

Title

D. Zack Garza

Contents

1	Linear Algebra	2
1.1	Notation	3
1.2	Big Theorems	3
1.3	Big List of Equivalent Properties	4
1.4	Vector Spaces	4
1.4.1	Linear Transformations	4
1.4.2	Linear Independence	5
1.4.3	Bases	5
1.4.4	The Inner Product	6
1.4.5	Gram-Schmidt Process	7
1.4.6	The Fundamental Subspaces Theorem	10
1.4.7	Computing change of basis matrices	11
1.5	Matrices	11
1.5.1	Systems of Linear Equations	12
1.5.2	Determinants	12
1.5.3	Computing Determinants	14
1.5.4	Inverting a Matrix	15
1.5.5	Bases for Spaces of a Matrix	17
1.5.6	Eigenvalues and Eigenvectors	18
1.5.7	Useful Counterexamples	19

1 | Linear Algebra

Remark 1.0.1 : The underlying field will be assumed to be \mathbb{R} for this section.

1.1 Notation

$\text{Mat}(m, n)$	the space of all $m \times n$ matrices
T	a linear map $\mathbb{R}^n \rightarrow \mathbb{R}^m$
$A \in \text{Mat}(m, n)$	an $m \times n$ matrix representing T
$A^t \in \text{Mat}(n, m)$	an $n \times m$ transposed matrix
\mathbf{a}	a $1 \times n$ column vector
\mathbf{a}^t	an $n \times 1$ row vector
$A = [\mathbf{a}_1, \dots, \mathbf{a}_n]$	a matrix formed with \mathbf{a}_i as the columns
V, W	vector spaces
$ V , \dim(W)$	dimensions of vector spaces
$\det(A)$	the determinant of A
$[A \mid \mathbf{b}] := [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n, \mathbf{b}]$	augmented matrices
$[A \mid B] := [\mathbf{a}_1, \dots, \mathbf{a}_n, \mathbf{b}_1, \dots, \mathbf{b}_m]$	block matrices
$\text{Spec}(A)$	the multiset of eigenvalues of A
$A\mathbf{x} = \mathbf{b}$	a system of linear equations
$r := \text{rank}(A)$	the rank of A
$r_b = \text{rank}([A \mid \mathbf{b}])$	the rank of A augmented by \mathbf{b} .

1.2 Big Theorems

Theorem 1.2.1 (Rank-Nullity).

$$|\ker(A)| + |\text{im}(A)| = |\text{dom}(A)|,$$

where $\text{nullspace}(A) = |\ker A|$, $\text{rank}(A) = |\text{im}(A)|$, and n is the number of columns in the corresponding matrix.

Generalization: the following sequence is always exact:

$$0 \rightarrow \ker(A) \xrightarrow{\text{id}} \text{dom}(A) \xrightarrow{A} \text{im}(A) \rightarrow 0.$$

Moreover, it always splits, so $\text{dom } A = \ker A \oplus \text{im } A$ and thus $|\text{dom}(A)| = |\ker(A)| + |\text{im}(A)|$.

Remark 1.2.1 : We also have

$$\dim(\text{rowspace}(A)) = \dim(\text{colspace}(A)) = \text{rank}(A).$$

1.3 Big List of Equivalent Properties

Let A be an $m \times n$ matrix. TFAE: - A is invertible and has a unique inverse A^{-1} - A^T is invertible - $\det(A) \neq 0$ - The linear system $A\mathbf{x} = \mathbf{b}$ has a unique solution for every $\mathbf{b} \in \mathbb{R}^m$ - The homogeneous system $A\mathbf{x} = \mathbf{0}$ has only the trivial solution $\mathbf{x} = \mathbf{0}$ - $\text{rank}(A) = n$ - i.e. A is full rank - $\text{nullity}(A) := \dim \text{nullspace}(A) = 0$ - $A = \prod_{i=1}^k E_i$ for some finite k , where each E_i is an elementary matrix. - A is row-equivalent to the identity matrix I_n - A has exactly n pivots - The columns of A are a basis for \mathbb{R}^n - i.e. $\text{colspace}(A) = \mathbb{R}^n$ - The rows of A are a basis for \mathbb{R}^m - i.e. $\text{rowspace}(A) = \mathbb{R}^m$ - $(\text{colspace}(A))^\perp = (\text{rowspace}(A))^\perp = \{\mathbf{0}\}$ - Zero is not an eigenvalue of A . - A has n linearly independent eigenvectors - The rows of A are coplanar.

