

# **Week 2**

**Inclass**

**210914**

# Contents

- Class Review (in Korean)
- Taylor Series and the proof of the condition (in English)
- Gradient and Hessian matrix (in English)
- Solving exercises (in English and Korean)

# Formulation of Optimization Problem

$$\begin{array}{ll} \underset{\mathbf{x}}{\text{minimize}} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in \mathcal{X} \end{array}$$

- $x_i$  : a design variable (구성하려고 하는 시스템의 속성을 수치화하여 표현하는 변수)
- $\mathbf{x} = (x_1, x_2, \dots, x_n)$  : a design point (수치화한 속성들을 모아서 구성한 벡터.  $n$ 차원 공간상의 점에 대응)
- $f$  : The objective function (디자인포인트를 실수에 대응시키는 함수로 현재 디자인의 성능을 평가)
- $\mathbf{X}$  : The feasible set (시스템 속성의 제한 constraints 사항을 모두 만족하는 design point의 집합)
- A design point that minimizes  $f$  is called a **solution**.
- Maximizing problems can be converted to minimizing problems.

# No Free Lunch Theorem

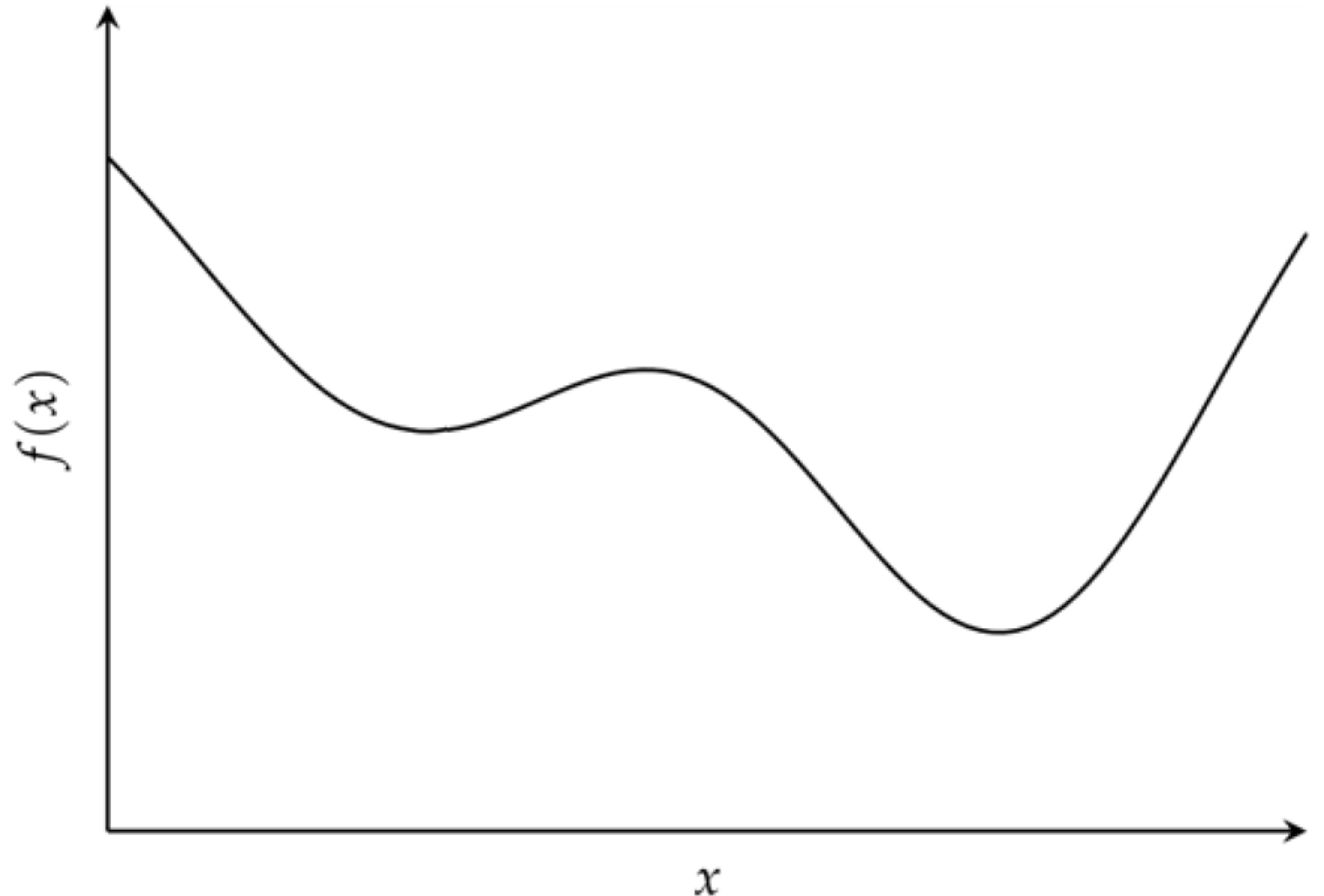
There is no magical algorithm.

