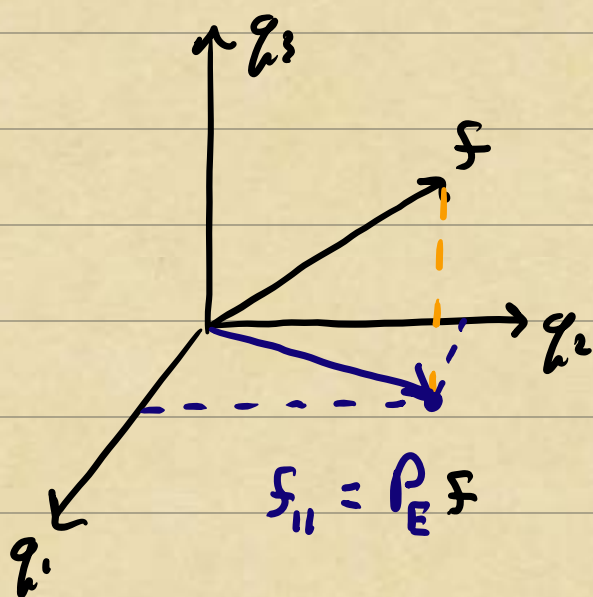


Best Approx. in Hilbert Space

Question: How to choose c_1, c_2, \dots, c_n so that $f - f_n$ is as "small" as possible?

$$(*) \quad \begin{array}{ccc} \left[\begin{array}{c} | \\ f(x) \\ | \end{array} \right] & \approx & \left[\begin{array}{ccc} | & | & | \\ e_1 & e_2 & \dots & e_n \\ | & | & | \end{array} \right] \left[\begin{array}{c} c_1 \\ c_2 \\ \vdots \\ c_n \end{array} \right] \\ f & & E \quad c \end{array}$$

Goal: Minimize $\|f - E c\|$ in Hilbert norm.



Two step procedure:

$$\Rightarrow \text{Project } f_{11} = P_E f$$

$$\Rightarrow \text{Solve } E c = f_{11}$$

Today: Orthogonal Projection in Hilbert Spaces.

Orthogonal Residual Criterion

We want to establish that $\|f - E_{\mathcal{C}}\|$ is minimized when $f - E_{\mathcal{C}} \perp \text{col}(E)$. The key property we need is that $\text{col}(E)$ is closed.

A **closed** subspace $V \subset H$, where H is a Hilbert space, has $f \in V$ whenever $\{f_n\} \subset V$ converges to f , i.e., $\lim_{n \rightarrow \infty} \|f - f_n\| = 0$.

Example: The space $P_n = \text{span}\{1, x, \dots, x^n\}$ is a closed subspace of $L^2([-1, 1])$, but the space $IP = \bigcup_{n=1}^{\infty} P_n$ is not closed in $L^2([-1, 1])$.

Theorem: Suppose V is a closed subspace of H and $f \in H$. Then,

i) There is a unique $g_* \in V$ s.t.
$$\|f - g_*\| = \inf_{g \in V} \|f - g\|.$$

ii) The element $f - g_*$ is \perp to V , i.e.
$$\langle f - g_*, g \rangle = 0 \text{ for all } g \in V$$

pf | If $f \in V$, then $g_x = f$. Otherwise,

$$d = \inf_{g \in V} \|f - g\| > 0 \quad (\text{since } V \text{ closed and } f \notin V).$$

Consider a sequence $\{g_n\}_{n=1}^{\infty} \subset V$ s.t.

$$\lim_{n \rightarrow \infty} \|f - g_n\| = d.$$

The idea is to show that $\{g_n\}_{n=1}^{\infty}$ is Cauchy and, therefore, has a limit in V . We will use the Parallelogram Law, which states

$$\|u+v\|^2 + \|u-v\|^2 = 2(\|u\|^2 + \|v\|^2) \quad u, v \in H.$$

(derive by expanding norms in inner products)

