EN530.678 Nonlinear Control and Planning in Robotics
Lecture 1: Matrix Algebra Basics

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1 Mathematical Preliminaries I: Matrix Algebra

- vectors $x = (x_1, ..., x_n) \in \mathbb{R}^n$ and matrices $A = \begin{bmatrix} a_{11} & .. & a_{1n} \\ . & .. & . \\ . & .. & . \\ a_{n1} & .. & a_{nn} \end{bmatrix} \in \mathbb{R}^{n\times n}$

- scalar t denotes time, we write $x(t)$ and $A(t)$ when they are function of time

- Inner products

$$x^T y \equiv x' y \equiv x \cdot y \equiv \langle x, y \rangle \equiv \sum_{i=1}^{n} x_i y_i$$

- Matrix *determinant* $\det(A)$ or $|A|$ is

$$\det(A) = a_{11}C_{11} + a_{12}C_{12} + \cdots + a_{1n}C_{1n},$$

  where C_{1i} is called the $1i$-th cofactor, which is the determinant of the reduced matrix obtained by crossing out the first row and i-th column multiplied by $(-1)^{i+1}$.

- The determinant is also the *signed volume* of the parallellepiped whose sides corresponds to the columns of the matrix

- Matrix Inverse

$$(A^{-1})_{ij} = \frac{1}{\det(A)} C_{ji}, \quad \text{for} \quad \det(A) \neq 0$$

- Linear Independence: a set of vectors $a_1 \in \mathbb{R}^n, ..., a_n \in \mathbb{R}^n$ are linearly independent if it is not possible to express one a linear combination of the others, i.e.

$$x_1 a_1 + \cdots + x_n a_n = 0$$

  implies that all scalars $x_1, ..., x_n$ are zero. The *rank* of a matrix is the maximum number of linearly independent columns or rows. A square n-by-n matrix with rank less than n is called *singular*.

- The solutions λ_i to the equation

$$\det(A - \lambda I) = 0,$$

where I is the identity matrix, are called the *eigenvalues* of A. If $Ax = y$ then $\lambda x = y$ and the vectors x^i corresponding to λ_i are called the *eigenvectors* of A. Combining all solutions we have

$$A\left[x^1 \mid \cdots \mid x^n\right] = \left[x^1 \mid \cdots \mid x^n\right] \operatorname{diag}([\lambda_1, \cdots, \lambda_n]) \quad \Leftrightarrow \quad AS = S\Lambda,$$

or

$$S^{-1}AS = \Lambda,$$

which is called *similarity transformation*, i.e. A is similar to the diagonal matrix Λ. Two similar matrices A and B satisfy $\lambda_i(A) = \lambda_i(B)$. We have the relationship

$$\operatorname{trace}(A) = \sum_1^n a_{ii} = \sum_1^n \lambda_i(A)$$

If A is symmetric then $S^{-1} = S^T$, i.e. S is an orthogonal transformation.

- Consider the equation $Ax = y$, where $A \in \mathbb{R}^{n\times n}$. The following are equivelent:
  1. $\det(A) \neq 0$
  2. A^{-1} exists
  3. $Ax = y$ has a unique solution for $y \neq 0$
  4. A is full rank;
  5. we have $\lambda_i(A) \neq 0$, $i = 1, \ldots, n$ where $\lambda_i(A)$is the i-th eigenvalue
- The *null space* or *kernel* of a matrix $A \in \mathbb{R}^{m\times n}$ is

$$\operatorname{Null}(A) = \{x \in \mathbb{R}^n \mid Ax = 0\}$$

- The *norm* of a vector is $\|x\|^2 = x^T x$. For $y = Ax$ for non-singular matrix A we have

$$\|y\|^2 = x^T A^T Ax = \|x\|^2_{A^TA},$$

where $\|x\|^2_B$ is called a generalized norm, i.e. a norm in new coordinates defined by B. The matrix B is *positive definite* if $\|x\|^2_B > 0$ for all $x \neq 0$, which is written as $B > 0$. If $\|x\|^2_B \geq 0$ for all $x \neq 0$ then B is *positive semidefinite*, i.e. $B \geq 0$.

