

Vector Space

- Space \mathbb{R}^n consists of all column vectors with n components.

Ex: \mathbb{R}^2 : x - y plane

- A real vector space is a set of vectors together with 8 rules for vector *addition* and *scalar multiplication*. A vector produced by addition and scalar multiplication must be within the space.

- 8 rules to be satisfied:

1. $x+y=y+x$

2. $x+(y+z)=(x+y)+z$

3. $x+0=x$ for all x , where 0 is a unique zero vector

4. For each x , there exists a unique $-x$ such that $x+(-x)=0$

5. $1x=x$

6. $(c_1c_2)x=c_1(c_2x)$

7. $c(x+y)=cx+cy$

8. $(c_1+c_2)x=c_1x+c_2x$

Vector Subspace

- Any plane that contains the origin in the \mathbb{R}^3 space is itself a space. Why? This plane is a *subspace inside the original space* \mathbb{R}^3

Definition:

A subspace of a vector space is a nonempty subset that satisfies:

(i) x and y are in the subspace. Then, $x+y$ is in the subspace

(ii) x is in the subspace. Then, cx is in the subspace

- A subspace is *closed* under addition and scalar multiplication
- Zero vector must be contained in every subspace: rule (ii) with scalar $c=0$.
- The smallest possible vector space: *zero vector* (zero-dimensional space)
- The largest possible: the original space.

Example: Is the first quadrant ($x \geq 0, y \geq 0$) a subspace?

Example: Sets of lower triangular and symmetric matrices

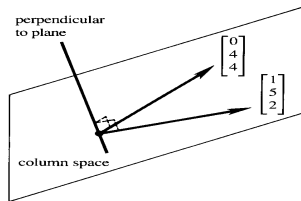
Vector Subspace and Column Space of A

$$\begin{bmatrix} 1 & 0 \\ 5 & 4 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

- 3 equations and 2 unknowns ($m > n$): usually no solution
- The system $Ax=b$ is solvable if and only if the vector b can be expressed as a combination of the columns of A .

$$u \begin{bmatrix} 1 \\ 5 \\ 2 \end{bmatrix} + v \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

- The set of all combination of the columns of A : the column space of A denoted by $\mathcal{R}(A)$ (the plane spanned by the two columns in our example)



The equation $Ax=b$ can be solved if and only if b lies in $\mathcal{R}(A)$.

For an m by n matrix A this will be a subspace of \mathbb{R}^m since the columns have m components.

Rule (i): $b=Ax$ and $b'=Ax'$ then $b+b'=A(x+x')$

Rule (ii): $b=Ax$ then $cb=A(cx)$

Nullspace of A

- The nullspace of a matrix consists of all vectors x such that $Ax=0$. It is denoted by $\mathcal{N}(A)$. It is a subspace of \mathbb{R}^n , just as the column space was a subspace of \mathbb{R}^m .
- Requirement (i): If $Ax=0$ and $Ax'=0$ then $A(x+x')=0$
- Requirement (ii): If $Ax=0$ then $A(cx)=0$
- When $Ax=b$ and $b \neq 0$, vectors x cannot form a subspace. (why?)
- $Ax=0$ is called *homogeneous* equation.

$$\begin{bmatrix} 1 & 0 \\ 5 & 4 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

- Only $u=v=0$, that is, zero vector space is the nullspace

$$B = \begin{bmatrix} 1 & 0 & 1 \\ 5 & 4 & 9 \\ 2 & 4 & 6 \end{bmatrix}$$

- B has the same column space as A , but it has the following nullspace:

$$\begin{bmatrix} 1 & 0 & 1 \\ 5 & 4 & 9 \\ 2 & 4 & 6 \end{bmatrix} \begin{bmatrix} c \\ c \\ -c \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

where c ranges from $-\infty$ to ∞ .

Note: the nullspace is a line passing through $(0, 0, 0)$.

