
Numerical Analysis Hilary Term 2021
Lecture 9: Best Approximation in Inner-Product Spaces

Best approximation of functions: given a function f on $[a, b]$, find the “closest” polynomial/piecewise polynomial (see later sections)/ trigonometric polynomial (truncated Fourier series).

Norms: are used to measure the size of/distance between elements of a vector space. Given a vector space V over the field \mathbb{R} of real numbers, the mapping $\|\cdot\| : V \rightarrow \mathbb{R}$ is a **norm** on V if it satisfies the following axioms:

- (i) $\|f\| \geq 0$ for all $f \in V$, with $\|f\| = 0$ if, and only if, $f = 0 \in V$;
- (ii) $\|\lambda f\| = |\lambda| \|f\|$ for all $\lambda \in \mathbb{R}$ and all $f \in V$; and
- (iii) $\|f + g\| \leq \|f\| + \|g\|$ for all $f, g \in V$ (the **triangle inequality**).

Examples: 1. For vectors $x \in \mathbb{R}^n$, with $x = (x_1, x_2, \dots, x_n)^T$,

$$\|x\| \equiv \|x\|_2 = (x_1^2 + x_2^2 + \dots + x_n^2)^{\frac{1}{2}} = \sqrt{x^T x}$$

is the ℓ^2 - or vector two-norm.

2. For continuous functions on $[a, b]$,

$$\|f\| \equiv \|f\|_\infty = \max_{x \in [a, b]} |f(x)|$$

is the L^∞ - or ∞ -norm.

3. For integrable functions on (a, b) ,

$$\|f\| \equiv \|f\|_1 = \int_a^b |f(x)| dx$$

is the L^1 - or one-norm.

4. For functions in

$$V = L_w^2(a, b) \equiv \{f : [a, b] \rightarrow \mathbb{R} \mid \int_a^b w(x)[f(x)]^2 dx < \infty\}$$

for some given **weight** function $w(x) > 0$ (this certainly includes continuous functions on $[a, b]$, and piecewise continuous functions on $[a, b]$ with a finite number of jump-discontinuities),

$$\|f\| \equiv \|f\|_2 = \left(\int_a^b w(x)[f(x)]^2 dx \right)^{\frac{1}{2}}$$

is the L^2 - or two-norm—the space $L^2(a, b)$ is a common abbreviation for $L_w^2(a, b)$ for the case $w(x) \equiv 1$.

Note: $\|f\|_2 = 0 \implies f = 0$ almost everywhere on $[a, b]$. We say that a certain property P holds *almost everywhere* (a.e.) on $[a, b]$ if property P holds at each point of $[a, b]$ except perhaps on a subset $S \subset [a, b]$ of zero measure. We say that a set $S \subset \mathbb{R}$ has *zero measure* (or that it is of *measure zero*) if for any $\varepsilon > 0$ there exists a sequence $\{(\alpha_i, \beta_i)\}_{i=1}^\infty$ of subintervals of \mathbb{R} such that

$S \subset \cup_{i=1}^{\infty} (\alpha_i, \beta_i)$ and $\sum_{i=1}^{\infty} (\beta_i - \alpha_i) < \varepsilon$. Trivially, the empty set $\emptyset (\subset \mathbb{R})$ has zero measure. Any finite subset of \mathbb{R} has zero measure. Any countable subset of \mathbb{R} , such as the set of all natural numbers \mathbb{N} , the set of all integers \mathbb{Z} , or the set of all rational numbers \mathbb{Q} , is of measure zero.

