

## NOTES ON HIGHER DIMENSIONAL DERIVATIVES

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### 1. SINGLE-VARIABLE RECAP

Let  $f(x)$  be a differentiable function of one variable.

**Definition 1.1.** The *derivative of  $f$  at  $a$*  is

$$f'(a) = f_x(a) = \frac{\partial f}{\partial x}(a) = \lim_{x \rightarrow a} \frac{f(x) - f(a)}{x - a} = \lim_{t \rightarrow 0} \frac{f(a+t) - f(a)}{t}. \quad (1)$$

**Remark 1.2.** The derivative of  $f$  at  $a$  is the instantaneous rate of change of  $f$  when increasing  $x$  at unit speed near  $a$ . It can also be thought of as the linear approximation (i.e. first order approximation) to  $f$ .

**Definition 1.3.** The *Taylor series approximation  $T = T_{f,a}$  for  $f$  at  $a$*  is

$$T(x) = \sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} (x - a)^k. \quad (2)$$

The  $n^{\text{th}}$ -*partial Taylor series approximation  $T_n = T_{n,f,a}$  for  $f$  at  $a$*  is

$$T_n(x) = \sum_{k=0}^n \frac{f^{(k)}(a)}{k!} (x - a)^k. \quad (3)$$

Here  $f^{(k)}$  is the  $k^{\text{th}}$  derivative of  $f$  and  $f^{(0)} = f$  by convention.

**Remark 1.4.** The idea here is that  $T_n$  and  $f$  have the same  $k^{\text{th}}$  derivative at  $a$  for all  $0 \leq k \leq n$ .

**Definition 1.5.** The *linearization of  $f$  at  $a$*  is  $L = T_1$ . That is,

$$L(x) = f(a) + f'(a)(x - a). \quad (4)$$

**Remark 1.6.** The linearization of  $f$  and  $f$  itself share the same order 0 and order 1 information at  $a$ . That is,  $L(a) = f(a)$  and  $L'(a) = f'(a)$ .

### 2. MORE VARIABLES

We want a notion of derivative in higher dimensions which generalizes the single variable derivative, so let's begin by looking at higher variable functions in only one direction at a time. Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a continuous function of multiple variables,  $P \in \mathbb{R}^n$  any point in the domain of  $f$ , and  $v \in \mathbb{R}^n$  any vector (thought of as emanating from  $P$ ).

**Definition 2.1.** The *directional derivative in the direction  $v$  of  $f$  at  $P$*  is

$$D_v f(a, b) = \frac{\partial f}{\partial x}(a) = \lim_{h \rightarrow 0} \frac{f(P + tv) - f(P)}{t}. \quad (5)$$

**Remark 2.2.** The directional derivative in the direction  $v$  of  $f$  at  $P$  is the instantaneous rate of change of  $f$  when moving (in the domain) through  $P$  with velocity  $v$ .

**Remark 2.3.** Consider the path through the domain  $\mathbb{R}^n$  given by  $\gamma(t) = P + tv$ . Then  $D_v f(P) = \frac{\partial}{\partial t}[f \circ \gamma](0)$ ; that is, the directional derivative in the direction  $v$  of  $f$  at  $P$  can be thought of as the single variable derivative of  $f$  restricted to the line determined by  $P$  and  $v$ .

**Theorem 2.4.** *As a function of  $v$ , the directional derivative of  $f$  at  $P$*

$$\begin{aligned} \mathbb{R}^n &\rightarrow \mathbb{R} \\ v &\mapsto D_v f(P) \end{aligned}$$

*is linear. This means  $D_{sv+tw}f(P) = sD_v f(P) + tD_w f(P)$  for any  $v, w$  vectors and any  $s, t$  scalars. In particular, there is a unique vector  $\nabla f(P)$  with the property that  $D_v f(P) = \nabla f(P) \cdot v$  for every vector  $v$ .*

*Proof.* For the first part, plug  $sv + tw$  into the definition of derivative. The “in particular” part is linear algebra magic.  $\square$

**Definition 2.5.** The vector  $\nabla f(P)$  is the *gradient* of  $f$  at  $P$ . The gradient of  $f$  is a *vector field*; i.e. a function  $\mathbb{R}^n \rightarrow \mathbb{R}^n$  where the input is thought of as a point and the output is thought of as a vector originating at the input point.

