

Linear Algebra

Vectors and Matrices

Fundamental Operations with Vectors

Vector: a directed line segments that has both magnitude and direction

- *notation*: $\vec{v} = \langle v_1, v_2, v_3, \dots, v_n \rangle = [v_1, v_2, v_3, \dots, v_n] = \mathbf{v}$ where v_1, v_2, \dots, v_n are the components of the vector.
- if $A(x_1, x_2, \dots, x_n)$ is the initial point of the vector and $B(y_1, y_2, \dots, y_n)$ is the terminal point then the components can be found using $\vec{AB} = [y_1 - x_1, y_2 - x_2, \dots, y_n - x_n]$
- graphically, a vector is drawn as an arrow such that the length of the arrow is the magnitude of the vector and the arrow points in the direction of the vector

A vector represents a single entity of magnitude and direction, only one vector is unique.

The zero vector ($\vec{0}$): the unique vector that has no magnitude and no direction, every component is zero: $\vec{0} = [0, 0, 0, \dots, 0]$.

The magnitude of a vector: given some vector \mathbf{v} with initial point $A(x_1, x_2, \dots, x_n)$ and terminal point $B(y_1, y_2, \dots, y_n)$, the magnitude of \mathbf{v} denoted $\|\vec{v}\|$ is the distance from A to B:

$$\|\vec{AB}\| = \|\vec{v}\| = \sqrt{(y_1 - x_1)^2 + (y_2 - x_2)^2 + \dots + (y_n - x_n)^2} = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2} .$$

The unit vector: any vector \mathbf{u} is a unit vector if its magnitude is 1.

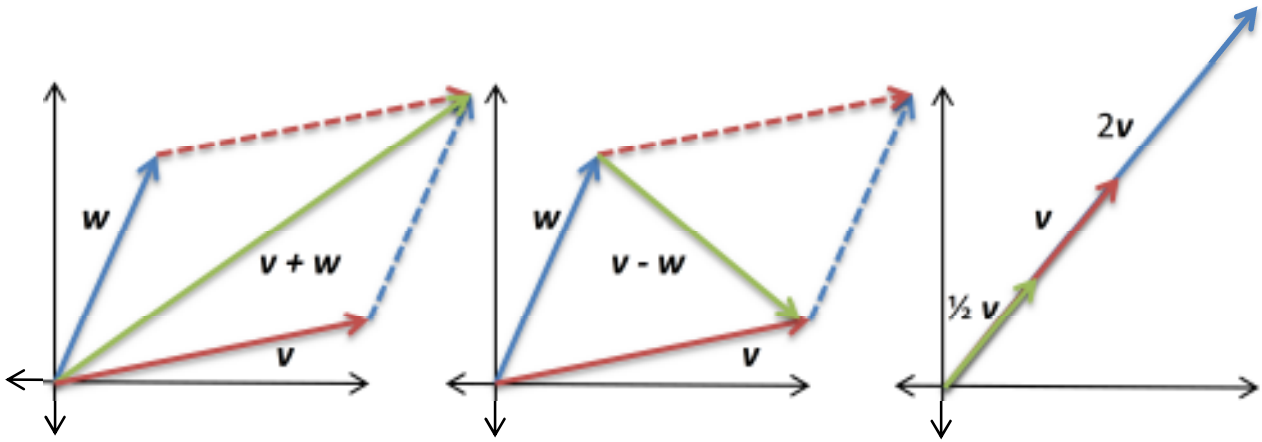
The standard unit vectors: any vector e_n is a standard unit vector for \mathfrak{R}^n is every component of e_n is a zero except the nth component, which is a 1.

2-D	3-D	n-D
$i = [1, 0]$	$i = [1, 0, 0]$	$e_1 = [1, 0, 0, 0, \dots, 0]$
$j = [0, 1]$	$j = [0, 1, 0]$	$e_2 = [0, 1, 0, 0, \dots, 0]$
	$k = [0, 0, 1]$	$e_3 = [0, 0, 1, 0, \dots, 0]$
		$e_n = [0, 0, 0, 0, \dots, 1]$

Operation of Vectors:

Let \mathbf{v} , \mathbf{w} , and \mathbf{z} be vectors in \mathfrak{R}^n and λ be a scalar (constant). Then we define:

- the sum of \mathbf{v} and \mathbf{w} as the vector
 $\vec{v} + \vec{w} = [v_1, v_2, \dots, v_n] + [w_1, w_2, \dots, w_n] = [v_1 + w_1, v_2 + w_2, \dots, v_n + w_n]$
- the scalar product of λ and \mathbf{v} is the vector $\lambda\vec{v} = \lambda[v_1, v_2, \dots, v_n] = [\lambda v_1, \lambda v_2, \dots, \lambda v_n]$
- the difference of \mathbf{v} and \mathbf{w} is the vector
 $\vec{v} - \vec{w} = [v_1, v_2, \dots, v_n] - [w_1, w_2, \dots, w_n] = [v_1 - w_1, v_2 - w_2, \dots, v_n - w_n]$
- the opposite of \mathbf{v} is the vector $-\vec{v} = -[v_1, v_2, \dots, v_n] = [-v_1, -v_2, \dots, -v_n]$



- Note \mathbf{v} and $\lambda\mathbf{v}$ are always parallel (but may be in opposite directions if λ is negative).

