

Machine Learning

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1 Change

Definition 1.1. *Metric*

Let X be a non-empty set..

Let $d : X \times X \rightarrow \mathbb{R}_0^+$ such that:

- $(\forall x \in X)d(x, x) = 0$
- $(\forall x, y \in X)d(x, y) = 0 \Leftrightarrow x = y$
- $(\forall x, y \in X)d(x, y) = d(y, x)$
- $(\forall x, y, z \in X)d(x, z) \leq d(x, y) + d(y, z)$

Then d is called a metric and (X, d) is called a metric space.

Reference

Definition 1.2. *Limit of a function*

Let $T : X \rightarrow Y$ where (X, d_X) and (Y, d_Y) are metric spaces.

Then fix $x_0 \in X$.

If:

$$(\exists L \in Y)(\forall \epsilon > 0)(\exists \delta > 0)(\forall x \in X)(d(x, x_0) < \delta \Rightarrow d(f(x), L) < \epsilon)$$

Then:

$$\lim_{x \rightarrow x_0} f(x) = L$$

Reference

Definition 1.3. *Derivative*

Let $\hat{f} : \mathbb{R} \rightarrow \mathbb{R}$

Further let $f = \hat{f}|_U$ where $U \in \tau_{\mathbb{R}}$

Then f is said to be differentiable at $x \in U$ if there exists an L_x such that:

$$L_x = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

If L_x exists for all $x \in U$ then we write:

$$\frac{d}{dx} f(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

Reference

Definition 1.4. Partial Derivative

Let $\hat{f} : \mathbb{R}^n \rightarrow \mathbb{R}$

Further let $f = \hat{f}|_U$ where $U \in \tau_{\mathbb{R}^n}$

Then f is said to be differentiable at $x \in U$ with respect to the i 'th component of x if there exists an L_{x_i} such that:

$$L_{x_i} = \lim_{h \rightarrow 0} \frac{f(x_1, \dots, x_i + h, \dots, x_n) - f(x_1, \dots, x_i, \dots, x_n)}{h}$$

If L_{x_i} exists for all $x \in U$ then we write:

$$\frac{\partial}{\partial x_i} f(x) = \lim_{h \rightarrow 0} \frac{f(x_1, \dots, x_i + h, \dots, x_n) - f(x_1, \dots, x_i, \dots, x_n)}{h}$$

Reference

Definition 1.5. Differentiability of a multi-variable function.

Let $\hat{f} : \mathbb{R}^m \rightarrow \mathbb{R}^n$ such that:

$$\hat{f}(x) = \begin{bmatrix} f_1(x) \\ \vdots \\ f_n(x) \end{bmatrix} \quad \text{and } (\forall j \in \mathbb{N}_n)(f_j : \mathbb{R}^m \rightarrow \mathbb{R})$$

Further let $f = \hat{f}|_U$ where $U \in \tau_{\mathbb{R}^m}$

Then f is said to be differentiable at $x \in U$ if there exists a linear operator $J_f : \mathbb{R}^m \rightarrow \mathbb{R}^n$ such that:

$$\lim_{h \rightarrow \vec{0}} \frac{\|f(x+h) - f(x) + J_f(h)\|_{\mathbb{R}^n}}{\|h\|_{\mathbb{R}^m}} = 0$$

Reference

Theorem 1.1. If a multi-variable function, f , is differentiable at x then the linear operator J is the Jacobian matrix.

So our guess is that:

$$J_f = \begin{bmatrix} \frac{\partial}{\partial x_1} f_1(x) & \cdots & \frac{\partial}{\partial x_n} f_1(x) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_1} f_m(x) & \cdots & \frac{\partial}{\partial x_n} f_m(x) \end{bmatrix}$$

since this form is a linear operator mapping from the appropriate space to the appropriate space. It should be noted that the transpose of this matrix can not satisfy the definition of differentiability of a multi-variable function and so it is not the correct linear operator.

Definition 1.6. Gradient

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a Differentiable function.

Then $\nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ where:

$$\nabla f(x) := \begin{bmatrix} \frac{\partial}{\partial x_1} f(x) \\ \vdots \\ \frac{\partial}{\partial x_n} f(x) \end{bmatrix} \quad \forall x \in \mathbb{R}^n$$

is called the Gradient of f .

