilde{u}_h] = \frac{1}{Q} \sum_{r=1}^Q \tilde{u}_h^r(x) = \mu_{Q,h}(x)$

$$\sigma_{Q,h}^2(x) = \frac{1}{Q-1} \left(\sum \tilde{u}_h^r(x)^2 - Q \mu_{Q,h}^2(x) \right)$$

E.g. Review how we get realization of $a(\cdot, w)$.

If we have explicit eigenfunction and eigenvalues, then by KL

$$a(x, w) = \mu + \sum_{k=1}^P \frac{\delta}{k^2 \pi^2} \cos(\pi k x) \zeta_k(w) \quad \zeta_k \sim U(-1, 1) \text{ i.i.d.}$$

Then apply each $a(\cdot, w)$, we can get $E[\tilde{u}_h]$ and $\text{Var}(\tilde{u}_h)$.

But here we find that the cost of MCFEM is $O(\varepsilon^{-4})$, and the convergence is very slow.

E.g. $C_{\text{all}} = \text{Cost}(\text{generating } Q \text{ samples of } a(x)) + \text{Cost}(\text{Solving } Q \text{ FEM problems})$

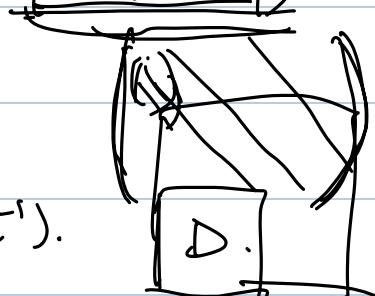
The size of A is $J \times J$. $O(h^{-2})$ (Take 2D problem).

The circulant embedding generate a matrix $4\hat{J} \times 4\hat{J}$

$$(\hat{J} = (1+\alpha)^2(n\delta+1)^2, h = \frac{1}{n\delta})$$

BCCB.M. ← Embedding.

BTTB.M.



Use FFT. the cost is $O(Q\hat{J} \log \hat{J})$.

$$\begin{aligned} \Rightarrow \text{Cost-all} &= O(Qh^{-2}) + O(Q\hat{J} \log \hat{J}) \\ &= O(Qh^{-2}) + O(Qh^{-2} \log h^{-1}). \end{aligned}$$

After we estimate the error of $E[\tilde{u}_h]$ with $E[u]$

$$\|E[u] - E[\tilde{u}_h]\|_{H_0^1(D)} = O(h) + O(Q^{-\frac{1}{2}}).$$

That is, if we control the error down to ε , then.

$$Q = O(\varepsilon^{-2}) \text{ and } h = O(\varepsilon).$$

\Rightarrow The cost is $O(\varepsilon^{-4})$!

$\phi_{\hat{J}}(x)$ red.

$\psi_{\hat{J}}(\zeta_j)$. $\zeta_j \in \Gamma$.

That is we need to develop new methods. We discuss the variational formulation on $D \times \Omega$. That is we try to

Seek weak solutions $u: D \times \Omega \rightarrow \mathbb{R}$. $\forall \cdot$ $L^2(D)$ -valued r.v.

Def (Weak solution on $D \times \Omega$) . A weak solution to (*) with $g \neq 0$ is a function $u \in V = \underline{\underline{L^2(\Omega, L^2(D))}}$ that satisfies

$$\alpha(u, v) = \lambda(v) \quad \forall v \in V.$$

where $\alpha(\cdot, \cdot) : V \times V \rightarrow \mathbb{R}$ and $\lambda : V \rightarrow \mathbb{R}$:

$$\left\{ \begin{array}{l} \alpha(u, v) = \underline{\underline{E}} \left[\int_D \alpha(x, \cdot) \nabla u(x, \cdot) \cdot \nabla v(x, \cdot) dx \right] \\ \lambda(v) = \underline{\underline{E}} \left[\int_D f(x, \cdot) v(x, \cdot) dx \right]. \end{array} \right.$$

