

Modern Methods of Statistical Learning sf2935: Vector Spaces Timo Koski

TK

2017-11-01



KTH Matematik



Prerequisites on Vector Spaces

A set \mathbf{X} with elements $\mathbf{x}, \mathbf{y}, \mathbf{z} \dots$, referred to as *vectors*, is called a *vector space*, if there are two operations called 'addition of two vectors' and 'multiplication of a vector by scalar', $\alpha \in \mathbb{R}$. These operations satisfy

- $\mathbf{x} + \mathbf{y} \in \mathbf{X}$
- There is a neutral element $\mathbf{0}$ such that $\mathbf{x} + \mathbf{0} = \mathbf{x}$
- $\alpha \mathbf{x} \in \mathbf{X}$
- $1\mathbf{x} = \mathbf{x} \in \mathbf{X}, 0\mathbf{x} = \mathbf{0} \in \mathbf{X}$



Prerequisites (A) on Vector Spaces

and in addition

- $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$
- $\alpha (\mathbf{x} + \mathbf{y}) = \alpha \mathbf{x} + \alpha \mathbf{y}$
- $(\alpha + \beta) \mathbf{x} = \alpha \mathbf{x} + \beta \mathbf{x}$

We take

$$\mathbf{x} - \mathbf{y} = \mathbf{x} + (-1)\mathbf{y}$$

and then

$$\mathbf{x} - \mathbf{x} = \mathbf{0}$$



Prerequisites (A) on Vector Spaces: An Example

The standard example is the set R^n of real column vectors of fixed dimension n . Let T denote transpose

$$\mathbf{x} = (x_1, x_2, \dots, x_n)^T$$

(a transposed row vector is a column vector), where $x_i \in R$, $i = 1, \dots, n$.

$$\mathbf{0} = (0, 0, \dots, 0)^T$$

We define

$$\mathbf{x} + \mathbf{y} = (x_1 + y_1, x_2 + y_2, \dots, x_n + y_n)^T$$

$$\alpha \mathbf{x} = (\alpha x_1, \alpha x_2, \dots, \alpha x_n)^T$$



Prerequisites (A): Vector Spaces and Norms

A vector space \mathbf{X} is called a *normed linear space*, if there is a real-valued function that maps each $\mathbf{x} \in \mathbf{X}$ to a number $\|\mathbf{x}\|$ with the following properties

- $\|\mathbf{x}\| \geq 0$ for all $\mathbf{x} \in \mathbf{X}$
- $\|\mathbf{x}\| = 0$ if and only if $\mathbf{x} = \mathbf{0}$.
- $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ (triangle inequality)
- $\|\alpha\mathbf{x}\| = |\alpha|\|\mathbf{x}\|$ (homogeneity)



Linear Vector Spaces and Norms: Examples

Consider R^n . Then $\|\mathbf{x}\|_2$ and $\|\mathbf{x}\|_\infty$ are norms on R^n :

- $\|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^n x_i^2}$ (Euclidean norm)
- $\|\mathbf{x}\|_\infty = \max_{1 \leq i \leq n} |x_i|$



Prerequisites (A): Norms and Distances

In a normed linear space \mathbf{X} the real-valued function

$$d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$$

is called the *distance* between \mathbf{x} and \mathbf{y} .

- $d(\mathbf{x}, \mathbf{y}) \geq 0$ for all $\mathbf{x} \in \mathbf{X}$
- $d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$.
- $d(\mathbf{x}, \mathbf{y}) = 0$ if and only if $\mathbf{x} = \mathbf{y}$.
- $d(\mathbf{x}, \mathbf{y}) \leq d(\mathbf{x}, \mathbf{z}) + d(\mathbf{y}, \mathbf{z})$ (triangle inequality)
- $d(\alpha\mathbf{x}, \alpha\mathbf{y}) = |\alpha|d(\mathbf{x}, \mathbf{y})$ (homogeneity)



Lengths and Balls in Normed Spaces

Then the *length* of \mathbf{x} is the distance from \mathbf{x} to $\mathbf{0}$, i.e.,

$$d(\mathbf{x}, \mathbf{0}) = \|\mathbf{x} - \mathbf{0}\| = \|\mathbf{x}\|$$

The **open ball** $\mathcal{B}_\tau(\mathbf{x}) \subset X$ of radius τ around $\mathbf{x} \in X$ is

$$\mathcal{B}_\tau(\mathbf{x}) \stackrel{\text{def}}{=} \{\mathbf{y} \in X \mid \|\mathbf{y} - \mathbf{x}\| < \tau\}$$



Prerequisites (A): Inner Product Spaces

A vector space \mathbf{X} is called an *inner product space*, if there is a function, called inner product¹, that maps each pair \mathbf{x}, \mathbf{y} of vectors in \mathbf{X} to a number $\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle$ with the following properties