Least-squares polynomial approximation: aim to find the best polynomial approximation to $f \in L_w^2(a, b)$, i.e., find $p_n \in \Pi_n$ for which

$$\|f - p_n\|_2 \leq \|f - q\|_2 \quad \forall q \in \Pi_n.$$

Seeking p_n in the form $p_n(x) = \sum_{k=0}^n \alpha_k x^k$ then results in the minimization problem

$$\min_{(\alpha_0, \dots, \alpha_n)} \int_a^b w(x) \left[f(x) - \sum_{k=0}^n \alpha_k x^k \right]^2 dx.$$

The unique minimizer can be found from the (linear) system

$$\frac{\partial}{\partial \alpha_j} \int_a^b w(x) \left[f(x) - \sum_{k=0}^n \alpha_k x^k \right]^2 dx = 0 \quad \text{for each } j = 0, 1, \dots, n,$$

but there is important additional structure here.

Inner-product spaces: a real **inner-product space** is a vector space V over \mathbb{R} with a mapping $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ (the **inner product**) for which

- (i) $\langle v, v \rangle \geq 0$ for all $v \in V$ and $\langle v, v \rangle = 0$ if, and only if $v = 0$;
- (ii) $\langle u, v \rangle = \langle v, u \rangle$ for all $u, v \in V$; and
- (iii) $\langle \alpha u + \beta v, z \rangle = \alpha \langle u, z \rangle + \beta \langle v, z \rangle$ for all $u, v, z \in V$ and all $\alpha, \beta \in \mathbb{R}$.

Examples: 1. $V = \mathbb{R}^n$,

$$\langle x, y \rangle = x^T y = \sum_{i=1}^n x_i y_i,$$

where $x = (x_1, \dots, x_n)^T$ and $y = (y_1, \dots, y_n)^T$.

2. $V = L_w^2(a, b) = \{f : (a, b) \rightarrow \mathbb{R} \mid \int_a^b w(x)[f(x)]^2 dx < \infty\}$,

$$\langle f, g \rangle = \int_a^b w(x) f(x) g(x) dx,$$

where $f, g \in L_w^2(a, b)$ and w is a weight-function, defined, positive and integrable on (a, b) .

Notes: 1. Suppose that V is an inner product space, with inner product $\langle \cdot, \cdot \rangle$. Then $\langle v, v \rangle^{\frac{1}{2}}$ defines a norm on V (see the final paragraph on the last page for a proof). In Example 2 above, the norm defined by the inner product is the (weighted) L^2 -norm.

2. Suppose that V is an inner product space, with inner product $\langle \cdot, \cdot \rangle$, and let $\|\cdot\|$ denote the norm defined by the inner product via $\|v\| = \langle v, v \rangle^{\frac{1}{2}}$, for $v \in V$. The angle θ between $u, v \in V$ is

$$\theta = \cos^{-1} \left(\frac{\langle u, v \rangle}{\|u\| \|v\|} \right).$$

Thus u and v are orthogonal in $V \iff \langle u, v \rangle = 0$.

E.g., x^2 and $\frac{3}{4} - x$ are orthogonal in $L^2(0, 1)$ with inner product $\langle f, g \rangle = \int_0^1 f(x)g(x) dx$ as

$$\int_0^1 x^2 \left(\frac{3}{4} - x\right) dx = \frac{1}{4} - \frac{1}{4} = 0.$$

3. Pythagoras Theorem: Suppose that V is an inner-product space with inner product $\langle \cdot, \cdot \rangle$ and norm $\| \cdot \|$ defined by this inner product. For any $u, v \in V$ such that $\langle u, v \rangle = 0$ we have

$$\|u \pm v\|^2 = \|u\|^2 + \|v\|^2.$$

Proof.

$$\begin{aligned} \|u \pm v\|^2 &= \langle u \pm v, u \pm v \rangle = \langle u, u \pm v \rangle \pm \langle v, u \pm v \rangle && \text{[axiom (iii)]} \\ &= \langle u, u \pm v \rangle \pm \langle u \pm v, v \rangle && \text{[axiom (ii)]} \\ &= \langle u, u \rangle \pm \langle u, v \rangle \pm \langle u, v \rangle + \langle v, v \rangle \\ &= \langle u, u \rangle + \langle v, v \rangle && \text{[orthogonality]} \\ &= \|u\|^2 + \|v\|^2. \end{aligned}$$