So if $g \neq 0$ the extension is natural. just find

$$u \in W = \underline{\underline{L^2(\Omega, H_g^1(D))}}.$$

When we have the approximate random fields $\tilde{\alpha}, \tilde{f} : D \times \Omega \rightarrow \mathbb{R}$ to $\alpha(x)$ and $f(x)$, the problem leads to find $\tilde{u} : D \times \Omega \rightarrow \mathbb{R}$

s.t. P. a.s.

$$\left\{ \begin{array}{l} -\nabla \cdot (\tilde{\alpha}(x, w) \cdot \nabla \tilde{u}(x, w)) = \tilde{f}(x, w) \quad x \in D \\ \tilde{u}(x, w) = g(x) \quad x \in \partial D \end{array} \right.$$

The corresponding weak form is find $\tilde{u} \in W$ s.t.

$$\tilde{\alpha}(\tilde{u}, v) = \tilde{\lambda}(v) \quad \forall v \in V.$$

where $\tilde{\alpha} : W \times V \rightarrow \mathbb{R}$. $\tilde{\lambda} : V \rightarrow \mathbb{R}$:

$$\left\{ \begin{array}{l} \tilde{\alpha}(\tilde{u}, v) = \underline{\underline{E}} \left[\int_D \tilde{\alpha}(x, \cdot) \cdot \nabla \tilde{u}(x, \cdot) \cdot \nabla v(x, \cdot) dx \right] \\ \tilde{\lambda}(v) = \underline{\underline{E}} \left[\int_D f(x, \cdot) v(x, \cdot) dx \right]. \end{array} \right.$$

So after we have the approximation., the weak form still hard to solve. Since the integrals involve the abstract set Ω .

i.e.

$$\int \tilde{\alpha}(u, v) = \int \int_D \tilde{\alpha}(x, w) \cdot \nabla u(x, w) \cdot \nabla v(x, w) dx dP(w).$$

$$\int \tilde{f}(v) = \int \int_D \tilde{f}(x, w) \cdot v(x, w) dx dP(w)$$

If we can let $\tilde{\alpha}(x), \tilde{f}(x)$ only depend on finite number of random variables. $\tilde{\zeta}_k : \Omega \rightarrow T_k \subset \mathbb{R}$. We can make a change of variable and get an equivalent weak form on $D \times \Gamma$. where $\Gamma = \Gamma_1 \times \dots \times \Gamma_M \subset \mathbb{R}^M$.

Def: Let $\tilde{\zeta}_k : \Omega \rightarrow \Gamma_k$ for $k=1, \dots, M$. be real-valued r.v.

Then $v \in L^2(\Omega, L^2(D))$ of the form $v(x, \tilde{\zeta}(w))$ for $x \in D, w \in \Omega$.

Where $\tilde{\zeta}(w) = [\tilde{\zeta}_1(w), \tilde{\zeta}_2(w), \dots, \tilde{\zeta}_M(w)]^\top : \Omega \rightarrow \Gamma \subset \mathbb{R}^M$. is called finite-dimensional (M -dimensional noise).

E.g. We can take the truncated KL expansion.

$$\left\{ \begin{array}{l} \alpha(x, w) = M_\alpha(x) + \sum_{k=1}^{\infty} \sqrt{V_k^\alpha} \phi_k^\alpha(x) \tilde{\zeta}_k(w) \\ f(x, w) = M_f(x) + \sum_{k=1}^{\infty} \sqrt{V_k^f} \phi_k^f(x) \eta_k(w) \end{array} \right.$$

Where $\sqrt{V_k^\alpha}, \phi_k^\alpha$ & $\sqrt{V_k^f}, \phi_k^f$ are eigenpairs of C_α and C_f , resp.

$\tilde{\zeta}_k, \eta_k$ are random variables. Here for simplicity. assume $\tilde{\zeta}_k$ and η_k have the same distribution. Now truncated the expansion.

$$\left\{ \begin{array}{l} \alpha(x, w) = M_\alpha(x) + \sum_{k=1}^P \sqrt{V_k^\alpha} \phi_k^\alpha(x) \tilde{\zeta}_k(w) \\ f(x, w) = M_f(x) + \sum_{k=1}^N \sqrt{V_k^f} \phi_k^f(x) \tilde{\zeta}_k(w) \end{array} \right.$$

$\tilde{\zeta}_k$ i.i.d.

