

Week 5: Higher Order Derivatives and Taylor's Theorem

Iterated Partial Derivatives

(M&T p. 150)

If $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ is differentiable then we can form the following partial derivatives.

rate of change in the x -direction $\longrightarrow \frac{\partial f}{\partial x} \quad \frac{\partial f}{\partial y} \longleftarrow$ rate of change in the y -direction

These derivatives are themselves functions $\mathbb{R}^2 \rightarrow \mathbb{R}$.

Therefore, we have the following second order partial derivatives.

$$\frac{\partial}{\partial x} \left[\frac{\partial f}{\partial x} \right] = \frac{\partial^2 f}{\partial x^2} \quad \frac{\partial}{\partial y} \left[\frac{\partial f}{\partial x} \right] = \frac{\partial^2 f}{\partial y \partial x} \quad \frac{\partial}{\partial x} \left[\frac{\partial f}{\partial y} \right] = \frac{\partial^2 f}{\partial x \partial y} \quad \frac{\partial}{\partial y} \left[\frac{\partial f}{\partial y} \right] = \frac{\partial^2 f}{\partial y^2}$$

In general, the k th order partial derivatives involve k differentiations. We call these mixed partial derivatives or iterated partial derivatives.

Four types of second derivatives.

Example: Calculate Some Mixed Partial Derivatives

Calculate the following mixed partial derivative.

$$\frac{\partial}{\partial x} \left[\frac{\partial}{\partial y} \left[\frac{\partial}{\partial z} [\sin(xyz)] \right] \right]$$

Work from inside outwards.

compute derivative in z -direction

$$\frac{\partial}{\partial x} \left[\frac{\partial}{\partial y} [xy \cos(xyz)] \right]$$

compute derivative in y -direction

$$\begin{aligned} &= \frac{\partial}{\partial x} [x \cos(xyz) + xy (-\sin(xyz) xz)] \\ &= \frac{\partial}{\partial x} [x \cos(xyz) - x^2 y z \sin(xyz)] \end{aligned}$$

compute derivative in x -direction

$$\begin{aligned} &= \cos(xyz) - xyz \sin(xyz) - 2xyz \sin(xyz) \\ &\quad - x^2 y z^2 \cos(xyz) \end{aligned}$$

Recall: Class C^k

(M&T p. 150)

Recall that f is C^1 if all its partial derivatives exist and are continuous.

We say that f belongs to class C^k (or is C^k) if all its derivatives of order $\leq k$ exist and are continuous.

★ Theorem: Equality of Mixed Partial

(M&T p. 151)

If $f(x, y)$ belongs to class C^2 then the mixed partial derivatives are equal.

Question:

Is this an
equivalence?

$$\frac{\partial^2 f}{\partial x \partial y} = \frac{\partial^2 f}{\partial y \partial x}$$

Proof in B42

This theorem generalizes to k th order derivatives of C^k functions.

Example: Check the Equality of Mixed Partial

Check the equality of mixed partial derivatives by verifying:

$$\frac{\partial}{\partial x} \left[\frac{\partial}{\partial y} [1x^2 + 2xy + 3y^2] \right] = \frac{\partial}{\partial y} \left[\frac{\partial}{\partial x} [1x^2 + 2xy + 3y^2] \right]$$

This works
for all
polynomials.

$$= \frac{\partial}{\partial x} [0 + 2x + 0]$$

$$= 0 + 2 + 0 = 2$$

$$= \frac{\partial}{\partial y} [1 \cdot 2 + 2y + 0] \quad \left| \begin{array}{l} \text{Polynomials} \\ \text{are in } C^k \\ \text{for all } k. \end{array} \right.$$

$$= 0 + 2 + 0 = 2$$

Yay! They match. 😊

Subscript Notation for Derivatives

(M&T p. 152)

An alternative notation for partial derivatives is the following.

$$f_{yx} = [f_y]_x = \frac{\partial}{\partial x} \left[\frac{\partial f}{\partial y} \right]$$

Notice that the order of x and y is reversed in the two notations! Luckily, for C^2 functions, $f_{xy} = f_{yx}$.

🏃 Activity: Calculate as a Class (3 min)

Consider the function $f(x, y, z) = x^2y + xy^2 + yz^2$.

