

Theory Assignment: Vector Spaces and Geometry of Data.

1) Explain the concept of a vector in \mathbb{R}^n . How does the mathematical definition of a vector relate to feature representation in machine learning?

Solution: A vector in \mathbb{R}^n is an ordered n -tuple of real numbers written as

$$X = (x_1, x_2, x_3, \dots, x_n)^T$$

Each component represents a coordinate along a specific axis in n -dimensional space. In machine learning, each coordinate corresponds to a feature of a data point. Thus a data set with n features is mathematically represented as vectors in \mathbb{R}^n .

2) Define a vector space over \mathbb{R} . Discuss why closure under addition and scalar multiplication are essential properties?

Solution: A vector space over \mathbb{R} is a set V equipped with vector addition and scalar multiplication such that for all $u, v \in V$ and $c \in \mathbb{R}$:

$$u+v \in V \quad ; \quad cu \in V.$$

Closure under addition ensures combining two elements remain within space, closure under scalar multiplication ensures scaling a vector doesn't leave the space.

These properties guarantee algebraic consistency.

3) What is a subspace? State and explain the three necessary conditions required to prove that a subset is a subspace.

Solution: A subspace H of a vector space V is a subset that is itself a vector space. It must satisfy:

a) The zero vector $0 \in H$

b) closure under addition:

if $u, v \in H$, then $u+v \in H$.

c) closure under scalar multiplication:

if $u \in H$ and $c \in \mathbb{R}$ then $cu \in H$.

4) Explain the concept of linear combination. why is linear combination fundamental in understanding span & basis?

Solution: A linear combination of vectors v_1, \dots, v_p is $c_1v_1 + c_2v_2 + \dots + c_pv_p$.

Linear combination describes all possible weighted sum of vectors and form the foundation of span and basis.

5) Define the span of a set of vectors. Explain its geometric meaning in \mathbb{R}^2 and \mathbb{R}^3 .

Solution: The span of vectors $\{v_1, \dots, v_p\}$ is the set of

all Linear combinations of those vectors:

$$\text{Span}\{v_1, \dots, v_p\}.$$

In \mathbb{R}^2 , the span of non zero vector forms a line through the origin. Two linearly independent vectors

span the entire plane. In \mathbb{R}^3 , one vector spans

a line, two independent vectors span a plane, and

three independent vectors span the entire space.

6. What is Linear independence? Explain the diff betⁿ

Linear independence and linear dependence with a clear mathematical condition.

Solutions:

A set of vectors is linearly independent if

$$c_1 v_1 + \dots + c_p v_p = 0.$$

implies $c_1 = \dots = c_p = 0$. If there exists a non-

trivial solution (some $c_i \neq 0$), the vectors are

linearly dependent.

7. Discuss the problem of redundant features in ML from the perspective of linear dependence.

Solution:

In ML, redundant features occur when one feature can be expressed as a linear combination of others. This creates linear dependence, leading to multicollinearity, unstable parameter estimates, and reduced model interpretability.

8. Define a basis of a vector space. Why must a basis satisfy both spanning and linear independence conditions?

Solution:

A basis of a vector space V is a set of vectors that:

a) Span V

b) Are linearly independent

Spanning ensures coverage of the entire space, while independence ensures no redundancy.

9) What is the max dimension of a vector space?
explain its relationships with basis and matrix rank.

Solution:

The dimension of a vector space is the number of vectors in any basis of the space:

$$\dim(V) = \text{number of basis space.}$$

It is equal to the rank of a matrix whose rows (or columns) form a basis, since rank represent the number of linearly independent vectors.

10) Explain the importance of understanding vector space in ML, especially in dimensionality reduction technique such as PCA.

Solution:

Understanding vector space allows us to analyze data geometrically. Dimensionality reduction methods,

Such as PCA. identify a lower-dimensional subspace that captures maximum variance. This improves computational efficiency and reduces redundancy while preserving essential structure.

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