Elimination on a m by n Matrix A

$$ax=b$$

Nonsingular: $a \neq 0$, $x = b/a$, unique. (Ex. $3x=4$)

Undetermined: $a=0$ and $b=0$, infinitely many solutions

Inconsistent: $a=0$ and $b \neq 0$, no solution

- For $Ax=b$ with square matrices, $a \neq 0 \equiv A$ is invertible.
- For rectangular matrices, existence with uniqueness is impossible.

$$A = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 2 & 6 & 9 & 7 \\ -1 & -3 & 3 & 4 \end{bmatrix} \xrightarrow{\text{Gaussian Elimination}} \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$L = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & 2 & 1 \end{bmatrix}$$

- **Echelon Form:**

$$U = \begin{bmatrix} \textcircled{*} & * & * & * & * & * & * & * \\ 0 & \textcircled{*} & * & * & * & * & * & * \\ 0 & 0 & 0 & \textcircled{*} & * & * & * & * \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \textcircled{*} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

- To any A (m by n) with a corresponding permutation matrix P , $PA=LU$, where L is m by m with unit diagonal and U is a m by n echelon matrix.

Nullspace: $Ax=0 \equiv Ux=0$

- $Ax=0 \Rightarrow L^{-1}Ax=0 \Rightarrow Ux=0$; $Ux=0 \Rightarrow LUx=0 \Rightarrow Ax=0$

$$Ux = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{aligned} u + 3v + 3w + 2y &= 0 & \rightarrow & u = -3v - 3w - 2y & \rightarrow & u = -3v + y \\ 3w + 3y &= 0 & \rightarrow & w = -y & \rightarrow & w = -y \end{aligned}$$

$$\begin{aligned} u &= -3v + y \\ v &= v \\ w &= -y \\ y &= y \end{aligned} \Rightarrow x = \begin{bmatrix} -3v + y \\ v \\ -y \\ y \end{bmatrix} = v \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + y \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}$$

- The result can be obtained exactly by back-substitution.
 - **Pivot variables:** u and w corresponding to pivots 1 and 3.
 - **Free variables:** v and y corresponding to zero pivots
 - Nullspace of A is a two-dimensional subspace in \mathbb{R}^4
 - If a homogeneous system $Ax=0$ has more unknowns than equations ($n>m$), it has a nontrivial solution: There is a solution x other than the trivial solution $x=0$.
 - If $n>m$, number of free variables $\geq n-m$. ($m \geq \#$ of pivots)
- The nullspace dimension = no. of free variables $\geq n-m$.

Complete Solution of $Ax=b$

When $b \neq 0$, $Ux = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 - 2b_1 \\ b_3 - 2b_2 + 5b_1 \end{bmatrix}$

- If the system is solvable, $b_3 - 2b_2 + 5b_1$ must be 0, i.e. the last equation can be omitted, and the system becomes a 2 by 4 system (2 equations and 4 unknowns)
- By columns, b must lie in the plane by columns of A and this plane is (b_1, b_2, b_3) satisfying $5b_1 - 2b_2 + b_3 = 0$ or the plane with a perpendicular vector $(5, -2, 1)$, geometrically.
- Let $b = (1, 5, 5)$,

$$Ux = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \\ 0 \end{bmatrix} \rightarrow \begin{matrix} u = 1 - 3v - 3w - 2y \\ w = 1 \\ -y \end{matrix} \rightarrow \begin{matrix} u = -2 - 3v + y \\ w = 1 \\ -y \end{matrix}$$

$$\begin{matrix} u = -2 - 3v + y \\ v = v \\ w = 1 \\ y = y \end{matrix} \Rightarrow x = \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix} + v \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + y \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}$$

- $x_{\text{complete}} = x_{\text{particular}} + x_{\text{nullspace}}$ where $x_{\text{particular}}$ can be found by setting all free variables to be zero.