Calculate f_{xy} , f_{yz} , and f_{xyz} . Write your final answers on the board.

$$f_{xy} = 2x + 2y = f_{yx}$$

$$f_{yz} = 2z = f_{zy}$$

$$f_{xyz} = 0$$

LOTS of equations in physics are PDEs.

The Heat Equation (Sneak Peek to MAT B42)

(M&T p. 154)

Let $\mathcal{B} \subset \mathbb{R}^2$ denote some physical body in two dimensional space. Suppose that $T(x, y, t)$ is the temperature at time t of the point $(x, y) \in \mathcal{B}$. The temperature must satisfy the heat equation:

$$k \left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} \right) = \frac{\partial T}{\partial t} \quad \leftarrow \text{B42: How do we solve the Heat Equation?}$$

In this equation k is a constant which describes the heat conductivity of the body $\mathcal{B}$.

Example: A Solution of the Heat Equation

Check that $T(x, y, t) = e^{-kt}(\cos(x) + \cos(y))$ satisfies the heat equation.

$$\begin{aligned} \frac{\partial T}{\partial t} &= \frac{\partial}{\partial t} \left[e^{-kt} (\cos(x) + \cos(y)) \right] \\ &= -k e^{-kt} (\cos(x) + \cos(y)) \end{aligned} \quad \leftarrow \text{Yay! They match.}$$

$$\begin{aligned} k \left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} \right) &= k \left(\frac{\partial^2}{\partial x^2} \left[e^{-kt} (\cos(x) + \cos(y)) \right] \right. \\ &\quad \left. + \frac{\partial^2}{\partial y^2} \left[e^{-kt} (\cos(x) + \cos(y)) \right] \right) \\ &= k \left(\frac{\partial}{\partial x} \left[e^{-kt} (-\sin(x) + 0) \right] \right. \\ &\quad \left. + \frac{\partial}{\partial y} \left[e^{-kt} (0 + (-\sin(y))) \right] \right) \\ &= k \left(-e^{-kt} \cos(x) - e^{-kt} \cos(y) \right) \\ &= -k e^{-kt} (\cos(x) + \cos(y)) \end{aligned} \quad \leftarrow$$

The Wave Equation (Sneak Peek to MAT B42)**(M&T p. 155)**

Consider a string stretched along the x -axis. Its height at position x and time t is given by $u(x, t)$. If it is disturbed then it will vibrate according to the wave equation:

$$c^2 \frac{\partial^2 u}{\partial x^2} = \frac{\partial^2 u}{\partial t^2}$$

The constant c is the rate at which vibrations travel along the string. We will usually pick $c = 1$.

Example: A Solution of the Wave Equation

Check that $u(x, t) = \sin(x) \sin(ct)$ is a solution of the wave equation.

$$\begin{aligned} & \frac{\partial^2 u}{\partial x^2} \\ &= \frac{\partial^2}{\partial x^2} [\sin(x) \sin(ct)] \\ &= \frac{\partial}{\partial x} [\cos(x) \sin(ct)] \\ &= -\sin(x) \sin(ct) \end{aligned}$$

$$\begin{aligned} & c^2 \frac{\partial^2 u}{\partial t^2} \\ &= c^2 \frac{\partial^2}{\partial t^2} [\sin(x) \sin(ct)] \\ &= c^2 \frac{\partial}{\partial t} [\sin(x) \cos(ct) \cdot c] \\ &= c^2 \cancel{\sin(x)} [-\sin(ct) \cdot c^2] \\ &= -c^4 \sin(x) \sin(ct) \end{aligned}$$

Oops! These c 's should cancel out.
will check book for correct formula.

The c^2 should be with the
space variables (x) and not
the time variable (t).

