

# 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

**Theorem 1.1. Fundamental increment lemma**

Let  $f$  be described as above and be differentiable at  $x$ .

Then there exists a function  $\phi : \mathbb{R} \rightarrow \mathbb{R}$  such that:

$$f(x+h) = f(x) + \frac{d}{dx}f(x)h + \phi(x)h$$

and

$$\lim_{h \rightarrow 0} \phi(h) = 0$$

*Proof:*

Define:  $\phi(h) = \frac{f(x+h)-f(x)}{h} - \frac{d}{dx}f(x)$

Then:  $\phi(h)h = f(x+h) - f(x) - \frac{d}{dx}f(x)h$

Then:  $\phi(h)h + f(x) - \frac{d}{dx}f(x)h = f(x+h)$

And so we have property 1.

Next:

$$\begin{aligned} \lim_{h \rightarrow 0} \phi(h) &= \lim_{h \rightarrow 0} \left[ \frac{f(x+h) - f(x) - \frac{d}{dx}f(x)h}{h} \right] = \lim_{h \rightarrow 0} \left[ \frac{f(x+h) - f(x)}{h} - \frac{d}{dx}f(x) \right] \\ &= \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} - \lim_{h \rightarrow 0} \frac{d}{dx}f(x) = \frac{d}{dx}f(x) - \frac{d}{dx}f(x) = 0 \end{aligned}$$

**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 1.2.** *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  $\hat{f} : \mathbb{R}^n \rightarrow \mathbb{R}$  and let  $f : U \rightarrow \mathbb{R}$  such that  $f = \hat{f}|_U$  where  $U \in \tau_{\mathbb{R}^n}$   
 $f$  is said to be differentiable at  $x \in U$  if  $\exists \nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  such that:*

$$\lim_{h \rightarrow 0} \frac{|f(x+h) - f(x) - \langle \nabla f(x), h \rangle|}{||h||} = 0$$

**Theorem 1.3. Form of the Gradient**

*Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a Differentiable function with respect to  $x_j$  for all  $j \in \mathbb{N}_n$ .  
Then  $\nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  where:*

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

*is called the Gradient of  $f$ .*

*Reference*

**Definition 1.7. Matrix operator differentiability**

Let  $T : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}^n$  such that:

$$T(A) = \begin{bmatrix} T_1(A) \\ \vdots \\ T_n(A) \end{bmatrix} \quad \forall A \in \mathbb{R}^{n \times m} \text{ and } (\forall j \in \mathbb{N}_n)(T_j : \mathbb{R}^{n \times m} \rightarrow \mathbb{R})$$

Then  $T$  is said to be differentiable at  $A \in \mathbb{R}^{n \times m}$  if there exists a linear operator  $D : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}^n$  where:

$$\lim_{h \rightarrow 0} \frac{\|T(A+h) - T(A) + D(h)\|_{\mathbb{R}^n}}{\|h\|_{\mathbb{R}^{n \times m}}} = 0$$

If  $D$  exists then it is called the Matrix operator derivative and is written:  $D_{\mathbb{R}^{n \times m}} T(A)$

**Theorem 1.4. The form of the Matrix operator derivative.**

Let  $T$  be described as above and differentiable at  $A \in \mathbb{R}^{n \times m}$

$$\frac{T(A+h) - T(A)}{\|h\|} = \begin{bmatrix} \frac{T_1(A+h) - T_1(A)}{\|h\|} \\ \vdots \\ \frac{T_n(A+h) - T_n(A)}{\|h\|} \end{bmatrix}$$

and so:

$$\lim_{h \rightarrow 0} \frac{T(A+h) - T(A)}{\|h\|} = \begin{bmatrix} \lim_{h \rightarrow 0} \frac{T_1(A+h) - T_1(A)}{\|h\|} \\ \vdots \\ \lim_{h \rightarrow 0} \frac{T_n(A+h) - T_n(A)}{\|h\|} \end{bmatrix}$$

a

**Definition 1.8. Subspace Differentiability**

Let  $X = \{X_j\}_{j=1}^n$  be a sequence of finite dimensional vector spaces where  $\dim(X_j) = k_j = m_j \times n_j$   
 Let  $T : \prod_{j=1}^n X_j \rightarrow Y$  where  $Y$  is a finite dimensional vector space with  $\dim(Y) = k_y$   
 Let  $x_j \in X_j$  for some  $j \in \mathbb{N}_n$