From this we see a method to determine if two vectors are parallel: two vectors \mathbf{v} and \mathbf{w} are **parallel** if they are **scalar multiples** of one another.

The Standard Unit Vectors:

Every vector can be written as a linear combination of the standard unit vectors.

Let \mathbf{v} be a vector in \mathfrak{R}^n such that. Let $\vec{e}_1, \vec{e}_2, \dots, \vec{e}_n$ be the standard unit vectors. Then we see:

$$\begin{aligned}\vec{v} &= [v_1, v_2, \dots, v_n] = [v_1, 0, 0, \dots, 0] + [0, v_2, 0, \dots, 0] + [0, 0, \dots, v_n] = \\ &= v_1[1, 0, 0, \dots, 0] + v_2[0, 1, 0, \dots, 0] + \dots + v_n[0, 0, \dots, 1] = v_1\vec{e}_1 + v_2\vec{e}_2 + \dots + v_n\vec{e}_n\end{aligned}$$

Suppose we want to find a unit vector \mathbf{u} in the same direction as a given vector \mathbf{v} . How do we do it?

This can be done by using the following formula $\vec{u} = \frac{\vec{v}}{\|\vec{v}\|}$. This works by the following

Since $\frac{\vec{v}}{\|\vec{v}\|} = \vec{v} \left(\frac{1}{\|\vec{v}\|} \right)$, $\|\vec{u}\| = \left\| \frac{\vec{v}}{\|\vec{v}\|} \right\| = \left\| \vec{v} \left(\frac{1}{\|\vec{v}\|} \right) \right\| = \|\vec{v}\| \left(\frac{1}{\|\vec{v}\|} \right) = 1$ so since the magnitude of \mathbf{u} is 1 and $\frac{\vec{v}}{\|\vec{v}\|}$ is in the direction of \mathbf{v} then \mathbf{u} is in the direction of \mathbf{v} .

Ex: Given $\vec{v} = [1, -2, 3]$ $\vec{w} = [-4, 1, 1]$ $\vec{z} = [2, -3, -4]$

1. Find $\|\vec{w}\|$ and $\|\vec{z}\|$
2. $4\vec{v}$
3. $3\vec{w} - 2\vec{v} + 5\vec{z}$
4. The unit vector is the same direction as \vec{w} and another in the same direction as \vec{v} .

Properties of Vector Operations:

Let $\vec{v} = [v_1, v_2, \dots, v_n]$, $\vec{w} = [w_1, w_2, \dots, w_n]$, and $\vec{z} = [z_1, z_2, \dots, z_n]$ be vectors in \mathfrak{R}^n . Also let λ and k be scalars and $\vec{0}$ be the zero vector in \mathfrak{R}^n . Then

- $\vec{v} + \vec{w} = \vec{w} + \vec{v}$ *commutative property for addition*
- $(\vec{v} + \vec{w}) + \vec{z} = \vec{v} + (\vec{w} + \vec{z})$ *associative property for addition*
- $\vec{v} + \vec{0} = \vec{0} + \vec{v} = \vec{v}$ *additive identity property, which is zero*
- $\vec{v} + (-\vec{v}) = (-\vec{v}) + \vec{v} = \vec{0}$ *additive inverse property which is $-\vec{v}$*
- $\lambda(\vec{v} + \vec{w}) = \lambda\vec{v} + \lambda\vec{w}$ and $(\lambda + k)\vec{v} = \lambda\vec{v} + k\vec{v}$ *distributive laws for scalars*
- $(\lambda k)\vec{v} = \lambda(k\vec{v}) = k(\lambda\vec{v})$ *associative property for scalar multiplication*
- $1(\vec{v}) = \vec{v}(1) = \vec{v}$ *multiplicative identity property for scalar multiplication, which is 1*

Theorem: Let $\vec{v} \in \mathfrak{R}^n$ and $\lambda \in \mathfrak{R}$. If $\lambda\vec{v} = \vec{0}$, then either $\lambda = 0$ or $\vec{v} = \vec{0}$

Linear Combination of Vectors: Let $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$ be vectors in \mathfrak{R}^n then the vector \vec{v} is a linear combination of vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$ if and only if there exists scalars $\lambda_1, \lambda_2, \dots, \lambda_k$ such that $\vec{v} = \lambda_1\vec{v}_1 + \lambda_2\vec{v}_2 + \dots + \lambda_k\vec{v}_k$.

The Dot Product: Let \vec{v} and \vec{w} be vectors in \mathfrak{R}^n . Then the dot product of \vec{v} and \vec{w} is the scalar denoted, $\vec{v} \cdot \vec{w}$ given by: $\vec{v} \cdot \vec{w} = [v_1, v_2, \dots, v_n] \cdot [w_1, w_2, \dots, w_n] = v_1w_1 + v_2w_2 + \dots + v_nw_n$

- the dot product produces a scalar, not a vector
- the dot product is also known as the inner product
- there are many useful properties that come about from the dot product

Properties of the Dot Product: Let \vec{v}, \vec{w} , and \vec{z} be vectors in \mathfrak{R}^n and $\lambda \in \mathfrak{R}$ be a scalar.