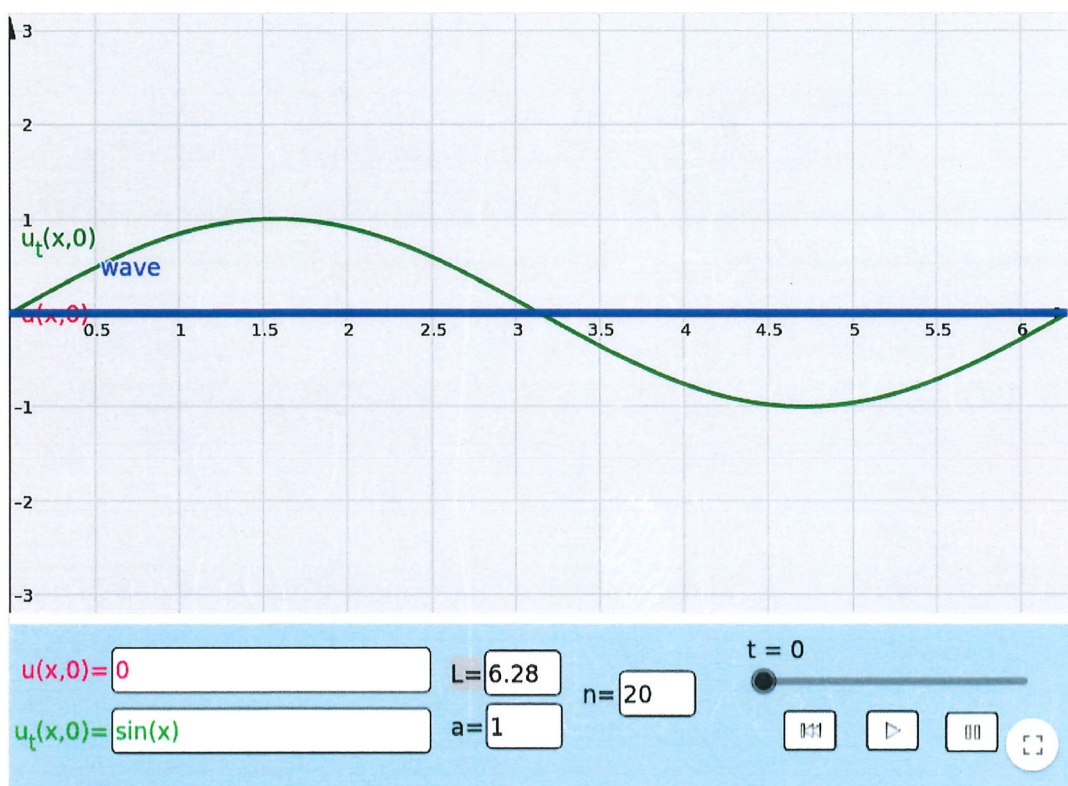
Activity: Simulate a Wave (5 min)

Juan Carlos Ponce Campuzano (University of Queensland, Australia) has a wonderful simulator.

<https://www.geogebra.org/m/eKkFV8uz>

Play around with it! Check out various waves.

The solution $u(x, t) = \sin(x) \sin(ct)$ (with $c = 1$) corresponds to the following settings.



In the settings: $L = \text{Length} = 6.28 \approx 2\pi$ and $a = c = 1$.

Taylor's Theorem in One-Dimension

(M&T p. 159)

The single variable Taylor's Theorem (roughly) says:

 $f(x) \rightsquigarrow \text{polynomial}$

$$f(x) \approx f(a) + \frac{f'(a)}{1!}(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f'''(a)}{3!}(x-a)^3 + \dots$$

The important message of Taylor's Theorem is this:

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

Knowing the derivatives of a function at any point a allows you to approximate the function.

Example: Approximating the Exponential Function

Approximate $f(x) = e^x$ at $a = 0$ using Taylor's Theorem in One-Dimension.How close is the approximation at $x = 1$ after taking ten terms of the sum?# Compute derivatives of e^x .

$$f(x) = e^x \Rightarrow f'(x) = e^x \Rightarrow f''(x) = e^x \dots \Rightarrow f^{(n)}(x) = e^x$$

$$\text{We get } f^{(n)}(a) = f^{(n)}(0) = e^0 = 1.$$

Apply the formula for Taylor's Theorem

$$\begin{aligned} f(x) &\approx f(0) + \frac{f'(0)}{1!}(x-0) + \frac{f''(0)}{2!}(x-0)^2 + \dots \\ &\approx 1 + \frac{x}{1!} + \frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + \dots + \frac{x^n}{n!} \end{aligned}$$

Taking $n \rightarrow \infty$ we get:

$$e^x = \lim_{n \rightarrow \infty} \sum_{k=0}^n \frac{x^k}{k!}$$

How accurate is the approximation by the first 10 terms of the series?

$$1 + \frac{1}{1!} + \frac{1}{2!} + \frac{1}{3!} + \frac{1}{4!} + \frac{1}{5!} + \frac{1}{6!} + \frac{1}{7!} + \frac{1}{8!} + \frac{1}{9!} + \frac{1}{10!} = \frac{9864101}{3628800} \approx$$

$$e^1 = e \approx$$

2.718281801146...

