

19MA701

OPTIMIZATION THEORY

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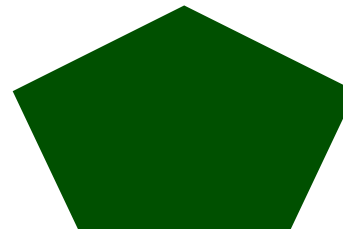
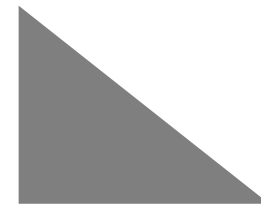
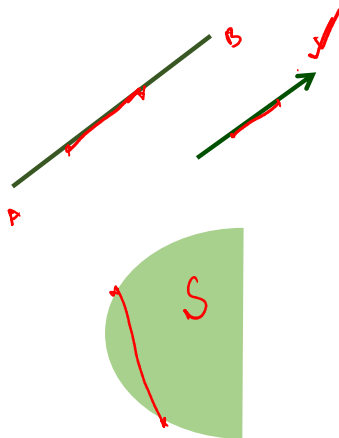
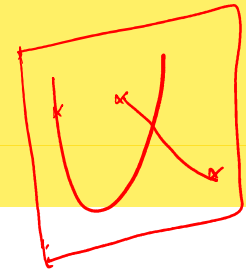
Department of Mathematics

Convex Sets

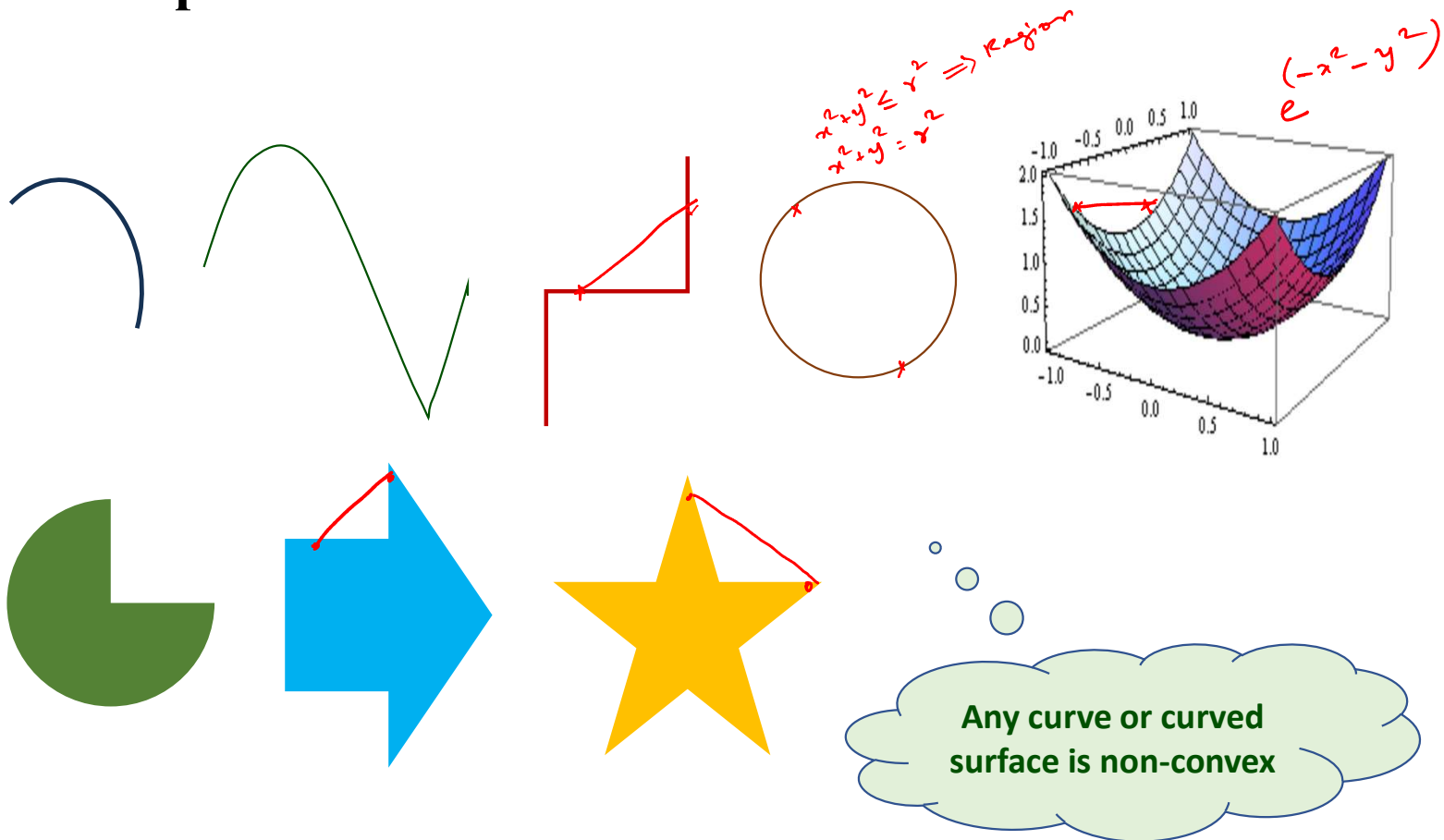
- Let S be a set and let x_1 and x_2 be elements of the set. If the line segment joining x_1 and x_2 is also an element of S , then we say that S is convex
- Mathematically:

