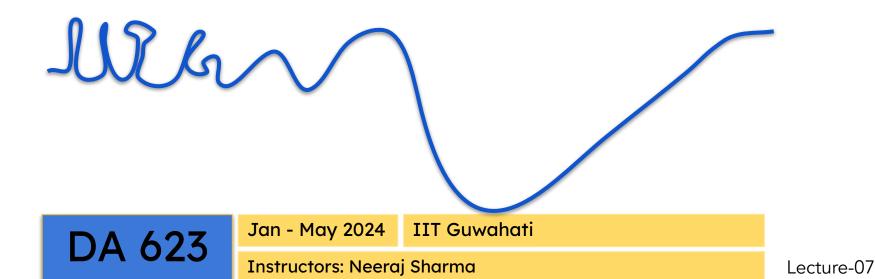
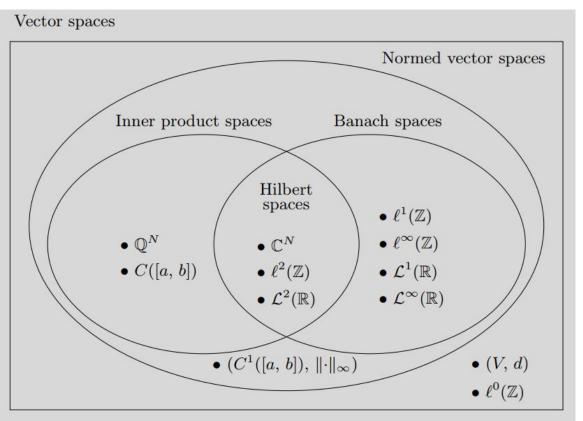
Computing with Signals

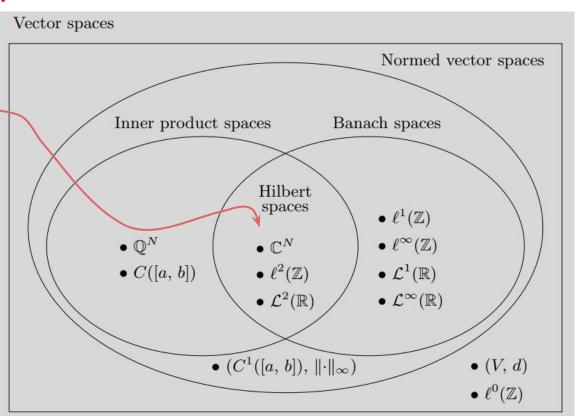


Vector Space review



Hilbert Space

To ease our analysis we will enforce that our signal/data resides (mostly)



DEFINITION 2.17 (LINEAR OPERATOR) A function $A: H_0 \to H_1$ is called a *linear* operator from H_0 to H_1 when, for all x, y in H_0 and α in \mathbb{C} (or \mathbb{R}), the following hold:

- (i) Additivity: A(x+y) = Ax + Ay.
- (ii) Scalability: $A(\alpha x) = \alpha(Ax)$.

DEFINITION 2.19 (INVERSE) A bounded linear operator $A: H_0 \to H_1$ is called invertible if there exists a bounded linear operator $B: H_1 \to H_0$ such that

$$BAx = x$$
, for every x in H_0 , and $(2.46a)$

$$ABy = y$$
, for every y in H_1 . (2.46b)

Definition 2.22 (Unitary operator) A bounded linear operator $A: H_0 \rightarrow H_1$ is called *unitary* when

- (i) it is *invertible*; and
- (ii) it preserves inner products,

$$\langle Ax, Ay \rangle_{H_1} = \langle x, y \rangle_{H_0}$$
 for every x, y in H_0 . (2.55)

DEFINITION 2.24 (EIGENVECTOR OF A LINEAR OPERATOR) An eigenvector of a linear operator $A: H \to H$ is a nonzero vector $v \in H$ such that

$$Av = \lambda v, \tag{2.58}$$

for some $\lambda \in \mathbb{C}$. The constant λ is called the corresponding eigenvalue and (λ, v) is called an eigenpair.

Most of the linear operators we will encounter in this course are (orthogonal) projection operators

What is the approximation problem?

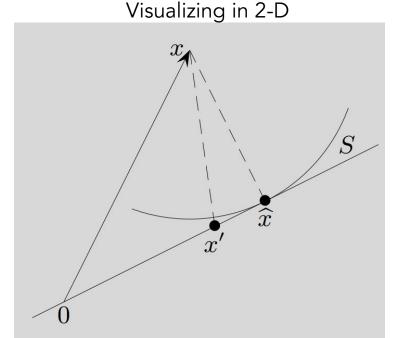
$$\widehat{x} = \underset{s \in S}{\operatorname{arg\,min}} \|x - s\|$$
 resides in a subspace S resides in H

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What is the approximation problem?

$$\widehat{x} = \underset{s \in S}{\operatorname{arg\,min}} \|x - s\|$$
 resides in a subspace S resides in H

Most commonly the Hilbert norm used here is the 2-norm. Least squares approximation.