Then the following are true:

- $\vec{v} \cdot \vec{w} = \vec{w} \cdot \vec{v}$ (commutative law for dot product)
- $\vec{v} \cdot \vec{v} = \|\vec{v}\|^2 \geq 0$
- $\vec{v} \cdot \vec{v} = 0$ iff $\vec{v} = \vec{0}$
- $\lambda(\vec{v} \cdot \vec{w}) = (\lambda\vec{v}) \cdot \vec{w} = \vec{v} \cdot (\lambda\vec{w})$
- $\vec{v} \cdot (\vec{w} + \vec{z}) = (\vec{v} \cdot \vec{w}) + (\vec{v} \cdot \vec{z})$
- $(\vec{v} + \vec{w}) \cdot \vec{z} = (\vec{v} \cdot \vec{z}) + (\vec{w} \cdot \vec{z})$

Ex: Let $\vec{v} = [3, -1]$, $\vec{w} = [5, 2]$, $\vec{z} = [2, -1, 3, 5]$, $\vec{b} = [-3, -2, 1, 4]$, find the following if possible.

- a. $\vec{v} \cdot \vec{w}$ b. $\vec{w} \cdot \vec{v}$ c. $\vec{z} \cdot \vec{b}$ d. $\vec{v} \cdot \vec{b}$ e. $\vec{z} \cdot \vec{z}$ f. $\|\vec{z}\|$

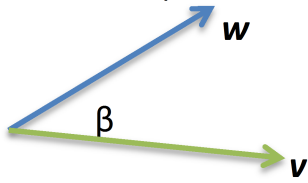
Inequalities Involving the Dot Product

Cauchy-Schwartz Inequality: Let \vec{v} and \vec{w} be vectors in \mathfrak{R}^n . Then $|\vec{v} \cdot \vec{w}| \leq \|\vec{v}\| * \|\vec{w}\|$

The Triangle Inequality: Let \vec{v} and \vec{w} be vector in \mathfrak{R}^n . Then $\|\vec{v} + \vec{w}\| < \|\vec{v}\| + \|\vec{w}\|$

(both proofs can be found in the textbook)

The Angle between Two Vectors: Let \mathbf{v} and \mathbf{w} be vectors in \mathbb{R}^n such that they have a common initial point. Let β be the angle between the vectors,



then $\cos \beta = \frac{\vec{v} \cdot \vec{w}}{\|\vec{v}\| * \|\vec{w}\|}$ or $\beta = \arccos\left(\frac{\vec{v} \cdot \vec{w}}{\|\vec{v}\| * \|\vec{w}\|}\right)$, also $\vec{v} \cdot \vec{w} = \|\vec{v}\| * \|\vec{w}\| \cos \beta$

- two vectors \mathbf{v} and \mathbf{w} are orthogonal (perpendicular) if and only if $\vec{v} \cdot \vec{w} = 0$ ($\beta = \pi/2$)
- $0 \leq \beta \leq \pi$
- when β is 0 or π ($\cos \beta = \pm 1$), \mathbf{v} and \mathbf{w} are parallel

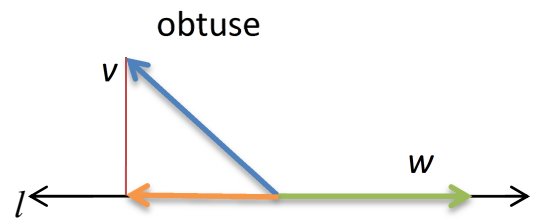
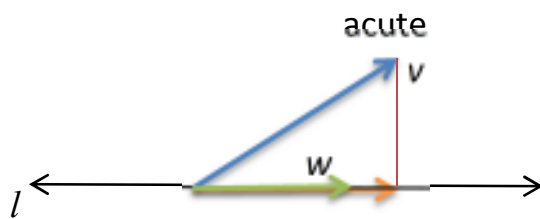
Theorem: Let \mathbf{v} and \mathbf{w} be vectors in \mathbb{R}^n . Then \mathbf{v} and \mathbf{w} are parallel if and only if

$$\vec{v} \cdot \vec{w} = \pm \|\vec{v}\| * \|\vec{w}\|$$

Ex: Find the angle between $\langle 3, -1, 2 \rangle$ and $\langle 1, -1, -2 \rangle$

Projection Vectors:

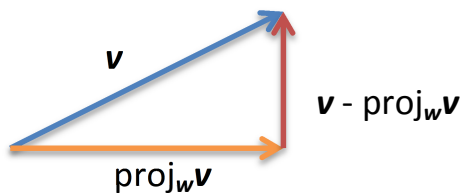
Let \mathbf{v} and \mathbf{w} be vectors in \mathbb{R}^n that have the same initial point. Let l be a line containing \mathbf{w} .