Similarly, by taking negations, TFAE:

- A is not invertible
- A is singular
- A^T is not invertible
- $\det A = 0$
- The linear system $A\mathbf{x} = \mathbf{b}$ has either no solution or infinitely many solutions.
- The homogeneous system $A\mathbf{x} = \mathbf{0}$ has nontrivial solutions
- $\text{rank } A < n$
- $\dim \text{nullspace } A > 0$
- At least one row of A is a linear combination of the others
- The *RREF* of A has a row of all zeros.

Reformulated in terms of linear maps T , TFAE: - $T^{-1} : \mathbb{R}^m \rightarrow \mathbb{R}^n$ exists - $\text{im}(T) = \mathbb{R}^n$ - $\ker(T) = \mathbf{0}$ - T is injective - T is surjective - T is an isomorphism - The system $A\mathbf{x} = \mathbf{0}$ has infinitely many solutions

1.4 Vector Spaces

1.4.1 Linear Transformations

Definition 1.4.1 (Linear Transformation).

todo

Remark 1.4.1 : It is common to want to know the range and kernel of a specific linear transformation T . T can be given in many ways, but a general strategy for deducing these properties involves:

- Express an arbitrary vector in V as a linear combination of its basis vectors, and set it equal to an arbitrary vector in W .

- Use the linear properties of T to make a substitution from known transformations
- Find a restriction or relation given by the constants of the initial linear combination.

Remark 1.4.2 : Useful fact: if \$

Definition 1.4.2 (Kernel).

todo

Proposition 1.4.1 (*Two-step vector subspace test*).

If $V \subseteq W$, then V is a subspace of W if the following hold:

- (1) $\mathbf{0} \in V$
- (2) $\mathbf{a}, \mathbf{b} \in V \implies t\mathbf{a} + \mathbf{b} \in V.$

1.4.2 Linear Independence

Proposition 1.4.2 (?).

Any set of two vectors $\{\mathbf{v}, \mathbf{w}\}$ is linearly **dependent** $\iff \exists \lambda : \mathbf{v} = \lambda \mathbf{w}$, i.e. one is not a scalar multiple of the other.

1.4.3 Bases

Definition 1.4.3 (Basis and dimension).

A set S forms a **basis** for a vector space V iff

1. S is a set of linearly independent vectors, so $\sum \alpha_i \vec{s}_i = \mathbf{0} \implies \alpha_i = 0$ for all i .
2. S spans V , so $\vec{v} \in V$ implies there exist α_i such that $\sum \alpha_i \vec{s}_i = \vec{v}$

In this case, we define the **dimension** of V to be $|S|$.

Show how to compute basis of kernel.

Show how to compute basis of row space (nonzero rows in $??A$)?

Show how to compute basis of column space: leading ones.

1.4.4 The Inner Product

The point of this section is to show how an inner product can induce a notion of “angle”, which agrees with our intuition in Euclidean spaces such as \mathbb{R}^n , but can be extended to much less intuitive things, like spaces of functions.

Definition 1.4.4 (The standard inner product).

The **Euclidean inner product** is defined as

$$\langle \mathbf{a}, \mathbf{b} \rangle = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n.$$

Also sometimes written as $\mathbf{a}^T \mathbf{b}$ or $\mathbf{a} \cdot \mathbf{b}$.

Proposition 1.4.3 (*Inner products induce norms and angles*).

Yields a norm

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

which has a useful alternative formulation

$$\langle \mathbf{x}, \mathbf{x} \rangle = \|\mathbf{x}\|^2.$$

This leads to a notion of angle:

$$\langle \mathbf{x}, \mathbf{y} \rangle = \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta_{x,y} \implies \cos \theta_{x,y} := \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} = \langle \hat{\mathbf{x}}, \hat{\mathbf{y}} \rangle$$

where $\theta_{x,y}$ denotes the angle between the vectors \mathbf{x} and \mathbf{y} .