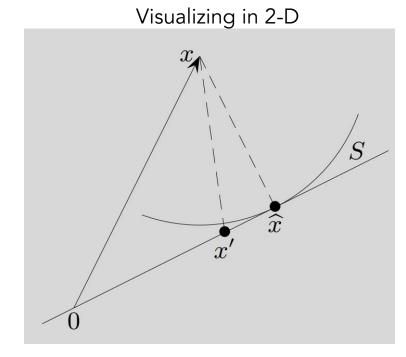


Most of the linear operators we will encounter in this course are (orthogonal) projection operators

What is the approximation problem?

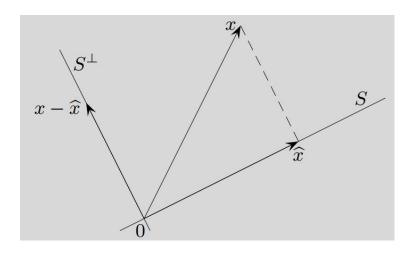
$$\widehat{x} = \underset{s \in S}{\operatorname{arg\,min}} \|x - s\|$$

$$x - \widehat{x} \perp S$$
 (residual)



Most of the linear operators we will encounter in this course are (orthogonal) projection operators

The best approximation of $x \in H$ within a closed subspace S is uniquely determined by $x - \widehat{x} \perp S$. The solution generates an orthogonal decomposition of x into $\widehat{x} \in S$ and $x - \widehat{x} \in S^{\perp}$.



Consider the function $x(t) = \cos(\frac{3\pi}{2}t)$ in the Hilbert space $\mathcal{L}^2([0,1])$. Find the degree-1 polynomial closest to x. Use ideas from orthogonal projection.

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Defining the approximation problem?

$$\min_{a_0, a_1} \int_0^1 \left| \cos \left(\frac{3}{2} \pi t \right) - (a_0 + a_1 t) \right|^2 dt$$

 $a_0 + a_1 a_2$

Consider the function $x(t) = \cos(\frac{3\pi}{2}t)$ in the Hilbert space $\mathcal{L}^2([0,1])$. Find the degree-1 polynomial closest to x. Use ideas from orthogonal projection.

$$x(t) - \widehat{x}(t) = \cos\left(\frac{3}{2}\pi t\right) - (a_0 + a_1 t)$$

should be orthogonal to

the entire subspace of degree-1 polynomials

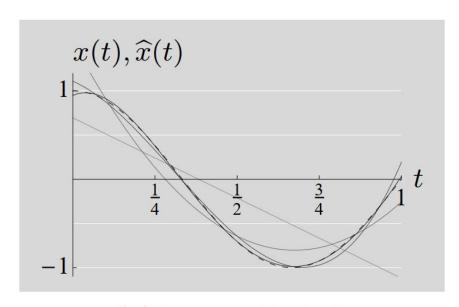
$$0 = \langle x(t) - \widehat{x}(t), 1 \rangle = \int_0^1 \left(\cos \left(\frac{3}{2} \pi t \right) - (a_0 + a_1 t) \right) \cdot 1 \, dt = -\frac{2}{3\pi} - a_0 - \frac{1}{2} a_1,$$

$$0 = \langle x(t) - \widehat{x}(t), t \rangle = \int_0^1 \left(\cos \left(\frac{3}{2} \pi t \right) - (a_0 + a_1 t) \right) \cdot t \, dt = \frac{4 + 6\pi}{9\pi^2} - \frac{1}{2} a_0 - \frac{1}{3} a_1.$$

$$a_0 = \frac{8+4\pi}{3\pi^2}, \qquad a_1 = -\frac{16+12\pi}{3\pi^2}.$$

Consider the function $x(t) = \cos(\frac{3\pi}{2}t)$ in the Hilbert space $\mathcal{L}^2([0,1])$. Find the degree-1 polynomial closest to x. Use ideas from orthogonal projection.

$$x(t) - \widehat{x}(t) = \cos\left(\frac{3}{2}\pi t\right) - (a_0 + a_1 t)$$



(b) K = 1, 2, 3, 4.

Bases

DEFINITION 2.34 (BASIS) The set of vectors $\Phi = \{\varphi_k\}_{k \in \mathcal{K}} \subset V$, where \mathcal{K} is finite or countably infinite, is called a *basis* for a normed vector space V when

(i) it is *complete* in V, meaning that, for any $x \in V$, there is a sequence $\alpha \in \mathbb{C}^{\mathcal{K}}$ such that

$$x = \sum_{k \in \mathcal{K}} \alpha_k \varphi_k; \tag{2.87}$$

and

(ii) for any $x \in V$, the sequence α that satisfies (2.87) is unique.

