

Ridge Problem in Stochastic Gradient Descent: An Analytical Solution

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Abstract

1 Introduction

2 Proof

$$f(x, y) = \begin{cases} \phi(x, y) & \text{if } x = 2y, \\ \psi(x, y) & \text{otherwise;} \end{cases}$$

where

$$\begin{aligned} \phi(x, y) &= x^2 + y^2 - 8x - 4y + 10, \\ \psi(x, y) &= x^2 + y^2 - 4x - 2y. \end{aligned}$$

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2.1 First Partial Derivatives

We examine the first derivatives of our function f at point $(2, 1)$.

$$\frac{\partial f}{\partial x}(2, 1) = \lim_{h \rightarrow 0} \frac{f(2 + h, 1) - f(2, 1)}{h} \quad (1)$$

Because the numerator

$$f(2 + h, 1) = \psi(2 + h, 1) \quad (2)$$

$$\begin{aligned} f(2, 1) &= \phi(2, 1) \\ &= -5 \\ &= \psi(2, 1) \end{aligned} \quad (3)$$

it holds that

$$\begin{aligned} \frac{\partial f}{\partial x}(2, 1) &= \frac{\partial \psi}{\partial x}(2, 1) \\ &= 2x - 4 \\ &= 0 \end{aligned} \quad (4)$$

Similarly,

$$\begin{aligned} \frac{\partial f}{\partial y}(2, 1) &= \frac{\partial \psi}{\partial y}(2, 1) \\ &= 2y - 2 \\ &= 0 \end{aligned} \quad (5)$$

Hence

$$\nabla_f(2, 1) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (6)$$

2.2 Second Partial Derivatives

We then consider the second partial derivatives of our function at the same point.

2.2.1 Second Partial Derivative With Respect To x

We begin with $f_{xx}(2, 1)$:

$$\frac{\partial}{\partial x} \left(\frac{\partial f}{\partial x} \right) (2, 1) = \lim_{h \rightarrow 0} \frac{\frac{\partial f}{\partial x}(2 + h, 1) - \frac{\partial f}{\partial x}(2, 1)}{h} \quad (7)$$

Assessing the first component of the numerator

$$\frac{\partial f}{\partial x}(2 + h, 1) = \lim_{k \rightarrow 0} \frac{f(2 + h + k, 1) - f(2 + h, 1)}{k} \quad (8)$$

We observe that

$$f(2 + h + k, 1) = \begin{cases} \psi(2 + h + k, 1) & \text{if } h \rightarrow 0^-, k \rightarrow 0^- \\ \phi(2, 1) = -5 = \psi(2, 1) & \text{if } h \rightarrow 0^-, k \rightarrow 0^+ \\ \phi(2, 1) = -5 = \psi(2, 1) & \text{if } h \rightarrow 0^+, k \rightarrow 0^- \\ \psi(2 + h + k, 1) & \text{if } h \rightarrow 0^+, k \rightarrow 0^+ \end{cases} \quad (9)$$

$$= \psi(2 + h + k, 1) \quad (10)$$

and

$$f(2 + h, 1) = \psi(2 + h, 1) \quad (11)$$

Hence

$$\frac{\partial f}{\partial x}(2 + h, 1) = \frac{\partial \psi}{\partial x}(2 + h, 1) \quad (12)$$

By equations 4 and 12,

$$\frac{\partial}{\partial x} \left(\frac{\partial f}{\partial x} \right) (2, 1) = \frac{\partial}{\partial x} \left(\frac{\partial \psi}{\partial x} \right) (2, 1) \quad (13)$$

$$= 2 \quad (14)$$

2.2.2 Second Partial Derivative With Respect To x Then y

We continue by examining $f_{yx}(2, 1)$:

$$\frac{\partial}{\partial y} \left(\frac{\partial f}{\partial x} \right) (2, 1) = \lim_{h \rightarrow 0} \frac{\frac{\partial f}{\partial x}(2, 1 + h) - \frac{\partial f}{\partial x}(2, 1)}{h} \quad (15)$$

Again, we assess the first component of the numerator

$$\frac{\partial f}{\partial x}(2, 1 + h) = \lim_{k \rightarrow 0} \frac{f(2 + k, 1 + h) - f(2, 1 + h)}{k} \quad (16)$$

Similar to $f_{xx}(2, 1)$, we observe that

$$f(2+k, 1+h) = \begin{cases} \psi(2+k, 1+h) & \text{if } h \rightarrow 0^-, k \rightarrow 0^- \\ \psi(2+k, 1+h) & \text{if } h \rightarrow 0^-, k \rightarrow 0^+ \\ \psi(2+k, 1+h) & \text{if } h \rightarrow 0^+, k \rightarrow 0^- \\ \psi(2+k, 1+h) & \text{if } h \rightarrow 0^+, k \rightarrow 0^+ \end{cases} \quad (17)$$

$$= \psi(2+k, 1+h) \quad (18)$$

and

$$f(2, 1+h) = \psi(2, 1+h) \quad (19)$$

Hence

$$\frac{\partial f}{\partial x}(2, 1+h) = \frac{\partial \psi}{\partial x}(2, 1+h) \quad (20)$$

