

### Example

Show that the linear function  $f(x) = a^T x + b$ , where  $a, x \in \mathbb{R}^n$  and  $b \in \mathbb{R}$ , is a convex function.

### Example

Let  $f(x) = x_1^2 + x_2^2 + \dots + x_n^2$ ,  $x \in \mathbb{R}^n$ . Show that  $f$  is strictly convex function.

## Theorem

*Let  $f : \Omega \rightarrow \mathbb{R}$ ,  $\Omega \subset \mathbb{R}^n$ . If  $f$  is a convex function and  $x_0$  is a local minimum point of  $f$  over  $\Omega$ , then  $x_0$  is a global minimum point of  $f$  in  $\Omega$ , i.e.  $x_0 = \arg \min_{x \in \Omega} f(x)$ .*

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*Let  $f : \Omega \rightarrow \mathbb{R}$ ,  $\Omega \subset \mathbb{R}^n$ . If  $f$  is a strictly convex function and  $x_0$  is a local minimum point of  $f$  over  $\Omega$ , then  $x_0$  is the unique global minimum point of  $f$  in  $\Omega$ , i.e.  $x_0 = \arg \min_{x \in \Omega} f(x)$ .*

## Convexity by using the first order derivative

Let's denote by  $\nabla f(x)$  the gradient of  $f$  at  $x$  i.e.

$$\nabla f(x) = \left[ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right]^T.$$

## Theorem

*If  $\Omega \subset \mathbb{R}^n$  is an open convex set and  $f : \Omega \rightarrow \mathbb{R}$  is a differentiable function, then  $f$  is convex if and only if*

$$f(x) \geq f(x_0) + \nabla f(x_0)^T (x - x_0), \quad \forall x, x_0 \in \Omega.$$

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$$(\nabla f(x) - \nabla f(y))^T (x - y) \geq 0, \quad \forall x, y \in \Omega.$$

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$$(\nabla f(x) - \nabla f(y))^T (x - y) > 0, \quad \forall x, y \in \Omega, x \neq y.$$

## Convexity by using the second order derivative

### Theorem

*Let  $f : (a, b) \rightarrow \mathbb{R}$ . If  $f$  is a twice differentiable function on  $(a, b)$  then  $f$  is convex if and only if  $f''(x) \geq 0$ , for all  $x \in (a, b)$ .*

### Theorem

*Let  $f : (a, b) \rightarrow \mathbb{R}$ . If  $f$  is a twice differentiable function on  $(a, b)$  and  $f''(x) > 0$ , for all  $x \in (a, b)$ , then  $f$  is strictly convex.*

## Example

Check if the following functions are convex (strictly convex), concave (strictly concave), if

- a.  $\frac{1}{1+x^2}, \quad x \in \mathbb{R};$
- b.  $-\cos x, \quad x \in (0, \frac{\pi}{2});$
- c.  $-(x-1)^4 + 1, \quad x \in \mathbb{R}.$