Now, set $u = f - g_n$ and $v = f - g_m$, so

$$\|2f - (g_n + g_m)\|^2 + \|g_m - g_n\|^2 = 2(\|f - g_n\|^2 + \|f - g_m\|^2)$$

Since $g_n, g_m \in V$, $g_n + g_m \in V$, and

$$\|2f - (g_n + g_m)\| = 2\|f - \frac{1}{2}(g_n + g_m)\| \geq 2d.$$

Therefore, we can bound $\|g_n - g_m\|$ above:

$$\|g_n - g_m\|^2 \leq 2(\|f - g_n\|^2 + \|f - g_m\|^2) - 4d^2.$$

Since $\|f - g_n\| \rightarrow d$ and $\|f - g_m\| \rightarrow d$ by construction, we can for any $\varepsilon > 0$ find $N > 0$ s.t. $n, m > N$ implies $\|g_n - g_m\| < \varepsilon$. Consequently, $\{g_n\}_{n=1}^{\infty}$ is Cauchy and has a limit g_* in H . Moreover, since $\{g_n\} \subset V$ and V is closed,

$$\text{i)} \quad \Rightarrow \quad \lim_{n \rightarrow \infty} g_n = g_* \in V.$$

(uniqueness later)

To prove (ii), take $g \in V$ and $\varepsilon \in \mathbb{R}$, then

$$\|f - (g_* - \varepsilon g)\|^2 \geq \|f - g_*\|^2$$

Expanding the norms gives

$$(+ \quad 2\varepsilon \operatorname{Re} \langle f - g_*, g \rangle + \varepsilon^2 \|g\|^2 > 0$$

If $\operatorname{Re} \langle f - g_*, g \rangle < 0$, then taking $\varepsilon > 0$ suff. small contradicts (+). If $\operatorname{Re} \langle f - g_*, g \rangle > 0$, then taking $\varepsilon < 0$ suff. small contradicts (+). Therefore, $\operatorname{Re} \langle f - g_*, g \rangle = 0$. A similar argument with $g_* \pm i\varepsilon g$ shows $\operatorname{Im} \langle f - g_*, g \rangle = 0$.

$$(i) \Rightarrow \langle f - g_*, g \rangle = 0 \text{ for all } g \in V.$$

To establish uniqueness of g_* , suppose $\hat{g}_* \in V$ also achieves $\|f - \hat{g}_*\| = d$. Then, by (ii)

$$\langle f - g_*, \underbrace{g_* - \hat{g}_*}_{\in V} \rangle = 0.$$

$$\text{Pythagorean Thm.} \Rightarrow \|f - \hat{g}_*\|^2 = \|f - g_*\|^2 + \|g_* - \hat{g}_*\|^2$$

$$\begin{array}{l} \text{Since} \\ \|f - g_*\| = \|f - \hat{g}_*\| \\ = d \end{array} \Rightarrow \|g_* - \hat{g}_*\|^2 = 0 \quad \square$$

Theorem 1 establishes our geometric intuition, that the distance between f and $g \in V$ is minimized when $f - g \perp V$.

In the setting of best approximation by a dictionary, as in (*), Thm 1 tells us there is a unique point $f_{**} \in \text{col}(E)$.

This is the projection step (step 1) in our two-step framework to solve (*).

Orthogonal Projections

How do we actually compute g_{**} in Thm 1? We need the machinery of orthogonal projections.

Given a subspace $V \subset H$, the **orthogonal complement** of V is

$$V^\perp = \{f \in H \mid \langle f, g \rangle = 0 \text{ for all } g \in V\}.$$

V^\perp is a closed subspace of H and

$$H = V \oplus V^\perp,$$

meaning that every $f \in H$ has $f = \overset{\in V}{g} + \overset{\in V^\perp}{h}$.

