Linear Algebra

Hechen Hu

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Solving Linear Equations

1.1 Systems of Linear Equations

Definition. A *linear equation* in the variables $x_1, \cdots, x_n$ is an equation that can be written in the form

$$a_1x_1 + a_2x_2 + \cdots + a_nx_n = b$$

where b and coefficients a_i are real or complex numbers. A *linear system* is a collection of one or more linear equations involving the same variables. A *solution* of the system is a list of numbers that makes each equation a true statement when their values are substituted for $x_1, \cdots, x_n$ respectively. The set of all possible solutions is called the *solution set* of the linear system. Two linear systems are called *equivalent* if they have the same solution set.

Definition. A linear system is *consistent* if it has either one solution or infinitely many solutions. If it has no solution, it is called *inconsistent*.

Definition. The *coefficient matrix* is the matrix where the coefficients of each variable in a system aligned in columns. If additionally the coefficient of the right-hand side of equations are added to the coefficient matrix, a new matrix called *augmented matrix* is generated.

Definition. *Elementary row operations* on a matrix include:

- (*Replacement*) Replace one row by the sum of itself and a multiple of another row.
- (*Interchange*) Interchange two rows.
- (*Scaling*) Multiply all entries in a row by a nonzero constant.

Two matrices are *row equivalent* if there is a sequence of elementary operations that transforms one matrix into the other.

Theorem 1.1.1. *If the augmented matrices of two linear systems are row equivalent, then the two systems have the same solution set.*

1.2 Row Reduction and Echelon Forms

Definition. A rectangular matrix is in *echelon form* if it has the following properties:

- All nonzero rows are above any rows of all zeros;
- Each leading entry of a row is in a column to the right of the leading entry of the row above it;
- All entries in a column below a leading entry are zero.

If a matrix in echelon form satisfies the following additional conditions, then it is in *reduced echelon form*:

- The leading entry in each nonzero row is 1;
- Each leading 1 is the only nonzero entry in its column.

Theorem 1.2.1. *Each matrix is row equivalent to an unique reduced echelon matrix.*

If a matrix A is row equivalent to an (reduced)echelon matrix U, U is called an *(reduced) echelon form of A*. The abbreviation RREF and REF are used for reduced (row) echelon form and (row) echelon form respectively.

Definition. A *pivot position* in a matrix A is a location in A that corresponds to a leading entry in an echelon form of A. A *pivot column* is a column of A that contains a pivot position.

Theorem 1.2.2. *A linear system is consistent iff the rightmost column of the augmented matrix* ***is not*** *a pivot column, that is, iff an echelon form of the augmented matrix has* ***no*** *row of the form*

$$\begin{bmatrix} 0 & \cdots & 0 & b \end{bmatrix} \qquad \textit{with } b \textit{ nonzero}$$

If a linear system is consistent, then the solution set contains either

- *a unique solution, when there are no free variables.*
- *infinitely many solutions, when there is at least one free variable.*

1.3 Vector Equations

Definition. A matrix with only one column is called a *column vector*, or simply a *vector*.

Definition. Given vectors $\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_p$ in $\mathbb{R}^n$ and given scalars $c_1, c_2, \cdots, c_p$, the vector $\mathbf{y}$ defined by

$$\mathbf{y} = c_1\mathbf{v}_1 + \cdots + c_p\mathbf{v}_p$$

is called a *linear combination of* $\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_p$ *using weights* $c_1, c_2, \cdots, c_p$.

Definition. If $\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_p$ are in $\mathbb{R}^n$, then the set of all linear combinations of them is denoted by $\mathrm{Span}\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ and is called the *subset of* $\mathbb{R}^n$ *spanned (or generated) by* $\mathbf{v}_1, \cdots, \mathbf{v}_p$. That is, $\mathrm{Span}\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ is the collection of all vectors that can be written in the form

$$c_1\mathbf{v}_1 + \cdots + c_p\mathbf{v}_p$$

with $c_1, c_2, \cdots, c_p$ scalars.

