• Let f be a real valued function defined on $\Omega \subseteq \mathbb{R}^n$.

- Let f be a real valued function defined on $\Omega \subseteq \mathbb{R}^n$.
- The problem is to minimize or maximize $f(\mathbf{x})$ subject to $\mathbf{x} \in \Omega$, where f need not be a linear function.

- Let f be a real valued function defined on $\Omega \subseteq \mathbb{R}^n$.
- The problem is to minimize or maximize $f(\mathbf{x})$ subject to $\mathbf{x} \in \Omega$, where f need not be a linear function.
- **Definition 1:** A point (or an element) $\mathbf{x}^* \in \Omega$ is called a local minimum (maximum) of f if there exists an $\epsilon > 0$, such that
 - $\mathbf{x} \in \Omega$ and $\|\mathbf{x} \mathbf{x}^*\| < \epsilon$ implies $f(\mathbf{x}^*) \le f(\mathbf{x}) \ (f(\mathbf{x}^*) \ge f(\mathbf{x}))$.

- Let f be a real valued function defined on $\Omega \subseteq \mathbb{R}^n$.
- The problem is to minimize or maximize $f(\mathbf{x})$ subject to $\mathbf{x} \in \Omega$, where f need not be a linear function.
- **Definition 1:** A point (or an element) $\mathbf{x}^* \in \Omega$ is called a local minimum (maximum) of f if there exists an $\epsilon > 0$, such that
 - $\mathbf{x} \in \Omega$ and $\|\mathbf{x} \mathbf{x}^*\| < \epsilon$ implies $f(\mathbf{x}^*) \le f(\mathbf{x}) \ (f(\mathbf{x}^*) \ge f(\mathbf{x}))$.
- **Definition 2:** A point $\mathbf{x}^* \in \Omega$ is called a global minimum (maximum) of f if $f(\mathbf{x}^*) \leq f(\mathbf{x})$ ($f(\mathbf{x}^*) \geq f(\mathbf{x})$) for all $\mathbf{x} \in \Omega$.

- Let f be a real valued function defined on $\Omega \subseteq \mathbb{R}^n$.
- The problem is to minimize or maximize $f(\mathbf{x})$ subject to $\mathbf{x} \in \Omega$, where f need not be a linear function.
- **Definition 1:** A point (or an element) $\mathbf{x}^* \in \Omega$ is called a local minimum (maximum) of f if there exists an $\epsilon > 0$, such that
 - $\mathbf{x} \in \Omega$ and $\|\mathbf{x} \mathbf{x}^*\| < \epsilon$ implies $f(\mathbf{x}^*) \le f(\mathbf{x}) \ (f(\mathbf{x}^*) \ge f(\mathbf{x}))$.
- **Definition 2:** A point $\mathbf{x}^* \in \Omega$ is called a global minimum (maximum) of f if $f(\mathbf{x}^*) \leq f(\mathbf{x})$ ($f(\mathbf{x}^*) \geq f(\mathbf{x})$) for all $\mathbf{x} \in \Omega$.

• **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, $0 \le t \le c$, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.

- **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, 0 < t < c, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.
- **Example 1:** Let $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$

- **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, $0 \le t \le c$, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.
- **Example 1:** Let $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- At $[0,0]^T$ if $\mathbf{d} = [d_1,d_2]^T$ is a feasible direction then $d_1 \ge 0$ and $d_2 \ge 0$.

- **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, $0 \le t \le c$, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.
- **Example 1:** Let $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- At $[0,0]^T$ if $\mathbf{d} = [d_1,d_2]^T$ is a feasible direction then $d_1 \ge 0$ and $d_2 > 0$.
- At $[0, \frac{1}{2}]^T$ if **d** is a feasible direction then $d_1 \ge 0$ but d_2 can be any real number.

- **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, $0 \le t \le c$, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.
- **Example 1:** Let $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- At $[0,0]^T$ if $\mathbf{d} = [d_1,d_2]^T$ is a feasible direction then $d_1 \ge 0$ and $d_2 \ge 0$.
- At $[0, \frac{1}{2}]^T$ if **d** is a feasible direction then $d_1 \ge 0$ but d_2 can be any real number.
- At $[\frac{1}{2}, 0]^T$ if **d** is a feasible direction then $d_2 \ge 0$ but d_1 can be any real number.