2.718281828459...

seven decimal places

Taylor's Theorem in One-Dimension (h -version)**(M&T p. 159)**

Our textbook gives the following equivalent formulation of Taylor's Theorem:

$$f(x_0 + h) = f(x_0) + f'(x_0)h + \frac{f''(x_0)}{2!}h^2 + \cdots + \frac{f^{(k)}(x_0)}{k!}h^k + R_k(x_0, h)$$

The remainder term $R_k(x_0, h)$ satisfies $\lim_{h \rightarrow 0} \frac{R_k(x_0, h)}{h^k} = 0$.

Intuitively, this means " $R_k(x_0, h)$ goes to zero faster than h^k ."

Example: Verify That R_k Goes to Zero

Approximate $f(x) = e^x$ at $x_0 = 0$ and check that $\lim_{h \rightarrow 0} \frac{R_k(x_0, h)}{h^k} = 0$ for all k .

Big Idea: Factor out h^{k+1} and bound the left-over terms by e^h .

We have:

$$f(0+h) = e^0 + e^0 h + \frac{e^0}{2!} h^2 + \cdots + \frac{e^0}{k!} h^k + R_k(x_0, h)$$

$$e^h = 1 + h + \frac{1}{2!} h^2 + \cdots + \frac{1}{k!} h^k + R_k(x_0, h)$$

Use the Taylor expansion to find $R_k(x_0, h)$.

$$\text{We have } R_k(x_0, h) = \frac{1}{(k+1)!} h^{k+1} + \frac{1}{(k+2)!} h^{k+2} + \cdots$$

= "the remaining terms of the infinite sum"

Bound each term in the brackets by the corresponding term of e^h .

$$\begin{aligned} &= h^{k+1} \left(\frac{1}{(k+1)!} + \frac{h}{(k+2)!} + \frac{h^2}{(k+3)!} + \cdots \right) \\ &\leq h^{k+1} \left(1 + h + \frac{h^2}{2!} + \frac{h^3}{3!} + \cdots \right) \\ &= h^{k+1} e^h \end{aligned}$$

$$\text{This gives } \lim_{h \rightarrow 0} \frac{R_k(x_0, h)}{h^k} \leq \lim_{h \rightarrow 0} \frac{h^{k+1} e^h}{h^k} = \lim_{h \rightarrow 0} h e^h = 0.$$

Differentiability

(M&T p. 111)

Let $D = Df(x_0)$. We say that f is differentiable at x_0 if the following limit exists:

$$= Df(x_0)$$

$$\lim_{x \rightarrow x_0} \frac{\|f(x) - f(x_0) - D(x - x_0)\|}{\|x - x_0\|} = 0$$

This is like saying:
 $f(x) - f(x_0) \approx D(x - x_0)$

Note: The product $D(x - x_0)$ is a matrix D times the column vector $x - x_0$.

Example: A Quick Verification

Verify that $f(x, y) = x^2 + y^2$ is differentiable at $(0, 0)$.

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^1$$

Calculate the matrix D

$$Df = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}$$

$$= \begin{bmatrix} 2x & 2y \end{bmatrix} \rightarrow Df(0,0) = \begin{bmatrix} 0 & 0 \end{bmatrix}$$

Setup the limit

In one variable:

$$\underbrace{f(x) - f(x_0)}_{\text{number}} \approx \underbrace{f'(x_0)}_{\text{number}} \underbrace{(x - x_0)}_{\text{number}}$$

