

Mahindra École Centrale

MA 102: Linear Algebra and Analysis Key Concepts and Results

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Linear Algebra

Matrix Mathematics

System of Linear Differential Equations



Linear Spaces and Subspaces



Linear Spaces

- Closure, Associativity, Commutativity, Additive Identity & Inverse etc
- The scalars can be real or complex numbers (in general, any field)

Subspaces

- Subspace is a subset of a vector space which is a vector space itself
- Fact: Given a subset of a vector space, closure axioms are sufficient to check if a subset is a subspace



Independence, Basis, and Dimension



Dependent and Independent Sets

- If $\sum_{i=1}^{n} c_i v_i = 0$ (with not all zero c_i) then the set $\{v_1, \ldots, v_2\}$ is dependent
- If $\sum_{i=1}^{n} c_i v_i = 0$ implies $c_i = 0$ then $\{v_1, \dots, v_2\}$ is independent
- ► Span of a set S is the set of all finite linear combinations of elements of S

Basis and Dimension

- ► An independent set S is a basis for a linear space V if span(S) = V
- The number of elements of basis is dimension of the linear space



Facts on Basis and Dimension



- ▶ Fact: If $n = \dim(V)$ then every set with m > n elements is dependent
- ▶ Fact: If $n = \dim(V)$ then every independent set with n elements is basis
- ▶ Fact: If $n = \dim(V)$ then every independent set with m < n elements can be extended into a basis

Examples

- \mathbb{R}^3 : Unit vectors in x, y, and z-axis form the canonical basis
- ► Set of polynomials: {1, x, x², ···} forms a basis of this infinite-dimensional space



Inner Products and Norms



Inner Product

►
$$\langle \cdot, \cdot \rangle : V \times V \to \mathbb{R}$$
 is inner product on V if i) $\langle x, y \rangle = \langle y, x \rangle$,
ii) $\langle cx, y \rangle = c \langle x, y \rangle$, iii) $\langle x, x \rangle > 0$, $x \neq 0$,
iv) $\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$

Euclidean Norm

▶
$$||x|| = \langle x, x \rangle^{\frac{1}{2}}$$
: i) $||cx|| = c||x||$, ii) $||x|| > 0$ for $x \neq 0$,
iii) $||x + y|| \le ||x|| + ||y||$

Cauchy-Schwarz Inequality

$$\bullet |\langle x, y \rangle| \le \langle x, x \rangle^{\frac{1}{2}} \langle y, y \rangle^{\frac{1}{2}}$$

$$\bullet |\langle x, y \rangle| \le ||x|| ||y||$$

• Equality holds iff x, y are dependent



Orthogonality



Orthogonality and Orthonormal Basis

- x is orthogonal to $y (x \perp y)$ if $\langle x, y \rangle = 0$
- ► A set is orthogonal if all elements are mutually orthogonal
- An orthogonal set is orthonormal if every element has unit norm
- An orthonormal set that is a basis is an orthonormal basis
- Key Facts
 - Fact: Every orthogonal set with nonzero elements is independent
 - ► Fact: Gram-Schmidt algorithm generates orthogonal sets



Linear Maps and Operators



Definitions

- ► $T: V \to W$ is a linear map if T(x + y) = T(x) + T(y) and T(cx) = cT(x). If V = W then T is a linear operator
- $\mathcal{N}(T) \subseteq V$ is the null space of T given be $\{x \in V : T(x) = 0\}$
- ► $\mathcal{R}(T) \subseteq W$ is the range space of T given be $\{y \in W : y = T(x), x \in V\}$
- $\dim(\mathcal{N}(T))$ is the nullity or defect of T
- $\dim(\mathcal{R}(T))$ is the rank of T



Key Facts on Linear Maps



Key Results

- ► Fact: N(T) and R(T) are subspaces of V and W, respectively
- ► Rank-Nullity Theorem: $\dim(\mathcal{N}(T)) + \dim(\mathcal{R}(T)) = \dim(V)$
- ► Fact: If T is one-to-one (that is, $\mathcal{N}(T) = \{0\}$) then $\dim(W) \ge \dim(V)$
- ▶ Fact: If T is onto (that is, $\mathcal{R}(T) = W$) then $\dim(W) \leq \dim(V)$
- ► Fact: If T is invertible (one-to-one & onto) then dim(W) = dim(V)