The projection of \mathbf{v} onto \mathbf{w} ($\text{proj}_{\mathbf{w}}\mathbf{v}$) is the vector with same initial point as \mathbf{v} and \mathbf{w} and found by dropping perpendicular from the terminal point of \mathbf{v} onto the line l containing \mathbf{w} to create the terminal point of the projection. Therefore the projection of \mathbf{v} onto \mathbf{w} is a scalar multiple of \mathbf{w} and can be found by:

$$\text{proj}_{\vec{w}}\vec{v} = \left(\frac{\vec{v} \cdot \vec{w}}{\|\vec{w}\|^2}\right) \vec{w}$$

We can also decompose the vector \mathbf{v} using the projection vector and the perpendicular



Notice that $\text{proj}_{\mathbf{w}}\mathbf{v}$ is parallel to \mathbf{w} and $\mathbf{v} - \text{proj}_{\mathbf{w}}\mathbf{v}$ is orthogonal to \mathbf{w}

Ex: Given $\mathbf{v} = [3, -2, 1]$ and $\mathbf{w} = [4, 1, -5]$ find $\text{proj}_{\mathbf{v}}\mathbf{w}$ and $\text{proj}_{\mathbf{w}}\mathbf{v}$, then find the vector orthogonal to \mathbf{w}

$\frac{\vec{v} \cdot \vec{w}}{\|\vec{w}\|^2}$ is the scalar known as the **scalar component** of \vec{v} in the same direction of \vec{w} .

Fundamental Operation of Matrices

Matrices: a matrix is a rectangular array of real numbers arranged in m rows and n columns. We say the size or dimension of the matrix is $m \times n$. In general if matrix A is $m \times n$, then:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \cdot & \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \cdot & \dots & \cdot \\ a_{i1} & a_{i2} & a_{i3} & \dots & a_{in} \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}$$

- We use capital letters to denote matrices. We can think of an $m \times n$ matrix A as a collection of m row vectors of n column vectors.
- We typically use a_{ij} to represent the real number in the i^{th} row and j^{th} column.
- M_{mn} represents to set of all $m \times n$ matrices
- The diagonal entries are all $a_{11}, a_{22}, a_{33} \dots$

Special Matrices:

A **square matrix** B is a matrix with the same number of rows and columns. Therefore the size of B is either $m \times m$ or $n \times n$.

A **diagonal matrix** D is a square matrix such that all the entries not on the main diagonal are zeros. We use D_n to represent the set of all $n \times n$ diagonal matrices.

An **identity matrix** I is a diagonal matrix such that all the main diagonal entries are ones. We use I_n to represent the $n \times n$ identity matrix.

An **upper triangular matrix** is a square matrix such that all entries below the main diagonal entries are zeros. U_n represents all $n \times n$ triangular matrices.

A **lower triangular matrix** is a square matrix such that all entries above the main diagonal are zeros. L_n represents all $n \times n$ lower triangular matrices.

A **zero matrix** is any matrix such that all entire are zeros, denoted O_{mn} .

Addition of Matrices

Let A and B be $m \times n$ matrices The sum of A and B is the $m \times n$ matrix whose ij^{th} entry is equal to $a_{ij} + b_{ij}$.

Ex: $\begin{bmatrix} 3 & -1 & 4 & 6 \\ 2 & 5 & -3 & 2 \end{bmatrix} + \begin{bmatrix} 6 & 1 & 7 & 9 \\ -8 & -3 & 6 & 4 \end{bmatrix} =$

Let A be a $m \times n$ matrix and let λ be a real number then the $m \times n$ matrix λA , the **scalar multiplication of A by λ** , is the matrix whose ij^{th} entry is λa_{ij} .

Ex: $C = \begin{bmatrix} 3 & 2 \\ -1 & 7 \\ 6 & -9 \end{bmatrix}$ find $5C$

Properties of Addition and Scalar Multiplication of Matrices

Let A , B , and C be $m \times n$ matrices and λ and k be scalars. Then we have:

- $A + B = B + A$ *commutative property*
- $(A + B) + C = A + (B + C)$ *associative property*
- $A + 0_{mn} = 0_{mn} + A = A$ *existence of an additive identity*
- $A + (-1)A = -A + A = 0_{mn}$ *existence of an additive inverse*
- $k(A + B) = kA + kB$ *distributive laws for scalar multiplication and addition*
- $(k + \lambda)A = kA + \lambda A$ *distributive laws for scalar multiplication and addition*
- $(k\lambda)A = (kA)\lambda = (\lambda A)k$ *associativity of scalar multiplication*
- $1A = A$ *existence of identity element for scalar multiplication*

The Transpose of a Matrix and its Properties:

Let A be any $m \times n$ matrix then **the transpose matrix** of A is the $m \times n$ matrix A^T such that the ij^{th} entry of A^T is the ji^{th} entry from A . (*the rows of A are the columns of A^T and vice versa*)

Ex: Find A^T if $A = \begin{bmatrix} 3 & -1 & 7 & -2 & 4 \\ 2 & 5 & 6 & 9 & -3 \end{bmatrix}$