- **Definition 3:** A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ is said to be a **feasible direction** at $\mathbf{x}^* \in \Omega$, if there exists a c > 0 such that for all t, $0 \le t \le c$, $\mathbf{x}^* + t\mathbf{d} \in \Omega$.
- **Example 1:** Let $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- At $[0,0]^T$ if $\mathbf{d} = [d_1,d_2]^T$ is a feasible direction then $d_1 \ge 0$ and $d_2 \ge 0$.
- At $[0, \frac{1}{2}]^T$ if **d** is a feasible direction then $d_1 \ge 0$ but d_2 can be any real number.
- At $\left[\frac{1}{2},0\right]^T$ if **d** is a feasible direction then $d_2 \ge 0$ but d_1 can be any real number.
- At $\left[\frac{1}{2}, \frac{1}{2}\right]^T$ any $\mathbf{d} \in \mathbb{R}^2$ will be a feasible direction.

Remark 1: If x* is an interior point of Ω then any
 d ∈ Rⁿ, d ≠ 0 is a feasible direction at x*.

- Remark 1: If x* is an interior point of Ω then any
 d ∈ Rⁿ, d ≠ 0 is a feasible direction at x*.
- Theorem 1: Let $f:\Omega\to\mathbb{R}$ be a continuously differentiable function (that is, the first order partial derivatives of f exists and are continuous as functions from Ω to \mathbb{R}). If \mathbf{x}^* is a local minimum point then for any feasible direction \mathbf{d} at \mathbf{x}^* , $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$,

- Remark 1: If x* is an interior point of Ω then any
 d ∈ Rⁿ, d ≠ 0 is a feasible direction at x*.
- Theorem 1: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function (that is, the first order partial derivatives of f exists and are continuous as functions from Ω to \mathbb{R}). If \mathbf{x}^* is a local minimum point then for any feasible direction \mathbf{d} at \mathbf{x}^* , $\nabla f(\mathbf{x}^*)\mathbf{d} > 0$,
 - where $(\nabla f(\mathbf{x}^*))_i = (\frac{\partial f}{\partial x_i})(\mathbf{x}^*)$ (the gradient vector of f at \mathbf{x}^* is written as a row vector), and $\mathbf{d} \in \mathbb{R}^n$ is a column vector.

- Remark 1: If x* is an interior point of Ω then any
 d ∈ ℝⁿ, d ≠ 0 is a feasible direction at x*.
- Theorem 1: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function (that is, the first order partial derivatives of f exists and are continuous as functions from Ω to \mathbb{R}). If \mathbf{x}^* is a local minimum point then for any feasible direction \mathbf{d} at \mathbf{x}^* , $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$,
 - where $(\nabla f(\mathbf{x}^*))_i = (\frac{\partial f}{\partial x_i})(\mathbf{x}^*)$ (the gradient vector of f at \mathbf{x}^* is written as a row vector), and $\mathbf{d} \in \mathbb{R}^n$ is a column vector.
- Theorem 2 : Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. Let \mathbf{x}^* be an interior point of Ω . If \mathbf{x}^* is a local minimum point of f then $\nabla f(\mathbf{x}^*) = \mathbf{0}$

• **Example 1:** Consider the following problem:

• **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 - x_1^2 x_2 + 2x_2^2$ • **Example 1:** Consider the following problem:

Minimize $f(x_1, x_2) = x_1^3 - x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$

- **Example 1:** Consider the following problem:
 - Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions $x_1 = 0, x_2 = 0$ and $x_1 = 6, x_2 = 9$.

- Example 1: Consider the following problem:
 - Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions $x_1 = 0, x_2 = 0$ and $x_1 = 6, x_2 = 9$.
- So [6,9]^T and [0,0]^T satisfies the first order necessary conditions for a local minimum.

- Example 1: Consider the following problem:
 - Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions $x_1 = 0, x_2 = 0$ and $x_1 = 6, x_2 = 9$.
- So [6,9]^T and [0,0]^T satisfies the first order necessary conditions for a local minimum.
- $[0,0]^T$ is also a local minimum of f.

- Example 1: Consider the following problem:
 - Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}.$
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions $x_1 = 0, x_2 = 0$ and $x_1 = 6, x_2 = 9$.
- So [6,9]^T and [0,0]^T satisfies the first order necessary conditions for a local minimum.
- $[0,0]^T$ is also a local minimum of f.
- Exercise: Will $[0,0]^T$ be a local minimum point of f given in Example 1, if $\Omega = \mathbb{R}^2$?