$M = \max \{ P, N \}$

ζ_k needs control. Assume $\zeta_k \in [-\gamma, \gamma]$

Then we can define the weak solution on $D \times T$

Let $\tilde{a}(x)$ and $\tilde{f}(x)$ be the truncated KL expansion. we

define $L_p^2(T, H_g'(D)) = \{v: D \times T \rightarrow \mathbb{R} : \int p(y) \|v(\cdot, y)\|_{H_g'(D)}^2 dy < \infty \text{ and } v \in L^2(D)\}$
 similarly we can define $L_p^2(T, H_0'(D))$

Def: An equivalent weak solution on $D \times T$ is a solution

$$\tilde{a} \in L_p^2(T, H_g'(D)) \text{ s.t. } \tilde{a}(\tilde{u}, v) = \tilde{l}(v), \forall v \in V = L_p^2(T, H_0'(D))$$

where $\tilde{a}: W \times V \rightarrow \mathbb{R}$. $\tilde{l}: V \rightarrow \mathbb{R}$:

$$\tilde{a}(u, v) = \int_T \int_D p(y) \int_B \tilde{a}(x, y) \nabla u(x, y) \cdot \nabla v(x, y) dx dy.$$

$$\tilde{l}(v) = \int_T \int_D p(y) \int_D \tilde{f}(x, y) \cdot v(x, y) dx dy.$$

The $p: \Gamma \rightarrow \mathbb{R}^+$. Normally, we take as the joint density of ζ .

And we find that $\tilde{a}(u, v) = \tilde{l}(v)$ is an $(M+2)$ dim deterministic problem on $D \times T$.

The strong formulation is find $\tilde{u}: D \times T \rightarrow \mathbb{R}$ s.t.

$$\begin{cases} -\nabla \cdot (\tilde{a}(x, y) - \nabla \tilde{u}(x, y)) = \tilde{f}(x, y) & (x, y) \in D \times T \\ \tilde{u}(x, y) = g(x) & (x, y) \in D \times T. \end{cases}$$

Working on T instead of Ω , we have.

$$\begin{cases} \tilde{a}(x, y) = M_a(x) + \sum_{k=1}^P \sqrt{\nu_k^a} \phi_k^a(x) y_k & x \in D, y \in T, \phi_k \in T_k \\ \tilde{f}(x, y) = M_f(x) + \sum_{k=1}^P \sqrt{\nu_k^f} \phi_k^f(x) y_k \end{cases}$$

$y_j \quad \phi_j \checkmark$

After we construct the variational formula on $D \times T$, we can

apply Galerkin approximation on $D \times T$. First we replace $H_g^1(D)$ and $H_0^1(D)$ with the finite element space W^h and V^h , and study weak solutions $\tilde{u}_h \in L_p^2(T, W^h)$.

Def: A semi-discrete weak solution on $D \times T$ is $\tilde{u}_h \in L_p^2(T, W^h)$ s.t.

$$\tilde{\alpha}(\tilde{u}_h, v) = \tilde{l}(v) \quad \forall v \in L_p^2(T, V^h) \quad (W^h \subset H_g^1(D), V^h \subset H_0^1(D))$$

$L_p^2(T) \leftarrow S^k$

$w^h \rightarrow H_g^1(D)$

We can derive a fully discrete, finite-dimensional problem on $D \times T$

Def: A stochastic Galerkin solution is a function $\tilde{u}_{hk} \in W^{hk}$,

where $W^{hk} \subset W = L_p^2(T, H_g^1(D))$ s.t.

$$\tilde{\alpha}(\tilde{u}_{hk}, v) = \tilde{l}(v) \quad \forall v \in V^{hk} \subset V = L_p^2(T, H_0^1(D))$$

where $\tilde{\alpha}: W \times V \rightarrow \mathbb{R}$, $\tilde{l}: V \rightarrow \mathbb{R}$:

$$\begin{cases} \tilde{\alpha}(u, v) = \int_T p(y) \int_D \tilde{\alpha}(x, y) \nabla u(x, y) \cdot \nabla v(x, y) dx dy, \\ \tilde{l}(v) = \int_T p(y) \int_D \tilde{f}(x, y) \cdot v(x, y) dx dy. \end{cases}$$