$Ax=b \Rightarrow Ux=c$ back-substitution $\Rightarrow Rx=d$

$$U = \begin{bmatrix} \bullet & * & * & * & * & * & * & * & * \\ 0 & \bullet & * & * & * & * & * & * & * \\ 0 & 0 & 0 & \bullet & * & * & * & * & * \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \bullet \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \Rightarrow R = \begin{bmatrix} 1 & 0 & * & 0 & * & * & * & * & 0 \\ 0 & 1 & * & 0 & * & * & * & * & 0 \\ 0 & 0 & 0 & 1 & * & * & * & * & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

- Example:

$$\begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 3 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} = R$$

- Nullspace: $Ax=0 \Rightarrow Ux=0 \Rightarrow Rx=0$

$$Rx = \begin{bmatrix} 1 & 3 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \rightarrow \begin{matrix} u + 3v - y = 0 \\ w + y = 0 \end{matrix} \rightarrow \begin{matrix} u = -3v + y \\ w = -y \end{matrix}$$

- $Ux=c \Rightarrow Rx=d$:

$$Rx = \begin{bmatrix} 1 & 3 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = d = \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix} \rightarrow \begin{matrix} u + 3v - y = -2 \\ w + y = 1 \end{matrix} \rightarrow \begin{matrix} u = -2 - 3v + y \\ w = 1 - y \end{matrix}$$

$$\begin{matrix} u = -2 - 3v + y \\ v = v \\ w = 1 - y \\ y = y \end{matrix} \Rightarrow x = \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \end{bmatrix} + v \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + y \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}$$

Complete Solution of $Ax=b$: Summary

- If there are r pivots, there are r pivot variables and $n-r$ free variables.
- The number of pivots r is also called the *rank* of the $m \times n$ matrix A .

Summary: $Ax=b$ (A is $m \times n$) reduced to $Ux=c$ and $Rx=d$

1. If $r < m$, last $m-r$ rows of U are zero and the last $m-r$ components of c must be zero for the system to be solvable.
2. If $r=m$, there is always a solution.
3. The complete solution is the sum of a particular solution (with all free variables zero) and a nullspace solution (with the $n-r$ free variables as independent parameters).
4. If $r=n$, there are no free variables and the nullspace contains only $x=0$.
5. The number r is called the *rank* of the matrix A
 - If $r=n$, the only solution is $x_{\text{particular}}$.
 - If $r=m$, no constraints on b and the column space is \mathbb{R}^m .

Linear Independence

- The rank r counts the number of *linearly independent* rows in matrix A .
- If only the trivial combination gives zero, so that $c_1v_1 + \dots + c_kv_k = 0$ *only happens when* $c_1 = c_2 = \dots = c_k = 0$, then the vectors v_1, \dots, v_k are linearly independent. Otherwise they are linearly dependent and one of them is a linear combination of the others.
- A random choice of three vectors in \mathbb{R}^3 , without any special accident, should produce linear independence.
- Columns of the triangular matrix must be linearly independent.

Example: $A = \begin{bmatrix} 3 & 4 & 2 \\ 0 & 1 & 5 \\ 0 & 0 & 2 \end{bmatrix} \rightarrow c_1 \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix} + c_2 \begin{bmatrix} 4 \\ 1 \\ 0 \end{bmatrix} + c_3 \begin{bmatrix} 2 \\ 5 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$

By columns, the c_3 must first be zero, then $c_2=0$, then $c_1=0$.