• **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 - x_1 + x_2 + x_1x_2$ • **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 - x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}$

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}$
- Note that f is a continuously differentiable function

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Hence $\Omega = \{ [x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0 \}$
- Note that f is a continuously differentiable function
- Check that $\mathbf{x}^* = [\frac{1}{2}, 0]^T$, satisfies the first order necessary conditions for a locally minimum

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 > 0$, $x_2 > 0$.
- Hence $\Omega = \{ [x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0 \}$
- Note that f is a continuously differentiable function
- Check that $\mathbf{x}^* = [\frac{1}{2}, 0]^T$, satisfies the first order necessary conditions for a locally minimum
- Check that f has a global minimum at $x_1 = \frac{1}{2}, x_2 = 0$

• **Theorem 3:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).

• **Theorem 3:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).

If \mathbf{x}^* is a local minimum of f then for any feasible direction \mathbf{d} at \mathbf{x}^*

- Theorem 3: Let $f:\Omega\to\mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).
 - If \mathbf{x}^* is a local minimum of f then for any feasible direction \mathbf{d} at \mathbf{x}^*
 - 1. $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$.

- **Theorem 3:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).
 - If \mathbf{x}^* is a local minimum of f then for any feasible direction \mathbf{d} at \mathbf{x}^*
 - 1. $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$.
 - 2. If $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$, then $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} \geq 0$.

• **Theorem 3:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).

If \mathbf{x}^* is a local minimum of f then for any feasible direction \mathbf{d} at \mathbf{x}^*

- 1. $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$.
- 2. If $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$, then $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} \geq 0$.

Note: The matrix $\nabla^2 f$ (also denoted by H) is called the Hessian matrix of f,

• **Theorem 3:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function (that is all the second order partial derivatives of f (given by $\frac{\partial^2 f}{\partial x_j \partial x_i}$) exists and are continuous as functions from Ω to \mathbb{R}).

If \mathbf{x}^* is a local minimum of f then for any feasible direction \mathbf{d} at \mathbf{x}^*

- 1. $\nabla f(\mathbf{x}^*)\mathbf{d} \geq 0$.
- 2. If $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$, then $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} \geq 0$.

Note: The matrix $\nabla^2 f$ (also denoted by H) is called the Hessian matrix of f,

$$(\nabla^2 f(\mathbf{x}^*))_{ij} = \frac{\partial^2 f}{\partial x_j \partial x_i}(\mathbf{x}^*) = \left[\frac{\partial^2 f}{\partial x_j \partial x_i}\right]_{\mathbf{x}^*}.$$

• Theorem 4: Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function and let \mathbf{x}^* be an interior point of Ω . If \mathbf{x}^* is a local minimum of f then

• **Theorem 4:** Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function and let \mathbf{x}^* be an interior point of Ω . If \mathbf{x}^* is a local minimum of f then 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).
- **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 - x_1^2 x_2 + 2x_2^2$

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).
- **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$,

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).
- **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}$.

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).
- **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}$.
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions

- Theorem 4: Let f: Ω → ℝ be a twice continuously differentiable function and let x* be an interior point of Ω. If x* is a local minimum of f then
 - 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
 - 2. $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$ for all vectors $\mathbf{d} \in \mathbb{R}^n$ (or $\nabla^2 f(\mathbf{x}^*)$ is positive semidefinite).
- **Example 1:** Consider the following problem: Minimize $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ subject to $x_1 \ge 0$, $x_2 \ge 0$, hence $\Omega = \{[x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0\}$.
- $\nabla f(\mathbf{x}) = (3x_1^2 2x_1x_2, -x_1^2 + 4x_2) = [0, 0]$ has two solutions
- $x_1 = 0, x_2 = 0$ and $x_1 = 6, x_2 = 9$.

• $[6,9]^T$ is an interior point of the feasible region Ω hence any $\mathbf{d} \in \mathbb{R}^2$ is a feasible direction at $[6,9]^T$.

- $[6, 9]^T$ is an interior point of the feasible region Ω hence any $\mathbf{d} \in \mathbb{R}^2$ is a feasible direction at $[6, 9]^T$.
- [6,9]^T satisfies the **first order necessary conditions** for a local minimum.

