

Advanced Machine Learning Subsidiary Notes

Lecture 5: Vector Spaces

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1 Keywords

- Vectors, vector spaces, operators

2 Main Points

2.1 Vector Spaces

- Any set of objects with addition between members of the set and scalar multiplication forms a vector space if they satisfies 8 axioms
- Most of these axioms arise naturally if addition and scale multiplication behave normally
- The only additional axiom is closure
- Normal vectors, matrices and functions all form vector spaces

2.2 Distances

- A *proper distance* or *metric* between objects in a vector space satisfies 4 conditions
 1. $d(x, y) \geq 0$ (non-negativity)
 2. $d(x, y) = 0$ if and only if $x = y$ (identity of indiscernibles)
 3. $d(x, y) = d(y, x)$ (symmetry)
 4. $d(x, y) \leq d(x, z) + d(z, y)$ (triangular inequality)
- You can define different distances for the same set of objects
- Often we use *pseudo-metrics* that breaks one or other of the conditions
- Consider a function (mapping) $f : \mathbb{R} \rightarrow \mathbb{R}$ then a useful quantification of how big a change a mapping can produce is given by the Lipschitz condition

$$d(f(x), f(y)) \leq K d(x, y)$$

This is useful if for all x and y there exists some fixed K

- Lipschitz functions are continuous (have no jumps)
- If $K < 1$ the mapping is said to be a contractive mapping

2.3 Norms

- Norms provide a measure of the size of a vector
- They satisfy three conditions
 1. $\|v\| > 0$ if $v \neq 0$ (non-negativity)
 2. $\|a v\| = |a| \|v\|$ (linearity)
 3. $\|u + v\| \leq \|u\| + \|v\|$ (triangular inequality)
- Again if not all of these conditions are true we have *pseudo-norms*
- Norms provide a metric $d(x, y) = \|x - y\|$
- We will meet norms very often in this course
- **Vector Norms**
 - There are a large number of norms for normal vectors that people use
 1. Euclidean or 2-norm: $\|v\|_2 = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$
 2. p -norm: $\|v\|_p = (\sum_{i=1}^n |v_i|^p)^{1/p}$
 3. 1-norm: $\|v\|_1 = \sum_{i=1}^n |v_i|$
 4. ∞ -norm or max-norm: $\|v\|_\infty = \max_i |v_i|$
 - Note the 1-norm, 2-norm and ∞ -norm are all p -norms with different p
 - The 0-norm counts the number of non-zero components (it is a pseudo-norm as it is not linear)
- **Matrix Norms**
 - Matrices also have norm
 1. The Frobenius norm is $\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |A_{ij}|^2}$
 2. Also have 1-norm, max-norm, Hilbert-norm (the maximum absolute eigenvalue), nuclear-norm, etc.
 - Note that the determinant is not a norm because it can be negative and is not linear
 - Many of the commonly used matrix norms satisfy
$$\|AB\| \leq \|A\| \times \|B\|$$
 - This is really useful because we can quickly bound norms of products of matrices
 - Many matrix and vector norms are compatible
$$\|Mv\|_b \leq \|M\|_a \times \|v\|_b$$
 - E.g. Frobenius and Euclidean norms are compatible
 - One of the main uses of matrix norms is to understand by how much it can potentially increase the size of a vector
- **Function Norms**
 - The most common function norms are
 1. The L_2 -norm

$$\|f\|_{L_2} = \sqrt{\int_{x \in \mathcal{R}} f^2(x) dx}$$

where \mathcal{R} is the region over which the function is define

2. The L_1 -norm

$$\|f\|_{L_1} = \int_{\mathbf{x} \in \mathcal{R}} |f(\mathbf{x})| \, d\mathbf{x}$$

3. The ∞ or max-norm

$$\|f\|_{\infty} = \max_{\mathbf{x} \in \mathcal{R}} f(\mathbf{x})$$

- Function norms are also used to define vector spaces
 1. The L_2 vector space is the set of functions such that all functions satisfy $\|f\|_{L_2} < \infty$
 2. The L_1 vector space is the set of functions such that all functions satisfy $\|f\|_{L_1} < \infty$
- In these vector spaces we only consider functions that measurable in the sense that $\|f\| > 0$ for any non-zero function