1.4 The Matrix Equation $\mathbf{Ax} = \mathbf{b}$

Definition. If $\mathbf{A}$ is an $m \times n$ matrix, with columns $a_1, \cdots, a_n$, and if $\mathbf{x}$ is in $\mathbb{R}^n$, then the *product of* $\mathbf{A}$ *and* $\mathbf{x}$, denoted by $\mathbf{Ax}$, is the *linear combination of the columns of* $\mathbf{A}$ *using the corresponding entries in* $\mathbf{x}$ *as weights*, that is,

$$\mathbf{Ax} = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} \begin{bmatrix} x_1 \\ \cdots \\ x_n \end{bmatrix} = x_1a_1 + x_2a_2 + \cdots + x_na_n$$

$\mathbf{Ax}$ is defined only if the number of columns of $\mathbf{A}$ equals the number of entries in $\mathbf{x}$.

Definition. Equations having the form $\mathbf{Ax} = \mathbf{b}$ are called *matrix equations*.

Theorem 1.4.1. *If* $\mathbf{A}$ *is an* $m \times n$ *matrix, with columns* $a_1, \cdots, a_n$*, and* $\mathbf{b}$ *is in* $\mathbb{R}^m$*, the matrix equation*

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

has the same solution set as the vector equation

$$x_1a_1 + x_2a_1 + \cdots + x_na_n = \mathbf{b}$$

which has the same solution set as the system of linear equations whose augmented matrix is

$$\begin{bmatrix} a_1 & a_2 & \cdots & a_n & \mathbf{b} \end{bmatrix}$$

Definition. A set of vectors $\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ in $\mathbb{R}^m$ *spans (or generates)* $\mathbb{R}^m$ if $\mathrm{Span}\{\mathbf{v}_1, \cdots, \mathbf{v}_p\} = \mathbb{R}^m$.

Theorem 1.4.2. *Let* $\mathbf{A}$ *be an* $m \times n$ *coefficient matrix. Then the following statements are logically equivalent, that is, for a particular* $\mathbf{A}$*, either they are all true statements or they are all false.*

- *For each* $\mathbf{b}$ *in* $\mathbb{R}^m$*, the equation* $\mathbf{Ax} = \mathbf{b}$ *has a solution.*
- *The columns of* $\mathbf{A}$ *spans* $\mathbb{R}^m$*.*
- $\mathbf{A}$ *has a pivot position in every row.*

Theorem 1.4.3. *If* $\mathbf{A}$ *is an* $m \times n$ *matrix,* $\mathbf{u}$ *and* $\mathbf{v}$ *are vectors in* $\mathbb{R}^n$*, and* c *is a scalar, then*

- $\mathbf{A}(\mathbf{u} + \mathbf{v}) = \mathbf{Au} + \mathbf{Av}$.
- $\mathbf{A}(c\mathbf{u}) = c(\mathbf{Au})$.

1.5 Solution Sets of Linear Systems

Definition. A system of Linear equations is said to be *homogeneous* if it can be written in the form $\mathbf{Ax} = \mathbf{0}$. Such a system always has at least one solution, namely, $\mathbf{x} = \mathbf{0}$, and this solution is usually called the *trivial solution.* A homogeneous equation has a nontrivial solution iff the equation has at least one free variable.

Definition. Vector addition can be considered as a *translation.* e.g. the vector $\mathbf{v}$ is *translated by* $\mathbf{p}$ to $\mathbf{v} + \mathbf{p}$.

Definition. A *parametric vector equation* can be written as

$$\mathbf{x} = s\mathbf{u} + t\mathbf{v} \qquad (s, t \in \mathbb{R})$$

which describes explicitly the spanned plane by $\mathbf{u}$ and $\mathbf{v}$. Whenever a solution set is described explicitly with vectors, we say that the solution is in *parametric vector form.*

Theorem 1.5.1. *Suppose the equation* $\mathbf{Ax} = \mathbf{b}$ *is consistent for some given* $\mathbf{b}$*, and let* $\mathbf{p}$ *be a nonzero solution. Then the solution set of it is the set of all vectors of the form* $\mathbf{w} = \mathbf{p} + \mathbf{v}_h$*, where* $\mathbf{v_h}$ *is any solution of the homogeneous equation* $\mathbf{Ax} = \mathbf{0}$*.*

1.6 Linear Independence

Definition. An indexed set of vectors $\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ in $\mathbb{R}^n$ is said to be *linearly independent* if the vector equation

$$x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_p\mathbf{v}_p = \mathbf{0}$$

has only the trivial solution. The set $\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ is said to be *linearly dependent* if there exist weights $c_1, \cdots, c_p$, not all zero, such that

$$c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \cdots + c_p\mathbf{v}_p = \mathbf{0}$$

and this equation is called a *linear dependence relation* among $\mathbf{v}_1, \cdots, \mathbf{v}_p$.

