

LINEAR ALGEBRA REVIEW FOR COS424

RECTANGULAR MATRICES

Let $\mathbf{A} = [a_{ij}]_{\substack{i=1\dots m \\ j=1\dots n}}$ be a matrix with m lines and n columns.

Transposition: $\mathbf{B} = \mathbf{A}^\top \stackrel{\Delta}{\iff} \forall i = 1 \dots n \quad \forall j = 1 \dots m \quad b_{ij} = a_{ji}$.

- $(\mathbf{A}^\top)^\top = \mathbf{A}$, $(\mathbf{A} + \mathbf{B})^\top = \mathbf{A}^\top + \mathbf{B}^\top$, $(\lambda \mathbf{A})^\top = \lambda \mathbf{A}^\top$, $(\mathbf{AB})^\top = \mathbf{B}^\top \mathbf{A}^\top$.

Kernel (nullspace): $\mathcal{Ker}(\mathbf{A}) \triangleq \{\mathbf{x} : \mathbf{Ax} = \mathbf{0}\}$.

Image (column space): $\mathcal{Im}(\mathbf{A})$: the vectorial space spanned by the columns of \mathbf{A} .

- $\dim(\mathcal{Im}(\mathbf{A})) + \dim(\mathcal{Ker}(\mathbf{A})) = n$. — Hint: consider a basis of \mathbb{R}^n whose first elements span $\mathcal{Ker}(\mathbf{A})$.

Rank: $\text{rank}(\mathbf{A}) \triangleq \dim(\mathcal{Im}(\mathbf{A}))$.

- $\text{rank}(\mathbf{A}) \leq \min(m, n)$. — Proof: the n columns are elements of \mathbb{R}^m .
- $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^\top)$. — Hint: first show that $\text{rank}(\mathbf{A}^\top) \leq \text{rank}(\mathbf{A})$.

Orthogonal matrix: \mathbf{A} is orthogonal $\stackrel{\Delta}{\iff} \mathbf{A}^\top \mathbf{A} = \mathbf{I}$.

- Equivalent statement: the columns of \mathbf{A} are orthogonal unit vectors.
- \mathbf{A} is orthogonal $\implies \text{rank}(\mathbf{A}) = n \implies n \leq m$.
- The columns of a square *orthogonal matrix* form an *orthonormal basis*.

QR decomposition: $\mathbf{A} = \mathbf{QR}$ with \mathbf{Q} : $m \times r$, orthogonal, and \mathbf{R} : $r \times n$, upper triangular, $r = \text{rank}(\mathbf{A})$.

- *Gram-Schmidt orthogonalization algorithm:*

let \mathbf{u}_i be the columns of \mathbf{A} , \mathbf{v}_k be the columns of \mathbf{Q} , r_{ki} the coefficients of \mathbf{R} .

$k \leftarrow 0$; **for** $i = 1 \dots n$: **for** $j = 1 \dots k$: $r_{ij} = \mathbf{u}_i \cdot \mathbf{v}_j$; **endfor**; $\mathbf{x} \leftarrow \mathbf{u}_i - \sum_{j=1}^k r_{ji} \mathbf{v}_j$;
if $\mathbf{x} \neq \mathbf{0}$: $k \leftarrow k + 1$; $r_{ik} = \|\mathbf{x}\|$; $\mathbf{v}_k = r_{ik}^{-1} \mathbf{x}$; **endif**; **endfor**.

SQUARE MATRICES

Let $\mathbf{A} = [a_{ij}]_{\substack{i=1\dots n \\ j=1\dots n}}$ be a matrix with n lines and n columns.

Invertible matrix: \mathbf{A} is invertible $\stackrel{\Delta}{\iff} \text{rank}(\mathbf{A}) = n$

- $\mathbf{A} \mathbf{A}^{-1} = \mathbf{I}$ and $\mathbf{A}^{-1} \mathbf{A} = \mathbf{I}$.

Triangular matrix: All coefficients below (or above) the diagonal are null.

- \mathbf{A} is upper triangular $\stackrel{\Delta}{\iff} \forall j < i, a_{ij} = 0$.
- \mathbf{A} is lower triangular $\stackrel{\Delta}{\iff} \forall i < j, a_{ij} = 0$.

Determinant:

Let S_n is the set of the $n!$ permutations of $\{1 \dots n\}$.

Let $\mathcal{N}(\sigma)$ be the number of pairs of indices misordered pairs by permutation $\sigma \in S_n$.