- Wolpert, D.H., Macready, W.G. (1997), "[No Free Lunch Theorems for Optimization](#)"
- All optimization algorithms perform equally well when their performance is averaged over all possible cases.

	Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4	...
Problem 1	74	153	12	63	...
Problem 2	35	98	34	102	...
Problem 3	163	102	23	94	...
Problem 4	223	22	723	99	...
Problem 5	62	3	54	33	...
...	...	...	...	...	...
Average	100	100	100	100	

# Where is the solution?

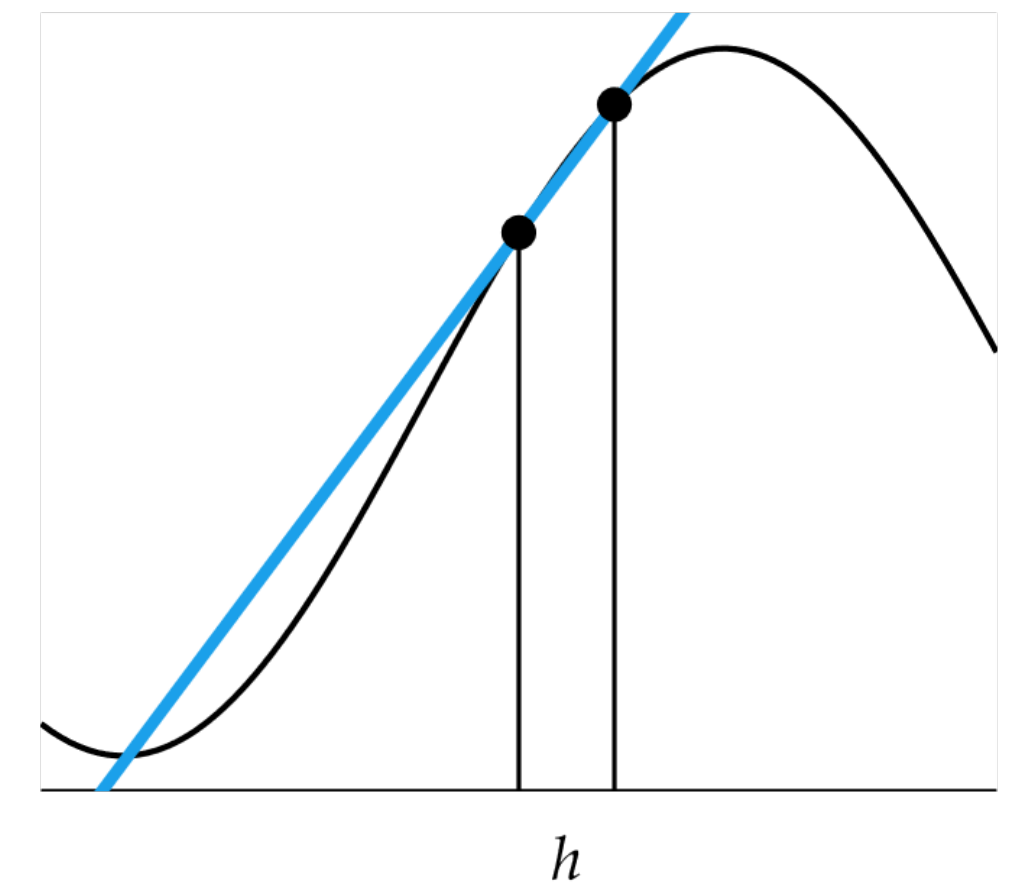