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System of Linear Equations



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Existence and Uniqueness

- Let $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$
- ► Fact: Ax = b has a solution if and only if rank(A) = rank([A b])
- ► Fact: Ax = b has a unique solution iff N(A) = {0} iff rank(A) = rank([A b]) = n
- ► Fact: If m = n, Ax = b has a unique solution iff A is invertible

Facts on Rank

- Fact: $rank(AB) \le min\{rank(A), rank(B)\}$
- Fact: rank(AB) = rank(A) if B has full rank

Gaussian Elimination



Solution Techniques and Related Concepts

- Gaussian elimination: elementary row operations, forward and backward substitutions
- Fact: Elementary row operations are equivalent to multiplication by elementary matrices
- ► Fact: Inverse of an elementary matrix is an elementary matrix
- ▶ Fact: Permutation matrices are idempotent $(P^2 = I)$
- Fact: Every invertible matrix can be written as a product of elementary matrices



Types of Matrices



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- Diagonal, triangular, block-diagonal, block-triangular
- Symmetric: $A = A^{T}$, skew-symmetric: $A = -A^{T}$
- Hermitian: $A = A^*$, skew-Hermitian: $A = -A^*$
- ▶ Idempotent: $A^2 = I$, nilpotent: $A^k = 0$ for some $k \ge 1$
- Normal: $A^{\mathrm{T}}A = AA^{\mathrm{T}}$ or $A^*A = AA^*$
- Orthogonal (orthonormal?): $A^{T}A = AA^{T} = I$
- Unitary: $A^*A = AA^* = I$
- ► Positive (nonnegative) definite: A > 0 (A ≥ 0) if A is Hermitian and x*Ax > 0, x ≠ 0 (x*Ax ≥ 0)

Determinant and Eigenvalues



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Determinant

- Fact: det(A) = 0 iff A is singular
- Fact: $det(A) \neq 0$ iff A is invertible
- Fact: Let $A \in \mathbb{F}^{n \times m}$, $B \in \mathbb{F}^{m \times n}$, and $\lambda \in \mathbb{F}$

$$\lambda^m \det(\lambda I_n + AB) = \lambda^n \det(\lambda I_m + BA)$$

Eigenvalues, Eigenvectors, & Singular Values

- If $Ax = \lambda x$ for $x \neq 0$ then λ is eigenvalue, x is eigenvector
- σ is a singular value of A if $\sigma^2 \in \operatorname{spec}(A^*A)$
- Fact: $\lambda \in \operatorname{spec}(A)$ iff $\det(\lambda I A) = 0$
- ▶ Fact: If $\lambda \in \operatorname{spec}(A)$ then $\lambda^n \in \operatorname{spec}(A^n)$ for all $n \ge 1$

Matrix Diagonalizability



Diagonalizability

- A is diagonalizable if $A = X\Lambda X^{-1}$ for Λ diagonal and nonsingular X
- Fact: In this case, elements of Λ are eigenvalues, columns of X are corresponding eigenvectors
- ▶ Fact: $A \in \mathbb{F}^{n \times n}$ is diagonalizable iff A has n independent eigenvectors
- ► Fact: If A has n distinct eigenvalues then A is diagonalizable
- ► Fact: If A is normal then A is diagonalizable
- ▶ Remark: A need not have distinct eigenvalues for diagonalizability (consider I_n)



Matrix Decompositions



Decompositions

- ► Schur Decomposition: $A = SUS^*$, S is unitary and U is upper triangular
- Singular Value Decomposition: A = UΣV*, where U, V are unitary, Σ is diagonal with elements as singular values
- ▶ Jordan Canonical Form: $A = SJS^*$, where S is unitary,

 $J = \text{block} - \text{diag}(J_1, \dots, J_m)$, J_i is a scalar block if λ_i is not repeated. Otherwise, $J_i = \lambda_i I + N_i$, where N_i is nilpotent

- ▶ Polar Decomposition: A = MU where $M \ge 0$ and U is unitary
- Euler's Identity: $A = Me^{j\Theta}$ where $M \ge 0$ and Θ is Hermitian