Reference

Definition 1.7. Derivative with respect to a vector and the subspace gradient.

Let $X = \{X_j\}_{j=0}^{n-1}$ be a sequence of finite dimensional vector spaces where $\dim(X_j) = k_j = m_j \times n_j$

Let $T : \prod_{j=0}^{n-1} X_j \rightarrow Y$ where Y is a finite dimensional vector space with $\dim(Y) = k_y$

Let $x \in X_j$ for some $j \in \{0, \dots, n-1\}$

Where

$$x = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n_j} \\ \vdots & \ddots & \vdots \\ x_{m_j,1} & \cdots & x_{m_j,n_j} \end{bmatrix}$$

$$D_x T(z) = \begin{bmatrix} \frac{\partial}{\partial x_{1,1}} T_1(z) & \cdots & \frac{\partial}{\partial x_{1,n_j}} T_1(z) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{m_j,1}} T_1(z) & \cdots & \frac{\partial}{\partial x_{m_j,n_j}} T_1(z) \\ \vdots & \vdots & \vdots \\ \frac{\partial}{\partial x_{1,1}} T_{k_y}(z) & \cdots & \frac{\partial}{\partial x_{1,n_j}} T_{k_y}(z) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{m_j,1}} T_{k_y}(z) & \cdots & \frac{\partial}{\partial x_{m_j,n_j}} T_{k_y}(z) \end{bmatrix}$$

Definition 1.8. Product space Derivative

Let $X = \{X_j\}_{j=0}^{n-1}$ be a sequence of finite dimensional vector spaces where $\dim(X_j) = k_j$

Let $T : \prod_{j=0}^{n-1} X_j \rightarrow Y$ where Y is a finite dimensional vector space with $\dim(Y) = k_y$

Let $\{x_j\}_{j=0}^{n-1}$ be a sequence of vectors such that: $(\forall j \in \{0, \dots, n-1\})(x_j \in X_j)$

The product space derivative at the point $z \in X$ is:

$$D_X T(z) = \begin{bmatrix} D_{x_0} T(z) \\ \vdots \\ D_{x_{n-1}} T(z) \end{bmatrix}$$

Definition 1.9. Fréchet derivative

Let V, W be normed vector spaces and $U \subset V$ be an open set.

An operator $f : U \rightarrow W$ is said to be Fréchet differentiable if there exists a bounded linear operator $A : V \rightarrow W$ such that:

$$\lim_{\|h\| \rightarrow 0} \frac{\|f(x+h) - f(x) - Ah\|_W}{\|h\|_V} = 0$$

Reference

Theorem 1.2. Fréchet derivative of a bounded linear operator

Let V, W be normed vector spaces and $U \subset V$ be an open set.

Let $\hat{f} : V \rightarrow W$ be a bounded linear operator.

Then let's look at $f = \hat{f}|_U$

My guess is that $A = \hat{f}$

Let $x \in U$ and $h \in U$ with $\|h\| \neq 0$ and $x+h \in U$, Then:

$$\frac{\|f(x+h) - f(x) - Ah\|_W}{\|h\|_V} = \frac{\|f(x) + f(h) - f(x) + \hat{f}(h)\|_W}{\|h\|_V} = \frac{\|f(x) + f(h) - f(x) + f(h)\|_W}{\|h\|_V} = 0$$

Thus let $\epsilon > 0$ and $\delta > 0$

Then if $0 < \|h\| < \delta$ we know that $\frac{\|f(x+h) - f(x) - Ah\|_W}{\|h\|_V} = 0 < \epsilon$

Therefore:

$$\lim_{\|h\| \rightarrow 0} \frac{\|f(x+h) - f(x) - Ah\|_W}{\|h\|_V} = 0$$

Thus $A = \hat{f}$ is the Fréchet derivative of f .

1.1 Finite Composition Operator**Definition 1.10. Finite Composition Operator**

Let the collection $X = \{X_j\}_{j=0}^n$ be a finite sequence of sets.

Further let $\{T_j\}_{j=0}^{n-1}$ be a finite sequence of operators such that $(\forall j \in \mathbb{N}_{n-1})(T_j : X_j \rightarrow X_{j+1})$

Then $T^n : X_0 \rightarrow X_n$ defined by:

$$T^n := \bigcirc_{j=0}^{n-1} T_j$$

is called the **Finite Composition Operator defined on X** .