Theorem 1.6.1. *The columns of a matrix $\mathbf{A}$ are linearly independent iff the equation $\mathbf{A}\mathbf{x} = \mathbf{0}$ has **only** the trivial solution.*

Theorem 1.6.2. *A set of two vectors $\{\mathbf{v}_1, \mathbf{v}_2\}$ is linearly dependent iff one of the vectors is a multiple of the other.*

Theorem 1.6.3. *An indexed set $S = \{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ of two or more vectors is linearly dependent iff at least one of the vectors in S is a linear combination of the others.*

Theorem 1.6.4. *Any set $\{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ in $\mathbb{R}^n$ is linearly dependent if $p > n$(Same as the criterion for the existence of solutions in a system of equations).*

Theorem 1.6.5. *If a set $S = \{\mathbf{v}_1, \cdots, \mathbf{v}_p\}$ in $\mathbb{R}^n$ contains the zero vector, then the set is linearly dependent.*

1.7 Linear Transformations

Definition. A *transformation*(or *function* or *mapping*) from $\mathbb{R}^n$ to $\mathbb{R}^m$ is a rule that assigns to each vector $\mathbf{x} \in \mathbb{R}^n$ a vector $T(\mathbf{x}) \in \mathbb{R}^m$. $\mathbb{R}^n$ is called the *domain* of T, and $\mathbb{R}^m$ is called the *codomain* of T. For $\mathbf{x} \in \mathbb{R}^n$, the vector $T(\mathbf{x}) \in \mathbb{R}^m$ is called the *image* of $\mathbf{x}$ under T. The set of all images $T(\mathbf{x})$ is called the *range* of T.

***Example* 1.1.** *Given a scalar r, define $T : \mathbb{R}^2 \to \mathbb{R}^2$ by $T(\mathbf{x}) = r\mathbf{x}$. T is called a contraction when $0 \leqslant r \leqslant 1$ and a dilation when $r > 1$.*

Theorem 1.7.1. *Let $T : \mathbb{R}^n \to \mathbb{R}^m$ be a linear transformation. Then there exists a unique matrix $\mathbf{A}$ such that*

$$T(\mathbf{x}) = \mathbf{A}\mathbf{x} \quad \forall \mathbf{x} \in \mathbb{R}^n$$

In fact, $\mathbf{A}$ is the $m \times n$ matrix whose jth column is the vector $T(\mathbf{e}_j)$, where $\mathbf{e}_j$ is the jth column of the identity matrix in $\mathbb{R}^n$.

$$\mathbf{A} = \begin{bmatrix} T(\mathbf{e}_1) & \cdots & T(\mathbf{e}_n) \end{bmatrix}$$

The matrix $\mathbf{A}$ is called the standard matrix for the linear transformation T.

Theorem 1.7.2. *Let $T : \mathbb{R}^n \to \mathbb{R}^m$ be a linear transformation. Then T is injective iff the equation $T(\mathbf{x}) = \mathbf{0}$ has only the trivial solution.*

Theorem 1.7.3. *Let $T : \mathbb{R}^n \to \mathbb{R}^m$ be a linear transformation and let $\mathbf{A}$ be the standard matrix for T. Then*

- *T is surjective iff the columns of $\mathbf{A}$ span $\mathbb{R}^m$;*
- *T is injective iff the columns of $\mathbf{A}$ are linearly independent.*

Definition. If there is a matrix $\mathbf{A}$ such that

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k \quad \text{for } k = 0, 1, 2, \cdots$$

then the equation above is called a *linear difference equation* (or *recurrence relation*).

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Matrices

2.1 Matrices and Arithmetic Operations on Them

Definition. A *diagonal matrix* is a square matrix whose nondiagonal entries are zero.

Definition. Two matrices are equal if they have the same size and each entries are equal.

Definition. The *sum* of two matrices is the sum of each corresponding entries in these two matrices. Thus the sum is defined only when they have the same size.

Definition. The *scalar multiple* of a matrix has entries of the product of the scalar and each corresponding original entries.