Properties of the Transpose

Let A and B be $m \times n$ matrices and k be a scalar then:

- $(A^T)^T = A$
- $(A + B)^T = A^T + B^T$
- $(kA)^T = kA^T$

Symmetric and Skew-Symmetric Matrices

A matrix A is a **symmetric matrix** iff $A = A^T$

A matrix B is a **skew-symmetric matrix** iff $B = -B^T$

only square matrices can be symmetric or skew symmetric

Ex: $A = \begin{bmatrix} 2 & 3 & -1 \\ 3 & 4 & 6 \\ -1 & 6 & 7 \end{bmatrix}$ is symmetric

Theorem: Every square matrix A can be decomposed uniquely as a sum of a symmetric matrix S and a skew symmetric V . It can be shown that $S = \frac{1}{2}(A + A^T)$ and $V = \frac{1}{2}(A - A^T)$.

Matrix Multiplication

If A is a $m \times n$ matrix and B is a $n \times p$ matrix, then their matrix product AB is the $m \times p$ matrix whose ij^{th} entry is the dot product of the i^{th} row of A and the j^{th} column of B.

- The dimension of AB is the (number of rows of A) \times (number of columns of B)
- AB exists only if the number columns of A equals the number of rows of B.

AB may exist but BA may not

$$AB = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1p} \\ b_{21} & b_{22} & \dots & b_{2p} \\ \cdot & \cdot & \cdot & \cdot \\ b_{n1} & b_{n2} & \dots & b_{np} \end{bmatrix} = \begin{bmatrix} a_{11}b_{11} + a_{12}b_{21} + \dots + a_{1n}b_{n1} \\ a_{21}b_{12} + a_{22}b_{22} + \dots + a_{2n}b_{n2} \\ \dots \\ a_{m1}b_{1p} + a_{m2}b_{2p} + \dots + a_{mn}b_{np} \end{bmatrix}$$

Ex: Let $A = \begin{bmatrix} 3 & 5 \\ -1 & 6 \\ 4 & -2 \end{bmatrix}$ and $B = \begin{bmatrix} 4 & -2 & 5 & 6 \\ 3 & -7 & -1 & 0 \end{bmatrix}$ find AB if possible

Ex: For $D = \begin{bmatrix} -2 & 1 \\ 0 & 5 \\ 4 & -3 \end{bmatrix}$ $E = \begin{bmatrix} 2 & -1 \\ 3 & 0 \end{bmatrix}$ $F = [-6 \ 3 \ 1]$ $G = \begin{bmatrix} 2 \\ -4 \\ 5 \end{bmatrix}$ $H = \begin{bmatrix} 3 & 0 \\ -2 & 1 \end{bmatrix}$

Find DE, ED, FG, GF, and HD if possible.

- In the special case where $AB = BA$ we say A and B commute
- If A is $m \times n$ and I represents an identity matrix with the appropriate number of rows and columns such that AI_n exists or $I_m A$ exists then $AI_n = A = I_m A$. I is called the multiplicative identity.

Properties of Matrix Products

Suppose that A, B, and C are matrices for which the following sums and products are defined. Let λ be a scalar then:

- $(AB)C = A(BC)$ *associative property*
- $A(B+C) = AB + AC$ *distributive property*
- $(A+B)C = AC + BC$ *distributive property*
- $\lambda(AB) = (\lambda A)B = A(\lambda B)$ *scalar multiple*

Let A be a $n \times n$ matrix then the non-negative powers of A are given by

$$A^0 = I_n A \text{ and for } k \geq 2 \ A^k = A^{(k-1)}A$$

If A is a square matrix and n, s and t are non-negative integers, then

$$A^{s+t} = A^s A^t \text{ and } (A^s)^t = A^{st} = (A^t)^s$$

If A is $m \times n$ and B is $n \times p$ then the transpose of the matrix product is $(AB)^T = B^T A^T$

Systems of Linear Equations

Solving Linear Systems using Gaussian Elimination

A **system of m linear equations** in n variables is a collection of m equations each containing a linear combination of the same variables summing to a scalar:

$$\begin{cases} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \\ \dots \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n = b_m \end{cases}$$

A **particular solution** (s_1, s_2, \dots, s_n) to a system of m equations in n variables is an ordered n-tuple of values satisfying every equation when substituted for x_1, x_2, \dots, x_n .

A **complete solution** to a system of m equations in n variables is the set of all ordered n-tuples that satisfy every equation.

The coefficients of all the m variables in all the n variables in the m equations can be collected in a matrix called a **coefficient matrix**.

