

# 1 Recap

1. Topology of  $\mathbb{R}^n$  and invariance of domain.
2. Continuity, differentiability, chain rule.
3. Gradient, first derivative test, global extrema.

# 2 Review of multivariable calculus

Higher derivatives: It is of course possible that a function is differentiable and the derivative is continuous, and all the second partials exist but it is not twice-differentiable.

Here is an even weirder example :  $f(x, y) = \frac{xy(x^2-y^2)}{x^2+y^2}$  for  $(x, y) \neq (0, 0)$  and  $f(0, 0) = 0$ .

By properties,  $f$  is differentiable on  $\mathbb{R}^2 - \{(0, 0)\}$ . At  $(0, 0)$  we claim that it is differentiable and the gradient is 0 :  $|f(x, y) - 0 - 0| = |xy| \frac{|x^2-y^2|}{x^2+y^2} \leq x^2 + y^2$  (why ?) Therefore,

if  $\sqrt{x^2 + y^2} < \epsilon$ , we are done (Why ?) Now  $f_x = \frac{y(x^2-y^2)(x^2+y^2)+2x^2y(x^2+y^2)-2x^2y(x^2-y^2)}{(x^2+y^2)^2} =$

$y \frac{x^4-y^4-4x^2y^2}{(x^2+y^2)^2}$ ,  $f_y = -x \frac{y^4-x^4-4x^2y^2}{(x^2+y^2)^2}$  away from  $(0, 0)$ . Thus  $f_x, f_y$  are continuous throughout.

However,  $f_{xy} = \lim_{h \rightarrow 0} \frac{f_y(h, 0) - f_y(0, 0)}{h} = 1$  and  $f_{yx} = \lim_{h \rightarrow 0} \frac{f_x(0, h) - f_x(0, 0)}{h} = -1$ .

Therefore,  $f_{xy} \neq f_{yx}$  in general !

Theorem (Clairaut) : If all the second partials exist and are continuous are  $a$ , then the mixed partials are equal.

A function is called  $C^2$  if  $DF$  is differentiable and  $D^2F$  is continuous ( and likewise for  $C^k$ ). Notation: If  $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_k)$  is a multi-index, often  $\alpha! := \alpha_1! \alpha_2! \dots$ , and  $|\alpha| = \alpha_1 + \alpha_2 + \dots$ .  $\partial_\alpha f = \frac{\partial^{|\alpha|} f}{\partial(x^1)^{\alpha_1} \partial(x^2)^{\alpha_2} \dots}$ . If a function is  $C^k$  for all  $k$ , it is said to be  $C^\infty$  or smooth.

Proof of Clairaut: We will prove it for two-variable functions. The general case follows from this special case (why?) Let  $u(h, k) = f(a + h, b + k) - f(a + h, b)$ ,  $v(h, k) = f(a + h, b + k) - f(a, b + k)$ , and  $w(h, k) = f(a + h, b + k) - f(a + h, b) - f(a, b + k) - f(a, b)$ . Now,  $w(h, k) = u(h, k) - u(0, k) = h \partial_x u(c_1, k)$  by MVT for  $c_1 \in [0, h]$ . This equals  $h(\partial_x f(a + c_1, b + k) - \partial_x f(a + c_1, b)) = hk \partial_y \partial_x f(a + c_1, b + c_2)$  where  $c_2 \in [0, k]$ . Likewise,  $w(h, k) = v(h, k) - v(h, 0) = hk \partial_x \partial_y f(a + d_1, b + d_2)$  where  $d_1 \in [0, h]$ ,  $d_2 \in [0, k]$ . Dividing by  $hk$ , we see that  $\partial_y \partial_x f(a + c_1, b + c_2) = \partial_x \partial_y f(a + d_1, b + d_2)$ . By assumption of continuity of the second partials, there exists a  $\delta > 0$  such that  $|\partial_y \partial_x f(a + c_1, b + c_2) - \partial_y \partial_x f(a, b)| < \frac{\epsilon}{2}$ , and  $|\partial_x \partial_y f(a + d_1, b + d_2) - \partial_x \partial_y f(a, b)| < \frac{\epsilon}{2}$  whenever  $|(h, k)| < \delta$  (why ?). Thus,  $|f_{xy}(a, b) - f_{yx}(a, b)| < \epsilon$  for all  $\epsilon > 0$ . We are done.  $\square$

Using the  $C^2$  Clairaut, we can prove the  $C^k$  Clairaut for any  $k$ .

