Multivariate Calc: gradients, Jacobians, Hessians

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Let $f : \mathbb{R}^n \to \mathbb{R}^m$, $f(\vec{x}) = \begin{bmatrix} f_1(\vec{x}) \\ \vdots \\ f_m(\vec{x}) \end{bmatrix} \in \mathbb{R}^m$

domain co-domain

Def The derivative or Jacobian of f at a point $\vec{x}$ (in the interior of its domain) is the matrix $Df(\vec{x})$ (or sometimes written $J_f(x)$ ... or all kinds of variants)

$$Df(\vec{x})_{i,j} = \frac{\partial f_i(\vec{x})}{\partial x_j}$$ ... if the partial derivatives exist.

$$Df(\vec{x}) \in \mathbb{R}^{m \times n}$$

Special case: $m=1$

Def The gradient of $f : \mathbb{R}^n \to \mathbb{R}^m$, written $\nabla f(\vec{x}) \in \mathbb{R}^n$, is the transpose of the Jacobian.

and $$\lim_{\vec{y} \to \vec{x}} \frac{\| f(\vec{y}) - \overbrace{\left(f(\vec{x}) + \nabla f(\vec{x})^T \cdot (\vec{y} - \vec{x}) \right)}^{1^{st} \text{ order Taylor series}} \|}{\| \vec{y} - \vec{x} \|} = 0$$

Def The Hessian of $f : \mathbb{R}^n \to \mathbb{R}^m$, written $\nabla^2 f(\vec{x}) \in \mathbb{R}^{n \times n}$, is the Jacobian of the gradient,

$$\nabla^2 f(\vec{x})_{ij} = \frac{\partial^2 f(\vec{x})}{\partial x_i \partial x_j}.$$

Clairut's Thm says that as long as all these entries are continuous, then $\nabla^2 f(\vec{x})$ is a symmetric matrix, i.e., order of partial derivatives doesn't matter: $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$

Example: $f : \mathbb{R}^2 \to \mathbb{R}^1$,

$$f(x,y) = 4x^3 + 2xy + 13y^2 - 9y^3$$

$$\nabla f(x,y) = \begin{bmatrix} 12x^2 + 2y \\ 2x + 26y - 27y^2 \end{bmatrix}, \quad \nabla^2 f(x,y) = \begin{bmatrix} 24x & 2 \\ 2 & 26 - 54y \end{bmatrix}$$

i.e. $\frac{\partial^2 f}{\partial x \partial y}$

Mathematical Formalities (optional, not covered in class)

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$f:\mathbb{R}^n \to \mathbb{R}$ i.e. $m=1$ on this page

Directional Derivatives : reducing to 1D case

Def The directional derivative of $f:\mathbb{R}^n\to\mathbb{R}$ at $\vec{x}$ along $\vec{d}$ is $(\vec{x},\vec{d}\in\mathbb{R}^n)$

$$f'(\vec{x};\vec{d}) := \lim_{h\to 0} \frac{f(\vec{x}+h\vec{d})-f(\vec{x})}{h} \quad \left(= \nabla f(\vec{x})^T\cdot\vec{d} = \vec{d}^{\,T}\cdot\nabla f(\vec{x}) \right)$$

i.e. the usual 1D derivative of $\varphi(t) = f(\vec{x}+t\cdot\vec{d})$

Multivariate Taylor Expansions

$$f(\vec{x}) = \underbrace{f(\vec{x}_0)}_{\text{scalar}} + \underbrace{\nabla f(\vec{x}_0)}_{\text{vector}}^T\cdot(\vec{x}-x_0) + (\vec{x}-\vec{x}_0)^T\cdot\underbrace{\nabla^2 f(x_0)}_{\text{matrix}}(\vec{x}-\vec{x}_0) + \underbrace{O(\|\vec{x}-\vec{x}_0\|^3)}_{\text{... tensors ...}}$$

Differentiability in $\mathbb{R}^n$ $n\geq 1$

There are different notions of differentiability. For $\mathbb{R}^1$, these all coincide luckily

1) (weakest) Partial derivatives exist, i.e., directional derivatives along coordinate axes

i.e., $\frac{\partial f}{\partial x_1}, \ldots, \frac{\partial f}{\partial x_n}$ all exist

ex, $\mathbb{R}^2$, $f(x,y) = (xy)^{1/3}$, $\frac{\partial f}{\partial x} = \frac{1}{3}x^{-2/3}y^{1/3}$ and $\frac{\partial f}{\partial y}$ also exists

but along line $y=x$, let $g(x) = f(x,x) = x^{2/3}$, not differentiable at 0 since $g'(x) = \frac{2}{3}x^{-1/3}$

2) (next weakest) Gateaux differentiable, version 1, i.e., directional derivatives exist for all directions

i.e., $\forall$ directions $d\in\mathbb{R}^n$, $f'(x;d) := \lim_{h\to 0}\frac{f(x+h\cdot d)-f(x)}{h}$ exists.