In multiple variables:

$$\underbrace{f(x) - f(x_0)}_{\text{vector}} = \underbrace{D}_{\text{matrix}} \underbrace{(x - x_0)}_{\text{vector}}$$

$$\lim_{(x,y) \rightarrow (0,0)} \frac{\|x^2 + y^2 - (0^2 + 0^2) - D(x - x_0)\|}{\|(x,y) - (0,0)\|}$$

$$Df = \begin{bmatrix} 0 & 0 \end{bmatrix}$$

$$= \lim_{(x,y) \rightarrow (0,0)} \frac{\|x^2 + y^2 - \cancel{[2x \ 2y]} \left(\begin{bmatrix} x \\ y \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)\|}{\left\| \begin{bmatrix} x \\ y \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right\|}$$

$$= \lim_{(x,y) \rightarrow (0,0)} \frac{\|x^2 + y^2 - \cancel{(2x^2 + 2y^2)}\|}{\sqrt{x^2 + y^2}} = \lim_{(x,y) \rightarrow (0,0)} \frac{\| -x^2 - y^2 \|}{\sqrt{x^2 + y^2}}$$

$$= \lim_{(x,y) \rightarrow (0,0)} \frac{x^2 + y^2}{\sqrt{x^2 + y^2}} = \lim_{(x,y) \rightarrow (0,0)} \sqrt{x^2 + y^2} = 0$$

First-Order Multivariable Taylor

(M&T p. 160)

Let $f : U \subset \mathbb{R}^n \rightarrow \mathbb{R}$ be differentiable at $\mathbf{x}_0$. We have the following approximation:

$$f(\mathbf{x}_0 + \mathbf{h}) = f(\mathbf{x}_0) + \sum_{i=1}^n h_i \frac{\partial f}{\partial x_i}(\mathbf{x}_0) + R_1(\mathbf{x}_0, \mathbf{h}) = f(\mathbf{x}_0) + [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h} + R_1(\mathbf{x}_0, \mathbf{h})$$

where $\lim_{\mathbf{h} \rightarrow 0} R_1(\mathbf{x}_0, \mathbf{h}) / \|\mathbf{h}\| = 0$. We call

$$f(\mathbf{x}_0 + \mathbf{h}) \approx f(\mathbf{x}_0) + [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h}$$

the first-order Taylor approximation of f at $\mathbf{x}_0$.

We need to check that $R_1(\mathbf{x}_0, \mathbf{h})$ goes to zero fast enough.

The Big Idea: Take $R_1(\mathbf{x}_0, \mathbf{h}) = f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h}$. Taking $\mathbf{h} = \mathbf{x} - \mathbf{x}_0$ we get:

$$\text{diff'able} \quad \lim_{\mathbf{x} \rightarrow \mathbf{x}_0} \frac{\|f(\mathbf{x}) - f(\mathbf{x}_0) - \mathbf{D}(\mathbf{x} - \mathbf{x}_0)\|}{\|\mathbf{x} - \mathbf{x}_0\|} = 0 \iff \lim_{\mathbf{h} \rightarrow 0} \frac{R_1(\mathbf{x}_0, \mathbf{h})}{\|\mathbf{h}\|} = 0$$

Assume f is differentiable at $\mathbf{x}_0$.

$$\text{We set: } R_1(\mathbf{x}_0, \mathbf{h}) = \underbrace{f(\mathbf{x}_0 + \mathbf{h})}_{\text{function}} - \underbrace{f(\mathbf{x}_0) - [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h}}_{\text{approximation}}$$

We calculate

$$\lim_{\mathbf{h} \rightarrow 0} \frac{R_1(\mathbf{x}_0, \mathbf{h})}{\|\mathbf{h}\|} = \lim_{\mathbf{h} \rightarrow 0} \frac{f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h}}{\|\mathbf{h}\|}$$

We pick $\mathbf{h} = \mathbf{x} - \mathbf{x}_0$ and get:

$$= \lim_{\mathbf{x} \rightarrow \mathbf{x}_0} \frac{f(\mathbf{x}) - f(\mathbf{x}_0) - [\mathbf{D}f(\mathbf{x}_0)](\mathbf{x} - \mathbf{x}_0)}{\|\mathbf{x} - \mathbf{x}_0\|}$$

This is the derivative at $\mathbf{x}_0$. It is a matrix $\mathbf{D}f$.

Norms are upper bounds

$$\leq \lim_{\mathbf{x} \rightarrow \mathbf{x}_0} \frac{\|f(\mathbf{x}) - f(\mathbf{x}_0) - \mathbf{D}f(\mathbf{x} - \mathbf{x}_0)\|}{\|\mathbf{x} - \mathbf{x}_0\|} = 0 \quad \text{by diff'able}$$

In summary: $f \approx f(\mathbf{x}_0) + [\mathbf{D}f(\mathbf{x}_0)]\mathbf{h}$ is a good approximation.