Remark 1.4.3 : Since $\cos \theta = 0$ exactly when $\theta = \pm \frac{\pi}{2}$, we can declare two vectors to be **orthogonal** exactly in this case:

$$\mathbf{x} \in \mathbf{y}^\perp \iff \langle \mathbf{x}, \mathbf{y} \rangle = 0.$$

Note that this makes the zero vector orthogonal to everything.

Definition 1.4.5 (Orthogonal Complement/Perp).

Given a subspace $S \subseteq V$, we define its **orthogonal complement**

$$S^\perp = \left\{ \mathbf{v} \in V \mid \forall \mathbf{s} \in S, \langle \mathbf{v}, \mathbf{s} \rangle = 0 \right\}.$$

Remark 1.4.4 : Any choice of subspace $S \subseteq V$ yields a decomposition $V = S \oplus S^\perp$.

Proposition 1.4.4 (*Formula expanding a norm and 'Pythagorean theorem'*).

A useful formula is

$$\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + 2\langle \mathbf{x}, \mathbf{y} \rangle + \|\mathbf{y}\|^2.$$

When $\mathbf{x} \in \mathbf{y}^\perp$, this reduces to

$$\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2.$$

Proposition 1.4.5 (*Properties of the inner product*).

1. **Bilinearity:**

$$\left\langle \sum_j \alpha_j \mathbf{a}_j, \sum_k \beta_k \mathbf{b}_k \right\rangle = \sum_j \sum_i \alpha_j \beta_i \langle \mathbf{a}_j, \mathbf{b}_i \rangle.$$

2. **Symmetry:**

$$\langle \mathbf{a}, \mathbf{b} \rangle = \langle \mathbf{b}, \mathbf{a} \rangle$$

3. **Positivity:**

$$\mathbf{a} \neq \mathbf{0} \implies \langle \mathbf{a}, \mathbf{a} \rangle > 0$$

4. **Nondegeneracy:**

$$\mathbf{a} = \mathbf{0} \iff \langle \mathbf{a}, \mathbf{a} \rangle = 0$$

Proof of Cauchy-Schwarz: See Goode page 346.

1.4.5 Gram-Schmidt Process

Extending a basis $\{\mathbf{x}_i\}$ to an orthonormal basis $\{\mathbf{u}_i\}$

$$\begin{aligned} \mathbf{u}_1 &= N(\mathbf{x}_1) \\ \mathbf{u}_2 &= N(\mathbf{x}_2 - \langle \mathbf{x}_2, \mathbf{u}_1 \rangle \mathbf{u}_1) \\ \mathbf{u}_3 &= N(\mathbf{x}_3 - \langle \mathbf{x}_3, \mathbf{u}_1 \rangle \mathbf{u}_1 - \langle \mathbf{x}_3, \mathbf{u}_2 \rangle \mathbf{u}_2) \\ &\vdots \\ \mathbf{u}_k &= N(\mathbf{x}_k - \sum_{i=1}^{k-1} \langle \mathbf{x}_k, \mathbf{u}_i \rangle \mathbf{u}_i) \end{aligned}$$

where N denotes normalizing the result.

In more detail The general setup here is that we are given an orthogonal basis $\{\mathbf{x}_i\}_{i=1}^n$ and we want to produce an **orthonormal** basis from them.

Why would we want such a thing? Recall that we often wanted to change from the standard basis \mathcal{E} to some different basis $\mathcal{B} = \{\mathbf{b}_1, \mathbf{b}_2, \dots\}$. We could form the change of basis matrix $B = [\mathbf{b}_1, \mathbf{b}_2, \dots]$ acts on vectors in the \mathcal{B} basis according to

$$B[\mathbf{x}]_{\mathcal{B}} = [\mathbf{x}]_{\mathcal{E}}.$$

But to change from \mathcal{E} to \mathcal{B} requires computing B^{-1} , which acts on vectors in the standard basis according to