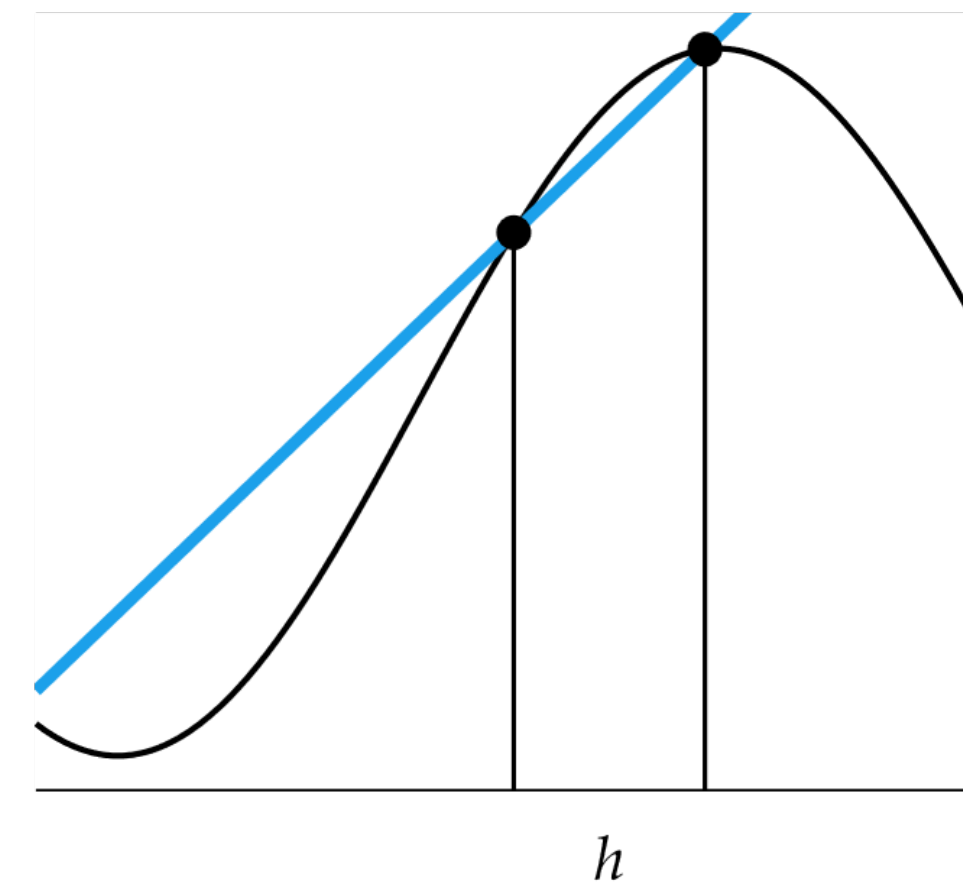
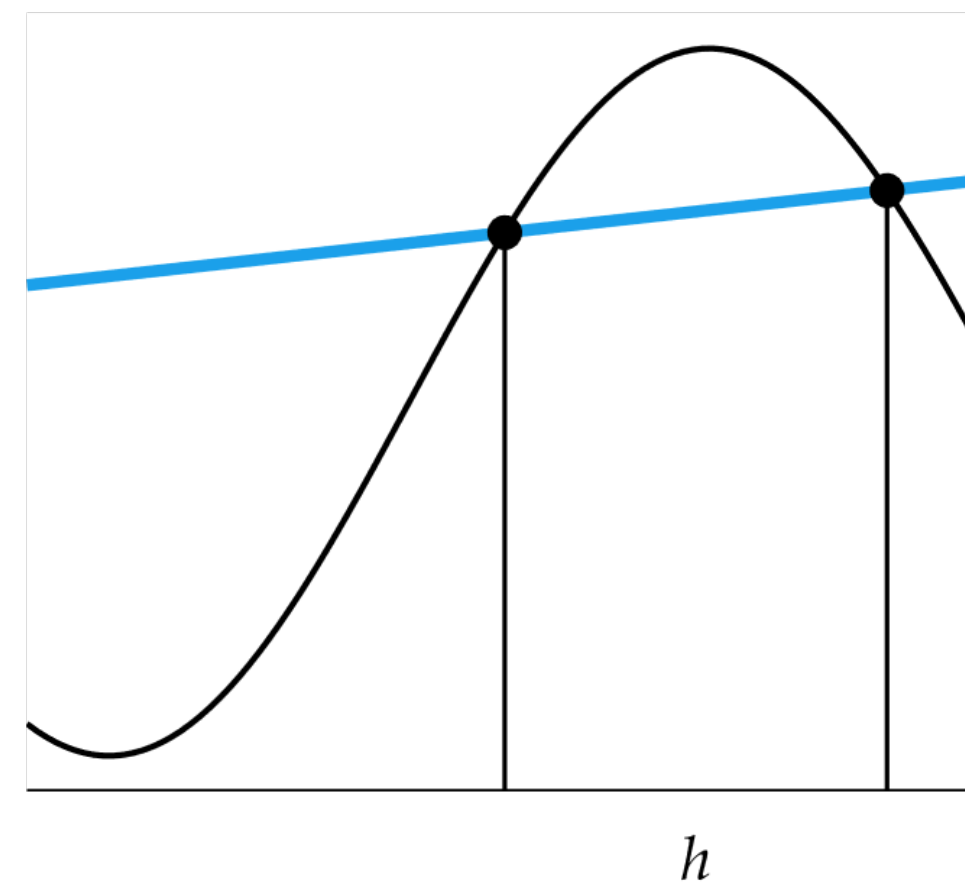
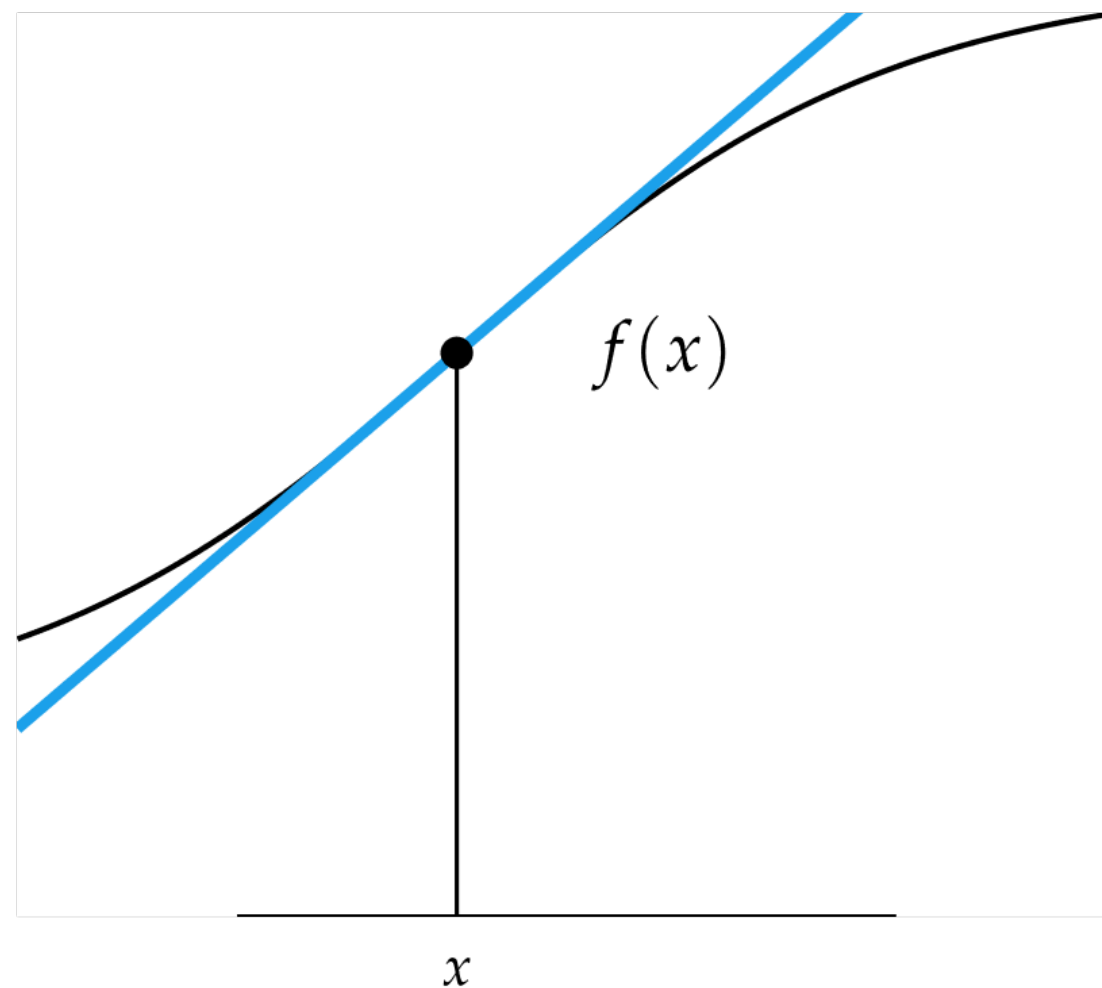
$$\begin{array}{ll}\underset{\mathbf{x}}{\text{minimize}} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in \mathcal{X}\end{array}$$



