

1,5 cont.

2016-01-20

Determinant for an $n \times n$ matrix: $(\det([a]) = a)$

$$\det(A) = \sum_{i=1}^n (-1)^{i+1} a_{i1} \det(A_i)$$

$$= \sum_{\sigma \in S^n} \text{sgn}(\sigma) \prod_{i=1}^n a_{i, \sigma_i}$$

For 2×2 :

$$\rightarrow \det \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = +a_{11} \det(a_{22}) - a_{12} \det(a_{21})$$

$$= \underbrace{a_{11} a_{22}}_{\text{downward diagonal}} - \underbrace{a_{12} a_{21}}_{\text{upward diagonal}}$$

Same thing

$$\rightarrow \det \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = \underbrace{(+1) a_{11} a_{22}}_{\sigma = \langle 1, 2 \rangle} + \underbrace{(-1) a_{12} a_{21}}_{\sigma = \langle 2, 1 \rangle}$$

For 3×3 :

$$\begin{aligned}
 \det \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} &= +a_{11} \det \begin{pmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{pmatrix} - a_{12} \det \begin{pmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{pmatrix} + a_{13} \det \begin{pmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \\
 &= a_{11} (a_{22} a_{33} - a_{23} a_{32}) - \dots + \dots \\
 &= (a_{11} a_{22} a_{33} + a_{12} a_{23} a_{31} + a_{13} a_{21} a_{32}) \\
 &\quad \text{downward diagonals} \\
 &\quad - (a_{11} a_{32} a_{23} + a_{12} a_{21} a_{33} + a_{13} a_{22} a_{31}) \\
 &\quad \text{upward diagonals}
 \end{aligned}$$

(Example) Prove that the inverse of $A = \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix}$ is

$$\frac{1}{\det A} \begin{bmatrix} b_2 & -a_2 \\ -b_1 & a_1 \end{bmatrix}$$

Multiply them together:

$$\begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix} \begin{bmatrix} b_2/\det A & -a_2/\det A \\ -b_1/\det A & a_1/\det A \end{bmatrix} = \begin{bmatrix} \frac{a_1 b_2 - a_2 b_1}{\det A} & \frac{-a_1 a_2 + a_2 a_1}{\det A} \\ \frac{b_1 b_2 - b_1 b_2}{\det A} & \frac{-b_1 a_2 + a_1 b_2}{\det A} \end{bmatrix}$$

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$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I.$$

2.3 Differentiation

Functions from $\mathbb{R}^n \rightarrow \mathbb{R}^m$

Denoted $\underline{f}: \mathbb{R}^n \rightarrow \mathbb{R}^m$ and

$$\begin{aligned}\underline{f}(\underline{x}) &= \underline{f}(x_1, \dots, x_n) \\ &= (f_1(\underline{x}), \dots, f_m(\underline{x})) \\ &= (f_1(x_1, \dots, x_n), \dots, f_m(x_1, \dots, x_n))\end{aligned}$$

For example: $\underline{f}: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ may be defined by

$$\underline{f}(x_1, x_2) = \underline{f}(x, y) = \left(\underbrace{x+y}_{f_1(x,y)}, \underbrace{xy}_{f_2(x,y)} \right)$$

$$\begin{aligned}\text{So } \underline{f}(0, -3) &= (0 + (-3), (0)(-3)) \\ &= (-3, 0).\end{aligned}$$

Partial
Derivative Matrix:

$$\underline{D}\underline{f}(\underline{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1} & \dots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

Using the prev. example... $\underline{f} = (x+y, xy)$

$$\underline{Df}(\underline{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x} & \frac{\partial f_1}{\partial y} \\ \frac{\partial f_2}{\partial x} & \frac{\partial f_2}{\partial y} \end{bmatrix} = \begin{bmatrix} 1+0 & 0+1 \\ y(1) & x(1) \end{bmatrix} \\ = \begin{bmatrix} 1 & 1 \\ y & x \end{bmatrix}$$