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \text{ we can also let } X = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ x_n \end{bmatrix} \text{ and } B = \begin{bmatrix} b_1 \\ b_2 \\ \cdot \\ b_m \end{bmatrix}$$

The above notation can be written as $AX=B$

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \cdot \\ b_m \end{bmatrix}$$

The augmented matrix is the matrix $[A|B]$

$$[A|B] = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} & b_1 \\ a_{21} & a_{22} & \dots & a_{2n} & b_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a_{m1} & a_{m2} & \dots & a_{mn} & b_m \end{bmatrix}$$

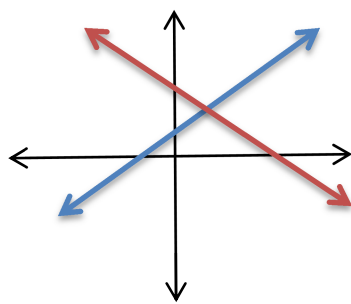
The Number of Solutions to a System

Any given set of equations in a system of linear equations will have one of the following possibilities for the total number of solutions:

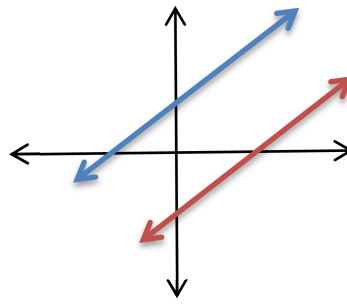
- one solution
- no solution
- infinitely many solutions (*if a system has more than one solution it is guaranteed to have infinitely many solutions*)

Any system that has a solution is called **consistent** and if there is no solution its **inconsistent**.

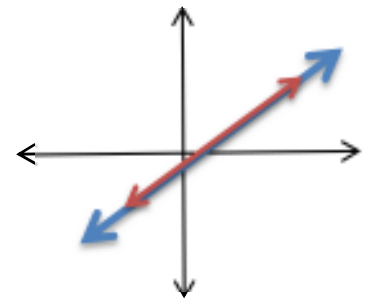
Consider a system of two linear equations:



one solution



no solutions



infinitely many solutions

Gaussian Elimination

Gaussian Elimination is a procedure that we use to solve a system. The procedure involves multiplying an entire equation by non-zero constants and adding the equations to another to eliminate a variable (*elimination by addition*). We will use Gaussian elimination on the augmented matrix $[A|B]$ to solve the systems.

There are three operations we can perform on any given row of a matrix so that the system retains the same solution:

1. multiply a row by a non-zero scalar
2. adding a scalar multiple of one row to another row (*while subtracting is a form of addition and can also be done between rows is very helpful to right operations only using addition*)
3. interchange the positions of any two rows

It is helpful to notate what you are doing to a given row using the previous operations. If we were planning on performing an operation of row 2 by multiplying row 1 by 3 and adding it to row 2 we would write that as: $R_2 = 3R_1 + R_2$.

If we want to interchange row 1 and row 2 we would write: $R_1 \leftrightarrow R_2$.

We begin by selecting a specific row of the matrix called the “home row” and a specific entry in that row called the “pivot”. We will convert the pivot to a 1 and use the home row and the pivot to zero out the entries above and below the pivot. This process then repeats until a solution is obtained.

Ex: Solve the system

$$\begin{cases} -5x - 2y + 2z = 14 \\ 3x + y - z = -8 \\ 2x + 2y - z = -3 \end{cases}$$

The methods we are using are called **row reduction**. We are turning the augmented matrix into an upper/lower triangular matrix and then **back substitute**. If we turn the augmented matrix into a diagonal matrix we do not need to back substitute.

Sometimes we have a row or column of all zeros. In these cases no pivot can be chosen and we move on to the next column. If a row consists of all zeros we will move that row to the bottom of the matrix.

$$\left[\begin{array}{ccc|c} 1 & 0 & 5 & 6 \\ 0 & 1 & 5 & 8 \\ 0 & 0 & 0 & ? \end{array} \right] \text{ the third row having all zeros to the right of the line amounts to}$$

$$0x + 0y + 0z = ?$$

If $? = 0$ there are two possibilities:

1. infinitely many solutions
2. one solution, the trivial solutions $(0,0,\dots,0)$

If $? \neq 0$ then there is no solution to the system.

If a column to the right of the augmentation bar has all zeros then there are infinitely many solutions.

Ex: Solve the system

$$\begin{cases} 3x + y + 7z + 2w = 13 \\ 2x - 4y + 14z - w = -10 \\ 5x + 11y - 7z + 8w = 59 \\ 2x + 5y - 4z - 3w = 39 \end{cases}$$

Gauss-Jordan Row Reductions and Reduced Row Reduction Form

A matrix in row-echelon form has the following properties:

- Any rows consisting entirely of zeros occur at the bottom of the matrix.
- The entry in row 1, column 1 is a 1 and zeros appear **below** it.
- The first non-zero entry of each row after the first row is a 1 with zeros **below** it.

The disadvantage to this method is we have to back substitute to solve the system

A matrix in reduced row echelon form has the following properties:

- Any rows consisting entirely of zeros occur at the bottom of the matrix.
- The entry in row 1, column 1 is a 1 and zeros appear **below** it.
- The first non-zero entry of each row after the first row is a 1 with zeros **below and above** it.

This method does not need back substitution.

Solving a system using row echelon form is called Gaussian elimination and solving a system using reduced row echelon form is called Gauss-Jordan elimination.