# Derivatives 미분

## Inspection method for functions

- The derivative  $f'(x)$  of a function  $f$  measures the behavior of  $f$  around  $x$ .
- For the univariate case,  $f'(x)$  measure the slope of the tangent line(접선의 기울기) of  $f$  at  $x$ .



$$f'(x) \equiv \frac{df(x)}{dx}$$

$$f'(x) \equiv \underbrace{\lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}}_{\text{forward difference}}$$

# Symbolic Differentiation

Producing a new formula which is the derivative of a given formula

- *Derivatives of powers.*

$$\frac{d}{dx} x^a = ax^{a-1}.$$

- *Exponential and logarithmic functions.*

$$\frac{d}{dx} e^x = e^x.$$

$$\frac{d}{dx} a^x = a^x \ln(a), \quad a > 0$$

$$\frac{d}{dx} \ln(x) = \frac{1}{x}, \quad x > 0.$$

$$\frac{d}{dx} \log_a(x) = \frac{1}{x \ln(a)}, \quad x, a > 0$$

- *Trigonometric functions.*

$$\frac{d}{dx} \sin(x) = \cos(x).$$

$$\frac{d}{dx} \cos(x) = -\sin(x).$$

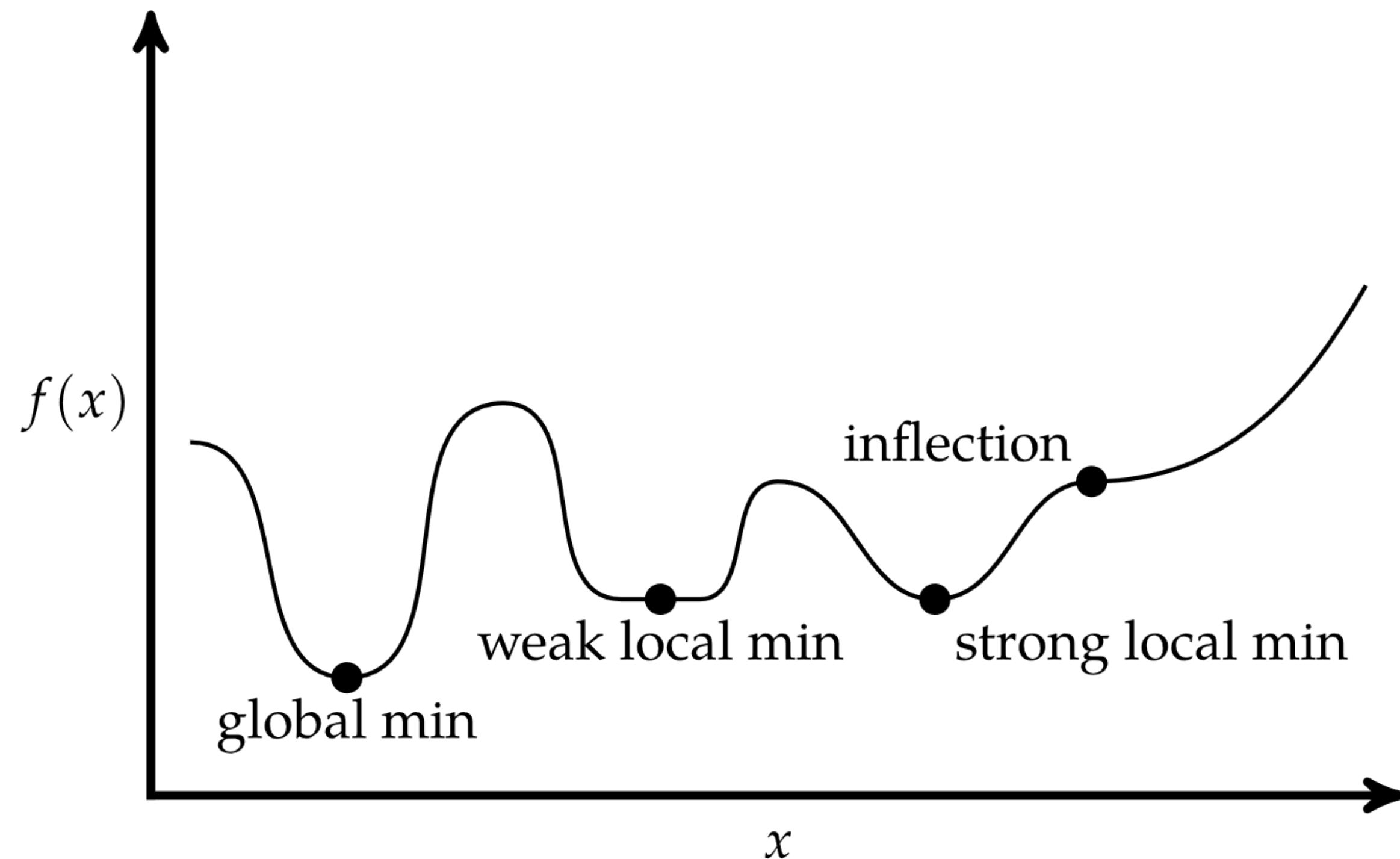
$$\frac{d}{dx} \tan(x) = \sec^2(x) = \frac{1}{\cos^2(x)} = 1 + \tan^2(x).$$

```
julia> using SymEngine
julia> @vars x; # define x as a symbolic variable
julia> f = x^2 + x/2 - sin(x)/x;
julia> diff(f, x)
1/2 + 2*x + sin(x)/x^2 - cos(x)/x
```

# Critical Points

## Candidates for the solution

- $x^*$  is a **local minimum** if there exists  $\delta > 0$  such that  $f(x^*) \leq f(x)$  for all  $x$  with  $|x - x^*| < \delta$ .
- The derivative is zero at all local and global minima of a differentiable function.