- The *norm* of a general matrix $A \in \mathbb{R}^{m\times n}$ is

$$\|A\| = \max_{\|x\|=1} \|Ax\|,$$

or equivalently (known as the *spectral norm*)

$$\|A\| = \sqrt{\lambda_{\max}(A^T A)} \triangleq \sigma_{\max}(A),$$

where $\sigma_{\max}(A)$ denotes the maximum *singular value* of A

- Norm inequalities:

$\|\alpha A\| = |a|\,\|A\|$, for all $\alpha \in \mathbb{R}, A \in \mathbb{R}^{m\times n}$

$\|A + B\| \leq \|A\| + \|B\|$, for all $A, B \in \mathbb{R}^{m\times n}$

$\|AB\| \leq \|A\|\|B\|$, for all $A, B \in \mathbb{R}^{n\times n}$

$\|Ax\| \leq \|A\|\|x\|$, for all $A \in \mathbb{R}^{m\times n}, x \in \mathbb{R}^n$

- *Symmetric* matrices have real eigenvalues and mutually orthogonal, real, non-zero eigenvectors $x_1, \ldots, x_n$. Assuming normalized $\|x_i\| = 1$ we have

$$A = \sum_{i=1}^{n} \lambda_i x_i x_i^T$$

  Let $\lambda_1 \leq \cdots \leq \lambda_n$ be the eigenvalues of symmetric matrix A, then we have

$$\|A\| = \max\{|\lambda_1|, |\lambda_n|\}, \qquad \lambda_1\|y\|^2 \leq y^T A y \leq \lambda_n \|y\|^2, \text{ for all } y \in \mathbb{R}^n$$

- Geometric Notions:
  - The scalar equation $(a^i)^T x - y_i = 0$ for a given scalar y_i and vector a^i defines a *hyperplane* in $\mathbb{R}^n$ with normal vector a^i. The intersection of n such hyperplanes is a point determined by $Ax = y$.
  - the equation $x^T B x - c = 0$ determines a quadratic surface. If $B > 0$ then this is an hyperellispoids in $\mathbb{R}^n$ with principal axes equal to $(\lambda_i/c)^{-1/2}$. Furthermore, since $B = S^T \Lambda S$ the axis of the ellipsoid are rotated by S. Clearly, if $\lambda_i = 0$ for some i then the hyperellipsoid is flat along that dimension and its volume (i.e. determinant) is zero.
  - more generally, a scalar function $f(x) = 0$ defines a hupersfurce in R^n. Taylor expansion gives:

$$f(x) \approx f(x_0) + \frac{\partial f}{\partial x}\Big|_{x=x_0}(x - x_0) = 0,$$

    so that the *normal* to the surface is simply the gradient. A closer approximation results from second-order expansion

$$f(x) \approx f(x_0) + \frac{\partial f}{\partial x}\Big|_{x=x_0}(x - x_0) + \frac{1}{2}(x - x_0)^T \frac{\partial^2 f}{\partial x^2}\Big|_{x=x_0}(x - x_0) = 0,$$

    where $\frac{\partial^2 f}{\partial x^2} \equiv B$ is the n-by-n *Hessian* matrix. If $B \geq 0$ (> 0) we call the function *locally convex* (strictly locally convex) near x_0. If it is true for all x_0 then f is convex (strictly convex).

- Derivative Notation: Let f be a function of two variables $x \in \mathbb{R}^n$ and $y \in \mathbb{R}^m$. The following euivalent notations will be used

$$\frac{\partial f}{\partial x}(x, y) \equiv \partial_x f(x, y) \equiv f_x(x, y) \equiv D_1 f(x, y)$$

$$\frac{\partial f}{\partial y}(x, y) \equiv \partial_y f(x, y) \equiv f_y(x, y) \equiv D_2 f(x, y)$$

Similar notation is used for higher derivatives, e.g.

$$\frac{\partial^2 f}{\partial x^2}(x, y) \equiv \partial_x^2 f(x, y) \equiv f_{xx}(x, y) \equiv D_2^2 f(x, y).$$

We regard $\partial_x f$ as a *row vector*, i.e.

$$\partial_x f = \left[\frac{\partial f}{\partial x_1}, \; \cdots, \frac{\partial f}{\partial x_n}\right]$$

The *gradient* of f denoted by $\nabla_x f$ is the column vector

$$\nabla_x f = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix} = \partial_x f^T.$$

The notation extends when $f(x)$ is a column vector of functions, in which case $\partial_x f$ is a matrix called the Jacobian.