Machine Learning

Daniel Drake

May 11, 2020

1 Gradients, Jacobian, Ferchet Drivative, and Sub-Gradients

Theorem 1.1. Gradient

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

Then $\nabla f : \mathbb{R}^n \to \mathbb{R}^n$ 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.

Theorem 1.2. Jacobian

Let $f: \mathbb{R}^n \to \mathbb{R}^m$ where:

$$f(x) = \begin{bmatrix} f_1(x) \\ \vdots \\ f_m(x) \end{bmatrix} \forall x \in \mathbb{R}^n and (\forall j \in \mathbb{N}_m) (f_j : \mathbb{R}^n \to \mathbb{R})$$

Then $J_f: \mathbb{R}^n \to \mathbb{R}^{n \times m}$ where:

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

Theorem 1.3. When the Jacobian is the Gradient

Let $f: \mathbb{R}^n \to \mathbb{R}$

Then $(\nabla f(x) = (J_f(x))^T)(\forall x \in \mathbb{R}^n)$

Theorem 1.4. Chain Rule Let $f: \mathbb{R}^n \to \mathbb{R}^m$ and $g: \mathbb{R}^m \to \mathbb{R}^k$ be differentiable functions. Then: $J_{g \circ f}(x) = J_g(f(x))J_f(x)$

2 Finite Composition Operator

Definition 2.1. 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 $(\forall j \in \mathbb{N}_{n-1})(T_j : X_j \to X_{j+1})$ Then $T : X_0 \to X_n$ defined by:

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

is called the Finite Composition Operator defined on X.

Theorem 2.1. Finite Composition Jacobian

Let T be defined as above.

Then:

$$J_T(x) = \dots$$

And so to calculate J_T we need to calculate each J_{T_j} for each j only once. Proof on the next page:

Proof:

Case: n = 1

$$X = \{X_0, X_1\}$$

$$T_0 : X_0 \to X_1$$

$$T^1(x) = T_0(x)$$

$$J_{T^1}(x) = J_{T_0}(x)$$

Case: n=2

$$T_0: X_0 \to X_1$$

$$T_1: X_1 \to X_2$$

$$T^2(x) = (T_1 \circ T_0)(x)$$

$$J_{T^2}(x) = J_{T_1 \circ T_0}(x) = J_{T_1}(T_0(x))J_{T_0}(x) = (J_{T_1} \circ T_0)(x) * J_{T_0}(x)$$

 $X = \{X_0, X_1, X_2\}$

Case: n = 3

$$X = \{X_0, X_1, X_2, X_3\}$$

$$T_0 : X_0 \to X_1$$

$$T_1 : X_1 \to X_2$$

$$T_2 : X_2 \to X_3$$

$$T^3(x) = (T_2 \circ T_1 \circ T_0)(x) = (T_2 \circ T^2)(x)$$

 $J_{T^3}(x) = J_{T_2 \circ T^2}(x) = J_{T_2}(T^2(x))J_{T^2}(x) = (J_{T_2} \circ T_1 \circ T_0)(x) * J_{T^2}(x) = (J_{T_2} \circ T_1 \circ T_0)(x) * (J_{T_1} \circ T_0)(x) * J_{T_0}(x))$

Case: n = k

$$X = \{X_0, ..., X_k\}$$

$$T_0 : X_0 \to X_1$$

$$\vdots$$

$$T_{k-1} : X_{k-1} \to X_k$$

$$T^k(x) = \left(\bigcap_{j=0}^{k-1} T_j\right)(x) = (T_{k-1} \circ T^{k-1})(x)$$

$$J_{T^k}(x) = J_{T_{k-1} \circ T^{k-1}}(x) = J_{T_{k-1}}(T^{k-1}(x))J_{T^{k-1}}(x)$$

Theorem 2.2. Examples:

Let $T: \mathbb{R}^n \to \mathbb{R}^n$ such that:

$$T(x) := \begin{bmatrix} \arctan(\pi_1(x)) \\ \vdots \\ \arctan(\pi_n(x)) \end{bmatrix} = \begin{bmatrix} \arctan(x_1) \\ \vdots \\ \arctan(x_n) \end{bmatrix}$$

Then

$$J_{T}(x) = \begin{bmatrix} \frac{\partial}{\partial x_{1}} T_{1}(x) & \cdots & \frac{\partial}{\partial x_{n}} T_{1}(x) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{1}} T_{n}(x) & \cdots & \frac{\partial}{\partial x_{n}} T_{n}(x) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x_{1}} \arctan(x_{1}) & \cdots & \frac{\partial}{\partial x_{n}} \arctan(x_{1}) \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{1}} \arctan(x_{1}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{\partial}{\partial x_{n}} \arctan(x_{n}) \end{bmatrix} = \begin{bmatrix} \frac{1}{x_{1}^{2}+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{x_{n}^{2}+1} \end{bmatrix} = I \begin{bmatrix} \frac{1}{x_{1}^{2}+1} \\ \vdots \\ \frac{1}{x_{n}^{2}+1} \end{bmatrix}$$

Theorem 2.3. Examples:

Let $T_b: \mathbb{R}^n \to \mathbb{R}^n$ such that:

$$T_b(x) := \begin{bmatrix} \pi_1(x) + b_1 \\ \vdots \\ \pi_n(x) + b_n \end{bmatrix} = \begin{bmatrix} x_1 + b_1 \\ \vdots \\ x_n + b_n \end{bmatrix}$$

Then

$$J_{T_b}(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} [x_1 + b_1] & \cdots & \frac{\partial}{\partial x_n} [x_1 + b_1] \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_1} [x_1 + b_1] & \cdots & \frac{\partial}{\partial x_n} [x_n + b_n] \end{bmatrix} = \begin{bmatrix} x_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & x_n \end{bmatrix} = Ix$$

Theorem 2.4. Examples:

Let $T_A: \mathbb{R}^n \to \mathbb{R}^m$ such that:

$$T_A(x) := \begin{bmatrix} \langle a_1, x \rangle \\ \vdots \\ \langle a_m, x \rangle \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^n a_{1,j} x_j \\ \vdots \\ \sum_{j=1}^n a_{m,j} x_j \end{bmatrix} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{m,1} & \cdots & a_{m,n} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = Ax$$

Then:

$$J_{T_A}(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} \left[\sum_{j=1}^n a_{1,j} x_j \right] & \cdots & \frac{\partial}{\partial x_n} \left[\sum_{j=1}^n a_{1,j} x_j \right] \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_1} \left[\sum_{j=1}^n a_{m,j} x_j \right] & \cdots & \frac{\partial}{\partial x_n} \left[\sum_{j=1}^n a_{m,j} x_j \right] \end{bmatrix} = \begin{bmatrix} a_{1,1} x_1 & \cdots & a_{1,n} x_n \\ \vdots & \ddots & \vdots \\ a_{m,1} x_1 & \cdots & a_{m,n} x_n \end{bmatrix}$$

3 Surjective Continuous Non-decreasing Bounded Functionals

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

Theorem 3.1. B is convex.

Theorem 3.2. B is translation invariant.

Theorem 3.3. B is not complete.

Theorem 3.4. Every element in B can be decomposed as a finite convex combination from B