Theorem 2.1.1. *The set of matrices of the same size with respect to matrix addition and scalar multiplication over the field of real numbers is a vector space.*

Definition. A square matrix is called *lower triangular* if all the entries above the main diagonal are zero. Similarly, a square matrix is called *upper triangular* if all the entries below the main diagonal are zero. A triangular matrix is one that is either lower triangular or upper triangular. A matrix that is both upper and lower triangular is called a *diagonal matrix*.

Definition. If $\mathbf{A}$ is an $m \times n$ matrix, and if $\mathbf{B}$ is an $n \times p$ matrix with columns $\mathbf{b}_1, \cdots, \mathbf{b}_p$, then the *product* $\mathbf{AB}$ is the $m \times p$ matrix whose columns are $\mathbf{Ab}_1, \cdots, \mathbf{Ab}_p$. Multiplication of matrices corresponds to composition of linear transformations.

Theorem 2.1.2. *The multiplication has the following properties:*

- *Associativity of multiplication;*

- *Left distribution;*
- *Right distribution;*
- *Associativity over scalar multiplication;*
- *Identity for matrix multiplication; i.e. If* $\mathbf{A}$ *is a matrix of size* $m \times n$*, then*
$$\mathbf{I}_m\mathbf{A} = \mathbf{A} = \mathbf{A}\mathbf{I}_n$$
where $\mathbf{I}_n$ *is the* $n \times n$ *identity matrix.*

Definition. In general, matrix multiplication is not commutative and the cancellation law do not hold. When two matrices' multiplication is commutative, they are said to be *commute* with one another. Also, if a product $\mathbf{AB}$ is the zero matrix, in general it does not mean that either $\mathbf{A} = \mathbf{0}$ or $\mathbf{B} = \mathbf{0}$.

Definition. If $\mathbf{A}$ is an $m \times n$ matrix and k is a positive integer, then $\mathbf{A}^k$ denoted the product of k copies of $\mathbf{A}$, i.e. the kth power of $\mathbf{A}$. The 0th power of a matrix is the identity matrix.

Definition. If $\mathbf{A}$ is an $m \times n$ matrix, the *transpose* of $\mathbf{A}$ is the $n \times m$ matrix, denoted $\mathbf{A}^T$, whose columns are formed from the corresponding rows of $\mathbf{A}$.

Theorem 2.1.3. *The transpose operation has the following properties:*

- $(\mathbf{A}^T)^T = \mathbf{A}$*;*
- $(\mathbf{A} + \mathbf{B})^T = \mathbf{A}^T + \mathbf{B}^T$*;*
- *Associativity with scalar multiplication;*
- $(\mathbf{AB})^T = \mathbf{B}^T\mathbf{A}^T$*, that is, the transpose of a product of arbitrary number of matrices equals the product of their transpose in the reverse order.*

2.2 The Inverse of a Matrix

Definition. If $\mathbf{A}$ is an $n \times n$ matrix, then if

$$\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}_n$$

we say that $\mathbf{A}$ is *invertible* and $\mathbf{A}^{-1}$ an *inverse* of $\mathbf{A}$. The inverse of a matrix is unique. If a matrix is not invertible, it is called a *singular matrix.*

Theorem 2.2.1. *A matrix* $\mathbf{A}$ *is invertible only if* $\det(\mathbf{A}) \neq 0$*, and in this case*

$$\mathbf{A}^{-1} = \frac{1}{\det(\mathbf{A})}\,\mathrm{Adj}(\mathbf{A})$$

Theorem 2.2.2. *If* $\mathbf{A}$ *is an invertible* $n \times n$ *matrix, then for each* $\mathbf{b} \in \mathbb{R}^n$*, the equation* $\mathbf{Ax} = \mathbf{b}$ *has the unique solution* $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$*.*

Theorem 2.2.3.

- *The inverse of the inverse of a invertible matrix is the matrix itself.*
- *The inverse of the product of arbitrary number of invertible square matrices is the product of the inverse of themselves multiplied in the reverse order.*
- *The transpose of a invertible matrix is also invertible. Moreover, the inverse of a matrix's transpose is the transpose of the matrix's inverse.*

Definition. An *elementary matrix* is a matrix obtained by performing a single elementary row operation on a identity matrix.

