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## Numerical Analysis Hilary Term 2025

### Lecture 9: Best Approximation in Inner-Product Spaces

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**Best approximation:** Given an element  $f$  of an inner-product space, we aim to find the “closest”/“best” approximation to  $f$  in a finite-dimensional subspace.

**Norm:** 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:

- For vectors  $x \in \mathbb{R}^n$ , with  $x = (x_1, x_2, \dots, x_n)^\top$ ,

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

is the  $\ell^2$ - or vector two-norm.

- For continuous functions on  $[a, b]$ ,

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

is the  $L^\infty$ - or  $\infty$ -norm.

- For integrable functions on  $(a, b)$ ,

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

is the  $L^1$ - or one-norm.

- For functions in

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

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),

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

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  $w(x) \equiv 1$ .

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**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  $S \subset \bigcup_{i=1}^\infty (\alpha_i, \beta_i)$  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.

### 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:

- $V = \mathbb{R}^n$ ,

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

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

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

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

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

### Notes:

- 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  $V$ , as we will show in the next section. We will abuse notation and refer to  $\|\cdot\| := \langle \cdot, \cdot \rangle^{\frac{1}{2}}$  as the norm induced by  $\langle \cdot, \cdot \rangle$  before we actually prove that  $\|\cdot\|$  is a norm. In second example above, the norm defined by the inner product is the (weighted)  $L^2$ -norm.
- 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  $\theta$  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  $V \iff \langle u, v \rangle = 0$ .

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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

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

### Properties of inner-product spaces

**Theorem. (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.** Let  $u, v \in V$ . Then, there holds

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

**Theorem. (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  $\lambda \in \mathbb{R}$ , there holds

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

which is a quadratic in  $\lambda$ . The minimizer of  $\phi$  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.  $\square$

**Theorem. (triangle inequality)** Suppose that  $V$  is an inner-product space with inner product  $\langle \cdot, \cdot \rangle$  and norm  $\| \cdot \|$  induced by this inner product. For any  $u, v \in V$ , there holds

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

**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

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

### Least-Squares Approximation

We now consider the abstract least squares approximation problem. Let  $V$  be an inner product space and let  $W \subset V$  be a finite-dimensional subspace of  $V$ . The least squares approximation problem is: Given  $f \in V$ , find  $p \in W$  such that

$$\|f - p\| \leq \|f - r\| \quad \forall r \in W, \quad (1)$$

where  $\| \cdot \|$  is the norm induced by the inner-product  $\langle \cdot, \cdot \rangle$  on  $V$ .

**Example: Polynomial Approximation.** An important example of best approximation is polynomial approximations to functions in  $L_w^2(a, b)$ . That is, given  $f \in L_w^2(a, b)$ , we seek  $p_n \in \Pi_n$  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

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

However, we seek an alternative approach that exploits the inner-product structure on  $L_w^2(a, b)$ .

**Theorem.** If  $f \in V$  and  $p \in W$  is such that

$$\langle f - p, r \rangle = 0 \quad \forall r \in W, \quad (2)$$

then  $p$  satisfies (1); i.e.,  $p$  is a best least-squares approximation to  $f$  in  $W$ .

**Proof.** Let  $f \in V$  and suppose that  $p \in W$  satisfies (2). Then, for all  $r \in W$ , there holds

$$\begin{aligned} \|f - p\|^2 &= \langle f - p, f - p \rangle \\ &= \langle f - p, f - r \rangle + \langle f - p, r - p \rangle \\ &= \langle f - p, f - r \rangle && [\text{by (2) since } r - p \in W] \\ &\leq \|f - p\| \|f - r\| && [\text{by the Cauchy-Schwarz inequality}]. \end{aligned}$$

Dividing both sides by  $\|f - p\|$  gives the required result. □

**Remark:** The converse is true too (see problem sheet 3).

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### Matrix form of least-squares approximation

Condition (2) give a direct way to calculate a best approximation. Let  $n = \dim W$  and let  $\{\phi_k\}_{k=1}^n$  be a basis for  $W$ . Then, we want to find  $p = \sum_{k=1}^n \alpha_k \phi_k$  such that

$$\left\langle f - \sum_{k=0}^n \alpha_k \phi_k, \sum_{i=0}^n \beta_i \phi_i \right\rangle = 0 \quad \forall \beta_1, \beta_2, \dots, \beta_n \in \mathbb{R},$$

which holds if and only if

$$\left\langle f - \sum_{k=1}^n \alpha_k \phi_k, \phi_i \right\rangle = 0 \quad \text{for } i = 1, 2, \dots, n. \quad (3)$$

However, (3) implies that

$$\sum_{k=0}^n \langle \phi_k, \phi_i \rangle \alpha_k = \langle f, \phi_i \rangle \quad \text{for } i = 1, 2, \dots, n,$$

which is the component-wise statement of a matrix equation

$$A\alpha = \varphi, \quad (4)$$

to determine the coefficients  $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_n)^\top$ , where  $A = \{a_{i,k}, i, k = 1, 2, \dots, n\}$ ,  $\varphi = (f_1, f_2, \dots, f_n)^\top$ ,

$$a_{i,k} = \langle \phi_k, \phi_i \rangle \quad \text{and} \quad f_i = \langle f, \phi_i \rangle.$$

The system (4) is called the **normal equations**.