- The r nonzero row of an echelon matrix U are linearly independent, and so are the r columns that contain pivots.
- A set of n vectors in \mathbb{R}^m must be linearly dependent if $n > m$

Spanning a Subspace by Basis

- If a vector space V consists of all linear combinations of the particular vectors w_1, w_2, \dots, w_l , then these vectors span the space. In other words, every vector v in V can be expressed as some combination of the w 's:

$$v = c_1 w_1 + \dots + c_l w_l \text{ for some coefficients } c_i.$$

- Column space of A = the space spanned by the columns
- e_1, e_2, \dots, e_n are not the only vectors that span \mathbb{R}^n !
- Independence involves the nullspace of A , and spanning involves the column space of A .
- A basis for a vector space is a set of vectors: (1) linearly independent (2) spanning the space.
- If $v = a_1 v_1 + \dots + a_k v_k$ and $v = b_1 v_1 + \dots + b_k v_k$, then $0 = (a_1 - b_1)v_1 + \dots + (a_k - b_k)v_k$. Every coeff. $a_i - b_i$ must be zero due to independence. A vector can uniquely expressed by a linear combination of a basis.
- A vector space has *infinitely many bases*.
- For U , the columns that contain pivots are a basis for the column space of U . But it is not the column space of A .

Dimension of a Vector Space

- All possible bases contain the same number of vectors. The number of vectors in bases expresses the number of degree of freedom of the space and is called the *dimension* of the space.

Proof: Let v_1, \dots, v_m and w_1, \dots, w_n , where $m < n$, be the bases for space V . Then, w_j can be expressed by the combination of v_i : $w_j = \sum_{i=1}^m a_{ij} v_i$. That is, $W = VA$ where w 's are columns of W and v 's are columns of V . Since $m < n$, $A_{m \times n} c = 0$ must have nontrivial solutions. This leads to $VAc = 0$ or $Wc = 0$. Since $c \neq 0$, columns in W are dependent! Contradiction.

- The dimension of the space \mathbb{R}^n is n .
- A basis is a maximal independent set and also a minimal spanning set of vectors.
- “basis of a matrix”, “rank of a space”, “dimension of a basis” are meaningless in linear algebra.
- Now, what is the relationship between the “*dimension of the column space*” and the “*rank of the matrix*”?

Four Fundamental Subspaces

Two ways of describing subspaces:

1. Space spanned by a given set of vectors (column space)

2. Space subject to a list of constraints (nullspace)

● Four subspaces of matrix A :

1. Column space, $\mathcal{R}(A)$

2. Nullspace, $\mathcal{N}(A)$

3. Row space or column space of A^T , $\mathcal{R}(A^T)$

4. Left nullspace or nullspace of A^T , $\mathcal{N}(A^T)$

● $\mathcal{N}(A)$ and $\mathcal{R}(A^T)$ are subspaces of \mathbb{R}^n

● $\mathcal{R}(A)$ and $\mathcal{N}(A^T)$ are subspace of \mathbb{R}^m

● It is easier to find subspaces of U instead of A .

● Problem: connect space for U to spaces for A .

Row Space of A

$$A = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 2 & 6 & 9 & 5 \\ -1 & -3 & 3 & 0 \end{bmatrix} \Rightarrow U = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

● Nonzero rows of U are independent (why?), and its row space has dimension r .

● *The row space of A has the same dimension r as the row space of U , and it has the same bases, because the two row spaces are the same.*

Reason: The rows in U are just combinations of the original rows in A . (Remember what Gaussian elimination does) And it is those combinations that make up the row space! The row space of U contains nothing new.

● Dimension of row space for $A = \text{rank of } A = r$

● $m-r$ rows should be discarded from A . But it is easier to discard rows in U than in A .

● For row space, we don't work with A^T . We work with the rows of A .

Nullspace of A

- Elimination process is to simplify the equations without changing any of the solutions even if $b=0$.
- Nullspace of A = solution space of $Ax=0$
 $=$ solution space of $Ux=0$ = nullspace of U
- Dimension of nullspace for $A = n-r$ = no. of free variables
 - Free variables are variables corresponding to the columns of U that do not contain pivots.
 - We give to each free variable the value 1, to the other free variables the value 0, and solve $Ux=0$.
 - We can therefore find $n-r$ vectors. The solution space is then form by the combinations of these $n-r$ vectors.
 - These $n-r$ vectors are the basis for $\mathcal{N}(A)$

$$Ux = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad x = \begin{bmatrix} -3v+y \\ v \\ -y \\ y \end{bmatrix} = v \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + y \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}$$

- The nullspace is also called the *kernel* of A .
- Its dimension $n-r$ is called the *nullity*.