**Theorem 2.6.** *The gradient is orthogonal to level sets of  $f$ .*

*Proof.* For any direction  $v$  tangent to a level set of  $f$  at  $P$ ,

$$0 = D_v f(P) = \nabla f(P) \cdot v \quad (6)$$

since  $f$  is constant along level sets.  $\square$

**Corollary 2.7.** *The direction of greatest increase (respectively, steepest descent) of  $f$  at  $P$  is given by  $\nabla f(P)$  (resp.  $-\nabla f(P)$ ).*

*Proof.* For any direction  $|v|^2 = 1$ ,  $D_v f(P) = \nabla f(P) \cdot v = |\nabla f(P)||v| \cos \theta$  is maximized (resp. minimized) when  $v$  and  $\nabla f(P)$  are (resp. anti-)parallel.  $\square$

### 3. LINEARIZATION

Again, let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a differentiable function of multiple variables and  $P \in \mathbb{R}^n$  a point in the domain of  $f$ . Just as in the single variable case, the linearization of  $f$  and  $f$  itself should share the same order 0 and 1 information at  $P$ .

**Definition 3.1.** The linearization  $L$  of  $f$  at  $P$  is the unique linear function on  $\mathbb{R}^n$  such that  $L(P) = f(P)$  and  $\nabla L(P) = \nabla f(P)$ .

**Remark 3.2.** To construct such a function, let  $L(Q) = f(P) + \nabla f(P) \cdot (Q - P)$ . Then

$$L(P) = f(P) + \nabla f(P) \cdot 0 = f(P) \text{ and} \quad (7)$$

$$D_v L(P) = \lim_{t \rightarrow 0} \frac{\nabla f(P) \cdot tv}{t} = \nabla f(P) \cdot v \quad (8)$$

so  $\nabla L(P) = \nabla f(P)$  by the defining property of the gradient.

#### 4. IN COORDINATES

So far we have done everything without using coordinates (which is hopefully a little satisfying). This is similar to how I defined dot/cross products in the first week using only algebraic properties with no coordinates. However, for the sake of homework and exams, where you are asked to do computations in a certain coordinate system, let's cover the coordinate dependent versions of these notions.

In this section, let's assume we are in the  $x : y : z$  coordinates of  $\mathbb{R}^3$ . This coordinate system has a "standard basis" comprised of the three standard unit vectors:  $\hat{i}, \hat{j}, \hat{k}$ .

**Definition 4.1.** The *partial derivatives* of  $f$  at  $P = (a, b, c)$  are the directional derivatives in the standard directions:

$$\begin{aligned} \frac{\partial f}{\partial x}(a, b, c) &= f_x(a, b, c) = D_{\hat{i}}f(P) \\ \frac{\partial f}{\partial y}(a, b, c) &= f_y(a, b, c) = D_{\hat{j}}f(P) \\ \frac{\partial f}{\partial z}(a, b, c) &= f_z(a, b, c) = D_{\hat{k}}f(P). \end{aligned}$$

**Remark 4.2.** We can write any vector  $v$  in coordinates by

$$v = (v \cdot \hat{i})\hat{i} + (v \cdot \hat{j})\hat{j} + (v \cdot \hat{k})\hat{k} = \langle v \cdot \hat{i}, v \cdot \hat{j}, v \cdot \hat{k} \rangle. \quad (9)$$

The gradient is no different. However, because of its defining property, the gradient takes on a nice coordinate dependent form.

$$\nabla f = \langle \nabla f \cdot \hat{i}, \nabla f \cdot \hat{j}, \nabla f \cdot \hat{k} \rangle = \langle D_{\hat{i}}f, D_{\hat{j}}f, D_{\hat{k}}f \rangle = \langle f_x, f_y, f_z \rangle. \quad (10)$$

Lastly, let's look at the linearization  $L$  of  $f$  at  $P = (a, b, c)$  in coordinates. Plugging  $Q = (x, y, z)$  and  $P = (a, b, c)$  into Remark 3.2, we get

$$\begin{aligned} L(x, y, z) &= f(a, b, c) + \nabla f(a, b, c) \cdot (\langle x, y, z \rangle - \langle a, b, c \rangle) \\ &= f(a, b, c) + \langle f_x(a, b, c), f_y(a, b, c), f_z(a, b, c) \rangle \cdot \langle x - a, y - b, z - c \rangle \\ &= f(a, b, c) + f_x(a, b, c)(x - a) + f_y(a, b, c)(y - b) + f_z(a, b, c)(z - c). \end{aligned}$$