The Cayley-Hamilton Theorem



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The Cayley-Hamilton Theorem

- Let the characteristic polynomial be given by χ_A(λ) = det(λI − A)
- Then $\chi_A(A) = 0$
- Corollary: Given $A \in \mathbb{F}^{n \times n}$ and $k \ge 0$,

$$A^{n+k} = c_0 I + c_1 A + c_2 A^2 + \dots + c_{n-1} A^{n-1}$$

► Fact: If
$$p(\cdot)$$
 is a polynomial then
 $p(A) = Xp(\Lambda)X^{-1} = Sp(U)S^* = Sp(J)S^*$

Facts on Hermitian Matrices



Key Results

- ► Fact: Eigenvalues of symmetric (Hermitian) matrices are real
- Fact: Eigenvalues of skew-symmetric (skew-Hermitian) matrices are imaginary
- Fact: Eigenvalues of orthogonal or unitary matrices has unit magnitude
- ► Fact: Eigenvalues of positive definite matrices are positive
- ► Fact: $A \in \mathbb{R}^{2 \times 2}$ is positive definite iff A is symmetric, tr(A) > 0, and det(A) > 0







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Matrix Exponential



Definition and Key Facts

• Let $A \in \mathbb{F}^{n \times n}$. Then

$$e^{A} = \sum_{n=0}^{\infty} \frac{A^{n}}{n!} = I + A + \frac{A^{2}}{2!} + \dots + \frac{A^{n}}{n!} + \dots$$

• Fact:
$$e^{\lambda I} = e^{\lambda}I \implies e^{0_{n \times n}} = I_n$$

• Fact:
$$e^{(x+y)A} = e^{xA}e^{yA} \Longrightarrow e^A e^{-A} = I$$

• Fact:
$$\frac{\mathrm{d}}{\mathrm{d}t}e^{At} = Ae^{At} = e^{At}A$$

▶ Fact: If
$$AB = BA$$
 then $e^{A+B} = e^A e^B = e^B e^A$

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Matrix Exponential Evaluation



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Key Methods

► Fact: If
$$A = X\Lambda X^{-1}$$
 then $e^A = Xe^{\Lambda}X^{-1}$
► Fact: If $N^k = 0$ then $e^{(\lambda I + N)t} = e^{\lambda t} \sum_{i=0}^{k-1} \frac{N^i t^i}{i!}$

$$\sum_{i=0}^{n-1} \frac{N^n t^n}{n!} = \begin{bmatrix} 0 & t & \cdots & \frac{t^{n-1}}{(n-1)!} \\ 0 & 0 & \cdots & \frac{t^{n-2}}{(n-2)!} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

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Vector Differential Equations I



The Homogeneous Case

- Fact: $\dot{x}(t) = Ax(t)$, $x(0) = x_0$ has a unique solution $x(t) = e^{At}x_0$
- ▶ Fact: $x(t) \to 0$ as $t \to \infty$ iff $\operatorname{Re}(\lambda) < 0 \forall \lambda \in \operatorname{spec}(A)$
- ► Fact: For $A \in \mathbb{R}^{2 \times 2}$, $\operatorname{Re}(\lambda) < 0$ iff $\operatorname{tr}(A) < 0$ and $\det(A) > 0$
- ► Fact: If A has only imaginary eigenvalues then x(t) will be harmonic

Vector Differential Equations II



The Nonhomogeneous Case

Fact:
$$\dot{x}(t) = Ax(t) + Bu(t)$$
, $x(0) = x_0$ has a unique solution

$$x(t) = e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau)\mathrm{d}\tau$$

Fact: If u(t) = sin(ωt) and ιω ∈ spec(A) then resonance occurs



The State-Space Approach I



Second-Order Differential Equation

▶ Fact: $\ddot{x}(t) + a\dot{x}(t) + bx(t) = 0$ can be transformed to

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -b & -c \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix},$$

where $x_1 = x$ and $x_2 = \dot{x}$



The State-Space Approach II



Higher-Order Differential Equation

▶ Fact: $x^{(n)}(t) + a_{n-1}x^{(n-1)}(t) + \cdots + a_1\dot{x}(t) + a_0x(t) = 0$ can be transformed to

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \vdots \\ \dot{x}_n(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 0 & 0 & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ -a_0 & -a_1 & \cdots & -a_{n-1} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix},$$

where $x_1 = x$, $x_2 = \dot{x}$, ..., $x_n = x^{(n-1)}$

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