Definition 1.11. Multi-variable Finite Composition Iteration

Let the collection $X = \{X_j\}_{j=0}^n$ and $Y = \{Y_j\}_{j=0}^{n-1}$ be finite sequences of sets.

Further let $\{T_j\}_{j=0}^{n-1}$ be a finite sequence of operators such that: $(\forall j \in \mathbb{N}_{n-1})(T_j : X_j \times Y_j \rightarrow X_{j+1})$

Let $T^n : X_0 \times \prod_{j=0}^{n-1} Y_j \rightarrow X_n$ where:

$$T^n(x, y) = z_n \text{ where } z_{j+1} = T_j(z_j, \pi_j(y)) \text{ or } z_{j+1} = T_j(z_j) \text{ and } z_0 = x \in X_0$$

Definition 1.12. Gradient Descent

Let $E : \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable operator.

The method of Gradient Descent says that a local minimum of E can be found using the following iteration:

$$a_{n+1} = a_n - \gamma \nabla E(a_n)$$

Where $\gamma > 0$

Example 1.1. *Objective Operator for Data Set Defined Operator Approximation*
Let $X \subset \mathbb{R}^n, Y \subset \mathbb{R}^m$ such that $X \times Y$ defines an operator T .

$$E(a) = \sum_{x \in X} ||T(x) - T^n(x, a)||$$

2 Surjective Continuous Non-decreasing Bounded Functionals

Let $B = \{f : \mathbb{R} \rightarrow [0, 1] \mid f \text{ is surjective, continuous, and non-decreasing.}\}$

Theorem 2.1. B is convex.

Let $f, g \in B$ and $h(x) := \lambda f(x) + (1 - \lambda)g(x)$ where $\lambda \in [0, 1]$

Then h is still continuous since the linear combination of continuous functions is continuous.

Since both f and g are surjective and non-decreasing, then there exists x_0, y_0, x_1, y_1 in \mathbb{R} such that:

$f(x_0) = 0 = g(y_0)$ and $f(x_1) = 1 = g(y_1)$

Suppose WLOG that $x_0 \leq y_0$ and $x_1 \leq y_1$

Then we know that:

$$h(x_0) = \lambda f(x_0) + (1 - \lambda)g(x_0) = \lambda 0 + (1 - \lambda)0 = 0$$

and

$$h(y_1) = \lambda f(y_1) + (1 - \lambda)g(y_1) = \lambda 1 + (1 - \lambda)1 = 1$$

Now if we pick $\alpha \in [0, 1]$ by the intermediate value theorem, we know that there exists an $x_\alpha \in [x_0, y_1]$ such that:

$$h(x_\alpha) = \alpha$$

Since α was arbitrary element, I have shown that h is surjective.

Finally, let $x_0 < x_1$ be elements in \mathbb{R}

Then we know that $f(x_0) \leq f(x_1)$ and $g(x_0) \leq g(x_1)$

$\Rightarrow \lambda f(x_0) \leq \lambda f(x_1)$ and $(1 - \lambda)g(x_0) \leq (1 - \lambda)g(x_1)$

$\Rightarrow \lambda f(x_0) + (1 - \lambda)g(x_0) \leq \lambda f(x_1) + (1 - \lambda)g(x_1)$

$\Rightarrow h(x_0) \leq h(x_1)$

Thus h is non-decreasing.

Since h is surjective, continuous, and non-decreasing, then $h \in B$

Thus B is convex.

Theorem 2.2. B is translation invariant.

Let $f \in B$ and $g(x) := f(x + c)$ where $c \in \mathbb{R}$

f is continuous and so is the addition operator so g is continuous.

Let $\alpha \in [0, 1]$ since f is surjective then $\exists x \in \mathbb{R} \cap f(x) = \alpha$

Then $g(x - c) = f(x + c - c) = f(x) = \alpha$ and so g is surjective.

Let $x < y$ be elements in \mathbb{R}

Then $f(x) \leq f(y) \Rightarrow f(x + c) \leq f(y + c)$

$\Rightarrow g(x) \leq g(y)$ and so g is non-decreasing.

Thus $g \in B$ and B is therefore translation invariant.

Theorem 2.3. B is not complete.

Theorem 2.4. Every element in B can be decomposed as a finite non-trivial convex combination from B