**Theorem.** The coefficient matrix  $A$  is nonsingular.

**Proof.** Suppose that  $A$  is singular. Then, there exists  $\alpha \neq 0$  with  $A\alpha = 0$ , and so  $\alpha^\top A\alpha = 0$ . In component form, this reads

$$0 = \sum_{i=1}^n \alpha_i (A\alpha)_i = 0 = \sum_{i=1}^n \alpha_i \sum_{k=0}^n a_{ik} \alpha_k,$$

and using the definition  $a_{ik} = \langle \phi_k, \phi_i \rangle$ , we obtain

$$\sum_{i,k=1}^n \alpha_i \langle \phi_k, \phi_i \rangle \alpha_k = 0.$$

Rearranging gives

$$0 = \left\langle \sum_{i=1}^n \alpha_i \phi_i, \sum_{k=1}^n \alpha_k \phi_k \right\rangle = \left\| \sum_{i=1}^n \alpha_i \phi_i \right\|^2$$

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which implies that  $\sum_{i=1}^n \alpha_i x^i = 0$  and thus  $\alpha_i = 0$  for  $i = 1, 2, \dots, n$ . This contradicts the initial supposition, and thus  $A$  is nonsingular.  $\square$

## Examples

**Approximation of functions in  $L_w^2(a, b)$ :** Recall that given  $f \in L_w^2(a, b)$ , we seek  $p_n \in \Pi_n$  for which

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

We will use monomials as a basis for  $\Pi_n$ :  $\phi_i = x^i$  for  $i = 0, 1, \dots, n$  (note that, for convenience, we are indexing from 0 rather than 1 for the basis). Then, the orthogonality conditions (3) read

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

or equivalently

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

Consider the best least-squares approximation to  $e^x$  on  $[0, 1]$  from  $\Pi_1$  in  $\langle f, g \rangle = \int_a^b f(x)g(x) dx$ . We want

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

which holds if and only if

$$\begin{aligned} \alpha_0 \int_0^1 dx + \alpha_1 \int_0^1 x dx &= \int_0^1 e^x dx \\ \alpha_0 \int_0^1 x dx + \alpha_1 \int_0^1 x^2 dx &= \int_0^1 e^x x dx. \end{aligned}$$

In matrix form, we obtain

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

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

**Linear least squares from lecture 4:** Recall the following least squares problem from lecture 4. Given  $A \in \mathbb{R}^{m \times n}$  with  $m \geq n$  and  $b \in \mathbb{R}^m$ , find the minimizer  $x \in \mathbb{R}^n$  to

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2. \quad (5)$$

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As before, we assume that  $A$  has full rank. We can recast this problem as a best approximation problem. Let  $V = \mathbb{R}^m$  be equipped with the standard inner product  $\langle u, v \rangle = u^\top v$  and  $W = \text{col}(A) \subset \mathbb{R}^m$ , the column space of  $A$ . Then, problem (5) is equivalent to

$$\min_{y \in \text{col}(A)} \|y - b\|_2.$$

Since  $A$  has full rank, the columns of  $A$ , denoted  $a_1, a_2, \dots, a_n$ , form a basis for  $\text{col}(A)$ . Choosing  $\phi_i = a_i$ , we have  $y = \sum_{i=1}^n x_i a_i$  and (3) reads

$$\left( \sum_{k=1}^n x_k a_k \right)^\top a_i = b^\top a_i, \quad i = 1, 2, \dots, n.$$

In matrix form (4), we have

$$A^\top A x = A^\top b \implies x = (A^\top A)^{-1} A^\top b.$$

If  $A = QR$  is the thin QR factorization of  $A$ , then

$$(A^\top A)^{-1} A^\top b = (R^\top Q^\top Q R)^{-1} R^\top Q^\top b = (R^\top R)^{-1} R^\top Q^\top b = R^{-1} R^{-\top} R^\top Q^\top b = R^{-1} Q^\top b,$$

which is the same solution derived in lecture 4.

**Remark:** The above results do 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.