Riesz Bases

DEFINITION 2.35 (RIESZ BASIS) The set of vectors $\Phi = \{\varphi_k\}_{k \in \mathcal{K}} \subset H$, where \mathcal{K} is finite or countably infinite, is called a *Riesz basis* for a Hilbert space H when

- (i) it is a basis for H; and
- (ii) there exist stability constants λ_{\min} and λ_{\max} satisfying $0 < \lambda_{\min} \le \lambda_{\max} < \infty$ such that, for any x in H, the expansion of x with respect to the basis Φ , $x = \sum_{k \in \mathcal{K}} \alpha_k \varphi_k$, satisfies

$$\lambda_{\min} ||x||^2 \le \sum_{k \in \mathcal{K}} |\alpha_k|^2 \le \lambda_{\max} ||x||^2.$$
 (2.89)

The largest such λ_{\min} and smallest such λ_{\max} are called *optimal stability* constants for Φ .

Synthesis operator

DEFINITION 2.36 (BASIS SYNTHESIS OPERATOR) Given a Riesz basis $\{\varphi_k\}_{k\in\mathcal{K}}$ for a Hilbert space H, the synthesis operator associated with it is

$$\Phi: \ell^2(\mathcal{K}) \to H, \quad \text{with} \quad \Phi\alpha = \sum_{k \in \mathcal{K}} \alpha_k \varphi_k.$$
 (2.90)

Synthesis operator

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 (2.90)

Analysis operator

DEFINITION 2.37 (BASIS ANALYSIS OPERATOR) Given a Riesz basis $\{\varphi_k\}_{k\in\mathcal{K}}$ for a Hilbert space H, the analysis operator associated with it is

$$\Phi^*: H \to \ell^2(\mathcal{K}), \quad \text{with} \quad (\Phi^* x)_k = \langle x, \varphi_k \rangle, \quad k \in \mathcal{K}.$$
 (2.91)

Analysis - Synthesis

Theorem 2.39 (Orthonormal basis expansions) Let $\Phi = \{\varphi_k\}_{k \in \mathcal{K}}$ be an orthonormal basis for a Hilbert space H. The unique expansion with respect to Φ of any x in H has expansion coefficients

$$\alpha_k = \langle x, \varphi_k \rangle \quad \text{for } k \in \mathcal{K}, \quad \text{or,}$$
 (2.93a)

$$\alpha = \Phi^* x. \tag{2.93b}$$

Synthesis with these coefficients yields

$$x = \sum_{k \in \mathcal{K}} \langle x, \varphi_k \rangle \varphi_k \tag{2.94a}$$

$$= \Phi \alpha = \Phi \Phi^* x. \tag{2.94b}$$

Parseval equalities

THEOREM 2.40 (PARSEVAL EQUALITIES) Let $\Phi = \{\varphi_k\}_{k \in \mathcal{K}}$ be an orthonormal basis for a Hilbert space H. Expansion with coefficients (2.93) satisfies the $Parseval\ equality$,

$$||x||^2 = \sum_{k \in \mathcal{K}} |\langle x, \varphi_k \rangle|^2 \tag{2.96a}$$

$$= \|\Phi^* x\|^2 = \|\alpha\|^2, \tag{2.96b}$$

and the generalized Parseval equality,

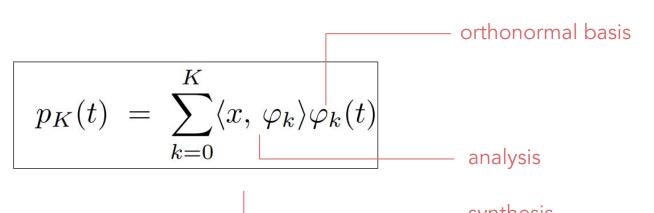
$$\langle x, y \rangle = \sum_{k \in \mathcal{K}} \langle x, \varphi_k \rangle \langle y, \varphi_k \rangle^*$$
 (2.97a)

$$= \langle \Phi^* x, \Phi^* y \rangle = \langle \alpha, \beta \rangle. \tag{2.97b}$$

Approximation of functions on finite intervals by polynomials

Let x be a real-valued function in $\mathcal{L}^2([a, b])$. An approximation \hat{x} that minimizes

$$||x - \widehat{x}||_2^2 = \int_a^b (x(t) - \widehat{x}(t))^2 dt$$



Legendre polynomials

$$L_k(t) = \frac{1}{2^k k!} \frac{d^k}{dt^k} (t^2 - 1)^k, \qquad k \in \mathbb{N}, \text{ are orthogonal on } [-1, 1]$$

$$\begin{bmatrix} L_0(t) &= 1, & L_3(t) &= \frac{1}{2} (5t^3 - 3t), \\ L_1(t) &= t, & L_4(t) &= \frac{1}{8} (35t^4 - 30t^2 + 3), \\ L_2(t) &= \frac{1}{2} (3t^2 - 1), & L_5(t) &= \frac{1}{8} (63t^5 - 70t^3 + 15t). \end{bmatrix}$$