V basis function $[S^k \otimes V^h]$

Hence we need to select finite-dimensional subspaces of W and V . Let $S^k \subset L_p^2(T)$: $S^k = \text{span}\{\psi_1, \dots, \psi_Q\}$

Then we can construct a finite-dimensional subspace of V by tensorising ψ_j with finite element basis ϕ_i for V^h .

That is $V^h = \text{span}\{\phi_1, \dots, \phi_J\}$.

$T_i, \psi_i, P_i \in L_{P_i}^2(T_i)$

$\Rightarrow V^h \otimes S^k = \text{span}\{\phi_i \psi_j : i=1 \dots J, j=1 \dots Q\} = V^{hk}$

So when $g \neq 0$, we need to construct W^{hk} .

$$W^{hk} = V^{hk} \oplus \text{span}\{\phi_{j+1}, \dots, \phi_{J+J_b}\}$$

$\Rightarrow \forall w \in W^{hk}$,

$$w(x, y) = \sum_{i=1}^J \sum_{j=1}^Q w_{ij} \phi_i(x) \psi_j(y) + \sum_{i=j+1}^{J+J_b} w_i \phi_i(x) = w_0(x, y) + w_g(x)$$

So here we only have the finite element basis functions.

Then how can I choose the basis for S^k . That is stochastic basis functions.

Let S_i^k denote the set of univariate polynomials of degree k .

or less in y_i on T_i : $S_i^k = \text{span}\{P_{\alpha_i}^i(y_i) : \alpha_i = 0, \dots, k\}$.

where $P_{\alpha_i}^i(y_i)$ is some polynomial of degree α_i on y_i .

Then $S^k = [S_1^k \otimes S_2^k \otimes \dots \otimes S_M^k]$.

$$S^k = \text{span}\left\{ \prod_{i=1}^M P_{\alpha_i}^i(y_i) : \alpha_i = 0, 1, \dots, k, i=1, \dots, M \right\}$$

$$\Rightarrow \dim(S^k) = Q = (k+1)^M$$

$$T_i \quad K_i$$

If the index of $k = (K_1, K_2, \dots, K_M)$, then $T_i \quad \{\psi_i\}$

$$S^k = \text{span}\left\{ \prod_{i=1}^M P_{\alpha_i}^i(y_i) : \alpha_i = 0, 1, \dots, K_i, i=1, \dots, M \right\}$$

Additionally, if the total order of polynomial is k or less.

$\Rightarrow |\alpha| \leq k$, then.

$$S^k = \text{span}\left\{ \prod_{i=1}^M P_{\alpha_i}^i(y_i) : \alpha_i = 0, 1, \dots, k, i=1, \dots, M, |\alpha| \leq k \right\}$$

where $|\alpha| = \sum \alpha_i$

$$\Rightarrow Q = \dim(S^k) = C_{m+k}^k = \frac{(m+k)!}{m! k!}$$

Dong bin Xiu.

SPDE
VR.

Then we need to think about how to generate $P_{\alpha_i}^i(y_i)$.

Here we introduce the generalized polynomial chaos, (GPC).

First we define the inner product. $f \sim N(0,1)$ $\Omega(-1,1)$.

$$\langle v, w \rangle_p = \int_{-1}^1 P_i(y) v(y) w(y) dy \text{ for } v, w: \Gamma \rightarrow \mathbb{R}.$$

Let $P_1 = 0$ $P_0 = 1$. We can construct a sequence of polys.