We say \underline{f} is differentiable at \underline{x}_0 if

$$\underline{f}(\underline{x}_0 + \underline{h}) \approx \underline{f}(\underline{x}_0) + [\underline{Df}(\underline{x}_0)] \underline{h} \text{ whenever } \underline{h} \approx \underline{0}.$$

Compare with...

$$\begin{aligned} f(x_0+h) &\approx f(x_0) + f'(x_0)h \quad \Leftrightarrow \cancel{f(x_0)} \approx \cancel{f(x_0+h)} \\ &\Leftrightarrow f'(x_0)h \approx f(x_0+h) - f(x_0) \\ &\Leftrightarrow f'(x_0) \approx \frac{f(x_0+h) - f(x_0)}{h} \\ &\text{because } f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} \end{aligned}$$

(Example) Prove that the definition of differentiability is equivalent to saying

$$\underline{f}(\underline{x}) \approx \underline{f}(\underline{x}_0) + [\underline{D}\underline{f}(\underline{x}_0)](\underline{x} - \underline{x}_0) \text{ whenever } \underline{x} \approx \underline{x}_0$$

Let $\underline{x} = \underline{x}_0 + \underline{h}$. Then $\underline{h} = \underline{x} - \underline{x}_0$, and if $\underline{h} \approx \underline{0}$, then $\underline{x} - \underline{x}_0 \approx \underline{0}$ and $\underline{x} \approx \underline{x}_0$. \square

(Example) Let $\underline{f}: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined by $\underline{f}(x, y) = (x^2 + y^2, xy)$, and let $\underline{I} = \underline{D}\underline{f}(1, 0)$. Compute $\underline{f}(1.1, -0.1)$ and $\underline{f}(1, 0) + \underline{I}(0.1, -0.1)$.

$$\begin{aligned} \underline{f}(1.1, -0.1) &= (1.21 + 0.01, -0.11) \\ &= (1.22, -0.11) \end{aligned}$$

$$\begin{aligned} \underline{I} = \underline{D}\underline{f}(1, 0) &= \begin{bmatrix} \frac{\partial f_1}{\partial x}(1, 0) & \frac{\partial f_1}{\partial y}(1, 0) \\ \frac{\partial f_2}{\partial x}(1, 0) & \frac{\partial f_2}{\partial y}(1, 0) \end{bmatrix} \\ &= \begin{bmatrix} 2x|_{(1,0)} & 2y|_{(1,0)} \\ y|_{(1,0)} & x|_{(1,0)} \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \end{aligned}$$

$$\begin{aligned}
\underline{f}(1,0) + \underline{I}(0.1, -0.1) &= \cancel{(1.1, -0.1)} \\
&= (1+0, 0) + \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} (0.1, -0.1) \\
&= \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0.1 \\ -0.1 \end{bmatrix} \\
&= \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0.2 + 0 \\ 0 + (-0.1) \end{bmatrix} \\
&= \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0.2 \\ -0.1 \end{bmatrix} = \boxed{\begin{bmatrix} 1.2 \\ -0.1 \end{bmatrix}} \\
&= \boxed{(1.2, -0.1)}
\end{aligned}$$

In that example, $\underline{x}_0 = (1, 0)$, $\underline{h} = (0.1, -0.1)$, $\underline{x} = (1.1, -0.1)$.

Note $\underline{h} \approx \underline{0}$. So it's reasonable that

$$\underline{f}(\underline{x}_0 + \underline{h}_0) = (1.22, -0.11) \approx (1.2, -0.1) = \underline{f}(\underline{x}_0) + \underbrace{\left[\underline{Df}(\underline{x}_0) \right]}_{\text{OR } \underline{I}} \underline{h}$$

FACT
IF $\frac{\partial f_i}{\partial x_j}$ is continuous near \underline{x}_0 for all values of i, j ,
 then \underline{f} is strongly differentiable a.k.a. class C^1 .

Most of what we'll see is C^2 .