Let $x_1, x_2 \in S$

If $\theta x_1 + (1 - \theta)x_2 \in S$ for $0 < \theta < 1$, then S is a Convex set.



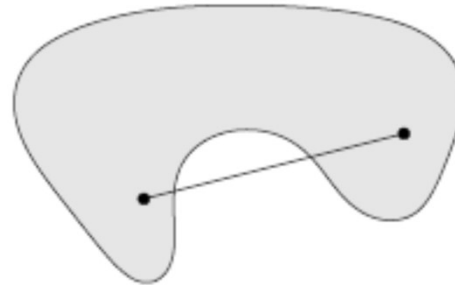
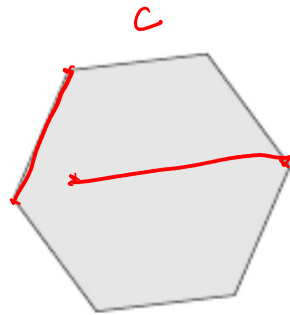
Examples : Non-Convex Sets



Convex Sets

Definition: A set C is convex if a line segment between any two points in C lies in C .

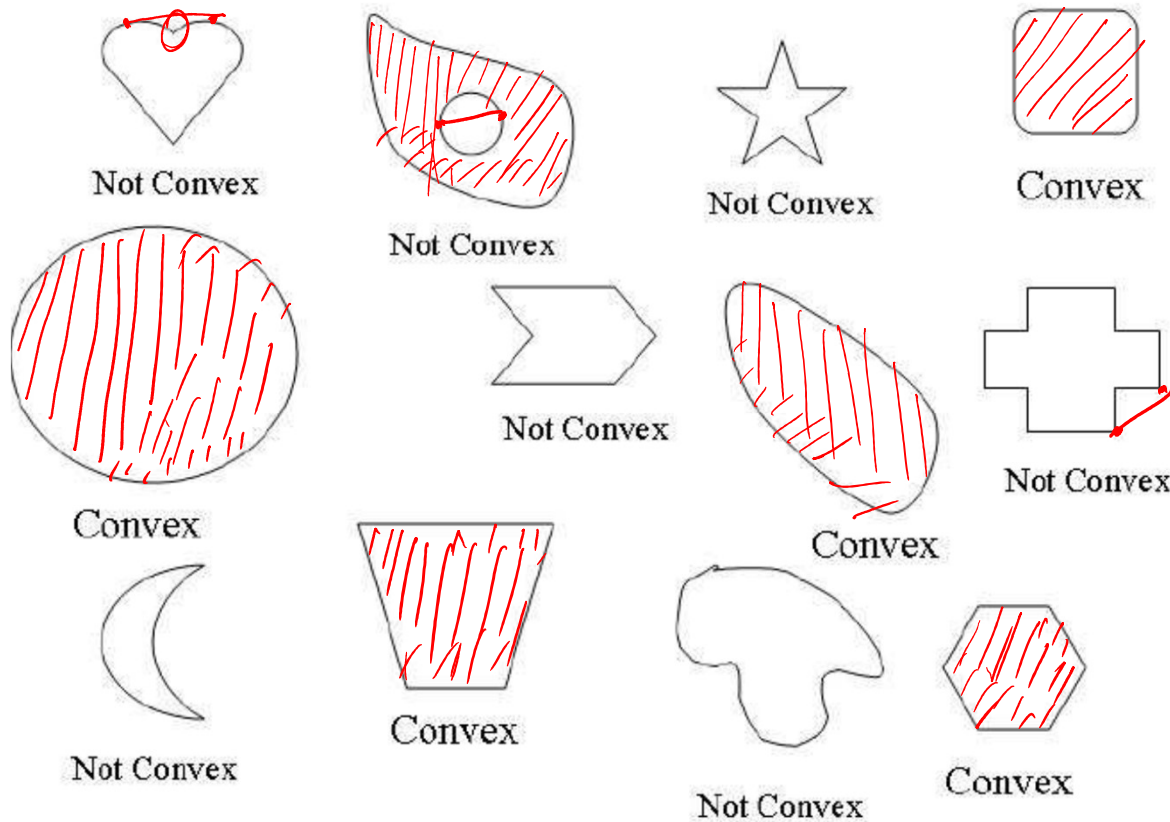
Ex: Which of the below are convex sets?