- [6,9]^T is an interior point of the feasible region Ω hence any d∈ R² is a feasible direction at [6,9]^T.
- [6,9]^T satisfies the first order necessary conditions for a local minimum.

- [6,9]^T is an interior point of the feasible region Ω hence any d∈ R² is a feasible direction at [6,9]^T.
- [6,9]^T satisfies the first order necessary conditions for a local minimum.

• At
$$\mathbf{x}^* = [6, 9]^T$$
, $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 18 & -12 \\ -12 & 4 \end{pmatrix}$.

• At
$$\mathbf{x}^* = [6, 9]^T$$
, $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 18 & -12 \\ -12 & 4 \end{pmatrix}$

• But $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} = -2$ for $\mathbf{d} = [1, 1]^T$.

• At
$$\mathbf{x}^* = [6, 9]^T$$
, $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 18 & -12 \\ -12 & 4 \end{pmatrix}$

- But $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} = -2$ for $\mathbf{d} = [1, 1]^T$.
- Hence x* = [6,9]^T since it does not satisfy the second order necessary conditions for a local minimum is not a local minimum point of f.

• At
$$\mathbf{x}^* = [6, 9]^T$$
, $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 18 & -12 \\ -12 & 4 \end{pmatrix}$

- But $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} = -2$ for $\mathbf{d} = [1, 1]^T$.
- Hence $\mathbf{x}^* = [6, 9]^T$ since it does not satisfy the **second** order necessary conditions for a local minimum is not a local minimum point of f.
- Hence the first order necessary conditions are necessary but not sufficient for a point to be a local minimum.

• At $\mathbf{x}^* = [0, 0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$.

• At $\mathbf{x}^* = [0, 0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$. Since $\nabla f(\mathbf{x}^*) = \mathbf{0}$, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} . • At $\mathbf{x}^* = [0, 0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$.

Since
$$\nabla f(\mathbf{x}^*) = \mathbf{0}$$
, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} .

Since
$$\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$$
,

• At $\mathbf{x}^* = [0, 0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$.

Since
$$\nabla f(\mathbf{x}^*) = \mathbf{0}$$
, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} .
Since $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$, $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} = 4d_2^2 \ge 0$ for

all **d**.

- At $\mathbf{x}^* = [0,0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$. Since $\nabla f(\mathbf{x}^*) = \mathbf{0}$, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} . Since $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$, $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} = 4d_2^2 \geq 0$ for all \mathbf{d} .
- [0,0]^T satisfies both the first and second order necessary conditions for a local minimum.

• At $\mathbf{x}^* = [0, 0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$. Since $\nabla f(\mathbf{x}^*) = \mathbf{0}$, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} .

Since
$$\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$$
, $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} = 4d_2^2 \ge 0$ for all \mathbf{d} .

- [0,0]^T satisfies both the first and second order necessary conditions for a local minimum.
- If $\Omega = \mathbb{R}^2$ in Example 1 then $[0,0]^T$ although satisfies both the **first and second order necessary conditions** is not a local minimum.

- At $\mathbf{x}^* = [0,0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$. Since $\nabla f(\mathbf{x}^*) = \mathbf{0}$, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} . Since $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$, $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} = 4d_2^2 \geq 0$ for
- [0,0]^T satisfies both the first and second order necessary conditions for a local minimum.

all d.

- If $\Omega = \mathbb{R}^2$ in Example 1 then $[0,0]^T$ although satisfies both the **first and second order necessary conditions** is not a local minimum.
- For $\mathbf{d} = [-1, 0]^T$ which is a feasible direction at $[0, 0]^T$, $f(\mathbf{x}^* + t\mathbf{d}) = f(\mathbf{0} + t\mathbf{d}) < f(\mathbf{0})$, for all t > 0,

- At $\mathbf{x}^* = [0,0]^T$, $\mathbf{d} \neq \mathbf{0}$ is a feasible direction if and only if $d_1 \geq 0$ and $d_2 \geq 0$. Since $\nabla f(\mathbf{x}^*) = \mathbf{0}$, $\nabla f(\mathbf{x}^*)\mathbf{d} = 0$ for all \mathbf{d} . Since $\nabla^2 f(\mathbf{x}^*) = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}$, $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*)\mathbf{d} = 4d_2^2 \geq 0$ for all \mathbf{d} .
- [0,0]^T satisfies both the first and second order necessary conditions for a local minimum.
- If $\Omega = \mathbb{R}^2$ in Example 1 then $[0,0]^T$ although satisfies both the **first and second order necessary conditions** is not a local minimum.
- For $\mathbf{d} = [-1, 0]^T$ which is a feasible direction at $[0, 0]^T$, $f(\mathbf{x}^* + td) = f(\mathbf{0} + td) < f(\mathbf{0})$, for all t > 0, so $[0, 0]^T$ is not a local minimum of f.