Theorem 2.2.4. *If an elementary row operations is performed on an* $m \times n$ *matrix* $\mathbf{A}$*, the resulting matrix can be written as* $\mathbf{EA}$*, where the* $m \times m$ *matrix* $\mathbf{E}$ *is created by performing the same row operation on* $\mathbf{I}_m$*.*

Theorem 2.2.5. *Each elementary matrix* $\mathbf{E}$ *is invertible. The inverse of* $\mathbf{E}$ *is the elementary matrix of the same type that transforms* $\mathbf{E}$ *back into* $\mathbf{I}$*.*

Theorem 2.2.6. *An* $n \times n$ *matrix* $\mathbf{A}$ *is invertible iff* $\mathbf{A}$ *is a row equivalent to* $\mathbf{I}_n$*, and in this case, any sequence of elementary row operations that reduces* $\mathbf{A}$ *to* $\mathbf{I}_n$ *also transforms* $\mathbf{I}_n$ *into* $\mathbf{A}^{-1}$*.*

Theorem 2.2.7. *Let* $\mathbf{A}$ *be a square* $n \times n$ *matrix. Then the following statements are equivalent.*

- $\mathbf{A}$ *is an invertible matrix.*
- $\mathbf{A}$ *is row equivalent to the* $n \times n$ *identity matrix.*
- $\mathbf{A}$ *has n pivot positions.*

- *The equation* $\mathbf{Ax} = \mathbf{0}$ *has only the trivial solution.*
- *The columns of* $\mathbf{A}$ *form a linearly independent set.*
- *The linear transformation* $\mathbf{x} \mapsto \mathbf{Ax}$ *is injective.*

- *The equation* $\mathbf{Ax} = \mathbf{b}$ *has at least one solution for each* $\mathbf{b}$ *in* $\mathbb{R}^n$*.*
- *The columns of* $\mathbf{A}$ *span* $\mathbb{R}^n$*.*

- *The linear transformation* $\mathbf{x} \mapsto \mathbf{A}\mathbf{x}$ *maps* $\mathbb{R}^n$ *onto* $\mathbb{R}^n$.

- *There is an* $n \times n$ *matrix* $\mathbf{C}$ *such that* $\mathbf{CA} = \mathbf{I}$.
- *There is an* $n \times n$ *matrix* $\mathbf{D}$ *such that* $\mathbf{AD} = \mathbf{I}$.
- $\mathbf{A}^T$ *is an invertible matrix.*

Proposition. Let $\mathbf{A}$ and $\mathbf{B}$ be square matrices. If $\mathbf{AB} = \mathbf{I}$, then $\mathbf{A}$ and $\mathbf{B}$ are both invertible, with $\mathbf{B} = \mathbf{A}^{-1}$ and $\mathbf{A} = \mathbf{B}^{-1}$

Definition. A linear transformation $T : \mathbb{R}^n \to \mathbb{R}^n$ is *invertible* if there exists a function $S : \mathbb{R}^n \to \mathbb{R}^n$ such that

$$\begin{aligned} (\forall \mathbf{x} \in \mathbb{R}^n) \quad S(T(\mathbf{x})) = \mathbf{x} \\ (\forall \mathbf{x} \in \mathbb{R}^n) \quad T(S(\mathbf{x})) = \mathbf{x} \end{aligned}$$

and S is called the *inverse* of T and denoted T^{-1}.

Theorem 2.2.8. *A linear transformation is invertible iff its standard matrix is invertible. In this case its inverse is unique.*

Theorem 2.2.9. *If* $\mathbf{A}$ *is* $m \times n$ *and* $\mathbf{B}$ *is* $n \times p$*, then*

$$\begin{aligned} \mathbf{AB} &= \begin{bmatrix} \mathrm{Col}_1(\mathbf{A}) & \mathrm{Col}_2(\mathbf{A}) & \cdots & \mathrm{Col}_n(\mathbf{A}) \end{bmatrix} \begin{bmatrix} \mathrm{Row}_1(\mathbf{B}) \\ \mathrm{Row}_2(\mathbf{B}) \\ \vdots \\ \mathrm{Row}_n(\mathbf{B}) \end{bmatrix} \\ &= \mathrm{Col}_1(\mathbf{A})\,\mathrm{Row}_1(\mathbf{B}) + \cdots \mathrm{Col}_n(\mathbf{A})\,\mathrm{Row}_n(\mathbf{B}) \end{aligned}$$

Definition. A *block matrix* is a partitioned matrix with zero blocks off the main diagonal. Such matrix is invertible iff each block on the diagonal is invertible.