2') (next weakest) Gateaux diff, version 2 (authors don't agree) **i.e. Gradient Exists** "$\nabla f(x)$"

same as 2) but also require $d\mapsto f'(x;d)$ is a bounded linear function

in $\mathbb{R}^n$, this comes for free

Saying it's linear means, in a Hilbert Space (i.e., using Riesz R)

we can write $f'(x;d) = \boxed{\langle \nabla f(x), d\rangle}$ COMMON NOTATION

3) (strictest) Fréchet differentiable

means $d\mapsto f'(x;d)$ is a linear function (like 2')

and there's a uniform rate of convergence (in "h") independent of the direction,

i.e., $$\lim_{\|d\|\to 0} \frac{\|\left(f(x)+\langle\nabla f(x), d\rangle\right) - f(x+d)\|}{\|d\|} = 0$$

in case $f:\mathbb{R}^n\to\mathbb{R}^m$, $m>1$

4) (even stricter than strict) $f\in C^1$ i.e., $\nabla f(x)$ exists $\forall x$ and it's continuous

This implies Fréchet (hence Gateaux) diff. *

[So for simplicity, we usually assume $f\in C^1$ and don't worry about the details]

*I'm pretty sure but not 100%... it's not obvious.

(In particular, we often assume ∇f is Lipschitz continuous, even stronger assumption than $f\in C^1$!)

Chain Rule

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Scalar Chain Rule $f(x) = g(h(x))$, $f: \mathbb{R}^1 \to \mathbb{R}^1$

$$f'(x) = g'(f(x)) \cdot h'(x)$$

Multivariate only twist: order matters! $f: \mathbb{R}^n \to \mathbb{R}^m$, $f(\vec{x}) = g(h(\vec{x}))$

$$\begin{tikzcd} \vec{x} \in \mathbb{R}^n \arrow[r, "h"] \arrow[rr, bend left, dashed, "f"] & h(\vec{x}) \in \mathbb{R}^p \arrow[r, "g"] & g(h(\vec{x})) \in \mathbb{R}^m \end{tikzcd}$$

$$J_f(\vec{x}) = \overbrace{\underbrace{J_g(h(\vec{x}))}_{m \times p} \cdot \underbrace{J_h(\vec{x})}_{p \times n}}^{m \times n \text{ matrix}}$$

$$\neq J_h(\vec{x}) \cdot J_g(f(\vec{x})) \quad \leftarrow \text{WRONG!}$$

Special case: $m = 1$

$$\nabla f(\vec{x})^T = J_f(\vec{x}) = J_g(h(\vec{x})) \cdot J_h(\vec{x}) = \nabla g(h(\vec{x}))^T \cdot J_h(\vec{x})$$

i.e. $\nabla f(\vec{x}) = J_h(\vec{x})^T \cdot \nabla g(h(\vec{x}))$ recall $(AB)^T = B^T A^T$

example from APPM 3310

$$f(\vec{x}) = \tfrac{1}{2}\|A\vec{x} - \vec{b}\|_2^2 = g(h(\vec{x})) \text{ with } h(\vec{x}) = A \cdot \vec{x} - \vec{b}, \; J_h(\vec{x}) = A$$

$$g(\vec{y}) = \tfrac{1}{2}\|\vec{y}\|_2^2 = \tfrac{1}{2}\sum_i y_i^2$$

$$\nabla g(\vec{y}) = \vec{y}$$

So via chain rule

$$\nabla f(\vec{x}) = J_h(\vec{x})^T \cdot \nabla g(h(\vec{x}))$$

$$= A^T \cdot (A\vec{x} - b)$$

thus setting $\nabla f(\vec{x}) = 0$ gives rise to $A^T(A\vec{x} - \vec{b}) = 0$, the normal equations!