The set on the left is convex. The set on the right is not.

Convex Sets

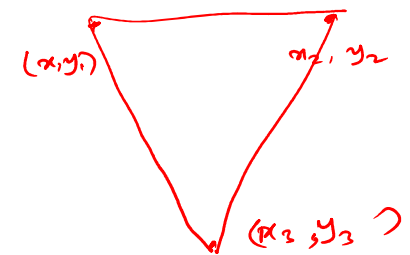
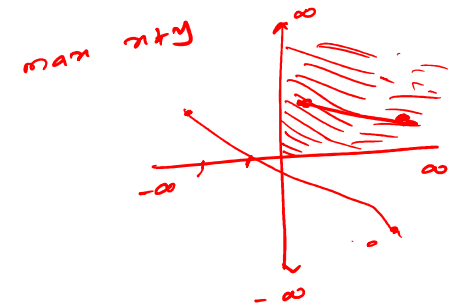
Definition: A set C is convex if a line segment between any two points in C lies in C .



Examples of Convex Sets

- The empty set Φ is a convex set. $\{ \}$
- A single point (singleton), i.e., $\{x_0\}$ is a convex set. $\{ \bullet \}$
- \mathbf{R} , \mathbf{R}^2 , \mathbf{R}^3 , ..., \mathbf{R}^n are convex sets.
- **X axis**, **Y axis** and any other **line** is convex.
- Any line segment and any ray is convex.
- Any vector space and subspace is convex.
- A **hyperplane** is convex.
 - Hyperplane is a solution set of a single linear equation.
 - In \mathbf{R}^2 it is a line, in \mathbf{R}^3 it is a plane.
- Solution set of linear equations, $C = \{x \mid Ax = b\}$ is convex
(point/ line/ plane/ hyperplane)

$$\begin{aligned} 3x - y &= 7 \\ y + 5x &= 3 \\ \hline x &= 3/4 \end{aligned}$$

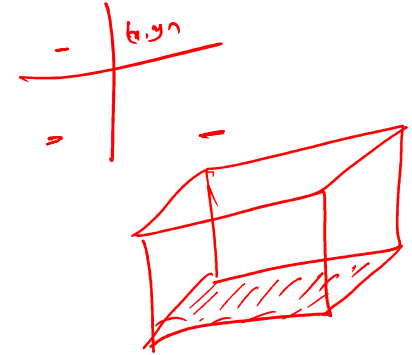


More Examples of Convex Sets

- A **halfspace** is convex.
 - Halfspace is the solution set of a single linear inequality.