P_j on Γ that are orthonormal with respect to $\langle \cdot, \cdot \rangle_p$.

and satisfies $P_j(y) = (a_j y + b_j) P_{j-1}(y) - c_j P_{j-2}(y)$. $j=1, 2, \dots$

Hence a_j, b_j, c_j depend on $P_i(y)$

$$\begin{cases} \langle P_j, P_{j+1} \rangle_p = 0 \\ \langle P_j, P_j \rangle_p = 1 \end{cases}$$

E.g. (Legendre polynomial) Let $\Gamma = [-\sqrt{3}, \sqrt{3}]$ and $p = \frac{1}{2\sqrt{3}}$

$$\Rightarrow L_j(y) = \hat{L}_j\left(\frac{y}{\sqrt{3}}\right) \quad \hat{L}_j(y) = \frac{\sqrt{2j+1}}{2^j j!} \frac{d^j}{dy^j} (y^2 - 1)^j$$

$$\Rightarrow \langle L_i, L_j \rangle_p = \frac{1}{2\sqrt{3}} \int_{-\sqrt{3}}^{\sqrt{3}} L_i(y) L_j(y) dy = \delta_{ij}$$

Thm. \leftarrow gPC.

$$\{ \sim U(-\sqrt{3}, \sqrt{3}) \}$$

$$(L_p(\Gamma)) \{ Y_j \}$$

Hence we can choose $\{P_{\alpha_i}^i(y_i)\}$ are orthonormal with respect to $\langle \cdot, \cdot \rangle_{p_i}$ on Γ_i for $i=1, \dots, M$. then the poly

$\psi_j = \prod_{i=1}^M P_{\alpha_i}^i(y_i)$ are orthonormal respect to $\langle \cdot, \cdot \rangle_p$ on Γ .

where $P(y) = P_1(y_1) P_2(y_2) \cdots P_M(y_M)$.

$$\text{i.e. } \langle \psi_r, \psi_s \rangle_p = \delta_{rs}.$$

$$r = (\alpha_1, \dots, \alpha_M) \quad \sum \alpha_i = k.$$

$$s = (\beta_1, \dots, \beta_M) \quad \sum \beta_i = k.$$

Sum up: the ψ is chosen by the distribution on Ξ .

Normally, ξ_i i.i.d. \Rightarrow note $P_{\alpha_i}^i$ as P_{α_i}

Then apply the basis for $S^K \subset L_p^2(\Gamma)$. $\forall \tilde{u}_{h,k} \in W^{hk}$

$$\boxed{\tilde{u}_{h,k}(x,y) = \sum_i^J \sum_j^Q u_{ij} \phi_i(x) \psi_j(y) + w_g(x).}$$

Assume $\psi_j(y)=1$

$$\begin{aligned}
 &= \sum_j^Q \left(\sum_i^J u_{ij} \phi_i(x) \right) \psi_j(y) + w_g(x). \\
 &= \sum_j^Q \boxed{u_j(x)} \psi_j(y) + w_g(x) \\
 &= \underline{(u_1(x) + w_g(x))} \psi_1 + \sum_{j=2}^Q u_j(x) \psi_j(y).
 \end{aligned}$$

FEM. u_i ψ_j

Since ψ_j are orthonormal, then.

$$\begin{aligned}
 E[\tilde{u}_{h,k}] &= \int_I p(y) \tilde{u}_{h,k}(.,y) dy = \langle \tilde{u}_{h,k}, \psi_1 \rangle_p \\
 &= \boxed{u_1 + w_g}.
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}[\tilde{u}_{h,k}] &= E[\tilde{u}_{h,k}^2] - (u_1 + w_g)^2 \\
 &= (u_1 + w_g)^2 + \sum_2^Q u_j^2 - (u_1 + w_g)^2 \\
 &= \sum_2^Q u_j^2.
 \end{aligned}$$

Ax=b

So, like FEM, we have the linear equation $\hat{A}u=b$.

