

Lecture 26 - Application of the Hessian to local extrema

December 5, 2022

$Hf(\vec{z}) \rightarrow$ matrix of 2nd partials
ij-entry is f_{xx}

Goals: Be able to classify critical points of a multivariable scalar function.

We will further elaborate on the second derivative test introduced in the previous lecture, since we only discussed it for functions $f: \mathbb{R}^2 \rightarrow \mathbb{R}$. Recall that the quadratic approximation of a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ at a critical point \mathbf{a} is

$$f(\mathbf{a} + \mathbf{h}) \approx f(\mathbf{a}) + \frac{1}{2} \mathbf{h}^\top Hf(\mathbf{a}) \mathbf{h} = f(\mathbf{a}) + \frac{1}{2} q_{Hf(\mathbf{a})}(\mathbf{h}),$$

since $\nabla f(\mathbf{a}) = \mathbf{0}$. For a single variable function $f: \mathbb{R} \rightarrow \mathbb{R}$, this says

$$\underline{f(a+h)} \approx \underline{f(a)} + \underline{f''(a)h^2}.$$

So if $f''(a) > 0$, then $f(a+h) > f(a)$, and so a is a local minimum. Similarly, if $f''(a) < 0$, then $f(a+h) < f(a)$ and so a is a local maximum. If $f''(a) = 0$, then the above approximation tells us nothing about whether the critical point is a local extrema. Before we generalize this to higher dimensions, let us more properly define a saddle point.

Definition: For $n > 1$ and a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$, a critical point $\mathbf{a} \in \mathbb{R}^n$ is a **saddle point** of f if there are different lines L and L' in \mathbb{R}^n through \mathbf{a} so that f evaluated on the line L has a local maximum at \mathbf{a} and f evaluated on the line L' has a local minimum at \mathbf{a} . $\text{TL } L = \vec{a} + t\vec{v}, \text{ look at } f(\vec{a} + t\vec{v}) \rightarrow \text{local max } \theta \rightarrow$
 $\text{TL } L' = \vec{a} + t\vec{v}', \text{ look at } f(\vec{a} + t\vec{v}') \rightarrow \text{local min } \theta \rightarrow$

Theorem 26.1.5: (Second Derivative Test, Version 1) Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a function, and $\mathbf{a} \in \mathbb{R}^n$ a critical point of f .

$$\downarrow Hf(\mathbf{a})(\vec{z}) > 0 \text{ for } \vec{z} \neq \mathbf{0}$$

1. If the Hessian $Hf(\mathbf{a})$ is positive-definite, then \mathbf{a} is a local minimum of f .
2. If the Hessian $Hf(\mathbf{a})$ is negative-definite, then \mathbf{a} is a local maximum of f .
3. If the Hessian $Hf(\mathbf{a})$ is indefinite, then \mathbf{a} is a saddle point of f , hence neither a local min nor a local max.

If the Hessian $Hf(\mathbf{a})$ is positive/negative-semidefinite, then we need more information to conclude the behavior of \mathbf{a} .

Example 1: Suppose $f(x, y, z)$ has a critical point at $(1, 1, 0)$ and $Hf(1, 1, 0) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 11 \end{bmatrix}$. What type of critical point is $(1, 1, 0)$?

$$\begin{aligned} Hf(1, 1, 0) &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 11 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 11 \end{bmatrix} \\ &= x^2 + 5y^2 + 11z^2 > 0 \text{ away from } (0, 0, 0) \\ &\Rightarrow \text{positive-definite} \Rightarrow \text{local min at } (1, 1, 0) \end{aligned}$$

Example 2: Let $f(x, y) = -2x^2 - \frac{1}{2}y^2 - xy$. Show that f has a critical point at $(0, 0)$ and classify it.

$$\begin{aligned} \nabla f &= \begin{bmatrix} -4x - y \\ -y - x \end{bmatrix} = \mathbf{0} \rightarrow \begin{cases} -4x - y = 0 \\ -y - x = 0 \end{cases} \rightarrow \begin{cases} -4x = -x \\ -y = -x \end{cases} \rightarrow \begin{cases} x = 0 \\ y = 0 \end{cases} \text{ is crit pt} \\ Hf(x, y) &= \begin{bmatrix} -4 & -1 \\ -1 & -1 \end{bmatrix} \quad \lambda^2 - \text{tr}(A) + \det(A) \rightarrow \lambda^2 + 6\lambda + 3 = 0 \Rightarrow \lambda = \frac{-6 \pm \sqrt{13}}{2} \\ &\text{Both eigenvalues are negative} \\ &\Rightarrow 0 \text{ is a local max} \end{aligned}$$

Example 3: Let $f(x, y) = x^4 + y^4$, $g(x, y) = x^4 - y^4$, and $h(x, y) = -x^4 - y^4$. What type of critical point is $(0, 0)$ for f , g , and h ?