Column Space of A

- Column space of A : range of A , x is in the domain and $f(x)$ is in the range. Here, $f(x)=Ax$. The range of $A = \mathcal{R}(A)$
- Range is the collection of all combinations of columns.
- Problem: $\mathcal{R}(U) \neq \mathcal{R}(A)$ but how to derive $\mathcal{R}(A)$ from $\mathcal{R}(U)$
- Dimension of $\mathcal{R}(U)$ =Dimension of $\mathcal{R}(A)$
- Basis of $\mathcal{R}(U)$ = columns with pivots \rightarrow the corresponding columns in A = Basis of $\mathcal{R}(A)$

Reason: Solutions of $Ux=0 \equiv$ Solutions of $Ax=0$

$$\text{If } x = \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix} \text{ is the solution then } [u_1] - [u_3] + [u_4] = 0 \text{ and}$$

$$[a_1] - [a_3] + [a_4] = 0$$

These are the dependence relationships among columns.

Dependence of columns of $U \equiv$ Dependence of columns of A

- Independent columns of $U \Leftrightarrow$ corresponding independent columns of A

Row Rank = Column Rank

- No. of independent columns = no. of independent rows

$$U = \begin{bmatrix} d_1 & * & * & * & * & * \\ 0 & 0 & 0 & d_2 & * & * \\ 0 & 0 & 0 & 0 & 0 & d_3 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

- Rank = $r \Rightarrow m-r$ rows are zero rows \Rightarrow only r nonzero components in columns \Rightarrow only r columns are indep.

$$c_1 \begin{bmatrix} d_1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + c_2 \begin{bmatrix} * \\ d_2 \\ 0 \\ 0 \end{bmatrix} + c_3 \begin{bmatrix} * \\ * \\ d_3 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow c_3, c_2 \text{ and } c_1 \text{ must be zero}$$

The three columns with pivots must be independent.

- $Ux=0$ if and only if $Ax=0 \Rightarrow$ The corresponding columns in A are also the basis for $\mathcal{N}(A)$
- For both $\mathcal{N}(A^T)$ and $\mathcal{N}(A)$, we only work with A and perform elimination on A .
- $\mathcal{N}(A^T)$ and $\mathcal{N}(A)$ have the same dimension and can be found at the same time from U .

Left Nullspace of A

- $\mathcal{N}(A^T) \rightarrow$ nullspace of $A^T \rightarrow A^T y = 0 \rightarrow y^T A = 0 \rightarrow$ left

nullspace of A

$$y^T A = [y_1 \quad \cdots \quad y_m] \begin{bmatrix} A \\ \end{bmatrix} = [0 \quad \cdots \quad 0]$$

- y^T is an operation performed on rows of A to give zeros
- Dimension of column space + dimension of nullspace = number of columns
- For A^T , there are m columns:

$$\text{Dimension of } \mathcal{N}(A^T) + \text{dimension of } \mathcal{R}(A^T) = m \Rightarrow$$

- Dimension of $\mathcal{N}(A^T) = m-r$
- Find y ?

$$1. PA=LU \quad 2. L^{-1}PA=U$$

3. The last $m-r$ rows of $L^{-1}P$ multiply A to give $m-r$ zero rows in U . These last $m-r$ rows of $L^{-1}P$ are the basis for $\mathcal{N}(A^T)$

$$L^{-1}PAx = Ux = \begin{bmatrix} 1 & 3 & 3 & 2 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ y \end{bmatrix} = L^{-1}Pb = \begin{bmatrix} b_1 \\ b_2 - 2b_1 \\ b_3 - 2b_2 + 5b_1 \end{bmatrix} \rightarrow \begin{matrix} m-r = 3-2 = 1 \\ y = [5 \quad -2 \quad 1] \end{matrix}$$