$$B^{-1}[\mathbf{x}]_{\mathcal{E}} = [\mathbf{x}]_{\mathcal{B}}.$$

If, on the other hand, the \mathbf{b}_i are orthonormal, then $B^{-1} = B^T$, which is much easier to compute. We also obtain a rather simple formula for the coordinates of \mathbf{x} with respect to \mathcal{B} . This follows because we can write

$$\mathbf{x} = \sum_{i=1}^n \langle \mathbf{x}, \mathbf{b}_i \rangle \mathbf{b}_i := \sum_{i=1}^n c_i \mathbf{b}_i,$$

and we find that

$$[\mathbf{x}]_{\mathcal{B}} = \mathbf{c} := [c_1, c_2, \dots, c_n]^T.$$

This also allows us to simplify projection matrices. Supposing that A has orthonormal columns and letting S be the column space of A , recall that the projection onto S is defined by

$$P_S = Q(Q^T Q)^{-1} Q^T.$$

Since Q has orthogonal columns and satisfies $Q^T Q = I$, this simplifies to

$$P_S = Q Q^T.$$

The Algorithm Given the orthogonal basis $\{\mathbf{x}_i\}$, we form an orthonormal basis $\{\mathbf{u}_i\}$ iteratively as follows.

First define

$$N : \mathbb{R}^n \rightarrow S^{n-1}$$

$$\mathbf{x} \mapsto \hat{\mathbf{x}} := \frac{\mathbf{x}}{\|\mathbf{x}\|}$$

which projects a vector onto the unit sphere in \mathbb{R}^n by normalizing. Then,

$$\begin{aligned}
\mathbf{u}_1 &= N(\mathbf{x}_1) \\
\mathbf{u}_2 &= N(\mathbf{x}_2 - \langle \mathbf{x}_2, \mathbf{u}_1 \rangle \mathbf{u}_1) \\
\mathbf{u}_3 &= N(\mathbf{x}_3 - \langle \mathbf{x}_3, \mathbf{u}_1 \rangle \mathbf{u}_1 - \langle \mathbf{x}_3, \mathbf{u}_2 \rangle \mathbf{u}_2) \\
&\vdots \\
\mathbf{u}_k &= N(\mathbf{x}_k - \sum_{i=1}^{k-1} \langle \mathbf{x}_k, \mathbf{u}_i \rangle \mathbf{u}_i)
\end{aligned}$$

In words, at each stage, we take one of the original vectors \mathbf{x}_i , then subtract off its projections onto all of the \mathbf{u}_i we've created up until that point. This leaves us with only the component of \mathbf{x}_i that is orthogonal to the span of the previous \mathbf{u}_i we already have, and we then normalize each \mathbf{u}_i we obtain this way.

Alternative Explanation:

Given a basis

$$S = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\},$$

the Gram-Schmidt process produces a corresponding orthogonal basis

$$S' = \{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\}$$

that spans the same vector space as S .

S' is found using the following pattern:

$$\begin{aligned}
\mathbf{u}_1 &= \mathbf{v}_1 \\
\mathbf{u}_2 &= \mathbf{v}_2 - \text{proj}_{\mathbf{u}_1} \mathbf{v}_2 \\
\mathbf{u}_3 &= \mathbf{v}_3 - \text{proj}_{\mathbf{u}_1} \mathbf{v}_3 - \text{proj}_{\mathbf{u}_2} \mathbf{v}_3
\end{aligned}$$

where

$$\text{proj}_{\mathbf{u}} \mathbf{v} = (\text{scal}_{\mathbf{u}} \mathbf{v}) \frac{\mathbf{u}}{\|\mathbf{u}\|} = \frac{\langle \mathbf{v}, \mathbf{u} \rangle}{\|\mathbf{u}\|} \frac{\mathbf{u}}{\|\mathbf{u}\|} = \frac{\langle \mathbf{v}, \mathbf{u} \rangle}{\|\mathbf{u}\|^2} \mathbf{u}$$

is a vector defined as the *orthogonal projection of \mathbf{v} onto \mathbf{u}* .

