

201

# Taylor expansions, first order

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Instructor: Nicolas Boumal



# Function value along a curve

Our smooth cost function is  $f: \mathcal{M} \rightarrow \mathbb{R}$ .

Algorithms move from  $x_k$  to  $x_{k+1}$  along a (retraction) curve.

The **value** of  $f$  changes **along curves**. How?

$$\begin{array}{l|l} \text{let } c: \mathbb{R} \rightarrow \mathcal{M}, \text{ a smooth curve.} & f: \mathcal{M} \rightarrow \mathbb{R} \\ \text{let } x = c(0), \text{ and let } v = c'(0). & c: \mathbb{R} \rightarrow \mathcal{M} \\ & g = f \circ c: \mathbb{R} \rightarrow \mathbb{R} \\ & g'(0) = (f \circ c)'(0) \\ & = Df(x)[v] \end{array}$$
$$g(t) = g(0) + t g'(0) + O(t^2)$$

$$f(c(t)) = f(x) + t \langle \text{grad} f(x), v \rangle_x + O(t^2) = \langle \text{grad} f(x), v \rangle_x$$

In particular, if  $R$  is a **retraction** on  $\mathcal{M}$ , consider  $c(t) = R_x(tv)$ .

$$f(R_x(tv)) = f(x) + t \langle \text{grad} f(x), v \rangle_x + O(t^2)$$

$$\vdots \quad \text{let } \Lambda = tv \in T_x \mathcal{M}$$

$$f(R_x(\Lambda)) = f(x) + \langle \text{grad} f(x), \Lambda \rangle_x + O(\|\Lambda\|_x^2)$$

# Take away

**Fact:** Consider  $f: \mathcal{M} \rightarrow \mathbf{R}$  smooth.

If  $c: \mathbf{R} \rightarrow \mathcal{M}$  is a smooth curve and  $c(0) = x$ ,  $c'(0) = \textcolor{brown}{v}$ , then

$$f(c(t)) = f(x) + t\langle \text{grad}f(x), \textcolor{brown}{v} \rangle_x + O(t^2).$$

Also, with  $R$  a retraction on  $\mathcal{M}$ , we have:

$$f(R_x(\textcolor{brown}{s})) = f(x) + \langle \text{grad}f(x), \textcolor{brown}{s} \rangle_x + O(\|\textcolor{brown}{s}\|_x^2).$$