$$\nabla f = \begin{pmatrix} 4x^3 \\ 4y^3 \end{pmatrix}, \quad H_f(x, y) = \begin{pmatrix} 12x^2 & 0 \\ 0 & 12y^2 \end{pmatrix}, \quad H_g(x, y) = \begin{pmatrix} 12x^2 & 0 \\ 0 & -12y^2 \end{pmatrix},$$

$$H_h(x, y) = \begin{pmatrix} -12x^2 & 0 \\ 0 & -12y^2 \end{pmatrix}$$

$$H_f(0, 0) = H_g(0, 0) = H_h(0, 0) = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad \therefore 2^{\text{nd}} \text{ derivative test is inconclusive}$$

$f(x, y) = x^4 + y^4 \geq 0$, equals 0 at $f(0, 0) \Rightarrow (0, 0)$ is a local minimum

$h(x, y) = -x^4 - y^4 \leq 0$, equals 0 at $h(0, 0) \Rightarrow (0, 0)$ is a local maximum

$g(x, y) = x^4 - y^4$ can be both pos & neg

Let $L = \{t(0), t \in \mathbb{R}\}$ (x-axis), $g(L) \rightarrow g(t(0)) = g(0, 0) = t^4 \geq 0$ local min on x-axis \Rightarrow saddle point

Let $L' = \{t(0), t \in \mathbb{R}\}$ (y-axis), $g(L') \rightarrow g(t(0)) = g(0, t) = -t^4 \leq 0$ local max on y-axis

Recall from lecture 24 that we can rewrite a quadratic form using the diagonalization formula, and so

$$q_{Hf(\mathbf{a})}(\mathbf{v}) = \sum_{i=1}^n \lambda_i (\mathbf{w}_i \cdot \mathbf{v}) t_i^2,$$

where $\mathbf{v} = \sum_{i=1}^n t_i \mathbf{w}_i$, and the \mathbf{w}_i are the eigenvectors of $Hf(\mathbf{a})$ with eigenvalues λ_i respectively. This gave us a different way to think about definiteness (Proposition 24.2.10), and thus we can show a different version of the second derivative test:

Theorem 26.3.1: (Second Derivative Test, Version II) Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a function, and $\mathbf{a} \in \mathbb{R}^n$ a critical point of f .

1. If the Hessian $Hf(\mathbf{a})$ has all eigenvalues positive, then \mathbf{a} is a local minimum of f .
2. If the Hessian $Hf(\mathbf{a})$ has all eigenvalues negative, then \mathbf{a} is a local maximum of f .
3. If the Hessian $Hf(\mathbf{a})$ has both positive and negative eigenvalues, then \mathbf{a} is a saddle point of f , hence neither a local min nor a local max.

We have the following useful shortcut for function $f : \mathbb{R}^2 \rightarrow \mathbb{R}$.

symmetric

Theorem 26.3.3: Consider a 2×2 matrix $A = \begin{bmatrix} a & b \\ b & d \end{bmatrix}$, so the eigenvalues are the roots of the characteristic polynomial $P_A(\lambda) = \lambda^2 - \text{tr}(A)\lambda + \det(A)$. For its two roots $\lambda_1, \lambda_2 \in \mathbb{R}$:

1. λ_1, λ_2 have opposite signs when their product $\det(A) = \lambda_1 \lambda_2$ is negative, so the indefinite case occurs exactly when $ad - b^2 = \det(A) < 0$;
2. λ_1, λ_2 are either both positive or both negative when their product $\det(A) = \lambda_1 \lambda_2$ is positive, so A is positive-definite or negative-definite precisely when $ad - b^2 = \det(A) > 0$;
3. in the case of (ii), the common sign of λ_1 and λ_2 is the same as that of their sum $\lambda_1 + \lambda_2 = \text{tr}(A) = a + d$.

Thus, we do not actually have to compute eigenvalues for 2×2 matrices to classify the critical points (though we do if we, for example, want a sketch of the contours of f near that critical point).

$$\lambda^2 - \text{tr}(A) \lambda + \det(A) = (\lambda - \lambda_1)(\lambda - \lambda_2)$$

$$= \lambda^2 - (\lambda_1 + \lambda_2)\lambda + \lambda_1 \lambda_2$$

$$\text{tr}(A) = \lambda_1 + \lambda_2$$

$$\det(A) = \lambda_1 \lambda_2$$

Example 4: Redo Example 2 without computing eigenvalues of $Hf(0,0)$.

$$f(x,y) = -2x^2 - \frac{1}{2}y^2 - xy$$

$$Hf(0,0) = \begin{bmatrix} -4 & -1 \\ -1 & -1 \end{bmatrix}$$

$\det(Hf(0,0)) = 4-1=3 > 0 \therefore Hf(0,0)$ is either pos or neg definite

$\det(Hf(0,0)) = -5 \Rightarrow \lambda_1 + \lambda_2 < 0$, sign of λ_1 is neg, λ_2 is neg

$\Rightarrow Hf(0,0)$ is negative definite $\Rightarrow (0,0)$ is local max

Example 5: Find the critical points of $f(x,y) = 3x^2y + 2y^3 - xy$ and classify them each as a local max, local min, or saddle point in two different ways (Theorem 26.3.1 and Theorem 26.3.3).