Definition. A *factorization* of a matrix is an equation that expresses it as a product of two or more matrices.

Definition. An square matrix is said to be *strictly diagonally dominant* if the absolute of each diagonal entry exceeds the sum of the absolute values of the other entries in the same row.

2.3 Subspaces of $\mathbb{R}^n$

Definition. A *subspace* of $\mathbb{R}^n$ is any set $H \in \mathbb{R}^n$ that has three properties:

- The zero vector is in H;
- For each vector $\mathbf{u}$ and $\mathbf{v}$ in H, their sum is in H (addition is closed on H);
- For each $\mathbf{u}$ in H and each scalar c, the vector $c\mathbf{u}$ is in H (scalar multiplication is closed on H).

Definition. The *column space* of a matrix $\mathbf{A}$ is the set $\operatorname{Col}\mathbf{A}$ of all linear combinations of the columns of $\mathbf{A}$.

Definition. The *null space* of a matrix $\mathbf{A}$ is the set $\operatorname{Nul}\mathbf{A}$ of all solutions to the homogeneous equation $\mathbf{Ax} = \mathbf{0}$.

Theorem 2.3.1. *The null space of a $m \times n$ matrix is a subspace of $\mathbb{R}^n$.*

Definition. A *basis* for a subspace H of $\mathbb{R}^n$ is a linearly independent set in H that spans H.

***Example* 2.1.** *The standard basis for $\mathbb{R}^n$ are vectors $\mathbf{e}_1, \cdots, \mathbf{e}_n$, where*

$$\mathbf{e}_1 = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \cdots, \mathbf{e}_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$$

Theorem 2.3.2. *The pivot columns of a matrix $\mathbf{A}$ form a basis for the column space of $\mathbf{A}$.*

Definition. Suppose the set $\mathcal{B} = \{\mathbf{b}_1, \cdots, \mathbf{b}_p\}$ is the basis for a subspace H. For each $\mathbf{x} \in H$, the *coordinates of $\mathbf{x}$ relative to the basis $\mathcal{B}$* are the weights $c_1, \cdots, c_p$ such that $\mathbf{x} = c_1\mathbf{b}_1 + \cdots + c_p\mathbf{b}_p$, and the vector in $\mathbb{R}^p$

$$[\mathbf{x}]_{\mathcal{B}} = \begin{bmatrix} c_1 \\ \cdots \\ c_p \end{bmatrix}$$

is called the *coordinate vector of $\mathbf{x}$ relative to $\mathcal{B}$.*

Definition. The *dimension* of a nonzero subspace H, denoted by $\dim H$, is the number of vectors in any basis for H. The dimension of the zero subspace $\{\mathbf{0}\}$ is defined to be zero.

Definition. The *rank* of a matrix $\mathbf{A}$, denoted by $\operatorname{rank}\mathbf{A}$, is the dimension of the column space of $\mathbf{A}$.

Theorem 2.3.3 (The Rank Theorem)**.** *If a matrix $\mathbf{A}$ has n columns, then* $\operatorname{rank}\mathbf{A} + \dim\operatorname{Nul}\mathbf{A} = n$.

Theorem 2.3.4 (The Basis Theorem)**.** *Let H be a p-dimensional subspace of $\mathbb{R}^n$. Any linearly independent set of exactly p elements in H is automatically a basis for H. Also, any set of p elements of H that spans H is a basis for H.*

3

Determinants

3.1 Determinants and some other Concepts

Definition. The *determinant* of the matrix $\mathbf{A}$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

denoted $\det \mathbf{A}$ and equals $ad - bc$. Determinant is only defined for a square matrix, but the procedure above can be repeated on higher dimension matrices, for example

$$\det \begin{bmatrix} a & b & c & d \\ e & f & g & h \\ i & j & k & l \\ m & n & o & p \end{bmatrix} = a \det \begin{bmatrix} f & g & h \\ j & k & l \\ n & o & p \end{bmatrix} - b \det \begin{bmatrix} e & g & h \\ i & k & l \\ m & o & p \end{bmatrix} + c \det \begin{bmatrix} e & f & h \\ i & j & l \\ m & n & p \end{bmatrix} - d \det \begin{bmatrix} e & f & g \\ i & j & k \\ m & n & o \end{bmatrix}$$