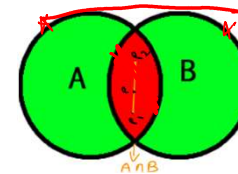
$$H = \{x \mid a^T x \leq b\}, \quad a \neq 0$$
 - Hyperplane divides the domain into 2 halfspaces.
- Every **quadrant**(n=2), **octant**(n=3) and **orthant**(n) is convex.
- A **polyhedron** and a **polytope** is convex.
 - Polyhedron is a solution set of finitely many inequalities.
 - A bounded polyhedron is often called a polytope.
- **Feasible region** of a linear optimization problem is always convex.

$$a^T x \leq b$$



Operations that preserve convexity

- Intersection of convex sets is convex
 (Union of convex sets need not be convex)



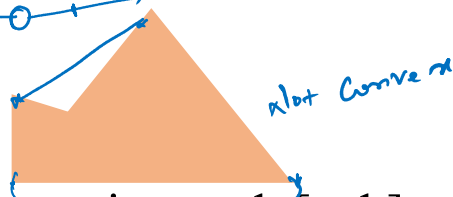
Problems

1. Which of the following sets are convex?

(a) $\mathbf{R} - \{0\}$



(b)



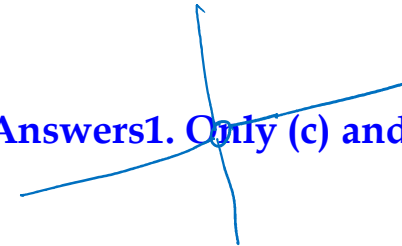
(c) All the points in an interval, $[a, b] \Rightarrow$ Convex

(d) All the points in an interval, $(a, b) \Rightarrow$ Convex

(e) All points in the XY plane except the origin \Rightarrow Not Convex

(f) All points in the parabola, $y = x^2 \Rightarrow$ Not Convex

Answers 1. Only (c) and (d) are convex



2. Find the domain of the following functions and mention if it is convex or not

(a) $f(x) = \frac{1}{x-1}$

(b) $g(x) = \sqrt{4-x^2}$

(c) $h(x) = \frac{\sqrt{x-1}}{x}$ $(1, \infty)$

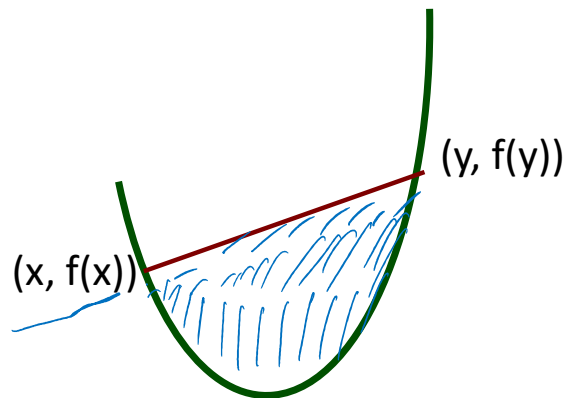
Answers 2. (a) Domain of f is $\mathbf{R} - \{1\}$, which is not convex

(b) Domain of g is $[-2, 2]$, which is convex

(c) Domain of h is $[1, \infty)$, which is convex

Convex functions

- A function $f: \mathbf{R}^n \rightarrow \mathbf{R}$ is a convex function if:
 - (i) the domain of f is convex and *slightly convex*
 - (ii) $f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$
for all $x, y \in \text{domain } f$ and $0 \leq \theta \leq 1$
- Graphically, a function $y=f(x)$ is convex if the curve $y = f(x)$ lies below the line segment joining any two points on the curve.