**Theorem 1 (Taylor).** Let  $U \subset \mathbb{R}^n$  be an open set and  $f : U \rightarrow \mathbb{R}$  be a  $C^k$  function on  $U$ . Let  $a \in U$  and  $|h| < \epsilon$  such that  $B_a(\epsilon) \subset U$ . Then the polynomial  $p_{a,k}(h) = f(a) + \sum_i \frac{\partial f}{\partial x_i}(a) h_i + \frac{1}{2} \sum_{i,j} \frac{\partial^2 f}{\partial x_i \partial x_j}(a) h_i h_j + \dots + \sum_{|\alpha|=k} \frac{D^\alpha f(a)}{\alpha!} h^\alpha$  is the unique polynomial of degree  $\leq k$  (degree meaning the maximum sum of powers) such that  $\lim_{h \rightarrow 0} \frac{f(a+h) - p_{k,a}(h)}{|h|^k} = 0$ . Moreover, if  $f$  is  $C^{k+1}$ , then  $f(a + h) = p_{k,a}(h) + \sum_{|\alpha|=k+1} \frac{D^\alpha f(\eta) h^\alpha}{\alpha!}$ , where  $\eta$  lies in  $B_a(h)$ .

Proof. Uniqueness is easy and left as an exercise. Let  $h \neq 0$  (if it is equal to 0, we are done). Consider the one-variable function  $q(t) = f(a + t \frac{h}{\|h\|})$  on  $|t| < \epsilon$ . This function

is  $C^k$  (because it is a composition of  $C^k$  functions). Thus we can apply the one-variable Taylor theorem to it to conclude that  $q(\|h\|) = q(0) + q'(0)\|h\| + \dots$

Now we claim inductively that  $\frac{q^{(m)}(t)\|h\|^m}{m!} = \sum_{|\alpha|=m} \frac{D^\alpha f(a+t\frac{h}{\|h\|})h^\alpha}{\alpha!}$ :

Indeed, for  $m = 1$  we are done by the Chain rule. Assume the truth of this statement for  $1, 2, \dots, m - 1$ . We apply the induction hypothesis to  $q^{(m-1)}(t)$  to conclude that

$$\frac{q^{(m)}(t)\|h\|^m}{m!} = \frac{\|h\|}{m} \sum_{|\alpha|=m-1} \frac{d}{dt} \frac{D^\alpha f(a+t\frac{h}{\|h\|})h^\alpha}{\alpha!} = \sum_{|\alpha|=m-1} \sum_i \frac{\partial_{x_i} D^\alpha f(a+t\frac{h}{\|h\|})h_i h^\alpha}{\alpha! m} = \sum_i \sum_{|\alpha|=m-1} \frac{\partial_{x_i} D^\alpha f(a+t\frac{h}{\|h\|})h_i h^\alpha}{\alpha! m}. \text{ We want to compare the last expression to } \sum_{|\beta|=m} \frac{D^\beta f(a+t\frac{h}{\|h\|})h^\beta}{\beta!}.$$

Given  $i$  such that  $\beta_i \geq 1$ , every multi-index vector  $\beta$  can be written uniquely as  $\beta = \alpha + e_i$  where  $|\alpha| = m - 1$ . However, this can be done for each such  $i$ . Hence, if we fix  $\beta$ , then  $\frac{1}{\alpha! m} = \frac{\alpha_i + 1 = \beta_i}{\beta! m}$  and if we sum over all  $i$  giving rise to the same  $\beta$ , then we get  $\sum_i \frac{\beta_i}{\beta! m} = \frac{1}{\beta!}$ . Hence these two expressions are the same, and we are done.

Now the one-variable Taylor theorem, i.e., the following theorem, completes the proof.