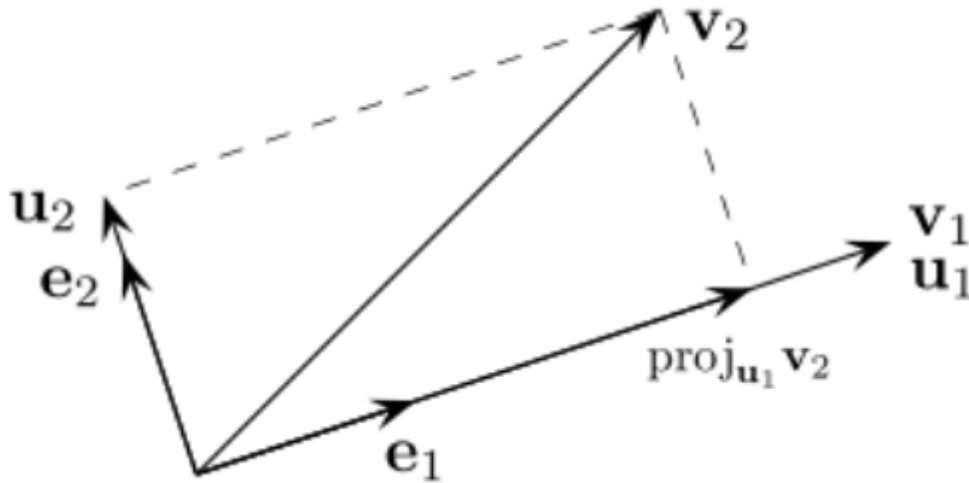


Figure 1: Image

The orthogonal set S' can then be transformed into an orthonormal set S'' by simply dividing the vectors $s \in S'$ by their magnitudes. The usual definition of a vector's magnitude is

$$\|\mathbf{a}\| = \sqrt{\langle \mathbf{a}, \mathbf{a} \rangle} \text{ and } \|\mathbf{a}\|^2 = \langle \mathbf{a}, \mathbf{a} \rangle$$

As a final check, all vectors in S' should be orthogonal to each other, such that

$$\langle \mathbf{v}_i, \mathbf{v}_j \rangle = 0 \text{ when } i \neq j$$

and all vectors in S'' should be orthonormal, such that

$$\langle \mathbf{v}_i, \mathbf{v}_j \rangle = \delta_{ij}$$

1.4.6 The Fundamental Subspaces Theorem

Given a matrix $A \in \text{Mat}(m, n)$, and noting that

$$\begin{aligned} A : \mathbb{R}^n &\rightarrow \mathbb{R}^m, \\ A^T : \mathbb{R}^m &\rightarrow \mathbb{R}^n \end{aligned}$$

We have the following decompositions:


$$\begin{aligned} \mathbb{R}^n &\cong \ker A \oplus \text{im } A^T && \cong \text{nullspace}(A) \oplus \text{colspace}(A^T) \\ \mathbb{R}^m &\cong \text{im } A \oplus \ker A^T && \cong \text{colspace}(A) \oplus \text{nullspace}(A^T) \end{aligned}$$

1.4.7 Computing change of basis matrices

todo

1.5 Matrices

Remark 1.5.1 : An $m \times n$ matrix is a map from n -dimensional space to m -dimensional space. The number of *rows* tells you the dimension of the codomain, the number of *columns* tells you the dimension of the *domain*.

 *Warning 1.1*: The space of matrices is not an integral domain! Counterexample: if A is singular and nonzero, there is some nonzero \mathbf{v} such that $A\mathbf{v} = \mathbf{0}$. Then setting $B = [\mathbf{v}, \mathbf{v}, \dots]$ yields $AB = 0$ with $A \neq 0, B \neq 0$.

Definition 1.5.1 (Rank of a matrix).

The **rank** of a matrix A representing a linear transformation T is $\dim \text{colspace}(A)$, or equivalently $\dim \text{im } T$.

Proposition 1.5.1 (?).

$\text{rank}(A)$ is equal to the number of nonzero rows in $\text{RREF}(A)$.

Definition 1.5.2 (Trace of a Matrix).

$$\text{Trace}(A) = \sum_{i=1}^m A_{ii}$$

Definition 1.5.3 (Elementary Row Operations).