By the Leibniz formula for the determinant of an $n \times n$ matrix $\mathbf{A}$ is

$$\det(\mathbf{A}) = \sum_{\sigma \in S_n} (\operatorname{sgn}(\sigma) \prod_{i=1}^{n} a_{i,\sigma_i})$$

Here the sum is computed over all permutations σ of the set $\{1, 2, \ldots, n\}$. A permutation is a function that reorders this set of integers. The value in the ith position after the reordering σ is denoted by σ_i. For example, for $n = 3$, the original sequence $1, 2, 3$ might be reordered to $\sigma = [2, 3, 1]$, with $\sigma_1 = 2$, $\sigma_2 = 3$, and $\sigma_3 = 1$. The set of all such permutations (also known as the symmetric group on n elements) is denoted by S_n.
For each permutation σ, $\operatorname{sgn}(\sigma)$ denotes the signature of σ, a value that is $+1$ whenever the reordering given by σ can be achieved by successively interchanging two entries an even number of times, and -1 whenever it can be achieved by an odd number of such interchanges.

Definition. If $\mathbf{A}$ is a square matrix, then the *minor* of the entry in the i-th row and j-th column (also called the (i, j) *minor*, or a *first minor*) is the determinant of the submatrix formed by deleting the i-th row and j-th column. This number is often denoted $M_{i,j}$. The (i, j) *cofactor* is obtained by multiplying the minor by $(-1)^{i+j}$ and is denoted $C_{i,j}$.

In general, let A be an $m \times n$ matrix and k an integer with $0 < k \leqslant m$, and $k \leqslant n$. A $k \times k$ minor of $\mathbf{A}$, also called minor determinant of order k of $\mathbf{A}$ or, if $m = n$, $(n-k)$th minor determinant of $\mathbf{A}$, is the determinant of a $k \times k$ matrix obtained from $\mathbf{A}$ by deleting $m - k$ rows and $n - k$ columns.

Definition. The matrix formed by all of the cofactors of a square matrix A is called the *cofactor matrix*.

Definition. The *adjugate* is the transpose of the cofactor matrix of it, that is, if $\mathbf{A}$ is a matrix and $\mathbf{C}$ is its cofactor matrix, then

$$\mathrm{Adj}(\mathbf{A}) = \mathbf{C}^T$$

Theorem 3.1.1. *For a matrix* $\mathbf{A}$

$$\mathbf{A}\,\mathrm{Adj}(\mathbf{A}) = \det(\mathbf{A})\mathbf{I}$$

Theorem 3.1.2. *The determinant of an square matrix can be computed by a cofactor expansion across any row or down any column. The expansion across the ith row is*

$$\det \mathbf{A} = a_{i1}C_{i1} + \cdots + a_{in}C_{in}$$

Theorem 3.1.3. *If* $\mathbf{A}$ *is a triangular matrix, then* $\det \mathbf{A}$ *is the product of the entries on the main diagonal of* $\mathbf{A}$.

3.2 Properties of Determinants

Theorem 3.2.1. *Let* $\mathbf{A}$ *be a square matrix.*

- *If a multiple of one row of* $\mathbf{A}$ *is added to another row to produce a matrix* $\mathbf{B}$, *then* $\det \mathbf{A} = \det \mathbf{B}$.
- *If two rows of* $\mathbf{A}$ *are interchanged to produce* $\mathbf{B}$, *then* $\det \mathbf{B} = -\det \mathbf{A}$.
- *If one row of* $\mathbf{A}$ *is multiplied by k to produce* $\mathbf{B}$, *then* $\det \mathbf{B} = k \cdot \det \mathbf{A}$.

Theorem 3.2.2. *If* $\mathbf{A}$ *is an $n \times n$ matrix, then* $\det \mathbf{A}^T = \det \mathbf{A}$.

Theorem 3.2.3. *If* $\mathbf{A}$ *and* $\mathbf{B}$ *are $n \times n$ matrices, then* $\det \mathbf{AB} = (\det \mathbf{A})(\det \mathbf{B})$.

***Example* 3.1.** *If all columns except one are held fixed in a square matrix, then its determinant is a linear function of that one(vector) variable.*