The first-order Taylor approximation of $f(\mathbf{x}_0)$ at $\mathbf{x}_0$ is:

$$f(\mathbf{x}_0 + \mathbf{h}) \approx f(\mathbf{x}_0) + [Df(\mathbf{x}_0)]\mathbf{h}$$

variable

Example: Approximate a Nice Function

Give the first order Taylor approximation of $f(x, y) = xye^{x+y}$ at $(x, y) = (1, 1)$.

Apply the approximation formula.

Calculate $Df(\mathbf{x}_0)$

$$Df = \left[\frac{\partial (xye^{x+y})}{\partial x}, \frac{\partial (xye^{x+y})}{\partial y} \right]$$

$$= \left[ye^{x+y} + xye^{x+y}, xe^{x+y} + xye^{x+y} \right]$$

$$Df(1,1) = [e^2 + e^2, e^2 + e^2] = [2e^2, 2e^2]$$

Calculate $f(\mathbf{x}_0)$

$$f(1,1) = 1 \cdot 1 \cdot e^{1+1} = e^2$$

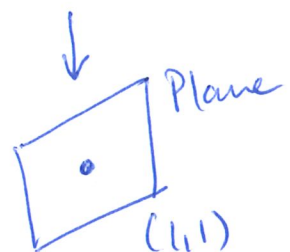
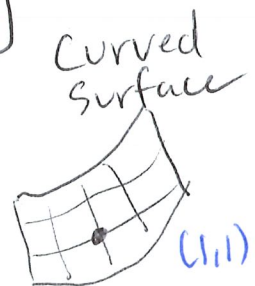
Putting the parts together we get:

$$f\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}\right) \approx e^2 + [2e^2, 2e^2] \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$$

Approximately equals $\rightarrow$

$$\approx e^2 + 2e^2 h_1 + 2e^2 h_2$$

$$\approx e^2(1 + 2h_1 + 2h_2)$$



$$f\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}\right) \approx e^2 + 2e^2(h_1 + h_2)$$

Quadratic Forms

(M&T p. 172)

Suppose that $M = [m_{ij}]$ is an $n \times n$ matrix. The quadratic form of M is:

$$Q_M(\mathbf{h}) = \mathbf{h}^T M \mathbf{h}$$

In coordinates:

$$Q_M(h_1, h_2, \dots, h_n) = [h_1 \ h_2 \ \dots \ h_n] \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1n} \\ m_{21} & m_{22} & & m_{2n} \\ \vdots & & \ddots & \\ m_{n1} & m_{n2} & & m_{nn} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix} = \sum_{i=1}^n \sum_{j=1}^n m_{ij} h_i h_j$$

Example: Nice Functions Arise as Quadratics

$$M = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \Rightarrow f_M(h_1, h_2) = [h_1 \ h_2] \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} = h_1^2 - h_2^2$$

The Big Idea: Locally, every function looks like a quadratic function. "Morse Theory"

$$[h_1 \ h_2] \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$$

$$= [h_1 \ h_2] \begin{bmatrix} h_1 \\ -h_2 \end{bmatrix} = h_1^2 - h_2^2 \quad \leftarrow \text{The result is a nice quadratic function}$$

The Hessian Function

(M&T p. 172)

Suppose that $f : U \subset \mathbb{R}^n \rightarrow \mathbb{R}$ is C^2 . The Hessian of f at $\mathbf{x}_0$ is the quadratic function:

$$Hf(\mathbf{x}_0)(\mathbf{h}) = \frac{1}{2} \sum_{i,j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x}_0) h_i h_j$$

Recall: $f_{x_i x_j} = f_{x_j x_i}$

$$= \frac{1}{2} [h_1, h_2, \dots, h_n] \begin{bmatrix} \frac{\partial^2 f}{\partial x_1 \partial x_1}(\mathbf{x}_0) & \frac{\partial^2 f}{\partial x_1 \partial x_2}(\mathbf{x}_0) & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n}(\mathbf{x}_0) \\ \frac{\partial^2 f}{\partial x_2 \partial x_1}(\mathbf{x}_0) & \frac{\partial^2 f}{\partial x_2 \partial x_2}(\mathbf{x}_0) & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n}(\mathbf{x}_0) \\ \vdots & & \ddots & \\ \frac{\partial^2 f}{\partial x_n \partial x_1}(\mathbf{x}_0) & \frac{\partial^2 f}{\partial x_n \partial x_2}(\mathbf{x}_0) & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_n}(\mathbf{x}_0) \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}$$

Notice: The Hessian is analogous to the second-derivative of f .