By equations 4 and 20,

$$\frac{\partial}{\partial y} \left(\frac{\partial f}{\partial x} \right) (2, 1) = \frac{\partial}{\partial y} \left(\frac{\partial \psi}{\partial x} \right) (2, 1) \quad (21)$$

$$= 0 \quad (22)$$

2.2.3 Hessian Determinant

Performing similar deductions for $f_{xy}(2, 1)$ and $f_{yy}(2, 1)$, we have

$$f_{xx}(2, 1) = 2 \quad (23)$$

$$f_{yx}(2, 1) = 0 \quad (24)$$

$$f_{xy}(2, 1) = 0 \quad (25)$$

$$f_{yy}(2, 1) = 2 \quad (26)$$

Hence the Hessian determinant

$$H_f = f_{xx}(2, 1) f_{yy}(2, 1) - f_{yx}(2, 1) f_{xy}(2, 1) \quad (27)$$

$$= 4 > 0 \quad (28)$$

2.3 Second Partial Derivative Test Contradiction

According to [1], by equations 6, 28, and the fact that $f_{xx}(2, 1) = 2 > 0$, we shall conclude $(2, 1)$ is a local minimum point. However, this is incorrect, as

for $h \in \mathbb{R}$, $h \rightarrow 0^+$:

$$f(2 + 2h, 1 + h) = \phi(2 + 2h, 1 + h) \quad (29)$$

$$< \phi(2, 1) = f(2, 1) \quad (30)$$

That is, $(2, 1)$ is not a local minimum point (proof in appendix).

3 Intuition

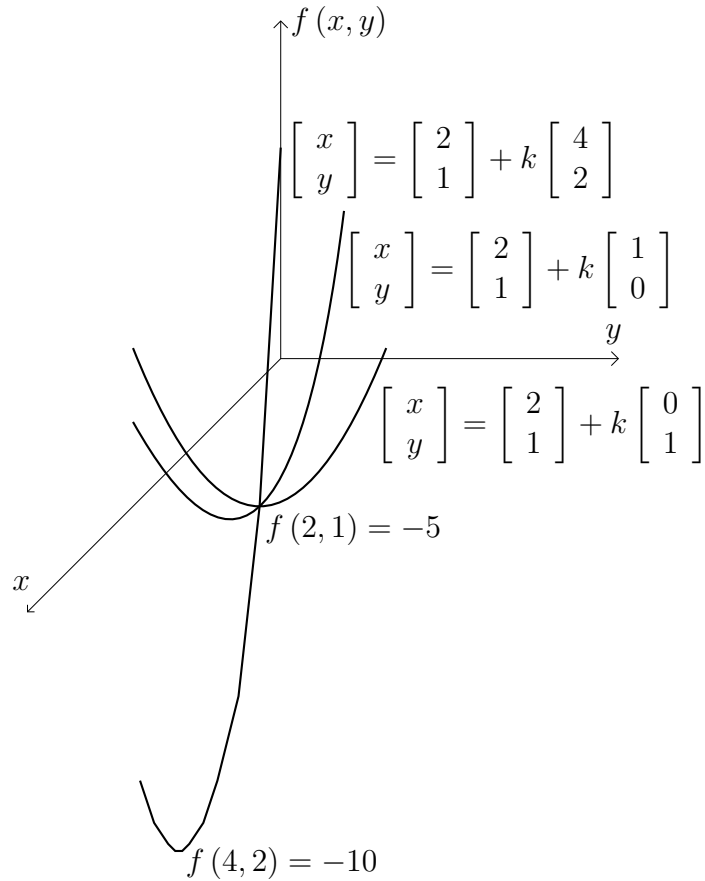


Figure 1: Partial graph of the function $f(x, y)$

Considering our function's graph depicted in Figure 1 at point $(2, 1)$, we observe that the first derivatives in the x and y directions are zeroes, making the zero gradient. Furthermore, the curvature of the function is up in all

directions at the point of interest, indicating the positive definite Hessian. With this premise, the second partial derivative test concludes that $(2, 1)$ is a local minimum point.

However, this is analytically and visually false. Even though the curvature along the $\mathbf{v} = (4, 2)$ direction is up, the corresponding first derivative differs from zero, invalidating the second partial derivative test.

4 Solution

For the tangent hyperplane of a multivariable function at a point to be flat, it is not enough for the gradient of the function at that point to be the zero vector, but the first derivatives of the function at the point of interest must equal to zero in all directions.