Summary of Subspaces

Fundamental Theorem of Linear Algebra, Part I

1. $\mathcal{R}(A)$ = column space of A ; dimension r
2. $\mathcal{N}(A)$ = nullspace of A ; dimension $n-r$
3. $\mathcal{R}(A^T)$ = row space of A ; dimension r
4. $\mathcal{N}(A^T)$ = left nullspace of A ; dimension $m-r$

Example:

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 6 \end{bmatrix}, m=n=2, r=1 \rightarrow$$

$$L^{-1}A = \begin{bmatrix} 1 & 0 \\ -3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 6 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix} = U$$

1. column space: $c \begin{bmatrix} 1 \\ 3 \end{bmatrix}$
2. nullspace: $c \begin{bmatrix} -2 \\ 1 \end{bmatrix}$
3. row space: $c \begin{bmatrix} 1 \\ 2 \end{bmatrix}$
4. left nullspace: $c \begin{bmatrix} -3 \\ 1 \end{bmatrix}$

Existence of Inverses

- If A has a left inverse and a right inverse, then

$$B=BI=B(AC)=(BA)C=IC=C$$

- An inverse exists only when the rank is as large as possible
- What we like to explain (prove):

$$1. r=m (m \leq n) \rightarrow \text{a right-inverse exist} \rightarrow A_{m \times n} C_{n \times m} = I_{m \times m}$$

There exists *at least* one solution for $Ax=b$

$$2. r=n (n \leq m) \rightarrow \text{a left-inverse exist} \rightarrow B_{n \times m} A_{m \times n} = I_{n \times n}$$

If there exist solution for $Ax=b$, the solution is unique

- One proof:

$$\text{Let } B=(A^T A)^{-1} A^T \text{ and } C=A^T (A A^T)^{-1}.$$

We will prove $(A^T A)^{-1}$ exists if the rank= n and $(A A^T)^{-1}$ exists if the rank= m in Chapter 3.

- Another approach:

$$AC=I \quad \text{or} \quad A \begin{bmatrix} x_1 & x_2 & \cdots & x_m \end{bmatrix} = \begin{bmatrix} e_1 & e_2 & \cdots & e_m \end{bmatrix}$$

Look at every $Ax_i=e_i$: To have solutions x_i 's, all e_i 's must be in the column space of A . But e_1, e_2, \dots, e_m fill up the entire \mathbb{R}^m space. That is, column space of A must fill up the space of $\mathbb{R}^m \rightarrow r=m$.

Existence of Inverses – Example 1

Example 1: $A = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 5 & 0 \end{bmatrix} \rightarrow r=m=2$

$$AC = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 5 & 0 \end{bmatrix} \begin{bmatrix} 1/4 & 0 \\ 0 & 1/5 \\ c_{31} & c_{32} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where c_{31} and c_{32} can be chosen arbitrarily.

→ There are many right-inverses!

- For solution of $Ax=b$: Substitute $x=Cb \Rightarrow Ax=ACb=Ib=b$

$$x = Cb = \begin{bmatrix} 1/4 & 0 \\ 0 & 1/5 \\ c_{31} & c_{32} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} b_1/4 \\ b_2/5 \\ c_{31}b_1 + c_{32}b_2 \end{bmatrix}$$

Solutions exist but are not unique

$$C = A^T(AA^T)^{-1} = \begin{bmatrix} 4 & 0 \\ 0 & 5 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1/16 & 0 \\ 0 & 1/25 \end{bmatrix} = \begin{bmatrix} 1/4 & 0 \\ 0 & 1/5 \\ 0 & 0 \end{bmatrix}$$

- In this formula, $c_{31}=c_{32}=0 \rightarrow$ pseudoinverse

Existence of Inverses – Example 2

Example 2: $A = \begin{bmatrix} 4 & 0 \\ 0 & 5 \\ 0 & 0 \end{bmatrix} \rightarrow r=n=2$

$$BA = \begin{bmatrix} 1/4 & 0 & \beta_{13} \\ 0 & 1/5 & \beta_{23} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 5 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where β_{13} and β_{23} can be chosen arbitrarily.