4. The Cauchy–Schwarz inequality: Suppose that V is an inner-product space with inner product $\langle \cdot, \cdot \rangle$ and norm $\| \cdot \|$ defined by this inner product. For any $u, v \in V$,

$$|\langle u, v \rangle| \leq \|u\| \|v\|.$$

Proof. For every $\lambda \in \mathbb{R}$,

$$0 \leq \langle u - \lambda v, u - \lambda v \rangle = \|u\|^2 - 2\lambda \langle u, v \rangle + \lambda^2 \|v\|^2 = \phi(\lambda),$$

which is a quadratic in λ . The minimizer of ϕ is at $\lambda_* = \langle u, v \rangle / \|v\|^2$, and thus since $\phi(\lambda_*) \geq 0$, $\|u\|^2 - \langle u, v \rangle^2 / \|v\|^2 \geq 0$, which gives the required inequality. \square

5. The triangle inequality: Suppose that V is an inner-product space with inner product $\langle \cdot, \cdot \rangle$ and norm $\| \cdot \|$ defined by this inner product. For any $u, v \in V$,

$$\|u + v\| \leq \|u\| + \|v\|.$$

Proof. Note that

$$\|u + v\|^2 = \langle u + v, u + v \rangle = \|u\|^2 + 2\langle u, v \rangle + \|v\|^2.$$

Hence, by the Cauchy–Schwarz inequality,

$$\|u + v\|^2 \leq \|u\|^2 + 2\|u\| \|v\| + \|v\|^2 = (\|u\| + \|v\|)^2.$$

Taking square-roots yields

$$\|u + v\| \leq \|u\| + \|v\|.$$

\square

Note: The function $\| \cdot \| : V \rightarrow \mathbb{R}$ defined by $\|v\| := \langle v, v \rangle^{\frac{1}{2}}$ on the inner-product space V , with inner product $\langle \cdot, \cdot \rangle$, trivially satisfies the first two axioms of norm on V ; this is a

consequence of $\langle \cdot, \cdot \rangle$ being an inner product on V . Result 5 above implies that $\| \cdot \|$ also satisfies the third axiom of norm, the triangle inequality.

Least-Squares Approximation

For the problem of least-squares approximation, $\langle f, g \rangle = \int_a^b w(x)f(x)g(x) dx$ and $\|f\|_2^2 = \langle f, f \rangle$ where $w(x) > 0$ on (a, b) .

Theorem. If $f \in L_w^2(a, b)$ and $p_n \in \Pi_n$ is such that

$$\langle f - p_n, r \rangle = 0 \quad \forall r \in \Pi_n, \quad (1)$$

then

$$\|f - p_n\|_2 \leq \|f - r\|_2 \quad \forall r \in \Pi_n,$$

i.e., p_n is a best (weighted) least-squares approximation to f on $[a, b]$.

Proof.

$$\begin{aligned} \|f - p_n\|_2^2 &= \langle f - p_n, f - p_n \rangle \\ &= \langle f - p_n, f - r \rangle + \langle f - p_n, r - p_n \rangle \quad \forall r \in \Pi_n \\ &\quad \text{Since } r - p_n \in \Pi_n \text{ the assumption (1) implies that} \\ &= \langle f - p_n, f - r \rangle \\ &\leq \|f - p_n\|_2 \|f - r\|_2 \text{ by the Cauchy-Schwarz inequality.} \end{aligned}$$

Dividing both sides by $\|f - p_n\|_2$ gives the required result. \square

Remark: the converse is true too (see problem sheet 4).