Where

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

$T$  is said to be differentiable at  $x \in X$  where  $x = (x_0, \dots, x_j, \dots, x_{n-1})$  with respect to  $X_j$  if there exists a linear operator  $D : X_j \rightarrow Y$ :

Given  $h \in X_j \setminus \{\vec{0}\}$  define  $\hat{h} = (0, \dots, h, \dots, 0) \in X$  where  $h$  is in the  $j$ 'th place of  $\hat{h}$ :

$$\lim_{h \rightarrow 0} \frac{\|T(x + \hat{h}) - T(x) + D(h)\|_X}{\|h\|_{X_j}} = 0$$

Then  $D$  is called the subspace derivative of  $T$  at  $x$  with respect to  $X_j$  and is written:  $D_{x_j}T(x)$

**Theorem 1.5. The form of the subspace derivative**

Let  $X = \{X_j\}_{j=1}^n$  be a sequence of finite dimensional vector spaces where  $\dim(X_j) = k_j = m_j \times n_j$   
 Let  $T : \prod_{j=1}^n X_j \rightarrow Y$  where  $Y$  is a finite dimensional vector space with  $\dim(Y) = k_y$   
 Let  $x_j \in X_j$  for some  $j \in \mathbb{N}_n$

Where

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

Further let  $T$  be differentiable at  $x \in X$  where  $x = (x_0, \dots, x_j, \dots, x_{n-1})$  with respect to  $X_j$  My guess is that:

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

Let  $h \in X_j$

Then:

$$D_{x_j}T(x)(h) = \begin{bmatrix} \frac{\partial}{\partial x_{1,1}}T_1(x) & \cdots & \frac{\partial}{\partial x_{m_j,1}}T_1(x) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{1,n_j}}T_1(x) & \cdots & \frac{\partial}{\partial x_{m_j,n_j}}T_1(x) \\ \vdots & \vdots & \vdots \\ \frac{\partial}{\partial x_{1,1}}T_{k_y}(x) & \cdots & \frac{\partial}{\partial x_{m_j,1}}T_{k_y}(x) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{1,n_j}}T_{k_y}(x) & \cdots & \frac{\partial}{\partial x_{m_j,n_j}}T_{k_y}(x) \end{bmatrix} \begin{bmatrix} h_{1,1} & \cdots & h_{1,n_j} \\ \vdots & \ddots & \vdots \\ h_{m_j,1} & \cdots & h_{m_j,n_j} \end{bmatrix}$$

$$= \begin{bmatrix} \sum_{i=1}^{m_j} h_{i,1} \frac{\partial}{\partial x_{i,1}} T_1(x) & \cdots & \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,1}} T_1(x) \\ \vdots & \ddots & \vdots \\ \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,n_j}} T_1(x) & \cdots & \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,n_j}} T_1(x) \\ \vdots & \vdots & \vdots \\ \sum_{i=1}^{m_j} h_{i,1} \frac{\partial}{\partial x_{i,1}} T_{k_y}(x) & \cdots & \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,1}} T_{k_y}(x) \\ \vdots & \ddots & \vdots \\ \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,n_j}} T_{k_y}(x) & \cdots & \sum_{i=1}^{m_j} h_{i,n_j} \frac{\partial}{\partial x_{i,n_j}} T_{k_y}(x) \end{bmatrix}$$

**Definition 1.9. *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 1.10. 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 1.6. 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 1.11. 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 1.12. 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 1.13. 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  $\alpha$  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  $B$**