

Unit 3

LOS 1. Understand the relation between Hilbert spaces and convergence

Hilbert space norm is L^2 norm.

LOS 2. Distinguish between L2-norm and uniform norm

Infinity-norm is used to assert stability. If boundary values are uniformly close, their solution should be uniformly close (for finite time interval).

Infinity-norm:

$$\begin{aligned}\|\phi\|_\infty &= \sup_x |\phi(x)| \\ \|\phi\| &= \max_x |\phi(x)| \\ \|\phi\|_T &= \max_{x, 0 \leq t \leq T} |\phi(x, t)|\end{aligned}$$

L^2 -norm:

- Definition:

$$\begin{aligned}\|\phi\| &= \sqrt{\int_{\mathbb{R}} |\phi(x)|^2 dx} \\ \|f\| &= (f, f)^{\frac{1}{2}}\end{aligned}$$

- For $v = C[0, 2\pi]$:

$$\begin{aligned}(f, g) &= \int_0^{2\pi} \overline{f(t)} g(t) \frac{dt}{2\pi} \\ \|f\| &= (f, f)^{\frac{1}{2}} = \left(\int_0^{2\pi} |f(t)|^2 \frac{dt}{2\pi} \right)^{\frac{1}{2}}\end{aligned}$$

LOS 3. Distinguish between uniform convergence and L2-convergence

Relationship between L^2 and uniform norm:

$$\begin{aligned}\int |f(t)|^2 \frac{dt}{x\pi} &\leq \int \max_s |f(s)|^2 \frac{dt}{2\pi} = \|f\|_\infty^2 \int_{-\pi}^{\pi} \frac{dt}{2\pi} \leq \|f\|_\infty^2 \\ \left(\int |f(t)|^2 \frac{dt}{x\pi} \right)^{\frac{1}{2}} &\leq \|f\|_\infty \\ \|f\|_2 &\leq \|f\|_\infty \\ \therefore 0 &\leq \|f_n - f\|_2 \leq \|f_n - f\|_\infty\end{aligned}$$

If uniform convergence goes to zero, then L^2 goes to zero by squeeze theorem. Therefore, uniform convergence implies L^2 convergence.

LOS 4. Learn the connection of convergence with the theory of orthonormal systems

Definition of an orthonormal system:

$$\begin{aligned}(x_j, x_k) &= \delta_{j,k} \\ \delta_{j,k} &= \begin{cases} 0 & x \neq j \\ 1 & x = j \end{cases}\end{aligned}$$

Assume we are estimating function x which we are estimating with (x_1, x_2, x_3, \dots) :

$$\begin{aligned}x &= \sum a_j x_j \\ \|\sum a_j x_j\|^2 &= \sum_j |g_j|^2 \\ a \perp b &\rightarrow \|a + b\|^2 = \|a\|^2 + \|b\|^2\end{aligned}$$

Lemma:

$$\begin{aligned}W &= \text{span}\{x_1, x_2, x_3, \dots\} \\ W &\in V \\ x &\notin V \\ P_x &= \sum_{j=1}^n (x_j, x) x_j \\ \|x - y\|^2 &= \|x - P_x + P_x - y\|^2 = \|x - P_x\|^2 + \|P_x - y\|^2 \geq \|x - P_x\|^2\end{aligned}$$

P_x is a projection of x unto W . To minimize $\|x - y\|^2$, we have to minimize $\|x - P_x\|^2 + \|P_x - y\|^2$. This upper bound is minimized when $y = P_x$. Therefore:

$$\begin{aligned}\|x - y\|^2 &\geq \|x - P_x\|^2 \\ \|x - y\| &\geq \|x - P_x\| \\ \inf \|x - y\| &= \|x - P_x\|, y \in W\end{aligned}$$

*(inf refers to the greatest lower bound of the set)

To ensure convergence:

$$\begin{aligned}\lim_{n \rightarrow \infty} \|x - \sum_{j=1}^n a_j x_j\| &= 0 \\ \lim_{n \rightarrow \infty} \|x - P_x\| &= 0 \\ \therefore W_n = \text{span}\{x_1, x_2, x_3, \dots, x_n\} &\rightarrow \lim_{n \rightarrow \infty} \|x - P_{W_n}\|\end{aligned}$$

Since $\sum_{j=1}^n a_j x_j$ must equal P_x to minimize $\|x - \sum_{j=1}^n a_j x_j\|$, then:

$$\begin{aligned}\sum_{j=1}^n a_j x_j &= \sum_{j=1}^n (x_j, x) x_j \\ a_j &= (x_j, x)\end{aligned}$$

The above coefficient is referred as generalized Fourier coefficient. The best approximation is therefore:

$$x = P_{W_n} = \sum_{j=1}^n (x_j, x) x_j$$

LOS 5. Study theorems on orthonormal projections and basis

Theorem:

1. Theorem A. $|g|_H$ is Hilbert-norm (the same as L^2 norm):

$$\begin{aligned}f &\in C[-\pi, \pi] \\ \lim_{n \rightarrow \infty} \|f - P_n(f)\|_H &= 0\end{aligned}$$

2. Theorem B. All function has a Fourier expansion that converges.

$$\begin{aligned}
 f &\in C[-\pi, \pi] \\
 \epsilon > 0 \quad \exists g_m &= \sum_{k=-m}^m a_k e_k \\
 \|f - g_m\|_\infty &\leq \epsilon \\
 \therefore \|f - P_n(f)\|_H &= \|f - g_m - P_n(f - g_m)\|_H \leq \|f - g_m\|_H \leq \|f - g_m\|_\infty \leq \epsilon
 \end{aligned}$$

Implication of theorems:

- Fourier expansion of any function will converge to f . Finite dimension $P_n(f)$ approximation makes the norm smaller:

$$\begin{aligned}
 f &= \sum_{k \in \mathbb{Z}} \hat{f}(k) f_k \\
 \int_{-\pi}^{\pi} |f(t)|^2 \frac{dt}{2\pi} &= \sum_{k \in \mathbb{Z}} |\hat{f}(k)|^2 \\
 \|P_n(f)\|^2 &= \sum_{k=-n}^n |\hat{f}(k)|^2 \\
 \|P_n(f)\|^2 &\leq \|f\|^2
 \end{aligned}$$

Above is the Bessel's inequality. $\|f\|^2$ is the sum over all the space while $\|P_n(f)\|^2$ is the sum over a finite space.

- For function to satisfy $\sum |\hat{f}(k)|^2 < \infty$:

$$\begin{aligned}
 L^2\text{-space} &= \{f = \lim_n f_n \text{ almost everywhere where} \\
 &\exists f_n \in C[-\pi, \pi], \|f_n - f_{n+1}\| < c2^{-n}\}
 \end{aligned}$$

LOS 6. Understand the importance of orthonormal basis in PDE systems

Using appropriate orthonormal basis, PDE can be solved in an easier manner.

Example of orthonormal basis to solve PDE:

1. Fourier coefficients: $e_k(t) = e^{ikt}$ (a periodic function). General formulation:

$$\begin{aligned}
 W_n &= \text{span}\{e_k \mid -n \leq k \leq n\} \\
 P_{W_n} &= \sum_{k=-n}^n (e_k, f) e_k = \sum_{k=-n}^n \hat{f}_k e_k \\
 \lim_n P_{W_n}(f) &= f
 \end{aligned}$$

*When f_{odd}, \hat{f}_{odd} .

2. Discrete Fourier coefficients: $\tilde{e}_k(j) = e^{\frac{2\pi i k}{n} j}$. Used to estimate piecewise, locally constant function. Continuous function can be approximated as the linear combination of the piecewise function.
3. Hermite polynomials. $He_k(x) = (-1)^k e^{\frac{x^2}{2}} \frac{d^k}{dx^k} e^{-\frac{x^2}{2}}$. Used to estimate $\partial\gamma(x) = e^{-\frac{|x|^2}{2}} \partial x$.
4. Sine function. $S_k = \sin(kx)$ forms an orthonormal basis in $f \in L^2(0, \pi)$.

Example problem using Fourier coefficients:

- Function to estimate:

$$f = \mathbb{1}_{[-\frac{\pi}{2}, \frac{\pi}{2}]}$$

- Estimate:

$$W_1 = \text{span}\{\mathbb{1}, x_1, -x_1\}$$

$$P_{W_1} = \sum_{j=1}^n (x_j, x) x_j = (\mathbb{1}, f) \mathbb{1} + (x_1, f) x_1 + (x_2, f) x_2$$

$$x_k = e^{ikt}$$

$$(x_1, f) = \hat{f}(1) = \int_{-\pi}^{\pi} e^{-it} f(t) \frac{dt}{2\pi} = \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} e^{-it} \frac{dt}{2\pi} = \frac{e^{-i\frac{\pi}{2}} - e^{i\frac{\pi}{2}}}{-2i\pi}$$

- e^{ikx} is periodic:

$$\begin{aligned} e^{i\frac{\pi}{2}} &= i & e^{-i\frac{\pi}{2}} &= -i \\ \frac{e^{i\frac{\pi}{2}} - e^{-i\frac{\pi}{2}}}{-2i\pi} &= \frac{-i - i}{-2i\pi} = \frac{1}{\pi} \\ (x_1, f) &= \frac{1}{\pi} \end{aligned}$$

- Using the same formula:

$$(\mathbb{1}, f) = \frac{1}{2} \quad (x_2, f) = -\frac{1}{\pi i}$$

- Therefore:

$$P_{W_1} = \frac{1}{2} \mathbb{1} + \frac{1}{\pi} e^{it} - \frac{1}{\pi} e^{-it}$$

General application to PDE:

- Assume there is operator such that:

$$\mathcal{L} = \sum_{j=0}^n a_j \frac{\partial^j}{\partial x^j} u$$

- Alternatively (P_n below is a polynomial, not a projection):

$$P_n(x) = \sum_{j=0}^n a_j x^j$$

$$\mathcal{L} = P_n\left(\frac{\partial}{\partial x}\right)$$

- Problem:

$$u_t = \mathcal{L}(u) \quad u(x, 0) = \phi(x)$$

- Assume that the following is true:

$$u(x, t) = \sum_{k \in \mathbb{Z}} \phi(k, t) e_k(x)$$

- Apply the operator:

$$u_t(x, t) = \sum_{k \in \mathbb{Z}} \frac{d}{dt} \phi(k, t) e_k(x)$$

$$\mathcal{L}(u)(x, t) = \sum_{k \in \mathbb{Z}} \phi(k, t) \mathcal{L}(e_k)(x) \quad (1)$$

- Evaluate $\mathcal{L}(e_k)(x)$:

$$\frac{d}{dt} e^{ikx} = (ik)^j e^{ikx}$$

$$\therefore \mathcal{L}(e_k)(x) = P_n(ik) e_k$$

Where P_n is a polynomial of ik (not the same as P_n defined above)

- Continuing on Equation (1):

$$\mathcal{L}(u)(x, t) = \sum_{k \in \mathbb{Z}} \phi(k, t) P_n(ik) e_k(x) = u_t(x, t)$$

$$\sum_{k \in \mathbb{Z}} \phi(k, t) P_n(ik) e_k(x) = \sum_{k \in \mathbb{Z}} \frac{d}{dt} \phi(k, t) e_k(x)$$

- Fourier coefficients must be the same:

$$\phi(k, t) P_n(ik) = \frac{d}{dt} \phi(k, t)$$

$$\phi(k, t) = C_k e^{t P_n(ik)}$$

$$\therefore u(x, t) = \sum_{k \in \mathbb{Z}} C_k e^{t P_n(ik)} e_k$$

- When $t = 0$:

$$u(x, 0) = \phi(x) = \sum_{k \in \mathbb{Z}} \hat{\phi}(k) e_k$$

$$\therefore C_k = \hat{\phi}(k)$$

- Convergence can be evaluated by looking at the $P_n(ik)$ term. For evaluation:

$$\mathcal{L} = \frac{d^2}{dx^2}$$

$$P_n(x) = x^2 P_n(ik) = (ik)^2 = -k^2 \rightarrow \text{in } u(x, t), \text{ the terms vanish}$$

$$f\mathcal{L} = \frac{d^4}{dx^4}$$

$$P_n(x) = x^4 P_n(ik) = (ik)^4 = k^4 \rightarrow \text{in } u(x, t), \text{ the terms does not vanish}$$

LOS 7. Apply Fourier series for energy problem

Problem:

$$\mathcal{L} = -\frac{\partial^4}{\partial x^4}$$

$$u_t = \mathcal{L}u = -u_{xxxx}$$

$$u(x, 0) = \phi(x)$$

Assume solution is in L^2 :

$$u^t = \sum_{k \in \mathbb{Z}} \hat{u}^t(k) e_k$$

$$\frac{d}{dt} u^t = \sum_{k \in \mathbb{Z}} \hat{u}^t(k) \mathcal{L}(e_k)$$

$$\mathcal{L}(e_k) = \mathcal{L}(e^{ikx}) = -\frac{\partial^4}{\partial x^4} (e^{ikx})$$

$$\mathcal{L}(e_k) = -k^4 e^{ikx} = -k^4 e_k$$

$$\frac{d}{dt} u^t = \sum_{k \in \mathbb{Z}} -k^4 \hat{u}^t(k) e_k$$

Assume x is constant:

$$\frac{d}{dt} u^t = \sum_{k \in \mathbb{Z}} \frac{d}{dt} \hat{u}^t(k) e_k = \sum_{k \in \mathbb{Z}} -k^4 \hat{u}^t(k) e_k$$

For two functions with Fourier coefficients, their Fourier coefficients have to be equal:

$$\frac{d}{dt}\hat{u}^t(k) = -k^4\hat{u}^t(k)$$

The above problem is an ODE:

$$\begin{aligned}\hat{u}^t(k) &= e^{-tk^4}\hat{u}^0(k) = e^{-tk^4}\hat{\phi}(k) \\ \therefore u(x, t) &= \sum_{k \in \mathbb{Z}} e^{-tk^4}\hat{\phi}(k)e_k\end{aligned}$$

Energy can be measured by the L^2 norm:

$$\begin{aligned}\|u^t\|_2^2 &= \sum \|\hat{u}^t(k)\|^2 = \sum_k \|e^{-tk^4}\hat{\phi}(k)\|^2 \leq \sum_k \|\hat{\phi}(k)\|^2 = \|u^0\|_2^2 \\ \|u^t\|_2^2 &\leq \|u^0\|_2^2 \\ \|u^t\|_2 &\leq \|u^0\|_2\end{aligned}$$