

5374 Fall '22

Numerical Linear Algebra

Lecture 11

Conjugation of matrices

Suppose A is a $m \times n$ matrix, this is the same as having a linear transformation
 $\mathbb{R}^n \longrightarrow \mathbb{R}^m$

Fix new bases in \mathbb{R}^n and \mathbb{R}^m , and let

$M = m \times n$ matrix

$N = n \times n$ matrix

such that the columns of M and N represent respectively the new bases in \mathbb{R}^m and \mathbb{R}^n

We have a transform $L: \mathbb{R}^n \rightarrow \mathbb{R}^m$

$$L(x) = Ax \quad (x \in \mathbb{R}^n)$$

what does L look like with respect to the new bases?

Let $x \in \mathbb{R}^n$, Then x can be written

↪ $x = N x'$ for some $x' \in \mathbb{R}^n$.

What this means is that a vector represented by x in the canonical basis is represented by x' in the new basis in \mathbb{R}^n .

Likewise, if $y \in \mathbb{R}^m$ then there is a $y' \in \mathbb{R}^m$ such that $y = M y'$, and y' represents the coordinates of the vector y in the new basis in \mathbb{R}^m .

Now, take $x \in \mathbb{R}^n$, and look at $L(x)$,

$$Lx = Ax$$

In the new basis, $x = N x'$, so

$$L(x) = ANx'$$

$L(x)$ is an element of \mathbb{R}^m , so it has an expression in the new basis, meaning there is a $y' \in \mathbb{R}^m$ such that

$$L(x) = M y'$$

so we have that x' and y' are related by

$$M y' = A N x'$$

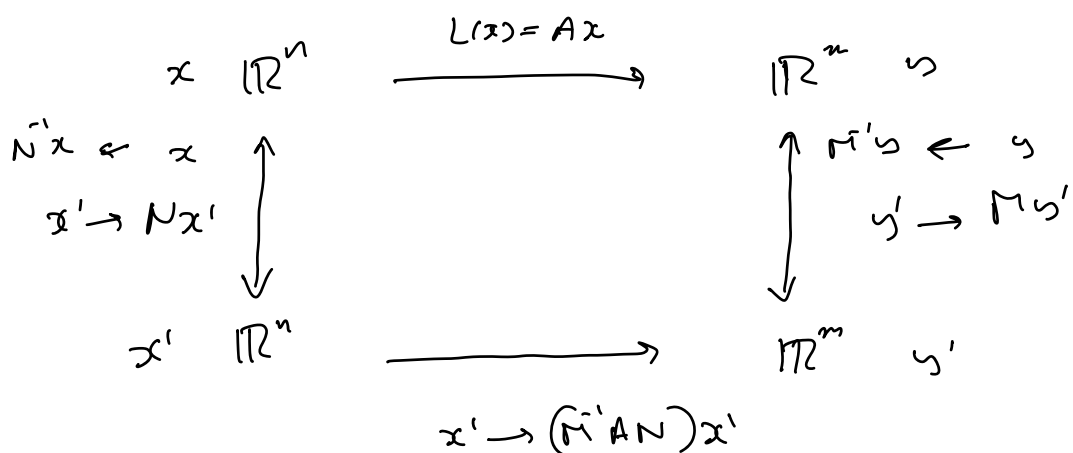
i.e.
$$y' = (M^{-1} A N) x'$$

(This corresponds to $y = Ax$ in the canonical basis)

In other words, the matrix of L in the new basis is

$$M^{-1} A N.$$

This is called a conjugation, and it can be visualized as follows



It is particularly interesting to look at

such conjugation when $m=n$ and $M=N$.

If A and A' are two matrices such that

$$A' = M^{-1} A M$$

for some $n \times n$ matrix M , we say A and A' are conjugate matrices

Exercise : Suppose A, A' , and M are as above. Suppose also that M preserves the Euclidean norm, i.e. $\|Ax\|_2 = \|x\|_2$ for all x . Show that

$$\|A\| = \|A'\|$$

$$\|A^{-1}\| = \|(A')^{-1}\|$$

In particular, $\text{cond}(A) = \text{cond}(A')$

Inner products and orthogonality

Given a vector space X , an inner product is a real valued function

$$X \times X \longrightarrow \mathbb{R} \quad (\text{or } \mathbb{C})$$

which is denoted $\langle x, y \rangle$ given $x, y \in X$ and which satisfies the following:

- Bilinearity

$$(\alpha_1 x_1 + \alpha_2 x_2, y) = \alpha_1 (x_1, y) + \alpha_2 (x_2, y)$$

$\alpha_1, \alpha_2 \in \mathbb{R}, x_1, x_2 \in X$

$$(x, \beta_1 y_1 + \beta_2 y_2) = \beta_1 (x, y_1) + \beta_2 (x, y_2)$$

$\beta_1, \beta_2 \in \mathbb{R}, x, y_1, y_2 \in X$

- Symmetry: $(x, y) = (y, x) \quad \forall x, y \in X$

- Positivity: $(x, x) \geq 0 \quad \forall x \in X$

and

$$(x, x) = 0 \iff x = 0.$$

When a vector space has an inner product we can define a norm in it, via

$$\|x\| = \sqrt{(x, x)}$$

If the space is complete with respect to this norm then $(X, (\cdot, \cdot))$ is called a (real) Hilbert space.