This decomposition is a direct consequence of Thm 1, since we can choose $g = g_x$ from i) and by part ii) $h = f - g \perp V$ so $h \in V^\perp$. Note the decomposition is unique!

The map $P_V : H \rightarrow V$ defined by $P_V f = g_x$ (from i) in Thm 1) is called the orthogonal projection onto V . It is

- i) $f \rightarrow P_V f$ is linear
- ii) $P_V f = f$ when $f \in V$
- iii) $P_V f = 0$ when $f \in V^\perp$
- iv) $\|P_V f\| \leq \|f\|$ for all $f \in H$.

Example: Fourier Series (Best Approx. in $L^2([-1, 1])$).

A continuous, periodic function f on $[-1, 1]$ has

$$f(x) = \frac{1}{\sqrt{2}} \sum_{k=-\infty}^{+\infty} \hat{f}_k e^{in k x}, \quad \hat{f}_k = \frac{1}{\sqrt{2}} \int_{-1}^{+1} f(x) e^{-in k x} dx.$$

Consider the best approximation of f in the

subspace $V_N = \{e^{-inNx}, \dots, e^{+inNx}\}$ of

$$L^2([-1,1]) = \left\{ f: [-1,1] \rightarrow \mathbb{R} \mid \int_{-1}^1 |f(x)|^2 dx < \infty \right\},$$

which is a Hilbert space w/inner product

$$\langle f, g \rangle = \int_{-1}^1 f(x) \overline{g(x)} dx.$$

Since $\{e^{ikx}\}_{k=-\infty}^{+\infty}$ are pairwise orthogonal,

$$f(x) = \underbrace{\frac{1}{\sqrt{2}} \sum_{k=-N}^{+N} \hat{f}_k e^{ikx}}_{f_N} + \underbrace{\frac{1}{\sqrt{2}} \sum_{|k| > N} \hat{f}_k e^{ikx}}_{f_N^\perp}$$

where $f_N \in V_N$ and $f_N^\perp \in V_N^\perp$. Therefore,
 $\langle f - f_N, g \rangle = 0$ for all $g \in V_N$ and f_N is
the best approximation of f in V_N . Moreover,
if P_N is the orthogonal projection onto V_N ,

$$P_N f = \frac{1}{\sqrt{2}} \sum_{k=-N}^N \hat{f}_k e^{ikx}, \quad \hat{f}_k = \frac{1}{\sqrt{2}} \int_{-1}^1 f(x) e^{-ikx} dx.$$

Fourier modes $\{e^{-inNx}, \dots, e^{+inNx}\}$ are an ONB for V_N .

Orthonormal Bases

An orthonormal basis for a subspace $V_N \subset H$ with dimension $N < \infty$ is a basis $\{q_1, \dots, q_N\} \subset V_N$ such that $\langle q_i, q_j \rangle = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$.

Claim: The orthogonal projection onto V_N can be computed explicitly via

$$P_N f = \sum_{k=1}^N \langle f, q_k \rangle q_k.$$

p.f. For any $f \in H$, we have that

$$f = f_N + f_N^\perp, \text{ where } f_N \in V_N, f_N^\perp \in V_N^\perp,$$

and $P_N f = f_N$ by definition. Since $\{q_1, \dots, q_N\}$ is a basis for V_N , there are unique scalars $\alpha_1, \dots, \alpha_N$ s.t.

$$f_N = \alpha_1 q_1 + \dots + \alpha_N q_N.$$

Using the orthonormality of $\{q_1, \dots, q_N\}$ and the linearity of $\langle \cdot, \cdot \rangle$, we have

$$\langle f_N, q_j \rangle = \alpha_1 \langle q_1, q_j \rangle + \dots + \alpha_j \langle q_j, q_j \rangle + \dots + \alpha_N \langle q_N, q_j \rangle$$

$$= \alpha_j$$

Therefore, $f_N = \sum_{k=1}^N \langle f, q_k \rangle q_k$ as claimed