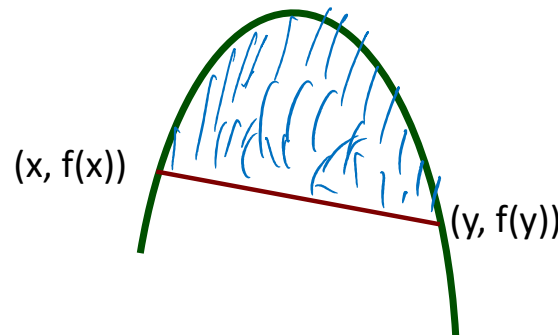


- The function is strictly convex if the inequality is strictly less ($<$)

Concave functions

- A function $f: \mathbf{R}^n \rightarrow \mathbf{R}$ is a concave function if $-f$ is convex, i.e., when,

$$f(\theta \mathbf{x} + (1 - \theta) \mathbf{y}) \geq \theta f(\mathbf{x}) + (1 - \theta) f(\mathbf{y})$$
for all $x, y \in \text{domain } f$ and $0 \leq \theta \leq 1$
- Graphically, a function $y=f(x)$ is concave if the curve $y = f(x)$ lies above the line segment joining any two points on the curve.

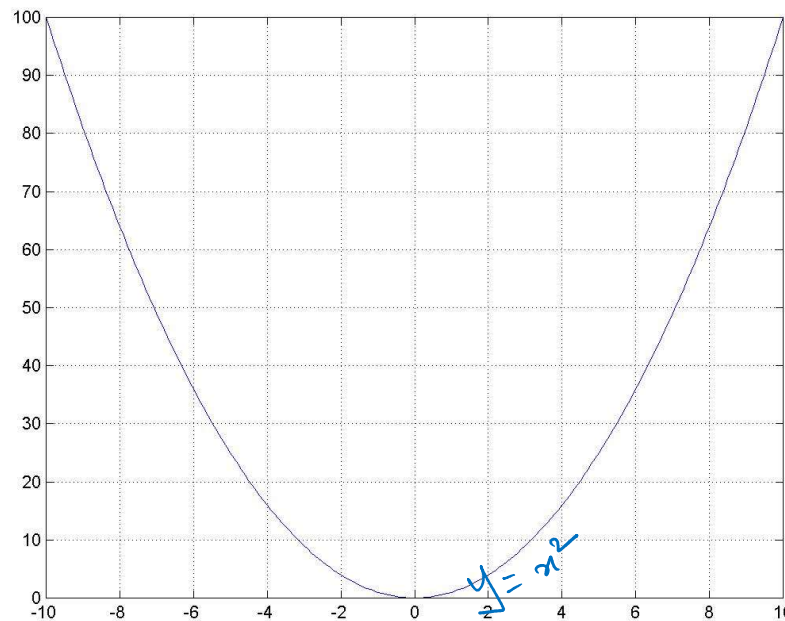


- The function is strictly concave if the inequality is strictly greater ($>$)

Convex functions

Definition: A function $f(x)$ is convex in an interval if its second derivative is positive on that interval.

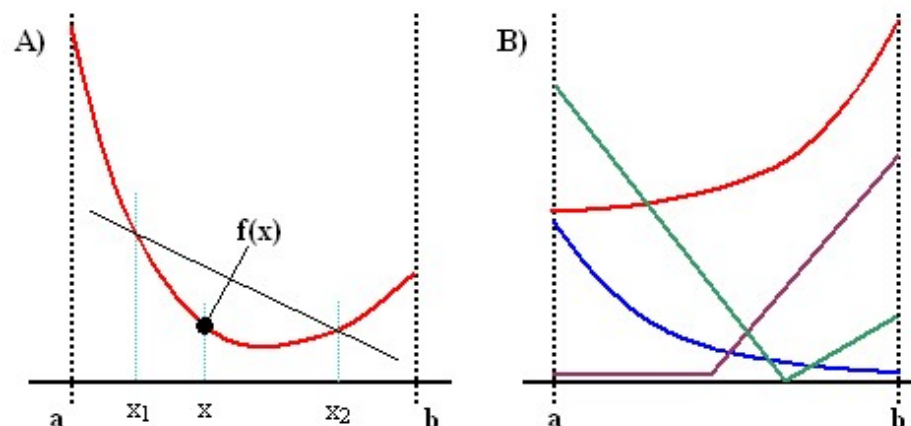
Example: $f(x)=x^2$ is convex since $f'(x)=2x$, $f''(x)=2>0$



