1.5 Linear Systems and Linear Independence

Definition:

A linear system is called *consistent* if it has *at least one* solution.

A linear system is called *inconsistent* if it does *not* have any solutions.

Theorem: Let $\vec{b} \in \mathbb{R}^m$ and let $S = {\vec{v}_1, \vec{v}_2, ..., \vec{v}_n}$ be a set of vectors from \mathbb{R}^m . Then $\vec{b} \in Span(S)$ if and only if the system of equations corresponding to the *augmented* matrix:

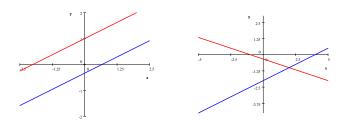
$$A = \left[\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n \ | \ \vec{b} \right]$$

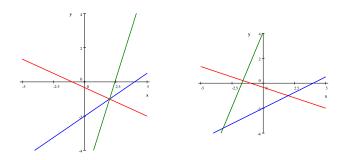
is *consistent*.

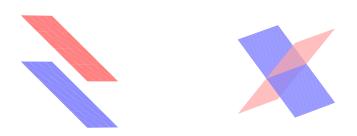
Definition: A linear system with *m* equations in *n* variables is called:

- 1. square if m = n.
- 2. underdetermined if m < n.
- 3. overdetermined if m > n.

Geometric Interpretation in \mathbb{R}^2 and \mathbb{R}^3











Example: Let us investigate the system:

$$2x + 3y - z = 5$$

$$5x + 4y - 3z = 7$$

$$-7x + 7y + 6z = 10$$

Homogeneous Systems

Definition: A homogeneous system of *m* equations in *n* unknowns is a system of linear equations where the right side of the equations consists entirely of zeros. In other words, the augmented matrix has the form:

$$\left[A\middle|\overrightarrow{0}_{m}\right],$$

where *A* is an *m* × *n* matrix. If the right side *b* is not the zero vector, we call the system *non-homogeneous*.

Clearly, $\vec{x} = \vec{0}_n = \langle 0, 0, ..., 0 \rangle$ is a solution to the homogeneous system. We call this the *trivial solution* to a homogeneous system, and any other solution is called a *non-trivial solution*.

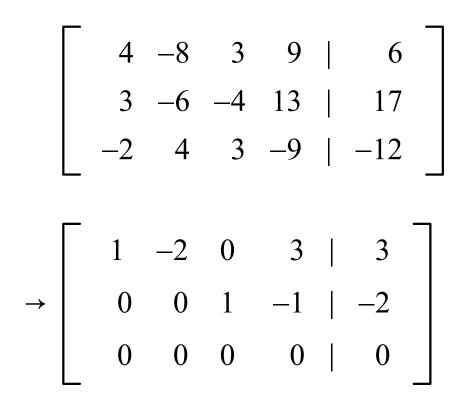
When do we get an Infinite Number of Solutions?

Theorem: A homogeneous system has an infinite number of solutions (and hence, non-trivial solutions) *if and only if* the rref of *A* has free variables.

What shape of system always has a free variable?

Theorem: An **underdetermined homogeneous system** always has an **infinite** number of solutions. In other words, a homogeneous system with **more variables than equations** has an infinite number of solutions.

Example:



Matrix Products

Set-up:

Identify a vector with a column matrix:

$$\vec{x} = \langle x_1, x_2, \dots, x_n \rangle = \begin{vmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{vmatrix}$$

Partition a matrix into *columns:*

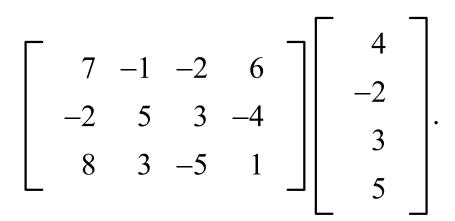
$$A = \begin{bmatrix} \vec{c}_1 & \vec{c}_2 & \cdots & \vec{c}_n \end{bmatrix},$$

Definition — Matrix Product: If $A = \begin{bmatrix} \vec{c}_1 & \vec{c}_2 & \cdots & \vec{c}_n \end{bmatrix}$ is an $m \times n$ matrix and $\vec{x} \in \mathbb{R}^n$, we define the matrix product $A\vec{x}$ to be the linear combination:

$$A\vec{x} = \begin{bmatrix} \vec{c}_1 & \vec{c}_2 & \cdots & \vec{c}_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$
$$= x_1\vec{c}_1 + x_2\vec{c}_2 + \cdots + x_n\vec{c}_n.$$

Notice that since each column is an $m \times 1$ matrix, the matrix product is again an $m \times 1$ matrix. Thus, $A\vec{x}$ is a *linear combination* of the columns of A with coefficients from \vec{x} , and so $A\vec{x} \in \mathbb{R}^{m}$.

Example:



Theorem — Properties of Matrix Multiplication:

For all $m \times n$ matrices A, for all $\vec{x}, \vec{y} \in \mathbb{R}^n$, and for all $k \in \mathbb{R}$, matrix multiplication enjoys the following properties:

The Additivity Property $A(\vec{x} + \vec{y}) = A\vec{x} + A\vec{y}.$

The Homogeneity Property

 $A(k\vec{x}) = k(A\vec{x}).$

The Matrix Product Form of Linear Systems

$$x_1\vec{v}_1 + x_2\vec{v}_2 + \dots + x_n\vec{v}_n = \vec{b}.$$

We formed the augmented matrix $\begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_n & \vec{b} \end{bmatrix}$ and looked at its rref.