• **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 - x_1 + x_2 + x_1x_2$ • **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 - x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 > 0$, $x_2 > 0$.
- Note that *f* is a twice continuously differentiable function.

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Note that *f* is a twice continuously differentiable function.
- Check that $\mathbf{x}^* = [\frac{1}{2}, 0]^T$, satisfies the first and the second order necessary conditions for \mathbf{x}^* to be locally minimum.

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Note that *f* is a twice continuously differentiable function.
- Check that $\mathbf{x}^* = [\frac{1}{2}, 0]^T$, satisfies the first and the second order necessary conditions for \mathbf{x}^* to be locally minimum.
- $\mathbf{x}^* = \begin{bmatrix} \frac{1}{2}, 0 \end{bmatrix}^T$, is the global minimum of f.

- **Example 2 :** Consider the following problem: Minimize $f(x_1, x_2) = x_1^2 x_1 + x_2 + x_1x_2$ subject to $x_1 \ge 0$, $x_2 \ge 0$.
- Note that *f* is a twice continuously differentiable function.
- Check that $\mathbf{x}^* = [\frac{1}{2}, 0]^T$, satisfies the first and the second order necessary conditions for \mathbf{x}^* to be locally minimum.
- $\mathbf{x}^* = \begin{bmatrix} \frac{1}{2}, 0 \end{bmatrix}^T$, is the global minimum of f.
- **Definition:** A real symmetric matrix A is said to be positive semidefinite (negative semidefinite) if $\mathbf{x}^T A \mathbf{x} \geq 0$ ($\mathbf{x}^T A \mathbf{x} \leq 0$) for all $\mathbf{x} \in \mathbb{R}^n$.

• **Definition:** A real symmetric matrix A is said to be positive definite (negative definite) if $\mathbf{x}^T A \mathbf{x} > 0$ ($\mathbf{x}^T A \mathbf{x} < 0$) for all **nonzero** vectors $\mathbf{x} \in \mathbb{R}^n$.

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- **Theorem:** If A is a symmetric, $n \times n$, real matrix then the following statements are equivalent:

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- **Theorem:** If A is a symmetric, $n \times n$, real matrix then the following statements are equivalent:
- A is positive semidefinite.

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- **Theorem:** If A is a symmetric, $n \times n$, real matrix then the following statements are equivalent:
- A is positive semidefinite.
- All eigenvalues of A are nonnegative.

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- Theorem: If A is a symmetric, n × n, real matrix then the following statements are equivalent:
- A is positive semidefinite.
- All eigenvalues of A are nonnegative.
- All principal minors of *A* are nonnegative.

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- **Theorem:** If A is a symmetric, $n \times n$, real matrix then the following statements are equivalent:
- A is positive semidefinite.
- All eigenvalues of A are nonnegative.
- All principal minors of A are nonnegative.
- **Definition:** $\lambda \in \mathbb{C}$ is called an eigenvalue of an $n \times n$ matrix A if there exists an $\mathbf{x} \in \mathbb{C}^n$, $\mathbf{x} \neq \mathbf{0}$ (that is atleast one component of \mathbf{x} is nonzero) such that $A\mathbf{x} = \lambda \mathbf{x}$.

- Definition: A real symmetric matrix A is said to be positive definite (negative definite) if x^TAx > 0 (x^TAx < 0) for all nonzero vectors x ∈ Rⁿ.
- **Theorem:** If A is a symmetric, $n \times n$, real matrix then the following statements are equivalent:
- A is positive semidefinite.
- All eigenvalues of A are nonnegative.
- All principal minors of *A* are nonnegative.
- **Definition:** $\lambda \in \mathbb{C}$ is called an eigenvalue of an $n \times n$ matrix A if there exists an $\mathbf{x} \in \mathbb{C}^n$, $\mathbf{x} \neq \mathbf{0}$ (that is atleast one component of \mathbf{x} is nonzero) such that $A\mathbf{x} = \lambda \mathbf{x}$.
- For example the 0 matrix has all n eigenvalues equal to 0, the identity matrix In has all n eigenvalues equal to 1, and for an upper triangular matrix, the diagonal entries are its eigenvalues.