$$y = x^2$$
$$f'(x) = 2x \rightarrow 0 \Rightarrow x = 0$$
$$f''(x) = 2$$


Convex functions

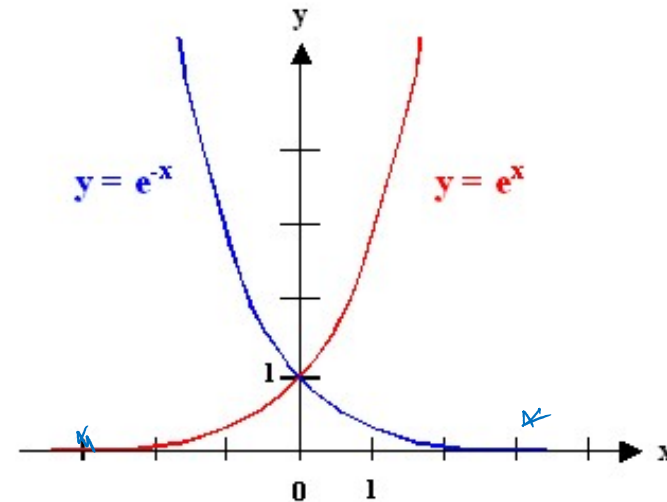
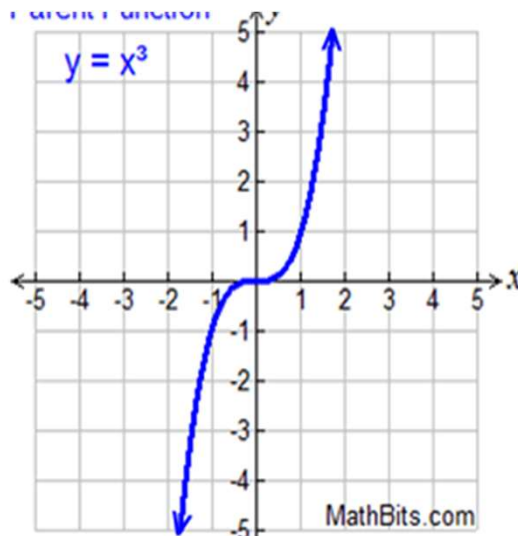
The second derivative test is sufficient but not necessary.



Definition : A function $f(x)$ is convex if a line drawn between any two points on the function remains on or above the function in the interval between the two points.

Examples

- Linear functions and affine functions are taken to be convex as well as concave as they don't have a curvature. *f(x) = x + 3y*
- $y = x^2$ is a convex function 
- $y = x^4, y = x^6, y = x^8, \dots$ are convex functions for all values of x .
- $y = x^3, y = x^5, y = x^7, \dots$ are convex functions if $x > 0$ (in the first quadrant) and concave in the third quadrant ($x < 0$).
- Exponential function, $y = e^{ax}$ for any $a \in \mathbf{R}$ is a convex function as it always curves up.



Second derivative test for convexity/concavity

- A twice differentiable function $f(x)$ is convex if its Hessian $\nabla^2 f(x)$ is at least positive definite.
- A twice differentiable function $f(x)$ is concave if its Hessian $\nabla^2 f(x)$ is at least negative definite.
- A function $f(x)$ is non-convex if its Hessian $\nabla^2 f(x)$ is indefinite

Examples:

1. $f(x) = x + 1/x$ is convex in $x > 0$

(Since $\nabla^2 f(x) = \frac{d^2 f}{dx^2} = \frac{2}{x^3} > 0$ for $x > 0$)

2. $f(x) = \cos x$ is concave in $x \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$



3. $f(x,y) = 5x^2 + 6xy + 7y^2$ is convex

4. $f(x,y) = -2x^2 + xy - 7y^2$ is concave

5. $f(x,y) = 5x^2 + 19xy + 7y^2$ is non-convex

6. $f(x,y) = x^2/y$ is convex if $y > 0$ and concave if $y < 0$

Handwritten notes and calculations:

$f''(\cdot) = 0$ (critical point)

$f'(x) = 0 \rightarrow p$

Second order partial Derivative matrix

③ $\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 10xy + 6y \\ 6x + 14y \end{bmatrix}$

