Foundations of Machine Learning in Python

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Derivatives and Gradients
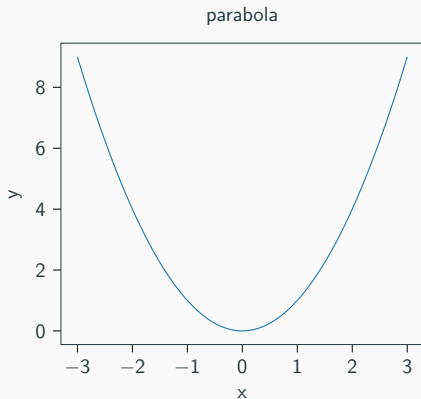
Optimization

Optimization

Traditionally, optimization means minimizing using a cost function $f(x)$. Given the cost, we must find the cheapest point x^* on the function, or in other words,
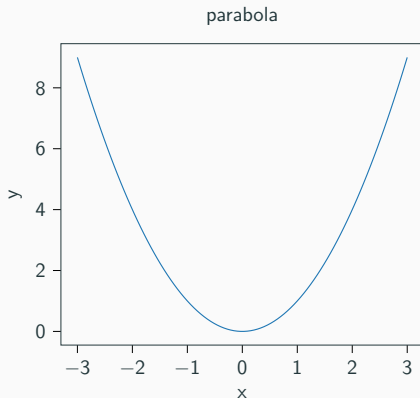
$$x^* = \min_{x \in \mathbb{R}} f(x) \tag{1}$$

Functions

Functions are mathematical mappings. Consider for example the quadratic funtion, $f(x) : \mathbb{R} \rightarrow \mathbb{R}$:

$$f(x) = x^2 \tag{2}$$

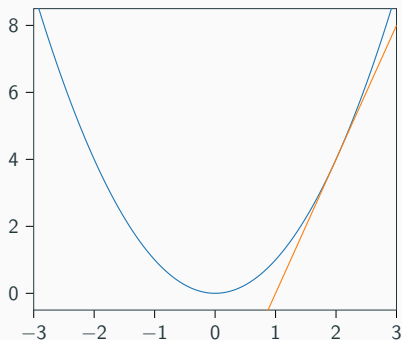parabola

Where is the minimum?

parabola

In this case we immediately see it's at zero. Finding it
algorithmically requires derivate information.

Derivatives and Gradients

The derivative

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h} \tag{3}$$

parabola with derivative at two

Derivation of the parabola derivative

$$\lim_{h \to 0} \frac{(x+h)^2 - x^2}{h} \Leftrightarrow \lim_{h \to 0} \frac{x^2 + 2xh + h^2 - x^2}{h} \qquad (4)$$

$$\Leftrightarrow \lim_{h \to 0} \frac{2xh + h^2}{h} \qquad (5)$$

$$\Leftrightarrow \lim_{h \to 0} \frac{h(2x + h)}{h} \qquad (6)$$
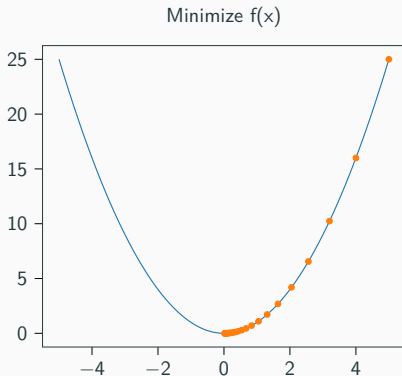
$$\Leftrightarrow \lim_{h \to 0} 2x + h \qquad (7)$$

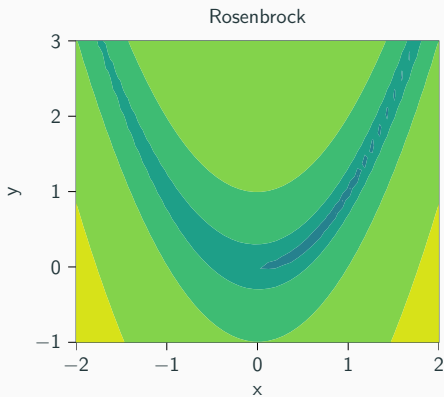$$\Leftrightarrow 2x \qquad (8)$$

Steepest descent on the parabola

$$x_n = x_{n-1} - \alpha \cdot \frac{df}{dx} \tag{9}$$

Working with $x_0 = 5$ and $\alpha = 0.1$ for 25 steps leads to:

Minimize f(x)

$$f(x, y) = (a - x)^2 + b(y - x^2)^2 \tag{10}$$

Rosenbrock

The gradient

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix} \tag{11}$$

Rosenbrock gradient

$$\nabla f(x, y) = \begin{pmatrix} -2a + 2x - 4byx + 4bx^3 \\ 2by - 2bx^2 \end{pmatrix} \qquad (12)$$

Gradient descent

$x_0 = [0.1, 3.], \alpha = 0.01$

$$x_n = x_{n-1} - \alpha \cdot \nabla f(x) \tag{13}$$

Rosenbrock Optimization

Rosenbrock Optimization

Optimization

Frame 2

TODO