The following are **elementary row operations** on a matrix:

- Permute rows
- Multiple a row by a scalar
- Add any row to another

Proposition 1.5.2 (*Formula for matrix multiplication*).

If $A = [\mathbf{a}_1, \mathbf{a}_2, \dots] \in \text{Mat}(m, n)$ and $B = [\mathbf{b}_1, \mathbf{b}_2, \dots] \in \text{Mat}(n, p)$, then

$$C := AB \implies c_{ij} = \sum_{k=1}^n a_{ik} b_{kj} = \langle \mathbf{a}_i, \mathbf{b}_j \rangle$$

where $1 \leq i \leq m$ and $1 \leq j \leq p$. In words, each entry c_{ij} is obtained by dotting *row* i of A against *column* j of B .

1.5.1 Systems of Linear Equations

Definition 1.5.4 (Consistent and inconsistent).

A system of linear equations is **consistent** when it has at least one solution. The system is **inconsistent** when it has no solutions.

Definition 1.5.5 (Homogeneous Systems).

?

Remark 1.5.2 : Homogeneous systems are always consistent, i.e. there is always at least one solution.

Remark 1.5.3 :

- Tall matrices: more equations than unknowns, *overdetermined*
- Wide matrices: more unknowns than equations, *underdetermined*

Proposition 1.5.3 (*Characterizing solutions to a system of linear equations*).

There are three possibilities for a system of linear equations:

1. No solutions (inconsistent)
2. One unique solution (consistent, square or tall matrices)
3. Infinitely many solutions (consistent, underdetermined, square or wide matrices)

These possibilities can be checked by considering $r := \text{rank}(A)$:

- $r < r_b$: case 1, no solutions.
- $r = r_b$: case 1 or 2, at least one solution.
 - $r_b = n$: case 2, a unique solution.
 - $r_b < n$: case 3, infinitely many solutions.

1.5.2 Determinants

Proposition 1.5.4 (?).

$$\det(A \pmod p) \pmod p \equiv (\det A) \pmod p$$

Proposition 1.5.5 (*Inverse of a 2×2 matrix*).

For 2×2 matrices,

$$A^{-1} = \begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{\det A} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

In words, swap the main diagonal entries, and flip the signs on the off-diagonal.

Proposition 1.5.6 (Properties of the determinant).

Let $A \in \text{Mat}(m, n)$, then there is a function

$$\begin{aligned} \det : \text{Mat}(m, m) &\rightarrow \mathbb{R} \\ A &\mapsto \det(A) \end{aligned}$$

satisfying the following properties:

- \det is a group homomorphism onto (\mathbb{R}, \cdot) :

$$\det(AB) = \det(A) \det(B)$$

- Some corollaries:

$$\begin{aligned} \det A^k &= k \det A \\ \det(A^{-1}) &= (\det A)^{-1} \det(A^t) = \det(A). \end{aligned}$$

- Invariance under adding scalar multiples of any row to another:

$$\det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \end{bmatrix} = \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i + t\mathbf{a}_j \text{ ---} \\ \vdots \end{bmatrix}$$

- Sign change under row permutation:

$$\det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_j \text{ ---} \\ \vdots \end{bmatrix} = (-1) \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_j \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \end{bmatrix}$$

- More generally, for a permutation $\sigma \in S_n$,

$$\det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_j \text{ ---} \\ \vdots \end{bmatrix} = (-1)^{\text{sgn}(\sigma)} \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_{\sigma(j)} \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_{\sigma(i)} \text{ ---} \\ \vdots \end{bmatrix}$$