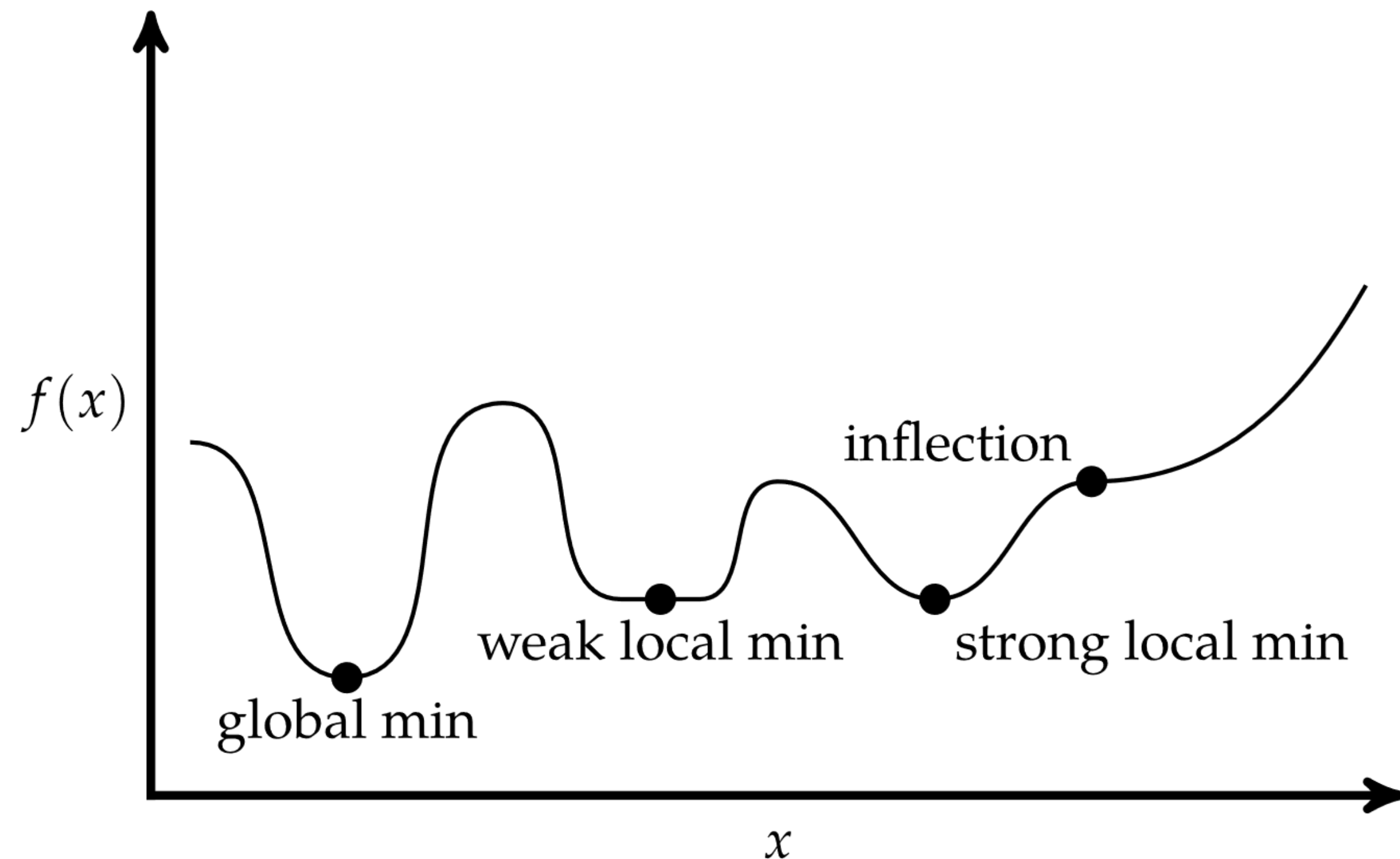




# Conditions for Local Minima

Candidates for the solution

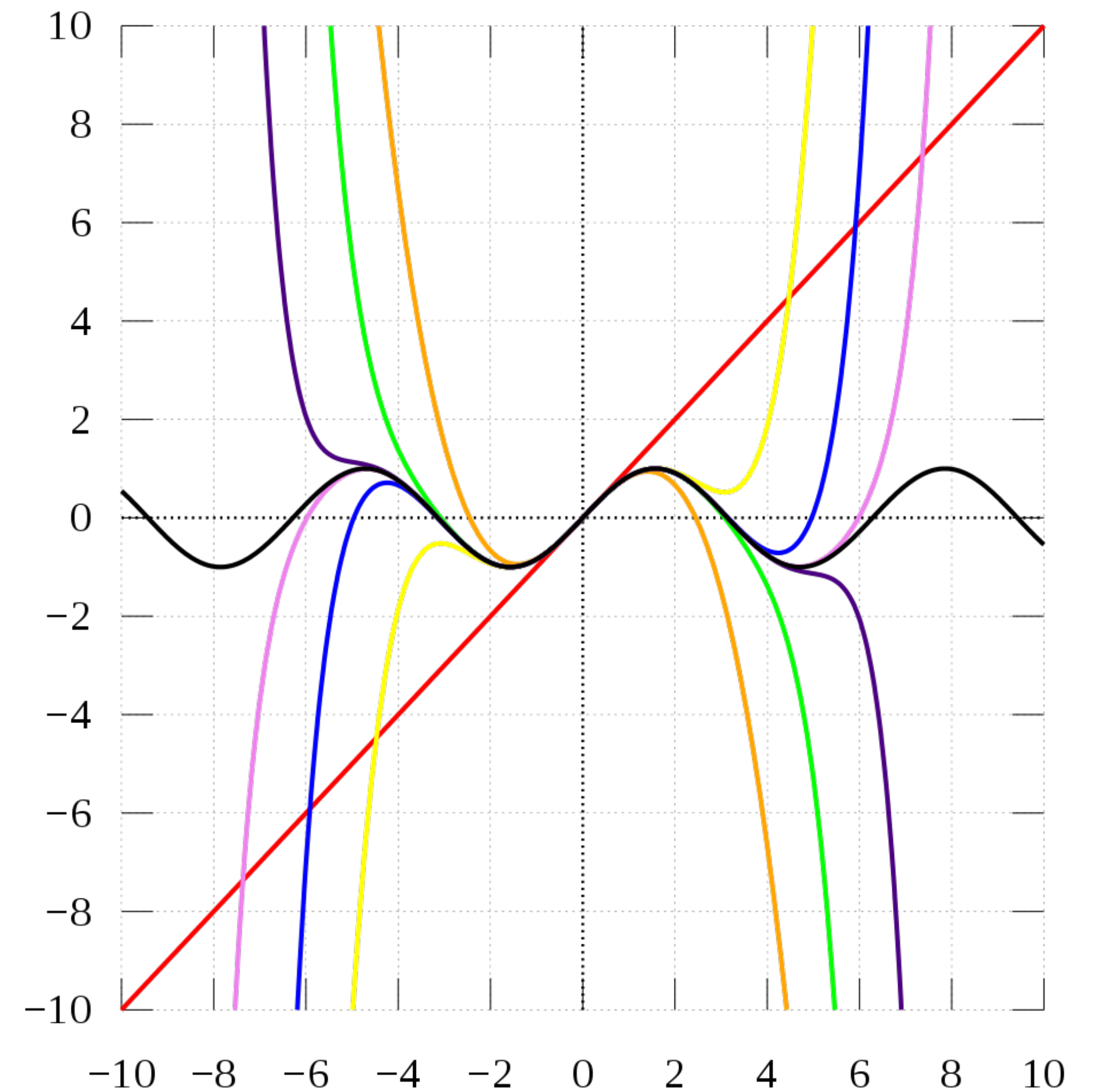
- If  $x^*$  is a **local minimum**, then  $f'(x^*) = 0$  and  $f''(x^*) \geq 0$ .
- If  $f'(x^*) = 0$  and  $f''(x^*) > 0$ , then  $x^*$  is a **strong local minimum**.



# Taylor series

- an **infinite sum of terms** that are expressed in terms of the function's derivatives **at a single point**
- The Taylor series of a function  $f(x)$  that is infinitely differentiable at  $a$ :

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



# Conditions for Local Minima - proof

Candidates for the solution

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

- If  $x^*$  is a **local minimum**, then  $f'(x^*) = 0$ .

$$\begin{aligned} f(x^* + h) &= f(x^*) + \frac{f'(x^*)}{1!}(h) + \frac{f''(x^*)}{2!}(h)^2 + \dots \\ f(x^* - h) &= f(x^*) + \frac{f'(x^*)}{1!}(-h) + \frac{f''(x^*)}{2!}(-h)^2 + \dots \end{aligned}$$

- If  $x^*$  is a **local minimum**, then  $f''(x^*) \geq 0$ .