This matrix is symmetric!

Example: Hessian of a Saddle

Compute $Hf(\mathbf{x}_0)(\mathbf{h})$ for $f(x, y) = x^2 - y^2$.

$$Hf(\mathbf{x}_0)(\mathbf{h}) = \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} \frac{\partial^2}{\partial x \partial x}(x^2 - y^2) & \frac{\partial^2}{\partial x \partial y}(x^2 - y^2) \\ \frac{\partial^2}{\partial y \partial x}(x^2 - y^2) & \frac{\partial^2}{\partial y \partial y}(x^2 - y^2) \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$$

$$= \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} \frac{\partial}{\partial x}(2x) & \frac{\partial}{\partial x}(-2y) \\ \frac{\partial}{\partial y}(2x) & \frac{\partial}{\partial y}(-2y) \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$$

$$= \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} 2 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} = \frac{1}{2} (2h_1^2 - 2h_2^2) = h_1^2 - h_2^2$$

Second-Order Multivariable Taylor

(M&T p. 160)

If $f : U \subset \mathbb{R}^n \rightarrow \mathbb{R}$ is C^3 then we have::

$$f(\mathbf{x}_0 + \mathbf{h}) = f(\mathbf{x}_0) + \underbrace{\sum_{i=1}^n h_i \frac{\partial f}{\partial x_i}(\mathbf{x}_0)}_{Df(\mathbf{x}_0)\mathbf{h}} + \underbrace{\frac{1}{2} \sum_{i,j=1}^n h_i h_j \frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x}_0)}_{Hf(\mathbf{h})} + R_2(\mathbf{x}_0, \mathbf{h})$$

Here, the term $R_2(\mathbf{x}_0, \mathbf{h})$ goes to zero faster than $\|\mathbf{h}\|^2$. Formally, $\lim_{\|\mathbf{h}\| \rightarrow 0} \frac{R_2(\mathbf{x}_0, \mathbf{h})}{\|\mathbf{h}\|^2} = 0$.

We define the second-order Taylor approximation of f at $\mathbf{x}_0$ to be:

$$f(\mathbf{x}_0 + \mathbf{h}) \approx f(\mathbf{x}_0) + [Df(\mathbf{x}_0)]\mathbf{h} + Hf(\mathbf{h})$$

Example: Second-Order Taylor of a Quadratic

Compute the second-order Taylor polynomial of $f(x, y) = x^2 + 2x + 3y + 4xy + 5y^2$ at $(x, y) = (0, 0)$.

Notice: The final answer ought to be $f(x, y)$ again because $f(x, y)$ is a polynomial of degree two.

$$Hf = \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} 2 & 4 \\ 4 & 10 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \quad "x^2 + 4xy + 5y^2"$$

$$Df = [2x+2+4y, 3+4x+10y] \rightarrow Df(0,0) = [2, 3] \quad "2x+3y"$$

calculation completed After Lecture

This gives:

$$\begin{aligned} f\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}\right) &\approx f(0,0) + [2 \ 3] \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} + \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} 2 & 4 \\ 4 & 10 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \\ &= 0 + 2h_1 + 3h_2 + \frac{1}{2} [h_1 \ h_2] \begin{bmatrix} 2h_1 + 4h_2 \\ 4h_1 + 10h_2 \end{bmatrix} \\ &= 2h_1 + 3h_2 + \frac{1}{2} [h_1(2h_1 + 4h_2) + h_2(4h_1 + 10h_2)] \\ &= 2h_1 + 3h_2 + \frac{1}{2} (2h_1^2 + 4h_1h_2 + 4h_2h_1 + 10h_2^2) \\ &= 2h_1 + 3h_2 + h_1^2 + 4h_1h_2 + 5h_2^2 \end{aligned}$$

OMG! It looks so much like the original polynomial

$$\rightarrow = h_1^2 + 2h_1 + 3h_2 + 4h_1h_2 + 5h_2^2$$