Ex: Is the following in reduced row echelon form? Why or why not?

$$\left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{array} \right]$$

Number of solutions to a System of Linear Equations

Let $AX = B$ be a system of linear equations. And let C be the reduced row echelon form augmented matrix.

- If a column to the right of the augmentation bar has all zeros then there are infinitely many solutions.
- If a row has all zeros to the right of the augmentation bar and a zero to the right there are infinitely many solutions
- If a row has all zeros to the right of the augmentation bar and a non-zero entry to the right there is no solution.
- If none of the previous apply there is a unique solution.

A system of linear equations having the form $AX = 0$ is called a **homogeneous system**.

A homogenous system will have the following properties:

- If the reduced row echelon form augmented matrix for a homogeneous system in n variables has fewer than n nonzero pivot entries, then the system has only the trivial solution $(0,0,\dots,0)$.
- Every homogeneous system has at least the trivial solution. Therefore if the system also has a nontrivial solution then it has infinitely many solutions.
- In a homogeneous system if there are more variables than equations then there are infinitely many solutions.

Ex: Solve

$$\begin{cases} 2x_1 + 4x_2 - x_3 + 5x_4 + 2x_5 = 0 \\ 3x_1 + 3x_2 - x_3 + 3x_4 = 0 \\ -5x_1 - 6x_2 + 2x_3 + 6x_4 - x_5 = 0 \end{cases}$$

Equivalent Systems, Rank, and Row Space

Equivalent Systems and Row Equivalence of Matrices:

Two systems of m linear equations in n variables are **equivalent** iff they have the same solution set.

Two matrices are **row equivalent** iff one matrix is obtained from the other by a finite number of row operations.

Each row operation we perform is reversible. To go backwards is called a **reverse** or **inverse row operation**.

If a matrix D is a row equivalent to a matrix C , then the matrix C is a row equivalent to the matrix D .

Let $AX = B$ be a system of linear equations. If $[C|D]$ is row equivalent to $[A|B]$ then the system $CX = D$ is equivalent to the system $AX = B$

Rank of a Matrix:

Every matrix is row equivalent to a unique matrix in reduced row echelon form. So no matter how we reduce a matrix we will always get the same matrix in reduced row echelon form.

The **rank of a matrix A** is the number of nonzero rows in the reduced row echelon form of A, denoted $\text{rank}(A)$.

Ex: Determine the rank of the following:

$$A = \begin{bmatrix} 1 & -2 & 3 \\ 3 & -6 & 9 \\ 7 & -14 & 21 \end{bmatrix} \quad B = \begin{bmatrix} 1 & -3 & 5 & 7 & -8 \\ 2 & 5 & -3 & 6 & 1 \\ -8 & -20 & 12 & -24 & 4 \end{bmatrix}$$

Homogeneous Systems and Rank:

Let $AX = 0$ be a homogeneous system in n variables:

- If $\text{rank}(A) < n$ the system has a nontrivial solution (\therefore infinitely many solutions)
- If $\text{rank}(A) = n$ the system has only the trivial solution

Corollary: Let $AX = 0$ be a homogeneous system on m linear equations in n variables. If $m < n$ then the system has a nontrivial solution.

Linear Combinations of Vectors:

Recall: a linear combination of vectors is a sum of scalar multiples of the vectors

Ex: Given $\vec{x} = [3, -1, 4, 5]$, $\vec{y} = [2, 7, -1, 6]$, and $\vec{z} = [1, 0, 0, -3]$ find $3\vec{x} - 2\vec{y} + 5\vec{z}$

Question: Given a vector, can we determine if the vector is a linear combination of some other vectors?

Answer: To determine whether \vec{v} is a linear combination of \vec{x}, \vec{y} , and \vec{z} , we must find C_1, C_2, C_3 such that $\vec{v} = C_1\vec{x} + C_2\vec{y} + C_3\vec{z}$. We can think of this as a system of linear

equations,
$$\begin{cases} x_1C_1 + y_1C_2 + z_1C_3 = v_1 \\ x_2C_1 + y_2C_2 + z_2C_3 = v_2 \\ x_3C_1 + y_3C_2 + z_3C_3 = v_3 \end{cases}$$
 and use an augmented matrix.

If there is a solution then we can write \vec{v} as a linear combination of \vec{x}, \vec{y} , and \vec{z} . If no solution then we can't.

Ex: Determine whether a $\vec{v} = [2, 2, 3]$ is a linear combination of

$$\vec{x} = [6, -2, 3], \quad \vec{y} = [0, -5, -1], \quad \vec{z} = [-2, 1, 2]$$

Row Space of a Matrix:

Let A be an $m \times n$ matrix. The subset of \mathbb{R}^n consisting of all vectors that are linear combinations of the rows of A is called the **row space of A**.

- Recall that if A is a $m \times n$ matrix, then each of the rows of A is a vector with n entries (or in other words a vector in \mathfrak{R}^n).
- We understand that the row space is a set of vectors that are all possible linear combinations of the vectors making up the rows of the matrix.
- The zero vector, $\vec{0}$ is guaranteed to be in the row space of every matrix.
- Each row of a matrix is also guaranteed to be in the row space of the matrix.