- Multilinearity in rows:

$$\det \begin{bmatrix} \vdots \\ \text{--- } t\mathbf{a}_i \text{ ---} \\ \vdots \end{bmatrix} = t \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \end{bmatrix}$$

$$\det \begin{bmatrix} \text{--- } t\mathbf{a}_1 \text{ ---} \\ \text{--- } t\mathbf{a}_2 \text{ ---} \\ \vdots \\ \text{--- } t\mathbf{a}_m \text{ ---} \end{bmatrix} = t^m \det \begin{bmatrix} \text{--- } \mathbf{a}_1 \text{ ---} \\ \text{--- } \mathbf{a}_2 \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_m \text{ ---} \end{bmatrix}$$

$$\det \begin{bmatrix} \text{--- } t_1\mathbf{a}_1 \text{ ---} \\ \text{--- } t_2\mathbf{a}_2 \text{ ---} \\ \vdots \\ \text{--- } t_m\mathbf{a}_m \text{ ---} \end{bmatrix} = \prod_{i=1}^m t_i \det \begin{bmatrix} \text{--- } \mathbf{a}_1 \text{ ---} \\ \text{--- } \mathbf{a}_2 \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_m \text{ ---} \end{bmatrix}.$$

- Linearity in each row:

$$\det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i + \mathbf{a}_j \text{ ---} \\ \vdots \end{bmatrix} = \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_i \text{ ---} \\ \vdots \end{bmatrix} + \det \begin{bmatrix} \vdots \\ \text{--- } \mathbf{a}_j \text{ ---} \\ \vdots \end{bmatrix}.$$

- $\det(A)$ is the volume of the parallelepiped spanned by the columns of A .
- If any row of A is all zeros, $\det(A) = 0$.

Proposition 1.5.7 (Characterizing singular matrices).

TFAE:

- $\det(A) = 0$
- A is singular.

1.5.3 Computing Determinants

Useful shortcuts:

- If A is upper or lower triangular, $\det(A) = \prod_i a_{ii}$.

Definition 1.5.6 (Minors).

The **minor** M_{ij} of $A \in \text{Mat}(n, n)$ is the *determinant* of the $(n - 1) \times (n - 1)$ matrix obtained by deleting the i th row and j th column from A .

Definition 1.5.7 (Cofactors).

The **cofactor** C_{ij} is the scalar defined by

$$C_{ij} := (-1)^{i+j} M_{ij}.$$

Proposition 1.5.8 (Laplace/Cofactor Expansion).

For any fixed i , there is a formula

$$\det(A) = \sum_{j=1}^n a_{ij} C_{ij}.$$

Example 1.5.1 (?): Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}.$$

Then

$$\det A = 1 \cdot \begin{vmatrix} 5 & 6 \\ 8 & 9 \end{vmatrix} - 2 \cdot \begin{vmatrix} 4 & 6 \\ 7 & 9 \end{vmatrix} + 3 \cdot \begin{vmatrix} 4 & 5 \\ 7 & 8 \end{vmatrix} = 1 \cdot (-3) - 2 \cdot (-6) + 3 \cdot (-3) = 0.$$

Proposition 1.5.9 (Computing determinant from RREF).

$\det(A)$ can be computed by reducing A to $\text{RREF}(A)$ (which is upper triangular) and keeping track of the following effects:

- $R_i \leftarrow R_i \pm tR_j$: no effect.
- $R_i \rightleftharpoons R_j$: multiply by (-1) .
- $R_i \leftarrow tR_i$: multiply by t .

1.5.4 Inverting a Matrix**Proposition 1.5.10 (Cramer's Rule).**

Given a linear system $A\mathbf{x} = \mathbf{b}$, writing $\mathbf{x} = [x_1, \dots, x_n]$, there is a formula

$$x_i = \frac{\det(B_i)}{\det(A)}$$

where B_i is A with the i th column deleted and replaced by \mathbf{b} .

Proposition 1.5.11 (Gauss-Jordan Method for inverting a matrix).

Under the equivalence relation of elementary row operations, there is an equivalence of augmented matrices:

$$[A \mid I] \sim [I \mid A^{-1}]$$

where I is the $n \times n$ identity matrix.

Proposition 1.5.12 (Cofactor formula for inverse).

$$A^{-1} = \frac{1}{\det(A)} [C_{ij}]^t.$$

where C_{ij} is the *cofactor* (Definition 1.5.7) at position i, j .^a

^aNote that the matrix appearing here is sometimes called the *adjugate*.

Example 1.5.2 (Inverting a 2×2 matrix):

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix} \quad \text{where } ad - bc \neq 0$$

What's the pattern?