→ many left-inverses

- For $Ax=b$, $Ax = \begin{bmatrix} 4 & 0 \\ 0 & 5 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$

→ solvable only if $b_3=0 \Rightarrow \begin{bmatrix} 4 & 0 \\ 0 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$

- Solution: $BAx=Bb \Rightarrow Ix=Bb \Rightarrow x=Bb$

$$x = Bb = \begin{bmatrix} 1/4 & 0 & \beta_{13} \\ 0 & 1/5 & \beta_{23} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{4}b_1 + \beta_{13}b_3 \\ \frac{1}{5}b_2 + \beta_{23}b_3 \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{4}b_1 \\ \frac{1}{5}b_2 \\ 0 \end{bmatrix}$$

→ If the solution exists, it must be unique!

Inverse of Square Matrix A

- *Existence implies uniqueness and uniqueness implies existence, when the matrix is square $\rightarrow r = m = n$*
 - Square matrix A invertible (nonsingular): sufficient and necessary test list
1. The columns span \mathbb{R}^m , so $Ax=b$ has at least one solution for every b .
 2. The columns are independent, so $Ax=0$ has only the solution $x=0$.
 3. The rows of A span \mathbb{R}^n .
 4. The rows are linearly independent.
 5. Elimination can be completed: $PA=LDU$, with all $d_i \neq 0$
 6. There exists a matrix A^{-1} such that $AA^{-1}=A^{-1}A=I$.
 7. The determinant of A is not zero.
 8. Zero is not an eigenvalue of A .
 9. $A^T A$ is positive definite

Vandermonde Matrix

- For any unknown function $f(t)$, if we can make n observations: $f(t_1)=b_1, f(t_2)=b_2, \dots, f(t_n)=b_n$, then we can find exactly one polynomial function of degree $n-1$ to fit these observations.

That is,
$$\begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^{n-1} \\ 1 & t_2 & t_2^2 & \cdots & t_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_n & t_n^2 & \cdots & t_n^{n-1} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$
 has only one

solution \Rightarrow
$$\begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^{n-1} \\ 1 & t_2 & t_2^2 & \cdots & t_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_n & t_n^2 & \cdots & t_n^{n-1} \end{bmatrix}$$
 must be nonsingular

(called *Vandermonde's matrix*.)

- Another perspective: A polynomial $P(t)$ of degree $n-1$ can have at most $n-1$ roots ($P(t)=0$). If there exist n points t_1, t_2, \dots, t_n that make $P(t_i)=0$, then this polynomial must be $0 + 0t + 0t^2 + \cdots + 0t^{n-1}$.

If
$$\begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^{n-1} \\ 1 & t_2 & t_2^2 & \cdots & t_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_n & t_n^2 & \cdots & t_n^{n-1} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$
 then
$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Matrices of Rank One

$$A = \begin{bmatrix} 2 & 1 & 1 \\ 4 & 2 & 2 \\ 8 & 4 & 4 \\ -2 & -1 & -1 \end{bmatrix}$$

\Rightarrow

$$A = \begin{bmatrix} 2 & 1 & 1 \\ 4 & 2 & 2 \\ 8 & 4 & 4 \\ -2 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 \\ 4 & 0 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \\ -1 \end{bmatrix} \begin{bmatrix} 2 & 1 & 1 \end{bmatrix}$$

- For any matrix of rank one:

Every matrix of rank one has the simple form $A=uv^T$

- The rows of A are all multiples of the same vector v^T
- The columns of A are all multiples of the same vector u
- The row space and column space are lines.