Total derivatives
Math 131 Multivariate Calculus
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Last time. We found that the total derivative of a scalar-valued function, also called a scalar field, $\mathbf{R}^{n} \rightarrow \mathbf{R}$, is the gradient

$$
\nabla f=\left(f_{x_{1}}, f_{x_{2}}, \ldots, f_{x_{n}}\right)=\left(\frac{\partial f}{\partial x_{1}}, \frac{\partial f}{\partial x_{2}}, \ldots, \frac{\partial f}{\partial x_{n}}\right)
$$

When $n=2$ the gradient, $\nabla f=\left(f_{x}, f_{y}\right)$, gives the slopes of the tangent plane in the $x$-direction and the $y$-direction.

## Total derivatives to vector-valued functions.

 Let $\mathbf{f}: \mathbf{R}^{n} \rightarrow \mathbf{R}^{m}$ be a vector-valued function. As always, a vector valued function is determined by its $m$ scalar-valued component functions:$$
\mathbf{f}(\mathbf{x})=\left(f_{1}(\mathbf{x}), f_{1}(\mathbf{x}), \ldots, f_{m}(\mathbf{x})\right) .
$$

We'll say $\mathbf{f}$ is differentiable if all its component functions are differentiable, and in that case, we'll take the derivative of $\mathbf{f}$, denoted $D \mathbf{f}$, to be the $m \times n$ matrix of partial derivatives of the component functions:

$$
D \mathbf{f}\left(x_{1}, x_{2}, \ldots, x_{n}\right)=\left[\begin{array}{cccc}
\frac{\partial f_{1}}{\partial x_{1}} & \frac{\partial f_{1}}{\partial x_{2}} & \ldots & \frac{\partial f_{1}}{\partial x_{n}} \\
\frac{\partial f_{2}}{\partial x_{1}} & \frac{\partial f_{2}}{\partial x_{2}} & \ldots & \frac{\partial f_{2}}{\partial x_{n}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial f_{m}}{\partial x_{1}} & \frac{\partial f_{m}}{\partial x_{2}} & \ldots & \frac{\partial f_{m}}{\partial x_{n}}
\end{array}\right]
$$

Thus, the $i j$-th entry is $\frac{\partial f_{i}}{\partial x_{j}}$, the $j$-th partial derivative of the $i$-component function $f_{i}$.

In terms of limits, a logically equivalent definition says $\mathbf{f}$ is differentiable at a if (1) all the $m n$ partial derivatives exist, and (2) the linear function

$$
\mathbf{h}(\mathbf{x})=\mathbf{f}(\mathbf{a})+D \mathbf{f}(\mathbf{a})(\mathbf{x}-\mathbf{a})
$$

is a good approximation of $\mathbf{f}$ near $\mathbf{a}$ in the sense that

$$
\lim _{\mathbf{x} \rightarrow \mathbf{a}} \frac{\mathbf{f}(\mathrm{x})-\mathbf{h}(\mathrm{x})}{\|\mathrm{x}-\mathbf{a}\|}=\mathbf{0}
$$

Note that when $m=1$, this definition says the derivative $D f$ of the scalar-valued function $f$ is the $1 \times n$ row-matrix

$$
D f\left(x_{1}, x_{2}, \ldots, x_{n}\right)=\left[\begin{array}{llll}
\frac{\partial f}{\partial x_{1}} & \frac{\partial f}{\partial x_{2}} & \ldots & \frac{\partial f}{\partial x_{n}}
\end{array}\right]
$$

which is the same thing as the gradient $\nabla f$, but written out as a row-matrix rather than an $n$-tuple.

Example 1. This derivative $D \mathbf{f}$ looks complicated, but it isn't, really. For an example, let $\mathbf{f}: \mathbf{R}^{3} \rightarrow \mathbf{R}^{4}$ be defined by

$$
\mathbf{f}(x, y, z)=(x+2 y+3 z, x y z, \cos x, \sin x)
$$

Then $D \mathbf{f}$ is the $4 \times 3$ matrix $D \mathbf{f}\left(x_{1}, x_{2}, \ldots, x_{n}\right)$

$$
=\left[\begin{array}{lll}
\frac{\partial f_{1}}{\partial x} & \frac{\partial f_{1}}{\partial y} & \frac{\partial f_{1}}{\partial z} \\
\frac{\partial f_{2}}{\partial x} & \frac{\partial f_{2}}{\partial y} & \frac{\partial f_{2}}{\partial z} \\
\frac{\partial f_{3}}{\partial x} & \frac{\partial f_{3}}{\partial y} & \frac{\partial f_{3}}{\partial z} \\
\frac{\partial f_{4}}{\partial x} & \frac{\partial f_{4}}{\partial y} & \frac{\partial f_{4}}{\partial z}
\end{array}\right]=\left[\begin{array}{ccc}
1 & 2 & 3 \\
y z & x z & x y \\
-\sin x & 0 & 0 \\
\cos x & 0 & 0
\end{array}\right]
$$

Rules of differentiation. Typically, when derivatives of multivariant functions are actually computed, they're computed one partial derivative at a time. Partial derivatives are just ordinary derivatives when only one variable actually varies, so no new rules of differentiation are needed for them. But there are rules for gradients and total derivatives.

The usual properties of derivatives for functions of one variable $f: \mathbf{R} \rightarrow \mathbf{R}$ are the sum rule, difference rule, product rule, quotient rule, and chain rule. For the most part, these properties are enjoyed by functions $\mathbf{f}: \mathbf{R}^{n} \rightarrow \mathbf{R}^{m}$, but the product and quotient rules will need to be modified and restricted.

For instance, derivatives are linear in the sense that they preserve addition and scalar multiplication, and therefore they preserve subtraction and, in general, all linear combinations. So, for vectorvalued differentiable functions $\mathbf{R}^{n} \rightarrow \mathbf{R}^{m}$, we have

$$
\begin{aligned}
D(\mathbf{f}+\mathbf{g}) & =D \mathbf{f}+D \mathbf{g} \\
D(c \mathbf{f}) & =c D \mathbf{f} \\
D(\mathbf{f}-\mathbf{g}) & =D \mathbf{f}-D \mathbf{g} \\
D\left(c_{1} \mathbf{f}_{1}+\cdots+c_{r} \mathbf{f}_{r}\right) & =c_{1} D \mathbf{f}_{1}+\cdots+c_{r} D \mathbf{f}_{r}
\end{aligned}
$$

When the functions are scalar-valued functions $\mathbf{R}^{n} \rightarrow \mathbf{R}$, i.e., when $m=1$, we can also write these rules in terms of gradients as

$$
\begin{aligned}
\nabla(f+g) & =\nabla f+D g \\
\nabla(c f) & =c \nabla f \\
\nabla(f-g) & =\nabla f-\nabla g \\
\nabla\left(c_{1} f_{1}+\cdots+c_{r} f_{r}\right) & =c_{1} \nabla f_{1}+\cdots+c_{r} \nabla f_{r}
\end{aligned}
$$

The product and quotient rules apply to scalarvalued functions $f$ and $g$, both $\mathbf{R}^{n} \rightarrow \mathbf{R}$ :

$$
\begin{aligned}
\nabla(f g) & =(\nabla f) g+f \nabla g \\
\nabla\left(\frac{f}{g}\right) & =\frac{(\nabla f) g-f \nabla g}{g^{2}}
\end{aligned}
$$

The product and quotient rules don't easily generalize to vector-valued functions.

Later, we'll see what happens to the chain rule.
Math 131 Home Page at
http://math.clarku.edu/~djoyce/ma131/