$H = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix}$

Operations that preserve convexity

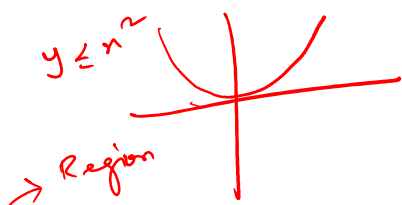
- If $f(x)$ is a convex function, then $\alpha f(x)$ is also convex for $\alpha > 0$
 - $f(x) = 8e^x$ is convex
- The sum of convex functions is also convex
 - $f(x,y) = x^4 + y^4 + e^x$ is convex
- Non-negative weighted sum of convex functions is convex
 - $f(x,y,z) = 4x^2 + 5y^2 + 3e^z$ is convex

Practical methods for establishing convexity of a function

- Verify definition ✓
- For twice differentiable functions, check whether hessian matrix is positive definite ✓
- Show that f is obtained from simple convex functions by operations that preserve convexity

Relation between convex sets and convex functions

The set of all points in the region $g(x) \leq 0$ is a convex set if the function $g(x)$ is a convex function.



A hand-drawn diagram in red ink. It shows a parabola opening upwards, representing a convex function $g(x)$. The region below the parabola is shaded and labeled "Region" with an arrow. The equation $y \leq x^2$ is written above the parabola.

Optimization Problem in standard form

Minimize $f(x)$ ⇝
subject to $g_i(x) \leq 0, i = 1, 2, \dots, m$
 $h_i(x) = 0, i = 1, 2, \dots, p$

x : decision variable

$f: \mathbf{R}^n \rightarrow \mathbf{R}$ is the objective function (or cost fn. if obj. is min.)

$g_i: \mathbf{R}^n \rightarrow \mathbf{R}$ are the inequality constraints

$h_i: \mathbf{R}^n \rightarrow \mathbf{R}$ are the equality constraints

Domain of the standard optimization problem:

$$\mathbf{D} = \bigcap_{i=1}^m \text{dom } g_i \cap \bigcap_{i=1}^p \text{dom } h_i$$

Convex Optimization Problem

An optimization problem in the standard form:

Minimize $f(x)$ ✓

subject to $\underline{g_i}(x) \leq 0, i = 1, 2, \dots, \underline{m}$

$\underline{h_i}(x) = 0, i = 1, 2, \dots, \underline{p}$

is said to be convex if

- (i) the objective function is convex
- (ii) the feasible region is convex

Convex Feasible regions

- Feasible region of the optimization problem is the intersection of each constraint $g_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, m, \quad h_j(\mathbf{x}) = 0, i = 1, 2, \dots, p$
- Since intersection of convex sets is convex, convexity of the feasible region can be checked by checking whether each constraint gives a convex set.
- $g_i(\mathbf{x}) \leq 0$ is a convex set if g_i is a convex function.
- $h_j(\mathbf{x}) = 0$ will be a convex set only if $h_j(\mathbf{x})$ is linear. (Any linear equality constraint represents a line or a plane or a hyperplane which is a convex set. Any non-linear equality constraint represents a curve or a curved surface which cannot be a convex set.)

Convex Optimization Problem

An optimization problem in the standard form:

Minimize $f(x)$

subject to $g_i(x) \leq 0, i = 1, 2, \dots, m$

$h_j(x) = 0, i = 1, 2, \dots, p$

is said to be convex if

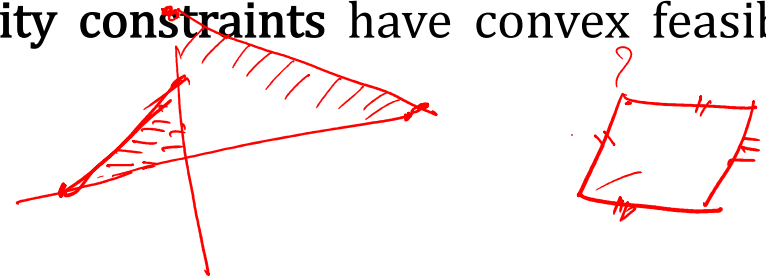
- (i) the objective function is convex
- (ii) the inequality constraint functions, $g_i(x)$ are convex
- (iii) the equality constraint functions, $h_j(x)$ are linear

Optimization problems with convex Feasible regions

- Optimization problems involving **linear inequality constraints** have convex feasible region.