• **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .

- **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .
- If $\alpha = \beta$, then $A[\alpha, \alpha]$ is called a **principal submatrix** of A and det $A[\alpha, \alpha]$ is called a **principal minor** of A.

- **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .
- If $\alpha = \beta$, then $A[\alpha, \alpha]$ is called a **principal submatrix** of A and det $A[\alpha, \alpha]$ is called a **principal minor** of A.
- If $\alpha = \beta = \{i\}$, where $i \in \{1, ..., n\}$, then $A[\alpha, \alpha] = [a_{ii}]$, and $detA[\alpha, \alpha] = a_{ii}$, the i th diagonal entry.

- Definition: If A is an n × n matrix and α ⊆ {1,...,n}, β ⊆ {1,...,n} then A[α, β] is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α, and by deleting all the columns of A which do not belong to β.
- If $\alpha = \beta$, then $A[\alpha, \alpha]$ is called a **principal submatrix** of A and det $A[\alpha, \alpha]$ is called a **principal minor** of A.
- If $\alpha = \beta = \{i\}$, where $i \in \{1, ..., n\}$, then $A[\alpha, \alpha] = [a_{ii}]$, and $det A[\alpha, \alpha] = a_{ii}$, the i th diagonal entry.
- If $\alpha = \beta = \{i, j\}$, where $i, j \in \{1, ..., n\}$ and i < j, then

- **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .
- If α = β, then A[α, α] is called a principal submatrix of A and det A[α, α] is called a principal minor of A.
- If $\alpha = \beta = \{i\}$, where $i \in \{1, ..., n\}$, then $A[\alpha, \alpha] = [a_{ii}]$, and $detA[\alpha, \alpha] = a_{ii}$, the i th diagonal entry.
- If $\alpha = \beta = \{i, j\}$, where $i, j \in \{1, ..., n\}$ and i < j, then $A[\alpha, \alpha] = \begin{bmatrix} a_{ii} & a_{ij} \\ a_{ji} & a_{jj} \end{bmatrix}$.

- **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .
- If $\alpha = \beta$, then $A[\alpha, \alpha]$ is called a **principal submatrix** of A and det $A[\alpha, \alpha]$ is called a **principal minor** of A.
- If $\alpha = \beta = \{i\}$, where $i \in \{1, ..., n\}$, then $A[\alpha, \alpha] = [a_{ii}]$, and $detA[\alpha, \alpha] = a_{ii}$, the i th diagonal entry.
- If $\alpha = \beta = \{i, j\}$, where $i, j \in \{1, \dots, n\}$ and i < j, then $A[\alpha, \alpha] = \begin{bmatrix} a_{ii} & a_{ij} \\ a_{ji} & a_{jj} \end{bmatrix}$. If $\alpha = \{1, \dots, n\}$, then $A[\alpha, \alpha] = A$, and det $A[\alpha, \alpha] = \det(A)$.

- **Definition:** If A is an $n \times n$ matrix and $\alpha \subseteq \{1, \ldots, n\}$, $\beta \subseteq \{1, \ldots, n\}$ then $A[\alpha, \beta]$ is the (sub)matrix obtained from A, by deleting all the rows of A which do not belong to α , and by deleting all the columns of A which do not belong to β .
- If $\alpha = \beta$, then $A[\alpha, \alpha]$ is called a **principal submatrix** of A and det $A[\alpha, \alpha]$ is called a **principal minor** of A.
- If $\alpha = \beta = \{i\}$, where $i \in \{1, ..., n\}$, then $A[\alpha, \alpha] = [a_{ii}]$, and $det A[\alpha, \alpha] = a_{ii}$, the i th diagonal entry.
- If $\alpha = \beta = \{i, j\}$, where $i, j \in \{1, ..., n\}$ and i < j, then $A[\alpha, \alpha] = \begin{bmatrix} a_{ii} & a_{ij} \\ a_{ji} & a_{jj} \end{bmatrix}$. If $\alpha = \{1, ..., n\}$, then $A[\alpha, \alpha] = A$, and det $A[\alpha, \alpha] = det(A)$.
- Remark: A nonsingular (nonzero determinant) positive semidefinite matrix is positive definite.