where A has block structure like

$$A = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1Q} \\ A_{21} & A_{22} & \cdots & A_{2Q} \\ \vdots & \vdots & & \vdots \\ A_{Q1} & A_{Q2} & \cdots & A_{QQ} \end{pmatrix} \quad u = \begin{pmatrix} u_1 \\ \vdots \\ u_Q \end{pmatrix} \quad b = \begin{pmatrix} b_1 \\ \vdots \\ b_Q \end{pmatrix}.$$

$$u_j = (u_{1j} \ u_{2j} \ \dots \ u_{Jj})^T. \quad \langle \psi_j, \psi_s \rangle_p = \underline{\underline{G}}_{j,s} k_0.$$

$$A_{sj} = \boxed{\langle \psi_j, \psi_s \rangle_p} k_0 + \sum_{l=1}^P \langle \psi_l \psi_j, \psi_s \rangle_p k_l \quad \underline{\underline{G}}_{\otimes Q}.$$

$$\underline{\underline{K}_0}_{ir} = \int_D M(x) \nabla \phi_i(x) \cdot \nabla \phi_r(x) dx \quad i, r = 1 \dots J.$$

$$\underline{\underline{K}_e}_{ir} = \int_D (\sqrt{v_e} \phi_e^a(x)) \nabla \phi_i(x) \cdot \nabla \phi_r(x) dx. \quad G_e \otimes K_0.$$

Similarly we can get. $\nabla \underline{\underline{G}_0} + \sum G_e \otimes K_0$.

pass the solver. $k=3$ can fit well. E Var.

GPC

Stochastic collocation method.

UQ

$\zeta(t, x)$

The second class of SPDE is the semilinear SPDE, which include the random fluctuations like

$$u_t = \Delta u + \zeta(t, x). \quad t > 0, x \in D.$$

So the $\zeta(t, x)$ depends on both t and x . (space and time)

Rewritten as $du = \Delta u dt + dW(t, x)$.

More generally, we consider semilinear SPDES like.

$$du = [\Delta u + f(u)] dt + G(u) dW(t, x). \quad \underline{\underline{L^2(D)}}$$

We prefer to think $u(t)$ as an H -valued stochastic process

$u(t, x, \omega)$. For fixed t , $u(t, \cdot, \cdot)$ is a R.F.

Called $u(\cdot, \cdot, \omega)$ a sample path.

$u(t, \cdot, \omega)$ a realization.

Here we need to define the Q -Wiener process.

Before this, we need some assumptions. Consider a separable Hilbert space U with $\|\cdot\|_U$, $\langle \cdot, \cdot \rangle_U$. We define a Q -Wiener process $\{W(t) : t \geq 0\}$ as a U -valued process.

That is, $W(t)$ is a U -valued r.v.

When $t=0$, note the covariance operator as Q .

Assumption: $Q \in L(U)$ is non-negative definite and symmetric.

Further, Q has an orthonormal basis $\{X_j, j \in \mathbb{N}\}$ of eigenfunctions with corresponding eigenvalue $\beta_j \geq 0$, s.t. $\sum \beta_j < \infty$.

$$Qu = \sum u_j \beta_j X_j, \quad u = \sum u_j \phi_j(x), \quad Q \in L(U), \quad \phi_j \in$$

Def: A U -valued stochastic process $\{W(t) : t \geq 0\}$ is

a Q -Wiener process if $\boxed{W(t)}$ $\stackrel{W(t,x)}{\sim} \mathcal{N}(0, Q)$, $W(t) : t \mapsto U$, $\stackrel{W(t,x)}{\sim} L^2(D)$.

1) $W(0) = 0$ a.s.

$W(t,x)$

$W(t)$

$x \in D$

$L^2(D)$

2) $W(t)$ is a continuous function $(\mathbb{R}_+ \rightarrow U)$ for each $x \in \mathbb{R}$.

3) $W(t)$ is \mathcal{F}_t -adapted and $W(t) - W(s)$ is independent of \mathcal{F}_s ($\forall s < t$).

$U \in L^2(D)$

4) $W(t) - W(s) \sim N(0, (t-s)Q)$ for $0 \leq s \leq t$.

$Q \sim X_j \beta_j$

~~* Thm.~~ $W(t)$ is a Q -Wiener process $\boxed{\mathcal{F}_t}$ D.

$$W(t) = \sum_{j=1}^{\infty} \sqrt{\beta_j} X_j \beta_j^{-1}(t) \quad (\beta_j^{-1}(t) \text{ i.i.d. for Brownian M.})$$

and it converges in $L^2(\Omega, U)$

$W(t) : \mathbb{R}_+ \rightarrow U$

truncated form: $\sum_{j=1}^J \sqrt{\beta_j} X_j \beta_j^{-1}(t)$.