1. Always divide by determinant
2. Swap the diagonals
3. Hadamard product with checkerboard

Example 1.5.3 (Inverting a 3×3 matrix):

$$\begin{bmatrix} + & - \\ - & + \end{bmatrix}$$

$$A^{-1} := \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}^{-1} = \frac{1}{\det A} \begin{bmatrix} ei - fh & -(bi - ch) & bf - ce \\ -(di - fg) & ai - cg & -(af - cd) \\ dh - eg & -(ah - bg) & ae - bd \end{bmatrix}.$$

The pattern:

1. Divide by determinant
2. Each entry is determinant of submatrix of A with corresponding col/row deleted
3. Hadamard product with checkerboard

$$\begin{bmatrix} + & - & + \\ - & + & - \\ + & - & + \end{bmatrix}$$

4. Transpose at the end!!

1.5.5 Bases for Spaces of a Matrix

Let $A \in \text{Mat}(m, n)$ represent a map $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$.

Add examples.

Definition 1.5.8 (Pivot).

?

todo

Proposition 1.5.13.

$$\dim \text{rowspace}(A) = \dim \text{colspace}(A).$$

The row space

$$\text{im}(T)^\vee = \text{rowspace}(A) \subset \mathbb{R}^n.$$

Reduce to RREF, and take nonzero rows of $\text{RREF}(A)$.

The column space

$$\text{im}(T) = \text{colspace}(A) \subseteq \mathbb{R}^m$$

Reduce to RREF, and take columns with pivots from original A .

Remark 1.5.4 : Not enough pivots implies columns don't span the entire target domain

The nullspace

$$\ker(T) = \text{nullspace}(A) \subseteq \mathbb{R}^n$$

Reduce to RREF, zero rows are free variables, convert back to equations and pull free variables out as scalar multipliers.

Eigenspaces For each $\lambda \in \text{Spec}(A)$, compute a basis for $\ker(A - \lambda I)$.

1.5.6 Eigenvalues and Eigenvectors

Definition 1.5.9 (Eigenvalues, eigenvectors, eigenspaces).

A vector \mathbf{v} is said to be an **eigenvector** of A with **eigenvalue** $\lambda \in \text{Spec}(A)$ iff

$$A\mathbf{v} = \lambda\mathbf{v}$$

For a fixed λ , the corresponding **eigenspace** E_λ is the span of all such vectors.

Remark 1.5.5 :

- Similar matrices have identical eigenvalues and multiplicities.
- Eigenvectors corresponding to distinct eigenvalues are **always** linearly independent
- A has n distinct eigenvalues $\implies A$ has n linearly independent eigenvectors.
- A matrix A is diagonalizable $\iff A$ has n linearly independent eigenvectors.

Proposition 1.5.14 (*How to find eigenvectors*).

For $\lambda \in \text{Spec}(A)$,

$$\mathbf{v} \in E_\lambda \iff \mathbf{v} \in \ker(A - I\lambda).$$

Remark 1.5.6 : Some miscellaneous useful facts:

- $\lambda \in \text{Spec}(A) \implies \lambda^2 \in \text{Spec}(A^2)$ with the same eigenvector.
- $\prod \lambda_i = \det A$
- $\sum \lambda_i = \text{Tr } A$

Finding generalized eigenvectors

todo

Diagonalizability

Remark 1.5.7 : An $n \times n$ matrix P is diagonalizable iff its eigenspace is all of \mathbb{R}^n (i.e. there are n linearly independent eigenvectors, so they span the space.)

Remark 1.5.8 : A is diagonalizable if there is a basis of eigenvectors for the range of P .

1.5.7 Useful Counterexamples

$$\begin{aligned}
 A &:= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \implies A^n = \begin{bmatrix} 1 & n \\ 0 & 1 \end{bmatrix}, & \text{Spec}(A) &= [1, 1] \\
 A &:= \begin{bmatrix} 1 & 1 \\ 0 & -1 \end{bmatrix} \implies A^2 = I_2, & \text{Spec}(A) &= [1, -1]
 \end{aligned}$$