Lemma: Suppose \vec{v} is a linear combination of the vectors $\vec{q}_1, \vec{q}_2, \dots, \vec{q}_4$ and suppose that each of the vectors $\vec{q}_1, \vec{q}_2, \dots, \vec{q}_4$ is itself a linear combination of the vectors $\vec{r}_1, \vec{r}_2, \dots, \vec{r}_j$. Then \vec{v} is a linear combination of $\vec{r}_1, \vec{r}_2, \dots, \vec{r}_j$.

Suppose that A and B are row equivalent matrices, then the row space of A is equal to the row space of B .

Ex: Determine whether $\vec{v} = [4, 0, -3]$ is in the row space of $A = \begin{bmatrix} 3 & 1 & 1 \\ 2 & -1 & 5 \\ -4 & -3 & 3 \end{bmatrix}$

If \vec{v} is in the row space of A then there exists real numbers $C_1, C_2,$ and C_3 such that $C_1[3, 1, 1] + C_2[2, -1, 5] + C_3[-4, -3, 3] = \vec{v}$

To check whether a vector \vec{v} is in the row space of matrix A we set up the augmented matrix: $[A^T | \vec{v}]$ the row reduce to see if there is exactly one solution.

Inverse Matrices

Let A be a square $n \times n$ matrix, if the inverse of A (denoted A^{-1}) exists then $AA^{-1} = A^{-1}A = I_n$
not all square matrices have inverses (most do!)

A $n \times n$ matrix A is **singular** iff the inverse of A does not exist. If the inverse does exist we say the matrix is **non-singular**.

Suppose the $n \times n$ matrices B and C are inverses of the $n \times n$ matrix A , then $B = C$. If an inverse exists then that matrix is unique.

Let A be a $n \times n$ non-singular matrix. Then we define negative powers of A using the inverse A^{-1} of A . In other words for $k \geq 2$ we have $A^{-k} = (A^{-1})^k$.

If A is a $n \times n$ non-singular matrix and s and t are any integers, then we have $A^s A^t = A^{s+t}$ and $(A^s)^t = (A^t)^s = A^{st}$

Let A and B be $n \times n$ non-singular matrices, then:

- A^{-1} is non-singular and $(A^{-1})^{-1} = A$
- A^k is non-singular and $(A^k)^{-1} = (A^{-1})^k$ for any integer k
- AB is non-singular and $(AB)^{-1} = B^{-1}A^{-1}$ (notice order of matrices)
- A^T is non-singular and $(A^T)^{-1} = (A^{-1})^T$

Inverses of 2x2 matrices:

Let $\delta = ad - bc$ (the determinant) then it is true that:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} = \begin{bmatrix} ad - bc & -ab + ab \\ cd - dc & -cd + da \end{bmatrix} = \\ \begin{bmatrix} ad - bc & 0 \\ 0 & ad - bc \end{bmatrix} = \begin{bmatrix} \delta & 0 \\ 0 & \delta \end{bmatrix} = \delta \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

If $\delta \neq 0$ we can divide a 2x2 matrix by δ and easily find its inverse so that if

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \text{ then } A^{-1} = \frac{1}{\delta} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

If $\delta = 0$ the A is singular.

Ex: Given $A = \begin{bmatrix} 2 & 4 \\ 3 & -1 \end{bmatrix}$ find A^{-1} if possible.

Ex: Given $B = \begin{bmatrix} 3 & 4 \\ 6 & 8 \end{bmatrix}$ find B^{-1} if possible.

Inverses of Larger Matrices

If A is a nxn matrix to find A^{-1} if it exists we need to:

- Set up the augmented matrix $[A|I_n]$
- Reduce A to its row reduced echelon form
- If the LHS of the augmented matrix cannot be made into I_n , then A is singular.
- If the LHS of the augmented matrix becomes I_n , then the RHS is A^{-1} .

$$[A|I_n] \Rightarrow [I_n|A^{-1}]$$

there is a way to find the inverse for larger matrices using determinants, we will discuss this later.

Ex: Find the inverse if it exists for $A = \begin{bmatrix} 1 & -5 & 2 \\ 3 & 1 & -2 \\ 5 & 7 & -6 \end{bmatrix}$

Let A be a nxn matrix, then A is non-singular iff $\text{rank}(A) = n$

Ex: Find the inverse if it exists for $B = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 1 & 4 \\ 5 & 6 & 0 \end{bmatrix}$

Solving a System using the Inverse of a Coefficient Matrix

Suppose $AX = B$ is a system with the same number of rows as variables. We know $AX = B$ has a unique solution iff A is non-singular, then:

$$AX = B$$

$$A^{-1}(AX) = A^{-1}B$$

$$(A^{-1}A)X = A^{-1}B$$

$$I_n X = A^{-1}B$$

$$X = A^{-1}B$$

Ex: Solve the system
$$\begin{cases} -5x + 3y + 6z = 4 \\ 3x - y - 7z = 11 \\ -2x + y + 2z = 2 \end{cases}$$