Gradient

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a real-valued function of multiple variables. Then,

$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_n} \right) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$$

$$\text{Ex: } f(x, y) = x^2 + 2xy + 3y^2 \Rightarrow \nabla f = \left(\overset{\partial f / \partial x}{2x + 2y}, \overset{\partial f / \partial y}{2x + 6y} \right).$$

Compare this with:

$$\cancel{\underline{Df}} = \cancel{\underline{Df}} = \underline{Df} = \left[\frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_n} \right] = (\nabla f)^T$$

$$\text{Ex: } \underline{Df} = \begin{bmatrix} \underset{\partial f / \partial x}{2x + 2y} & \underset{\partial f / \partial y}{2x + 6y} \end{bmatrix}$$

Fact: Let \underline{h} be an n -dimensional vector. Then

$$\begin{aligned} \underline{Df} \underline{h} &= \left[\frac{\partial f}{\partial x_1} \dots \frac{\partial f}{\partial x_n} \right] \begin{bmatrix} h_1 \\ \vdots \\ h_n \end{bmatrix} = \left(\frac{\partial f}{\partial x_1} \right) (h_1) + \dots + \left(\frac{\partial f}{\partial x_n} \right) (h_n) \\ &= \nabla f \cdot \underline{h} \end{aligned}$$

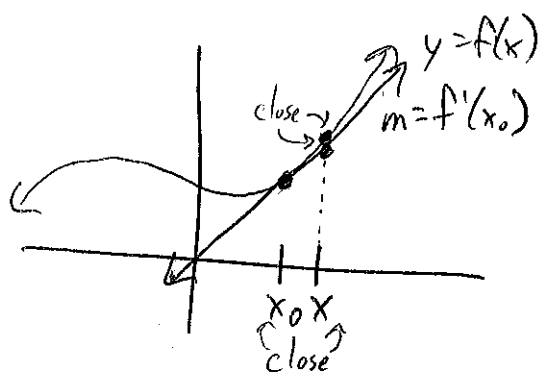
Linearizations & Tangent Hyperplanes

For $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ and a point $\underline{x}_0 \in \mathbb{R}^n$, let the linearization of f at \underline{x}_0 be

$$\underline{L}(\underline{x}) = f(\underline{x}_0) + [Df(\underline{x}_0)](\underline{x} - \underline{x}_0).$$

So by definition, $f(\underline{x}) \approx \underline{L}(\underline{x})$ whenever $\underline{x} \approx \underline{x}_0$ if f is differentiable.

Recall from Cal I:



So the tangent line is the linearization function:

$$y = \underline{L}(x) = f(x_0) + f'(x_0)(x - x_0)$$

(Example 5) Recall that the tangent plane to the surface $z=f(x,y)$ given by $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ passing thru $\underline{x}_0 \in \mathbb{R}^3$ is given by $\nabla f(\underline{x}_0)$. Show that $z=\underline{L}(x,y)$ is the equation of the tangent plane to the surface $z=\underbrace{x^2+y^4+e^{xy}}_{f(x,y)}$ at the point $\underbrace{(1,0,2)}_{\underline{x}_0}$.

$$z = L(x, y)$$

$$= f(1, 0) + \frac{d}{dt} f(1, 0) \left(\begin{matrix} x-1 \\ y-0 \end{matrix} \right) \quad \begin{matrix} (x, y) - (1, 0) \\ \downarrow \\ (x-1, y-0) \end{matrix}$$

$$= (1 + 0 + e^0) + \left[\frac{\partial f}{\partial x} \quad \frac{\partial f}{\partial y} \right]_{(1,0)} \begin{bmatrix} x-1 \\ y-0 \end{bmatrix}$$

$$= 2 + \left[2x + ye^{xy} \quad 4y^3 + xe^{xy} \right]_{(1,0)} \begin{bmatrix} x-1 \\ y-0 \end{bmatrix}$$

$$= 2 + \left[2+0 \quad 0+1e^0 \right] \begin{bmatrix} x-1 \\ y-0 \end{bmatrix}$$

$$= 2 + [2-1] \begin{bmatrix} x-1 \\ y-0 \end{bmatrix}$$

$$z = 2 + 2(x-1) + 1(y-0)$$

(to be concluded tomorrow...)