- $\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle = \langle\langle \mathbf{y}, \mathbf{x} \rangle\rangle$
- $\langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle \geq 0$ with $\langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle = 0$, if and only if $\mathbf{x} = \mathbf{0}$.
- $\langle\langle \mathbf{x} + \mathbf{y}, \mathbf{z} \rangle\rangle = \langle\langle \mathbf{x}, \mathbf{z} \rangle\rangle + \langle\langle \mathbf{y}, \mathbf{z} \rangle\rangle$
- $\langle\langle \mathbf{x}, \mathbf{y} + \mathbf{z} \rangle\rangle = \langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle + \langle\langle \mathbf{x}, \mathbf{z} \rangle\rangle$
- $\langle\langle \mathbf{x}, \alpha \mathbf{y} \rangle\rangle = \alpha \langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle$

¹Much of learning theory literature talks about dot products



Inner Product Spaces: Examples

- ① Take $\mathbf{X} = R^n$, and

$$\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle = \sum_{i=1}^n x_i y_i$$

- ② Take $\mathbf{X} = R^n$, and

$$\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle_A = \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i y_j = \langle\langle \mathbf{x}, A\mathbf{y} \rangle\rangle$$

where $A = (a_{ij})_{i,j=1}^{n,n}$ is a symmetric and non-negative definite matrix²

² $\langle\langle \mathbf{x}, A\mathbf{y} \rangle\rangle = \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j \geq 0$ for all \mathbf{x} .

Inner Product Spaces are Normed Spaces

An inner product space \mathbf{X} is automatically a normed linear space, since we can put

$$\|\mathbf{x}\| = \sqrt{\langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle}$$

and, since $\langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle \geq 0$,

$$\|\mathbf{x}\|^2 = \langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle$$

Example: $\mathbf{X} = R^n$

$$\|\mathbf{x}\| = \sqrt{\langle\langle \mathbf{x}, \mathbf{x} \rangle\rangle} = \sqrt{\sum_{i=1}^n x_i^2}$$



Examples: Mahalanobis distance

When we take $A = \Sigma^{-1}$ in $\ll \mathbf{x}, \mathbf{y} \gg_A$ and set

$$\|\mathbf{x} - \mathbf{y}\|_{\Sigma^{-1}}^2 = \ll \mathbf{x} - \mathbf{y}, \Sigma^{-1} (\mathbf{x} - \mathbf{y}) \gg$$

we obtain a useful distance in pattern recognition known as the (squared) *Mahalanobis distance*. Regions of constant Mahalanobis distance to a fixed vector \mathbf{y} are ellipsoids.



Properties of Inner Products

- Cauchy-Schwarz inequality

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\| \cdot \|\mathbf{y}\|$$

- $\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 + 2 \langle \mathbf{x}, \mathbf{y} \rangle$
- $\|\mathbf{x} - \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - 2 \langle \mathbf{x}, \mathbf{y} \rangle$



Properties of Inner Product Spaces

The angle θ between \mathbf{x} and \mathbf{y} in an inner product space is given by

- $\cos(\theta) = \frac{\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle}{\|\mathbf{x}\| \|\mathbf{y}\|}$

If $\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle = 0$, we say that \mathbf{x} and \mathbf{y} are *orthogonal*, since then $\cos(\theta) = 0$, and then $\theta = \pi/2$ (within period). Also, we have then the *Pythagorean relations*

- $\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2$
- $\|\mathbf{x} - \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2$



Orthonormal Vectors in Inner Product Spaces

Let ϕ_1, \dots, ϕ_n be a sequence of **orthonormal** vectors of an inner product space X . Orthonormality means that

- 1 $\langle \phi_i, \phi_j \rangle = 0$, for $i \neq j$.
- 2 $\|\phi_i\| = 1$ for all j .

We note an example.

- 1 $\mathbf{X} = R^n$, and $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n x_i y_i$. Then

$$\phi_i = \left(0, 0, \dots, \underbrace{1}_{i\text{th position}}, \dots, 0 \right), \quad i = 1, \dots, n$$

are orthonormal vectors in $\mathbf{X} = R^n$.



Basis and Dimension

We say that the orthonormal vectors ϕ_1, \dots, ϕ_n form an orthonormal *basis* for X , if every \mathbf{x} can be written

$$\mathbf{x} = \langle \mathbf{x}, \phi_1 \rangle \phi_1 + \dots + \langle \mathbf{x}, \phi_n \rangle \phi_n$$

and that this is unique, also in the sense ϕ_1, \dots, ϕ_n cannot be appended or reduced by a single orthonormal vector. Then n is the *dimension* of the inner product space X .



Inner Product Spaces

An inner product space supports thus geometric notions. Inner product spaces of finite dimension are often called Euclidean spaces. A Euclidean space X equipped with $\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle_X$ is *isomorphic* to R^n with $\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle = \sum_{i=1}^n x_i y_i$ in the sense that there is an invertible map $\psi : X \mapsto R^n$ such that

$$\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle_X = \langle\langle \psi(\mathbf{x}), \psi(\mathbf{y}) \rangle\rangle$$