There is an analogue of an inner product for complex vector spaces called a Hermitian form
(named after Hermite)

Hermitian form

$$\begin{array}{lcl} \text{A map} & X \times X & \longrightarrow \mathbb{C} \\ \text{Denoted} & x, y & \longrightarrow \langle x, y \rangle \end{array}$$

- Linearity and sesqui-linearity

$$\langle \alpha_1 x_1 + \alpha_2 x_2, y \rangle = \alpha_1 \langle x_1, y \rangle + \alpha_2 \langle x_2, y \rangle$$

$$\forall \alpha_1, \alpha_2 \in \mathbb{C}$$

$$x_1, x_2, y \in X$$

$$\langle x, \beta_1 y_1 + \beta_2 y_2 \rangle = \overline{\beta_1} \langle x, y_1 \rangle + \overline{\beta_2} \langle x, y_2 \rangle$$

$$\forall \beta_1, \beta_2 \in \mathbb{C}$$

$$x, y_1, y_2 \in X$$

- "Symmetry" $\overline{\langle x, y \rangle} = \langle y, x \rangle$

- Positivity $\langle x, x \rangle \geq 0 \quad \forall x \in X$
 $= 0 \iff x = 0$

In this case we can define a norm in X

$$\|x\| := \sqrt{\langle x, x \rangle}$$

If X is complete in this norm, the pair (X, \langle, \rangle) is called a Hilbert space.

Examples (of inner products and Hermitian forms)

①

\mathbb{R}^n , with inner product given by

$$(x, y) = y^t x = x_1 y_1 + \dots + x_n y_n$$

$$\left(\text{where } x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}, y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \right)$$

② \mathbb{C}^n , with Hermitian product given by

$$\langle x, y \rangle = y^* x, \quad (\text{where } y^* = \overline{y^t})$$

$$= x_1 \overline{y_1} + x_2 \overline{y_2} + \dots + x_n \overline{y_n}$$

$$\begin{aligned} \text{Note that } \langle x, x \rangle &= x_1 \overline{x_1} + \dots + x_n \overline{x_n} \\ &= |x_1|^2 + \dots + |x_n|^2 \end{aligned}$$

③

Let $L^2(\mathbb{R}) = \{ f: \mathbb{R} \rightarrow \mathbb{R} \mid \text{Lebesgue measurable} \}$

$$\int_{\mathbb{R}} f(x)^2 dx < \infty \}$$

$$(f, g) := \int_{\mathbb{R}} f(x) g(x) dx$$

$$(f, f) = \int_{\mathbb{R}} f(x)^2 dx$$

This is a real Hilbert space

$$(4) \quad L^2(\mathbb{R}, \mathbb{C}) = \{ f: \mathbb{R} \rightarrow \mathbb{C} \mid f \text{ is Lebesgue measurable}$$

$$\text{and } \int_{\mathbb{R}} |f(x)|^2 dx < \infty \}$$

$$\langle f, g \rangle = \int_{\mathbb{R}} f(x) \overline{g(x)} dx$$

(5) Consider the space of $n \times n$ real matrices, $M_{n \times n}(\mathbb{R})$ with inner product

$$(A, B) = \text{Tr}(B^t A)$$

Some remarks

1. The Cauchy-Schwartz inequality:

For any X with an inner product (x, y) , we have the inequality

$$(x, y) \leq \sqrt{(x, x)} \sqrt{(y, y)} = \|x\| \cdot \|y\|$$

Why? Consider the polynomial

$$\begin{aligned} P(t) &= (x + ty, x + ty) \\ &= (x, x + ty) + (ty, x + ty) \\ &= (x, x) + t(x, y) + t(y, x) + t^2(y, y) \\ &= (x, x) + 2t(x, y) + t^2(y, y) \end{aligned}$$

so since $P(t) \geq 0$, its discriminant must be ≤ 0 , so

$$(2(x, y))^2 - 4(x, x)(y, y) \leq 0$$

i.e.

$$4(x, y)^2 \leq 4(x, x)(y, y)$$

$$(x, y)^2 \leq (x, x)(y, y)$$

It also follows from the proof that

$$(x, y) = \|x\| \cdot \|y\|$$

if and only if x and y are parallel.

② (the triangle inequality) (\Leftarrow Cauchy-Schwarz inequality)

Let's show that for the norm induced by an inner product we have

$$\|x + y\| \leq \|x\| + \|y\|$$

$$\begin{aligned}\|x+y\| &= \sqrt{(x+y, x+y)} \\ &= \sqrt{(x,x) + 2(x,y) + (y,y)}\end{aligned}$$

By Cauchy-Schwarz

$$\begin{aligned}&\leq \sqrt{(x,x) + 2\|x\| \cdot \|y\| + (y,y)} \\ &= \sqrt{\|x\|^2 + 2\|x\| \cdot \|y\| + \|y\|^2} \\ &= \sqrt{(\|x\| + \|y\|)^2} \\ &= \|x\| + \|y\|\end{aligned}$$

So, $\|x+y\| \leq \|x\| + \|y\|.$