$\{u : D \rightarrow \mathbb{R}\}$

$L^2(D)$

So let's consider the $L^2(D)$ -valued \mathbb{Q} -Wiener process $W(t)$

We want to approximate the sample path of $W(t)$.

Since the eigenvalue / func of \mathbb{Q} is unknown.

If we have a finite set of sample points. $x_1, \dots, x_k \in D$.

try to seek $W(t, x_1) \dots W(t, x_k)$ numerically.

Take time-step as Δt_{ref} $\Delta W(t) = \sqrt{\Delta t} \zeta_j \sim N(0, 1)$.

$$\Rightarrow W^J(t_{n+1}) - W^J(t_n) = \sqrt{\Delta t_{\text{ref}}} \sum_j \sqrt{\theta_j} X_j \zeta_j^n.$$

$$\zeta_j^n = \frac{\beta_j(t_{n+1}) - \beta_j(t_n)}{\sqrt{\Delta t_{\text{ref}}}} \sim N(0, 1)$$

$W(t) - \mathbb{Q}\text{-valued}$
 $L^2(D)$.

E.g. Consider $H^r(0, \alpha)$ -valued process. We can choose

$$k=J-1 \text{ sample points } x_k = \frac{k\alpha}{J}, k=1 \dots J-1.$$

$$X_j = \sqrt{\frac{2}{\alpha}} \sin\left(\frac{x_j \alpha}{\alpha}\right) \quad j=1 \dots J-1.$$

$$\Rightarrow W^{J-1}(t_{n+1}, x_k) - W^{J-1}(t_n, x_k) = \sum_j b_j \sin\left(\frac{j\pi k}{J}\right) \zeta_j^n.$$

$$(b_j = \sqrt{\frac{2\theta_j \Delta t_{\text{ref}}}{\alpha}})$$

$$\int du = \int (u dt + B dW) \quad U\text{-valued}.$$

Then we need to develop the stochastic integral like

$$\boxed{\int_0^t B(s) dW(s)}, \quad \{B(s)\}.$$

Where $W(s)$ is a \mathbb{Q} -Wiener process, take values in U .

Then first we need to identify a suitable class of $B(s)$.

We treat SPDE in Hilbert space H and with Itô integral

take values in H . Hence. we consider B that are $L(U_0, H)$

valued process. $U_0 \subset U$ called "Caner-Martin space"

Def: Let $U_0 = \{Q^{\frac{1}{2}}u : u \in U\}$. L_0^2 is the set of linear operators $B: U_0 \rightarrow H$, s.t. $\int_0^t B(s) dW(s)$ is well-defined. $U, L^2(H)$.

$$\|B\|_{L_0^2} := \left(\sum_{j=1}^{\infty} \|B Q^{\frac{1}{2}} X_j\|_H^2 \right)^{\frac{1}{2}} = \|B Q^{\frac{1}{2}}\|_{HS(U, H)} < \infty.$$

L_0^2 is a Banach space with $\|\cdot\|_{L_0^2}$. $Qu = \sum x_i u_i \phi_i(x)$.

Rmk: Hilbert-Schmidt operators.

Let H, U be separable Hilbert Spaces with norms $\|\cdot\|$, $\|\cdot\|_U$, respectively. $\{\phi_j\}$ orthonormal basis of U . Define

Hilbert-Schmidt norm $\|L\|_{HS(U, H)} := \left(\sum_{j=1}^{\infty} \|L \phi_j\|_H^2 \right)^{\frac{1}{2}}$

$HS(U, H) = \{L \in \mathcal{L}(U, H) : \|L\|_{HS(U, H)} < \infty\}$ is Banach.

$L \in HS(U, H)$ is a Hilbert-Schmidt operator.