$$\nabla f = \begin{bmatrix} 6xy - y \\ 3x^2 + 6y^2 - x \end{bmatrix} = \vec{0} \rightarrow \begin{aligned} 6xy - y &= 0 \rightarrow y(6x-1) = 0 \rightarrow y=0 \text{ or } x = \frac{1}{6} \\ 3x^2 + 6y^2 - x &= 0 \end{aligned}$$

$$\begin{aligned} y &= 0 & x &= \frac{1}{6} \\ 3x^2 - x &= 0 & 3\left(\frac{1}{6}\right)^2 + 6y^2 - \frac{1}{6} &= 0 \\ x(3x-1) &= 0 & y &= \pm \frac{1}{6\sqrt{2}} \\ x &= 0, \frac{1}{3} & y &= 0, \pm \frac{1}{3} \end{aligned}$$

\therefore In total: 4 critical points: $(0,0)$, $(\frac{1}{3},0)$, $(\frac{1}{6}, \pm \frac{1}{6\sqrt{2}})$, $(\frac{1}{6}, -\frac{1}{6\sqrt{2}})$

$$Hf(x,y) = \begin{bmatrix} 6y & 6x-1 \\ 6x-1 & 12y \end{bmatrix}$$

$$(0,0) \quad Hf(0,0) = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$$

$\det(Hf(0,0)) = -1 < 0 \Rightarrow \lambda_1, \lambda_2$ has opp signs
 \Rightarrow saddle point
 or $\lambda^2 - 0 - 1 = 0 \rightarrow \lambda = \pm 1$

$$(\frac{1}{3},0) \quad Hf(\frac{1}{3},0) = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$\det(Hf(\frac{1}{3},0)) = -1 < 0 \Rightarrow$ saddle point
 or $\lambda^2 - 0 - 1 = 0 \rightarrow \lambda = \pm 1$

$$(\frac{1}{6}, \pm \frac{1}{6\sqrt{2}}) \quad Hf(\frac{1}{6}, \pm \frac{1}{6\sqrt{2}}) = \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \quad \lambda_1 = \frac{1}{\sqrt{2}}, \lambda_2 = \frac{1}{\sqrt{2}}$$

\Rightarrow both pos \Rightarrow local min

$$(\frac{1}{6}, -\frac{1}{6\sqrt{2}}) \quad Hf(\frac{1}{6}, -\frac{1}{6\sqrt{2}}) = \begin{bmatrix} -\frac{1}{\sqrt{2}} & 0 \\ 0 & -\frac{1}{\sqrt{2}} \end{bmatrix} \quad \lambda_1 = -\frac{1}{\sqrt{2}}, \lambda_2 = -\frac{1}{\sqrt{2}}$$

\Rightarrow both neg \Rightarrow local max

If there's time, here is an example that summarizes the main ideas from Chapters 25 and 26.

Example 6: For $f(x, y) = 2x^3 + xy^2 + 5x^2 + y^2$:

a) • Find the quadratic approximation to f at the point $(1, 0)$. $\rightarrow f(\text{approx}) = f(1, 0) + \nabla f(1, 0) \cdot h + \frac{1}{2} H_f(1, 0) h^2$

b) • Find all critical points of f .

c) • Classify them using the Hessian matrix.

d) • Sketch the approximate contours of f near each critical point.

$$\text{a) } \nabla f(x, y) = \begin{bmatrix} 6x^2 + y^2 + 10x \\ 2yx + 2y \end{bmatrix}, \quad H_f(x, y) = \begin{bmatrix} 12x + 10 & 2y \\ 2y & 2x + 2 \end{bmatrix}$$

$$f(1, 0) = 2 + 0 + 5 + 0 = 7, \quad \nabla f(1, 0) = \begin{bmatrix} 16 \\ 0 \end{bmatrix}, \quad H_f(1, 0) = \begin{bmatrix} 22 & 0 \\ 0 & 4 \end{bmatrix}$$

$$\vec{a} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad \vec{h} = \begin{pmatrix} h \\ k \end{pmatrix}$$

$$\begin{aligned} f\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix} + \vec{h}\right) &= f\left(1+h, 0+k\right) \approx 7 + \begin{bmatrix} 16 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} h \\ k \end{bmatrix} + \frac{1}{2} H_f\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix}\right)(h, k) \\ &= 7 + 16h + \frac{1}{2} \left(22h^2 + 4k^2 + 2 \cdot 0hk \right) \end{aligned}$$

$$= \boxed{11h^2 + 2k^2 + 16h + 7}$$

b) Crit. pts.: $(0, 0), (-\sqrt{2}/3, 0), (-1, 2), (-1, -2)$

c)

$\lambda = 12, 2$ local min	$\lambda = -2$ local max	$\lambda = 0$ saddle	$\lambda = 0$ saddle
--------------------------------	-----------------------------	-------------------------	-------------------------

d)

$\vec{w} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$	$\vec{w} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$	$\vec{w} = \begin{pmatrix} -\sqrt{10}/3 \\ -1 \end{pmatrix}$	$\vec{w} = \begin{pmatrix} \sqrt{10}/3 \\ -1 \end{pmatrix}$
--------------------------------------------------	--------------------------------------------------	--------------------------------------------------------------	-------------------------------------------------------------

