

DATA REDUNDANCY

1. Linear dependence

For the simple scalar mapping $f: \mathbb{R} \rightarrow \mathbb{R}$, $f(x) = ax$, the condition $f(x) = 0$ implies either that $a = 0$ or $x = 0$. Note that $a = 0$ can be understood as defining a zero mapping $f(x) = 0$. Linear mappings between vector spaces, $f: U \rightarrow V$, can exhibit different behavior, and the condition $f(\mathbf{x}) = \mathbf{A}\mathbf{x} = \mathbf{0}$, might be satisfied for both $\mathbf{x} \neq \mathbf{0}$, and $\mathbf{A} \neq \mathbf{0}$. Analogous to the scalar case, $\mathbf{A} = \mathbf{0}$ can be understood as defining a zero mapping, $f(\mathbf{x}) = \mathbf{0}$.

In vector space $\mathcal{V} = (V, S, +, \cdot)$, vectors $\mathbf{u}, \mathbf{v} \in V$ related by a scaling operation, $\mathbf{v} = a\mathbf{u}$, $a \in S$, are said to be colinear, and are considered to contain redundant data. This can be restated as $\mathbf{v} \in \text{span}\{\mathbf{u}\}$, from which it results that $\text{span}\{\mathbf{u}\} = \text{span}\{\mathbf{u}, \mathbf{v}\}$. Colinearity can be expressed only in terms of vector scaling, but other types of redundancy arise when also considering vector addition as expressed by the span of a vector set. Assuming that $\mathbf{v} \notin \text{span}\{\mathbf{u}\}$, then the strict inclusion relation $\text{span}\{\mathbf{u}\} \subset \text{span}\{\mathbf{u}, \mathbf{v}\}$ holds. This strict inclusion expressed in terms of set concepts can be transcribed into an algebraic condition.

DEFINITION. The vectors $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n \in V$, are *linearly dependent* if there exist n scalars, $x_1, \dots, x_n \in S$, at least one of which is different from zero such that

$$x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n = \mathbf{0}.$$

Introducing a matrix representation of the vectors

$$\mathbf{A} = [\mathbf{a}_1 \ \mathbf{a}_2 \ \dots \ \mathbf{a}_n]; \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

allows restating linear dependence as the existence of a non-zero vector, $\exists \mathbf{x} \neq \mathbf{0}$, such that $\mathbf{A}\mathbf{x} = \mathbf{0}$. Linear dependence can also be written as $\mathbf{A}\mathbf{x} = \mathbf{0} \Rightarrow \mathbf{x} = \mathbf{0}$, or that one cannot deduce from the fact that the linear mapping $f(\mathbf{x}) = \mathbf{A}\mathbf{x}$ attains a zero value that the argument itself is zero. The converse of this statement would be that the only way to ensure $\mathbf{A}\mathbf{x} = \mathbf{0}$ is for $\mathbf{x} = \mathbf{0}$, or $\mathbf{A}\mathbf{x} = \mathbf{0} \Rightarrow \mathbf{x} = \mathbf{0}$, leading to the concept of linear independence.

DEFINITION. The vectors $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n \in V$, are *linearly independent* if the only n scalars, $x_1, \dots, x_n \in S$, that satisfy

$$x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n = \mathbf{0}, \tag{1}$$

are $x_1 = 0, x_2 = 0, \dots, x_n = 0$.

2. Basis and dimension

Vector spaces are closed under linear combination, and the span of a vector set $\mathcal{B} = \{\mathbf{a}_1, \mathbf{a}_2, \dots\}$ defines a vector subspace. If the entire set of vectors can be obtained by a spanning set, $V = \text{span } \mathcal{B}$, extending \mathcal{B} by an additional element $\mathcal{C} = \mathcal{B} \cup \{\mathbf{b}\}$ would be redundant since $\text{span } \mathcal{B} = \text{span } \mathcal{C}$. This is recognized by the concept of a basis, and also allows leads to a characterization of the size of a vector space by the cardinality of a basis set.

DEFINITION. A set of vectors $\mathbf{u}_1, \dots, \mathbf{u}_n \in V$ is a *basis* for vector space $\mathcal{V} = (V, S, +, \cdot)$ if

1. $\mathbf{u}_1, \dots, \mathbf{u}_n$ are linearly independent;
2. $\text{span}\{\mathbf{u}_1, \dots, \mathbf{u}_n\} = V$.

DEFINITION. The number of vectors $\mathbf{u}_1, \dots, \mathbf{u}_n \in V$ within a basis is the *dimension* of the vector space $\mathcal{V} = (V, S, +, \cdot)$.

3. Dimension of matrix spaces

The domain and co-domain of the linear mapping $f: U \rightarrow V$, $f(\mathbf{x}) = \mathbf{A}\mathbf{x}$, are decomposed by the spaces associated with the matrix \mathbf{A} . When $U = \mathbb{R}^n$, $V = \mathbb{R}^m$, the following vector subspaces associated with the matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ have been defined:

- $C(\mathbf{A})$ the column space of \mathbf{A}

- $C(A^T)$ the row space of A
- $N(A)$ the null space of A
- $N(A^T)$ the left null space of A , or null space of A^T

DEFINITION. The *rank* of a matrix $A \in \mathbb{R}^{m \times n}$ is the dimension of its column space and is equal to the dimension of its row space.

DEFINITION. The *nullity* of a matrix $A \in \mathbb{R}^{m \times n}$ is the dimension of its null space.