Then $\det(\mathbf{A}) \triangleq \sum_{\sigma \in S_n} (-1)^{\mathcal{N}(\sigma)} \prod_{i=1}^n a_{i, \sigma(i)}$.

- $\det(\mathbf{I}) = 1$.
- $\det(\mathbf{A}) = 0 \iff \mathbf{A}$ is not invertible.

- $\det(\mathbf{A}) = \det(\mathbf{A}^\top)$.
- $\det(\mathbf{AB}) = \det(\mathbf{A}) \det(\mathbf{B})$.
- $|\det(\mathbf{A})|$ is proportional to the volume of the convex hull formed by the origin and the columns of \mathbf{A} .
- \mathbf{A} orthogonal $\implies \det(\mathbf{A}) = \pm 1$.
- \mathbf{A} triangular $\implies \det(\mathbf{A}) = \prod_{i=1}^n a_{ii}$.

Eigenspectrum: $\mathbf{x} \neq \mathbf{0}$ is an eigenvector of \mathbf{A} for eigenvalue $\lambda \iff \mathbf{Ax} = \lambda\mathbf{x}$.

- $\text{spectrum}(\mathbf{A})$ is the set of eigenvalues of \mathbf{A} .
- If $A - \lambda\mathbf{I}$ is invertible, $\lambda \notin \text{spectrum}(\mathbf{A})$. – Hint: then $\mathbf{Ax} = \lambda\mathbf{x}$ has only one solution: $\mathbf{x} = \mathbf{0}$.
- The eigenvalues of \mathbf{A} are the roots of the *characteristic polynomial* $P(\lambda) = \det(A - \lambda\mathbf{I})$.

Trace: $\text{trace}(\mathbf{A}) \triangleq \sum_{i=1}^n a_{ii}$.

- $\text{trace}(\mathbf{AB}) = \text{trace}(\mathbf{BA})$. — Proof: calculus.

SYMMETRIC MATRICES: $\mathbf{A}^\top = \mathbf{A}$

Spectral theorem: There is an orthogonal matrix \mathbf{Q} and a diagonal matrix \mathbf{D} such that $\mathbf{A} = \mathbf{Q}^\top \mathbf{D} \mathbf{Q}$.
— Hint: study the complex roots of the characteristic polynomial (tricky.)

- The columns of \mathbf{Q} are eigenvectors.
- The diagonal matrix \mathbf{D} contains the corresponding eigenvalues.

Positive definite symmetric matrix $\iff \forall \mathbf{x} \neq \mathbf{0}, \mathbf{x}^\top \mathbf{A} \mathbf{x} > 0$.

- All eigenvalues are > 0 .
- Equation $\mathbf{x}^\top \mathbf{A} \mathbf{x} = 1$ defines an ellipsoid whose principal axes are the eigenvectors.
- The *Cholesky decomposition algorithm* computes a lower triangular matrix \mathbf{U} such that $\mathbf{A} = \mathbf{U} \mathbf{U}^\top$.
- Weaker variant: *Positive symmetric matrix* \iff all eigenvalues are ≥ 0 .

NUMERICALLY SOLVING $\mathbf{Ax} = \mathbf{b}$

Avoid

- Cramer formulas involving ratios of determinants.
- Algorithms to compute the inverse of a matrix.

When \mathbf{A} is a triangular matrix: back-substitution

- Solve the equation with a single unknown
- Substitute into the remaining equations and repeat.
- Warning: when \mathbf{A} is not invertible, aim for the equation with the least unknowns.

When \mathbf{A} is an orthogonal matrix: transpose

- You already know the inverse: $\mathbf{x} = \mathbf{A}^\top \mathbf{Ax} = \mathbf{A}^\top \mathbf{b}$.

General case: use a decomposition algorithm.

- *QR decomposition:* $\mathbf{A} = \mathbf{QR}$ with \mathbf{Q} orthogonal and \mathbf{R} upper triangular; solve $\mathbf{Rx} = \mathbf{Q}^\top \mathbf{b}$ with one round of back-substitution.
Warning: when QR tells you that $\text{rank}(\mathbf{A}) < n$, verify the solution!
Understanding the QR decomposition is sufficient for most purposes.
- Cholesky decomposition is faster when \mathbf{A} is positive definite symmetric.
- See Trefethen and Bau for: Column pivoting, LU decomposition, and SVD.

REFERENCE

- Lloyd N. Trefethen and David Bau, III: *Numerical Linear Algebra*. SIAM, 1997.