Alternative way:

$$\begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \vec{b}.$$

Matrix Equation:

$$A\vec{x} = \vec{b}$$

Rephrase Consistency Requirement for Membership in a Span

Theorem: Suppose that $S = {\vec{v}_1, \vec{v}_2, ..., \vec{v}_n}$ be a set of vectors from \mathbb{R}^m , and $\vec{b} \in \mathbb{R}^m$. Let us form the $m \times n$ matrix:

$$A = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_n \end{bmatrix}.$$

Then, $\vec{b} \in \text{Span}(S)$ *if and only if* the matrix equation $A\vec{x} = \vec{b}$ is *consistent*.

Major Concept: Linear Dependence and Independence

Definition: A set of vectors $S = \{\vec{v}_1, \vec{v}_2, ..., \vec{v}_n\}$ from \mathbb{R}^m is *linearly dependent* if we can find a *non-trivial solution* $\vec{x} = \langle x_1, x_2, ..., x_n \rangle \in \mathbb{R}^n$, where at least one component is *not zero*, to the vector equation:

$$x_1\vec{v}_1+x_2\vec{v}_2+\cdots+x_n\vec{v}_n=\vec{0}_m.$$

We will call this equation the *dependence test equation* for S. An equation of this form where at least one coefficient is *not zero* will be referred to as a *dependence equation*. Thus, for S to be linearly dependent, we must find a non-trivial solution \vec{x} to the homogeneous system:

$$\vec{Ax} = \vec{0}_m,$$

where $A = \begin{bmatrix} \vec{v}_1 & | & \vec{v}_2 & | \\ \vec{v}_2 & | & \vec{v}_n \end{bmatrix}$ is the matrix with the vectors \vec{v}_1 , \vec{v}_2 , ..., \vec{v}_n as its *columns*. This is equivalent to the presence of a *free variable* in the rref of the matrix A. However, if only the trivial solution $\vec{x} = \vec{0}_n$ exists for the dependence test equation, we say that *S* is *linearly independent*.

We often drop the adjective "linearly" and simply say that a set *S* is *dependent* or *independent*.

Example: The standard basis $S = {\vec{e}_1, \vec{e}_2, ..., \vec{e}_m}$.

Example: Suppose that $\vec{v}_1 = \langle 4, -5, 3, -2 \rangle$, $\vec{v}_2 = \langle 7, -6, 2, -4 \rangle$ and $\vec{v}_3 = \langle -1, -7, 9, 2 \rangle$.

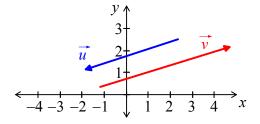
Classifying Small Sets of Vectors

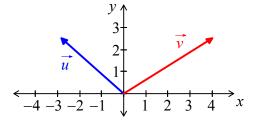
Theorem: Any set $S = \{ \vec{0}_n, \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \} \subset \mathbb{R}^m$ containing $\vec{0}_m$ is a *dependent* set.

Theorem: A set $S = \{\vec{v}\}$ consisting of a single **non-zero** vector $\vec{v} \in \mathbb{R}^m$ is **independent**.

When is $S = \{\vec{u}, \vec{v}\}$ linearly dependent / independent?

Theorem: A set $S = \{\vec{u}, \vec{v}\}$ consisting of *two* vectors from \mathbb{R}^m is *dependent* if and only if \vec{u} and \vec{v} are *parallel* to each other.





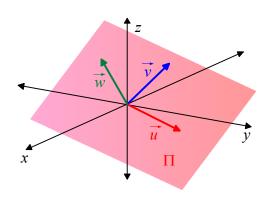
Two Dependent (Parallel) Vectors

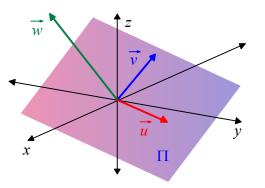
Two Independent (Non-Parallel) Vectors

Example: $\{\langle 15, -10, 20, -25 \rangle, \langle -9, 6, -12, 15 \rangle \}$

When is $S = {\vec{u}, \vec{v}, \vec{w}}$ linearly dependent / independent?

Theorem: A set $S = \{\vec{u}, \vec{v}, \vec{w}\}$ consisting of **three** non-zero vectors from \mathbb{R}^m is **dependent** if and only if \vec{u} , \vec{v} and \vec{w} are **coplanar**.





Three DependentThree Independent(Non-Parallel) Vectors(Non-Parallel) Vectorswherewhere $\vec{w} \in Span(\{\vec{u}, \vec{v}\}) = \Pi$ $\vec{w} \notin Span(\{\vec{u}, \vec{v}\}) = \Pi$

Example:

$$S = \{ \langle 2, -3, 4 \rangle, \langle 5, 3, -6 \rangle, \langle -4, -2, 7 \rangle \}.$$

Another Way to Think of Linear Dependence/Independence

Theorem: Suppose that $S = {\vec{v}_1, \vec{v}_2, ..., \vec{v}_n}$ is a set of non-zero vectors from some \mathbb{R}^m , and S contains at least two vectors. Then: S is linearly dependent *if and only if* at least one vector \vec{v}_i from S can be expressed as a linear combination of the other vectors in S.

Guaranteed Dependence

If the vectors are from \mathbb{R}^n , what is the minimum number of vectors required to produce an underdetermined system?

Theorem: A set $S = {\vec{v}_1, \vec{v}_2, ..., \vec{v}_m}$ of *m* vectors from \mathbb{R}^n is automatically linearly **dependent** if m > n.

Example:

$$S = \{ \langle 5, -3, 0, 2 \rangle, \langle 2, -7, 3, -8 \rangle, \langle 1, 0, -2, 4 \rangle, \\ \langle -5, 1, 6, -3 \rangle, \langle -2, 5, 1, 6 \rangle \}$$