Eg: $-x + y \leq 2, 2x + 3y \leq 12, x \geq 0, y \geq 0$

(Feasible region will be a null set, or a polyhedron)



- Optimization problems with **only linear equality constraints** have a convex feasible region.

(Feasible region will be a null set, or a singleton or a line or a plane)

- Optimization problems with **linear equality and inequality constraints** have convex feasible region.

Eg: $-x + 2y \leq 2, 2x + 3y = 12, x \geq 0, y \geq 0$

- Optimization problems involving **convex inequality constraints** have a convex feasible region.

Eg: $x^2 + y^2 \leq 1, (x - 1)^2 + (y - 1)^2 \leq 1, x \geq 0, y \geq 0$

Note :

Feasible region for an optimization problem with **non-linear equality constraint(s)** is **never a convex set** regardless of whether the equality constraints is convex or not.

$$\begin{aligned}x^2 + y^2 &= 1, \\x &\geq 0, \\y &\geq 0\end{aligned}$$

Examples:

1. Minimize $5x + 9y^2$

subject to $x^2 - 4y + 9x \leq 7$

$2x^2 + 3xy + 81y^2 \leq 5$

Is a C.O.P. since
 $f(x)$, $g_1(x)$ and
 $g_2(x)$ are convex

2. Minimize $(x - 1)^2 + (y - 1)^2 + xy$

subject to $x + y \leq 4$

$2x + x^2 + y^2 = 16$

Is not a C.O.P. since
the equality constraint
is non-linear

3. Maximize $x^2 + y^2$

subject to $x + y \leq 4$

$2x + x^2 + y^2 \leq 16$

Is not a C.O.P. since
the objective in the
standard form is
concave.

4. Maximize, $xy - (x - 1)^2 - (y - 1)^2$

subject to $2x + x^2 + y^2 \leq 16$

$3x - 7y = 9$

Is C.O.P. Since $f(x)$
(after writing in standard
form), $g_1(x)$ is convex
and $g_2(x)$ is linear

Fundamental Property of Convex Optimization Problems

Any locally optimal point of a convex optimization problem is globally optimal

Tutorial questions

1. Consider the function $f(x_1, x_2) = x_1^2 + 2x_2^2 - 4x_1x_2 - 4x_2 + 7x_1 + 15$. Is this function convex?
2. Is the given non-linear programming problem convex? Why or why not?
 Maximize $z = 9x_1^2 - 4x_1x_2 + 7x_2^2$
 Subject to $x_1^2 + 2x_1x_2 + 3x_2^2 = 40$; $2x_1^2 - x_2 \leq 80$; $x_1 \leq 60$.
3. Is the following statement true? Explain.
 “Maximize $(x - 3)^2 + (y - 8)^2$ is not a convex optimization problem but
 Minimize $(x - 3)^2 + (y - 8)^2$ is a convex optimization problem”
4. Determine if the following optimization problems are convex optimization problems. Use graphical methods to solve these problems.
 - (a) Maximize $-6x + 9y$
 subject to $x - y \geq 2$
 $3x + y \geq 1$
 $2x - 3y \geq 3$
 - (b) Minimize $x^2 + 2y^2$
 subject to $x + y \geq 1$; $x, y \geq 0$

Tutorial questions

5. Draw the feasible region and determine the convexity status:

$$\text{Minimize } x^2 + 2y^2 - 24x - 20y$$

$$\text{subject to } x + 2y \geq 0; x + 2y \leq 9; x + y \leq 8; x + y \geq 0$$

6. Explain why the given optimization problem is not convex.

$$\text{Maximize } (x - 2)^2 + (y - 10)^2$$

$$\text{subject to } x^2 + y^2 = 50$$

$$x^2 + y^2 + 2xy - x - y + 20 \geq 0; x, y \geq 0.$$

7. Determine if the following optimization problem is convex optimization problems or not:

$$\text{Minimize } \frac{100}{e^{2x+y}}$$

$$\text{subject to } e^x + e^y \leq 20;$$

$$x, y \geq 1.$$