• Sufficient conditions for a local minima : Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

1.
$$\nabla f(\mathbf{x}^*) = \mathbf{0}$$

Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

- 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$
- $2.\nabla^2 f(\mathbf{x}^*)$ is positive definite,

Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

- 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$
- $2.\nabla^2 f(\mathbf{x}^*)$ is positive definite, then \mathbf{x}^* is a local minimum point of f.

Theorem 4 : Let $f: \Omega \to \mathbb{R}$ be a twice continuously differentiable function.

- 1. $\nabla f(\mathbf{x}^*) = \mathbf{0}$
- $2.\nabla^2 f(\mathbf{x}^*)$ is positive definite, then \mathbf{x}^* is a local minimum point of f.
- **Remark:** Since maximizing f is same as minimizing -f, all the previous theorems have corresponding analogues for a maximization problem with some obvious changes.

• **Definition 4:** A real valued function f defined on a convex set $\Omega \subseteq \mathbb{R}^n$ is said to be a **convex function** on Ω if for all $\mathbf{x}, \mathbf{y} \in \Omega$ and all $0 \le \alpha \le 1$, $f(\alpha \mathbf{x} + (1 - \alpha)\mathbf{y}) \le \alpha f(\mathbf{x}) + (1 - \alpha)f(\mathbf{y})$.

- **Definition 4:** A real valued function f defined on a convex set $\Omega \subseteq \mathbb{R}^n$ is said to be a **convex function** on Ω if for all $\mathbf{x}, \mathbf{y} \in \Omega$ and all $0 \le \alpha \le 1$, $f(\alpha \mathbf{x} + (1 \alpha)\mathbf{y}) \le \alpha f(\mathbf{x}) + (1 \alpha)f(\mathbf{y})$.
- **Definition 5:** An $f: \Omega \to \mathbb{R}$ is said to be a **concave** function if -f is a **convex function**.

- **Definition 4:** A real valued function f defined on a convex set $\Omega \subseteq \mathbb{R}^n$ is said to be a **convex function** on Ω if for all $\mathbf{x}, \mathbf{y} \in \Omega$ and all $0 \le \alpha \le 1$, $f(\alpha \mathbf{x} + (1 \alpha)\mathbf{y}) \le \alpha f(\mathbf{x}) + (1 \alpha)f(\mathbf{y})$.
- **Definition 5:** An $f: \Omega \to \mathbb{R}$ is said to be a **concave** function if -f is a **convex function**.
- Theorem 1 : If f is a convex function on Ω (a convex set), then the set $S = \{ \mathbf{x} \in \Omega : f(\mathbf{x}) \le c \}$ is a convex set (for all real c).

- **Definition 4:** A real valued function f defined on a convex set $\Omega \subseteq \mathbb{R}^n$ is said to be a **convex function** on Ω if for all $\mathbf{x}, \mathbf{y} \in \Omega$ and all $0 \le \alpha \le 1$, $f(\alpha \mathbf{x} + (1 \alpha)\mathbf{y}) \le \alpha f(\mathbf{x}) + (1 \alpha)f(\mathbf{y})$.
- **Definition 5:** An $f: \Omega \to \mathbb{R}$ is said to be a **concave** function if -f is a **convex function**.
- Theorem 1 : If f is a convex function on Ω (a convex set), then the set $S = \{ \mathbf{x} \in \Omega : f(\mathbf{x}) \le c \}$ is a convex set (for all real c).
- **Theorem 2:** Let f be a continuously differentiable function defined on a convex set, $\Omega \subseteq \mathbb{R}^n$, then f is convex on Ω if and only if

- **Definition 4:** A real valued function f defined on a convex set $\Omega \subseteq \mathbb{R}^n$ is said to be a **convex function** on Ω if for all $\mathbf{x}, \mathbf{y} \in \Omega$ and all $0 \le \alpha \le 1$, $f(\alpha \mathbf{x} + (1 \alpha)\mathbf{y}) \le \alpha f(\mathbf{x}) + (1 \alpha)f(\mathbf{y})$.
- **Definition 5:** An $f: \Omega \to \mathbb{R}$ is said to be a **concave** function if -f is a **convex function**.
- Theorem 1 : If f is a convex function on Ω (a convex set), then the set $S = \{ \mathbf{x} \in \Omega : f(\mathbf{x}) \le c \}$ is a convex set (for all real c).
- **Theorem 2:** Let f be a continuously differentiable function defined on a convex set, $\Omega \subseteq \mathbb{R}^n$, then f is convex on Ω if and only if

$$f(\mathbf{y}) \ge f(\mathbf{x}) + \nabla f(\mathbf{x})(\mathbf{y} - \mathbf{x})$$
 for all $\mathbf{x}, \mathbf{y} \in \Omega$.

• Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if

• Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$,

• Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.

- Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- **Revisiting Example 1 :** Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on

- Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- Revisiting Example 1 : Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on $\Omega = \{ [x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0 \}.$

- **Theorem 3**: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- Revisiting Example 1 : Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on

$$\Omega = \{ [x_1, x_2]^T : x_1 \geq 0, x_2 \geq 0 \}.$$

• Since
$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 6x_1 - 2x_2 & -2x_1 \\ -2x_1 & 4 \end{pmatrix}$$
,

- **Theorem 3**: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- Revisiting Example 1 : Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on $\Omega = \{[x_1, x_2]^T : x_1 > 0, x_2 > 0\}.$

• Since
$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 6x_1 - 2x_2 & -2x_1 \\ -2x_1 & 4 \end{pmatrix}$$
,

• At
$$x_1 = 1, x_2 = 3$$
,

- **Theorem 3**: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- Revisiting Example 1 : Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on $\Omega = \{ [x_1, x_2]^T : x_1 \ge 0, x_2 \ge 0 \}.$

• Since
$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 6x_1 - 2x_2 & -2x_1 \\ -2x_1 & 4 \end{pmatrix}$$
,

• At
$$x_1 = 1$$
, $x_2 = 3$, $\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 0 & -2 \\ -2 & 4 \end{pmatrix}$ is clearly not positive semidefinite.

- Theorem 3: Let f be a twice continuously differentiable function on a convex set Ω (where Ω has atleast one interior point), then f is a **convex function** on Ω if and only if for all $\mathbf{x} \in \Omega$, $\nabla^2 f(\mathbf{x})$ is positive semidefinite.
- Revisiting Example 1 : Let $f(x_1, x_2) = x_1^3 x_1^2 x_2 + 2x_2^2$ be defined on $\Omega = \{[x_1, x_2]^T : x_1 > 0, x_2 > 0\}.$

• Since
$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 6x_1 - 2x_2 & -2x_1 \\ -2x_1 & 4 \end{pmatrix}$$
,

• At
$$x_1 = 1$$
, $x_2 = 3$, $\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 0 & -2 \\ -2 & 4 \end{pmatrix}$ is clearly not positive semidefinite.
Hence f is not a convex function on Ω .

• Remark: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.

• Remark: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.

Theorem 4: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function.

- Remark: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.
 - **Theorem 4:** Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω , then \mathbf{x}^* is a local (global) minimum of f if and only if

• **Remark**: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.

Theorem 4: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω , then \mathbf{x}^* is a local (global) minimum of f if and only if for all feasible direction d at x* $\nabla f(\mathbf{x}^*)\mathbf{d} > 0.$

- **Remark**: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.
 - **Theorem 4:** Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω , then \mathbf{x}^* is a local (global) minimum of f if and only if for all feasible direction d at x*

 $\nabla f(\mathbf{x}^*)\mathbf{d} > 0.$

• Corollary 4: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω and \mathbf{x}^* an interior point of Ω , then \mathbf{x}^* is a local (global) minimum for f if and only if

$$\nabla f(\mathbf{x}^*) = \mathbf{0}.$$

- **Remark**: Since minimizing f is same as maximizing -f, all the previous theorems for minimizing a convex function have corresponding analogues for maximizing a concave function.
 - **Theorem 4:** Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω , then \mathbf{x}^* is a local (global) minimum of f if and only if for all feasible direction d at x*
 - $\nabla f(\mathbf{x}^*)\mathbf{d} > 0.$
- Corollary 4: Let $f: \Omega \to \mathbb{R}$ be a continuously differentiable function. If f is a convex function on Ω and \mathbf{x}^* an interior point of Ω , then \mathbf{x}^* is a local (global) minimum for f if and only if $\nabla f(\mathbf{x}^*) = \mathbf{0}.$
- The above result is **not** necessarily true if f is **not convex** as you have already seen in **Example 1**.