If $U=H$, then $\|L\|_{HS} = \|L\|_{HS(H, H)}$

$$\begin{aligned} \|A\|_{HS(\mathbb{R}^d)} &= \left(\sum \|A e_j\|_.\right)^{\frac{1}{2}} \\ &= \left(\sum_{i,j} a_{ij}^2 \right)^{\frac{1}{2}} \end{aligned}$$

Then we build the H -valued Itô integral:

$$\int_0^t B(s) dW(s) = \sum_{j=1}^J \int_0^t B(s) \sqrt{g_j} X_j d\beta_j(s).$$

exists a limit as $J \rightarrow \infty$. noted as $\int_0^t B(s) dW(s)$.

Thm: Suppose $\{B(s) : s \in [0, T]\}$ is a L_0^2 -valued predictable process

$$\text{s.t. } \int_0^T E[\|B(s)\|_{L_0^2}^2] ds < \infty.$$

Then ⁽¹⁾ for $t \in [0, T]$. $\int_0^t B(s) dW(s)$ is H -valued.

$$\int_0^t B(s) dW(s) = \sum_{j=1}^{\infty} \int_0^t B(s) \sqrt{g_j} X_j d\beta_j(s).$$

is well-defined in $L^2([0, T], H)$.

~~(*)~~⁽²⁾ And we have the \mathbb{L}^2 isometry:

$$E \left[\left\| \int_0^t B(s) dW(s) \right\|^2 \right] = \int_0^t E \left[\|B(s)\|_{L^2}^2 \right] ds.$$

(3) $\left\{ \int_0^t B(s) dW(s) \right\}$ is an H -valued predictable process.

$L^2(D)$

$\Delta \cdot \nabla - (\alpha \nu) \nabla$

Back to semilinear evolution equations.

$$du = [-Au + f(u)] dt + G(u) dW(t) \quad u(0) = u_0. \quad (u_0 \in H).$$

Assume $A: D(A) \subset H \rightarrow H$ satisfy assumption 1(*). $(\star\star)$

$$f: H \rightarrow H \quad G: H \rightarrow L^2$$

$W(t)$.

A : nonnegative:

$$\exists \psi \in H. \quad g_\psi \geq 0.$$

E.g. (Stochastic heat equation).

$$du = \Delta u dt + \sigma dW(t). \quad u(0) = u_0 \in L^2(D).$$

$$\Rightarrow H = L^2(D) = U, \quad f = 0 \quad \text{and} \quad G(u) = \sigma I.$$

$u(t, \cdot)$ $W(t, \cdot)$

$$du = (-Au + f(u)) dt + G(u) dW.$$

Def: strong solution: A predictable H -valued process

$\{u(t): t \in [0, T]\}$ is called a strong solution of $(\star\star)$:

$$u(t) = u_0 + \int_0^t [-Au(s) + f(u(s))] ds + \int_0^t G(u(s)) dW(s). \quad \forall t \in [0, T]$$

The restriction is strong. since $u(t)$ requires: $u(t) \in D(A)$.

$$A = \Delta$$

$$dW(t) = (\beta_j).$$

Def: Weak solution:

$$\begin{aligned} \langle u(t), v \rangle &= \langle u_0, v \rangle + \int_0^t [-\langle u(s), Av \rangle + \langle f(u(s)), v \rangle] ds \\ &\quad + \int_0^t \langle G(u(s)) dW(s), v \rangle \quad \forall v \in D(A). \end{aligned}$$

$$\left(\int_0^t \langle G(u(s)) dW(s), v \rangle \right) = \sum_{j=1}^{\infty} \int_0^t \langle G(u(s)) \sqrt{g_j} X_j, v \rangle d\beta_j(s).$$

Def: Mild Solution:

$$u(t) = e^{-tA} u_0 + \int_0^t e^{-(t-s)A} f(u(s)) ds + \int_0^t e^{-(t-s)A} G(u(s)) dW(s).$$

where e^{-tA} is the semigroup generated by $-A$.

SPDE

$u_{ij}(x)$

$\phi_j(x) \gamma_j(\zeta)$

D&F.

ODEs.