**Theorem 2.** Let  $U \subset \mathbb{R}$  be an open set and  $f : U \rightarrow \mathbb{R}$  a  $C^k$  function on  $U$ . Let  $a \in U$  and  $|h| < \epsilon$  such that  $(a - \epsilon, a + \epsilon) \in U$ . Then the polynomial  $p_{k,a}(h) = f(a) + f'(a)h + \frac{f''(a)h^2}{2!} + \dots + \frac{f^{(k)}(a)h^k}{k!}$  is the unique polynomial of degree  $\leq k$  such that  $\lim_{h \rightarrow 0} \frac{f(a+h) - p_{k,a}(h)}{h^k} = 0$ . Moreover, if  $f$  is  $C^{k+1}$ , then  $f(a+h) = p_{k,a}(h) + \frac{f^{(k+1)}(\eta)h^{k+1}}{(k+1)!}$ , where  $\eta$  lies between  $a$  and  $a+h$ .

□

The second derivative test: Let  $U \subset \mathbb{R}^n$  be open and  $f : U \rightarrow \mathbb{R}$  be a  $C^1$  function. Suppose  $f$  is  $C^2$  at  $a \in U$  and  $Df_a = 0$ .

Theorem: If  $\sum_{i,j} f_{ij}(a)v^i v^j > 0$  for all  $v \neq 0$ , then  $a$  is a local minimum. If  $\sum_{i,j} f_{ij}(a)v^i v^j < 0$  for all  $v \neq 0$ , then  $a$  is a local maximum. Conversely, if  $a$  is a local minimum  $\sum_{i,j} f_{ij}(a)v^i v^j \geq 0$  for all  $v$  (and likewise for a local max).

Proof: Taylor's theorem (with the Peano form of the remainder) implies that if  $\sum_{i,j} f_{ij}(a)v^i v^j > 0$ ,  $f(a+v) - f(a) > 0$  for all small  $v$ . Thus  $a$  is a local minimum. Likewise for local maxima. Conversely, if  $\sum_{i,j} f_{ij}(a)v^i v^j < 0$  for some  $v$ , then  $f(a+v) - f(a) < 0$  and hence  $a$  cannot be a local minimum. (Likewise for local maxima.)

□

The matrix  $f_{ij}$  is called the 'Hessian' matrix of  $f$ . For future purposes a twice differentiable function whose second partials are continuous is said to be convex if  $\sum_{i,j} v_i f_{ij}(a)v_j \geq 0 \forall v \neq 0$ . Often, optimization studies convex functions. In general, given a symmetric  $n \times n$  real matrix  $A$ , i.e.,  $A^T = A$ , i.e.,  $A_{ij} = A_{ji}$ , it is said to be positive-definite if  $\sum_{i,j} A_{ij}v_i v_j > 0$  for all  $v \neq 0$ , i.e.,  $v^T A v > 0$  for all  $v \neq 0$ . This condition is somewhat subtle. For  $2 \times 2$  matrices,  $A = \begin{bmatrix} a & b \\ b & d \end{bmatrix}$ , supposing  $v^T = (x, y)$ , we see that  $v^T A v = ax^2 + dy^2 + 2bxy$ . This expression is positive for all  $(x, y) \neq (0, 0)$  if and only if  $a > 0$  and  $ad - b^2 = \det(A) > 0$ . (Why?) Similar but more complicated conditions exist for  $n \times n$  matrices. (Positive-definiteness is the same as having only positive eigenvalues by the way.)

Example: Find local extrema of  $f(x, y) = x^2 - y^2$  on  $\mathbb{R}^2$ :  $\nabla f = (2x, -2y) = (0, 0)$  only at the origin. The Hessian is  $\begin{bmatrix} 2 & 0 \\ 0 & -2 \end{bmatrix}$ . So the origin is neither a local max nor a local min (despite the second derivative being non-zero! (and none of the eigenvalues being zero)). There is a direction in which  $f$  increases and a direction in which it decreases. Such points are called "Saddle points". More generally, the eigenvectors and eigenvalues of the Hessian tell us about these "principal" directions.