In this work, we provide an analytical solution to this issue by redefining what it takes for the tangent hyperplane of a function at a point to be flat. Firstly, we define the concept of directional function:

Definition 4.1 *Given a multivariable function*

$$\begin{aligned} f: \mathbb{R}^n &\longrightarrow \mathbb{R} \\ \mathbf{x} &\longmapsto f(\mathbf{x}) \end{aligned}$$

where $\mathbf{x} = (x_1, x_2, \dots, x_n)$. For a direction¹ $\mathbf{v} \in \mathbb{R}^n$, the directional function of f at point \mathbf{x}_0 is the single variable function

$$\begin{aligned} \xi_{\mathbf{v}}: \mathbb{R} &\longrightarrow \mathbb{R} \\ k &\longmapsto f(\mathbf{x}_0 + k\mathbf{v}) \end{aligned}$$

We are now ready to redefine flat tangent hyperplane:

Definition 4.2 *Given a multivariable function f , its tangent hyperplane is flat at point \mathbf{x}_0 iff for all directions $\mathbf{v} \in \mathbb{R}^n$, the directional function $\xi_{\mathbf{v}}$ at that point has zero first derivative at $k = 0$ i.e. iff $\forall \mathbf{v} \in \mathbb{R}^n: \frac{d\xi_{\mathbf{v}}}{dk}(0) = 0$.*

From this definition, we can derive our new local minimum test:

Theorem 4.1 *Given a multivariable function f , if its tangent hyperplane is flat at point \mathbf{x}_0 , and for all directions $\mathbf{v} \in \mathbb{R}^n$, the directional function $\xi_{\mathbf{v}}$ at that point has positive second derivative at $k = 0$ i.e. if $\forall \mathbf{v} \in \mathbb{R}^n: \frac{d^2\xi_{\mathbf{v}}}{dk^2}(0) = 0 \wedge \frac{d^2\xi_{\mathbf{v}}}{dk^2}(0) > 0$, then \mathbf{x}_0 is a local minimum point.*

¹We exclude the vector $\mathbf{0}$ from all of our discussions on directional function.

4.1 False Local Minimum

We revisit our first example to see if the test works:

$$f(x, y) = \begin{cases} \phi(x, y) & \text{if } x = 2y, \\ \psi(x, y) & \text{otherwise;} \end{cases}$$

where

$$\begin{aligned} \phi(x, y) &= x^2 + y^2 - 8x - 4y + 10, \\ \psi(x, y) &= x^2 + y^2 - 4x - 2y. \end{aligned}$$

For the direction $\mathbf{v} = (4, 2)$, our directional function at $\mathbf{x}_0 = (2, 1)$ is

$$\xi_{\mathbf{v}}(k) = f(\mathbf{x}_0 + k\mathbf{v}) \quad (31)$$

$$= f\left(\begin{bmatrix} 2 \\ 1 \end{bmatrix} + k \begin{bmatrix} 4 \\ 2 \end{bmatrix}\right) \quad (32)$$

$$= f\left(\begin{bmatrix} 2 + 4k \\ 1 + 2k \end{bmatrix}\right) \text{ or } f(2 + 4k, 1 + 2k) \quad (33)$$

Since $x = 2y$,

$$\xi_{\mathbf{v}}(k) = \phi(2 + 4k, 1 + 2k) \quad (34)$$

$$= (2 + 4k)^2 + (1 + 2k)^2 - 8(2 + 4k) - 4(1 + 2k) + 10 \quad (35)$$

$$= 4 + 16k + 16k^2 + 1 + 4k + 4k^2 - 16 - 32k - 4 - 8k + 10 \quad (36)$$

$$= 20k^2 - 20k - 5 \quad (37)$$

We examine the directional function's first derivative at $k = 0$:

$$\frac{d\xi_{\mathbf{v}}}{dk}(0) = 40k - 20 \quad (38)$$

$$= -20 \neq 0 \quad (39)$$

Hence $\mathbf{x}_0 = (2, 1)$ is not a local minimum point!

4.2 True Local Minimum

We consolidate our test with the well-known function

$$f(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} \quad (40)$$

where $A \succ 0$. For any directions $\mathbf{v} \in \mathbb{R}^n$, our directional function at $\mathbf{x}_0 = \mathbf{0}$ is

$$\xi_{\mathbf{v}}(k) = f(\mathbf{x}_0 + k\mathbf{v}) \quad (41)$$

$$= (k\mathbf{v})^T A (k\mathbf{v}) \quad (42)$$

$$= k^2 \mathbf{v}^T A \mathbf{v} \quad (43)$$

We examine the directional function's first derivative at $k = 0$:

$$\frac{d\xi_{\mathbf{v}}}{dk}(0) = 2k\mathbf{v}^T A \mathbf{v} \quad (44)$$

$$= 0 \quad (45)$$

Furthermore,

$$\frac{d^2\xi_{\mathbf{v}}}{dk^2}(0) = 2\mathbf{v}^T A \mathbf{v} \quad (46)$$

Since $A \succ 0$, $\forall \mathbf{v} \neq \mathbf{0}$: $\mathbf{v}^T A \mathbf{v} > 0$. Thus, our directional function's second derivative is positive. According to Theorem 4.1, $\mathbf{x}_0 = \mathbf{0}$ is a local minimum point!

5 Conclusion

6 Future Work

References

- [1] Eric W. Weisstein. *Second Derivative Test*. URL: <https://mathworld.wolfram.com/SecondDerivativeTest.html> (visited on 07/15/2021).