This gives a direct way to calculate a best approximation: we want to find $p_n(x) = \sum_{k=0}^n \alpha_k x^k$

such that

$$\int_a^b w(x) \left(f - \sum_{k=0}^n \alpha_k x^k \right) x^i dx = 0 \quad \text{for } i = 0, 1, \dots, n. \quad (2)$$

[Note that (2) holds if, and only if,

$$\int_a^b w(x) \left(f - \sum_{k=0}^n \alpha_k x^k \right) \left(\sum_{i=0}^n \beta_i x^i \right) dx = 0 \quad \forall q = \sum_{i=0}^n \beta_i x^i \in \Pi_n.]$$

However, (2) implies that

$$\sum_{k=0}^n \left(\int_a^b w(x) x^{k+i} dx \right) \alpha_k = \int_a^b w(x) f(x) x^i dx \quad \text{for } i = 0, 1, \dots, n$$

which is the component-wise statement of a matrix equation

$$A\alpha = \varphi, \quad (3)$$

to determine the coefficients $\alpha = (\alpha_0, \alpha_1, \dots, \alpha_n)^T$, where $A = \{a_{i,k}, i, k = 0, 1, \dots, n\}$, $\varphi = (f_0, f_1, \dots, f_n)^T$,

$$a_{i,k} = \int_a^b w(x) x^{k+i} dx \quad \text{and} \quad f_i = \int_a^b w(x) f(x) x^i dx.$$

The system (3) are called the **normal equations**.

Example: the best least-squares approximation to e^x on $[0, 1]$ from Π_1 in $\langle f, g \rangle = \int_a^b f(x)g(x) dx$. We want

$$\int_0^1 [e^x - (\alpha_0 1 + \alpha_1 x)] 1 dx = 0 \quad \text{and} \quad \int_0^1 [e^x - (\alpha_0 1 + \alpha_1 x)] x dx = 0.$$

\iff

$$\alpha_0 \int_0^1 dx + \alpha_1 \int_0^1 x dx = \int_0^1 e^x dx$$

$$\alpha_0 \int_0^1 x dx + \alpha_1 \int_0^1 x^2 dx = \int_0^1 e^x x dx$$

i.e.,

$$\begin{bmatrix} 1 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} e - 1 \\ 1 \end{bmatrix}$$

$\implies \alpha_0 = 4e - 10$ and $\alpha_1 = 18 - 6e$, so $p_1(x) := (18 - 6e)x + (4e - 10)$ is the best approximation.

Proof that the coefficient matrix A is nonsingular will now establish existence and uniqueness of (weighted) $\|\cdot\|_2$ best-approximation.

Theorem. The coefficient matrix A is nonsingular.

Proof. Suppose not $\implies \exists \alpha \neq 0$ with $A\alpha = 0 \implies \alpha^T A\alpha = 0$

$$\iff \sum_{i=0}^n \alpha_i (A\alpha)_i = 0 \iff \sum_{i=0}^n \alpha_i \sum_{k=0}^n a_{ik} \alpha_k = 0,$$

and using the definition $a_{ik} = \int_a^b w(x) x^k x^i dx$,

$$\iff \sum_{i=0}^n \alpha_i \sum_{k=0}^n \left(\int_a^b w(x) x^k x^i dx \right) \alpha_k = 0.$$

Rearranging gives

$$\int_a^b w(x) \left(\sum_{i=0}^n \alpha_i x^i \right) \left(\sum_{k=0}^n \alpha_k x^k \right) dx = 0 \quad \text{or} \quad \int_a^b w(x) \left(\sum_{i=0}^n \alpha_i x^i \right)^2 dx = 0$$

which implies that $\sum_{i=0}^n \alpha_i x^i = 0$ and thus $\alpha_i = 0$ for $i = 0, 1, \dots, n$. This contradicts the initial supposition, and thus A is nonsingular. \square

Remark:

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- Note in the simplest least-squares approximation problem $\min_x \|Ax - b\|_2$ that we dealt with in lecture 4, the theorem gives the solution $A^T(Ax - b) = 0$, that is, $x = (A^T A)^{-1} A^T b$. This coincides with the QR-based solution derived in lecture 4.
 - The above theorem does not imply that the normal equations are usable in practice: the method would need to be stable with respect to small perturbations. In fact, difficulties arise from the “ill-conditioning” of the matrix A as n increases. The next lecture looks at a fix.