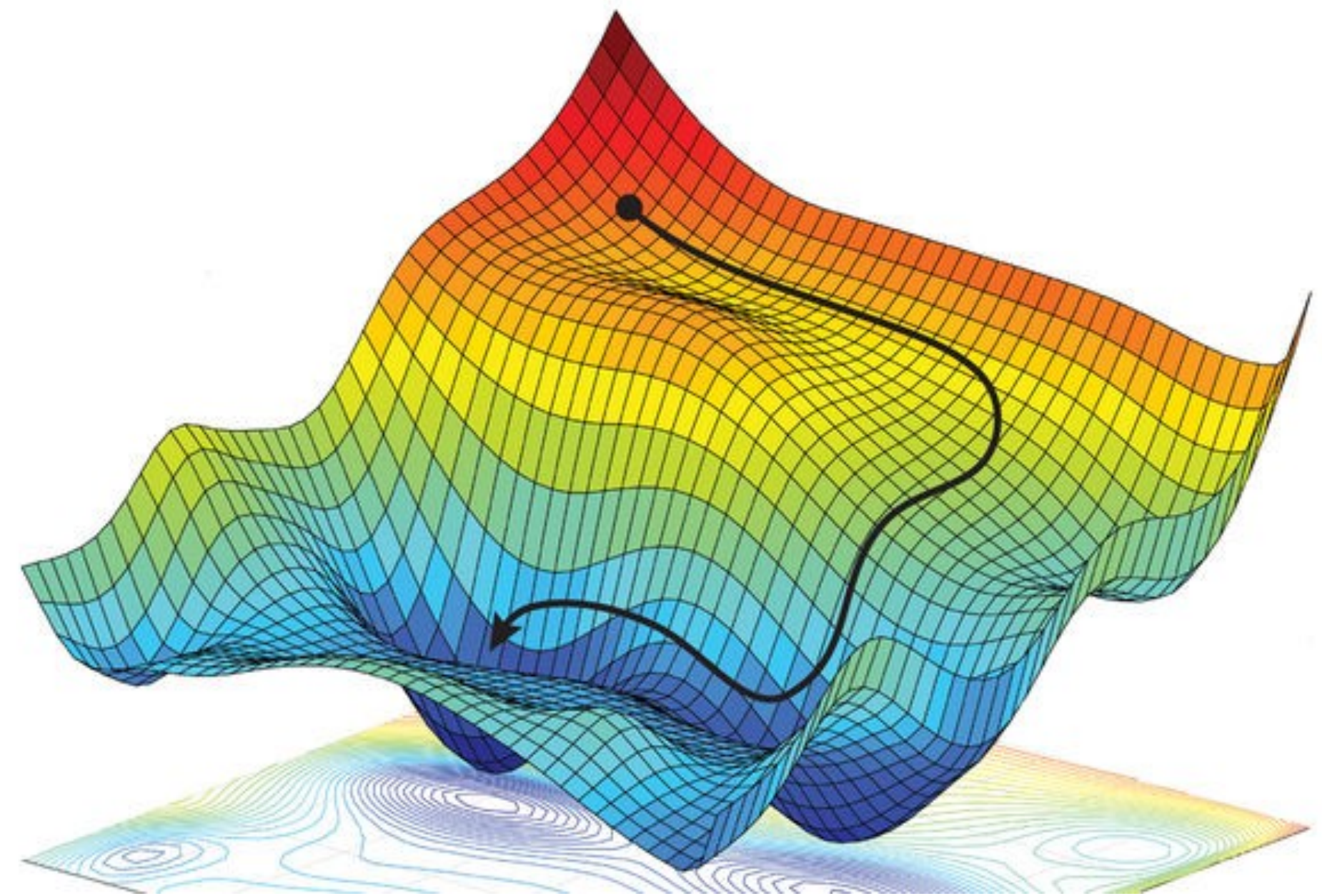
$$\begin{aligned} f(x^* + h) &= f(x^*) + \frac{f'(x^*)}{1!}(h) + \frac{f''(x^*)}{2!}(h)^2 + \frac{f'''(x^*)}{3!}(h)^3 \dots \\ f(x^* - h) &= f(x^*) + \frac{f'(x^*)}{1!}(-h) + \frac{f''(x^*)}{2!}(h)^2 + \frac{f'''(x^*)}{3!}(-h)^3 \dots \end{aligned}$$



# Gradient and Hessian matrix

- **Partial derivative** of a function of several variables is its derivative **with respect to one of those variables**, with the others held constant

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix} \text{ and } \nabla^2 f = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{pmatrix}$$



# Exercise

- **Exercise 1.1.** Give an example of a function with a local minimum that is not a global minimum.

# Excercise

- **Exercise 1.2.** What is the minimum of the function  $f(x) = x^3 - x$ ?

# Exercise

- **Exercise 1.3.** Does the first-order condition  $f'(x) = 0$  hold when  $x$  is the optimal solution of a constrained problem?

# Excercise

- **Exercise 1.4.** How many minima does  $f(x, y) = x^3 + y$ , subject to  $x > y \geq 1$ , have?



# Excercise

- **Exercise 1.5.** How many inflection points does  $x^3 - 10$  have?