

The property of "CONVEXITY" of sets and of functions is central to most approaches to nonlinear programming.

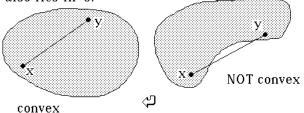
© Convex Set

Convex Function

The more "unified" approach first defines convexity of sets, and bases the definition of convex function upon convexity of sets.

Convex Set

A set S is CONVEX if for every pair of elements x and y in S, the line segment joining x and y also lies in S.



This means that, if we are solving the problem

Minimize f(x)subject to $x \in S$

and S is convex, that there is a linear path such that we can follow this path directly from the starting point $x \in S$ to the optimal solution $y \in S$ without leaving the set S.

Unfortunately, we are seldom able to determine this line/

The *line segment*

line segment between x and y is given by

$$\lambda y + (1\text{-}\lambda)x = x + \lambda(y\text{-}x) \qquad \text{ for } \quad \lambda \! \in \! [0,\!1]$$

where

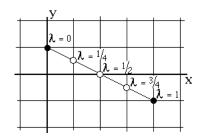
$$\begin{array}{ll} \lambda{=}0 & \Rightarrow \ \lambda y + (1{\text{-}}\lambda)x = x \\ \lambda{=}1 & \Rightarrow \ \lambda y + (1{\text{-}}\lambda)x = y \\ \lambda{=}^{1}\!\!/_{\!\!2} & \Rightarrow \ \lambda y + (1{\text{-}}\lambda)x = \frac{1}{2}(x{+}y) \quad \text{(midpt of segment),} \\ & \text{etc.} \end{array}$$

Example

line segment

Let x=(0,1) and y=(4,-1) be points in the plane.

λ	$\lambda y + (1-\lambda)x$
0	(0,1)
0.25	(1, 0.5)
0.50	(2, 0)
0.75	(3, -0.5)
1	(4, -1)



Convex Combination

If $x^{(1)}, x^{(2)}, \dots x^{(k)}$ are vectors in R^n , and $\lambda_1, \lambda_2, \dots \lambda_k$ are nonnegative numbers whose

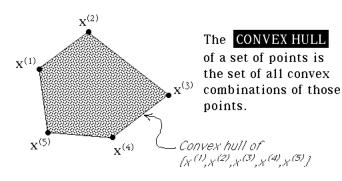
sum is 1, i.e.,
$$\sum\limits_{i=1}^k\,\lambda_i=1$$

 $then \hspace{0.5cm} \lambda_1 x^{(1)} + \hspace{0.1cm} \lambda_2 x^{(2)} + \cdots \lambda_k x^{(k)}$

is a convex combination (weighted average) of

$$\mathbf{x}^{(1)}$$
, $\mathbf{x}^{(2)}$, ... $\mathbf{x}^{(k)}$

In particular, a point on a line segment is a convex combination of the endpts of the segment/



Theorem If
$$x^{(1)}$$
, $x^{(2)}$, ... $x^{(k)} \in S$ where

S is a convex set, then every convex combination of the points $x^{(1)}$, $x^{(2)}$, ... $x^{(k)}$ is an element of S.

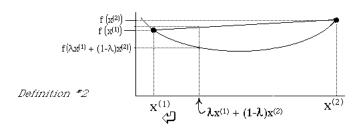
That is, if S is convex then S equals its convex hull.

K⊅

Convex Function

A function f(x) is *convex* if:

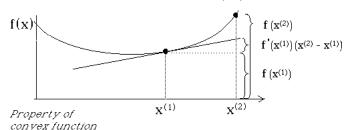
$$f\!\left(\!\lambda x^{(1)} + (1\!-\!\lambda)x^{(2)}\!\right) \!\leq\! \lambda f\!\left(x^{(1)}\right) + (1\!-\!\lambda)\,f\left(x^{(2)}\right) \quad \forall \; \lambda \in \left[0,1\right]$$



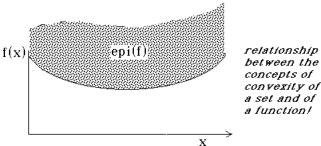
Convex Function

A differentiable function f(x)is convex if:

$$f(x^{(1)}) + f'(x^{(1)})(x^{(2)} - x^{(1)}) \le f(x^{(2)})$$



A function f(x) is *convex* if Convex Function the set epi(f) is convex

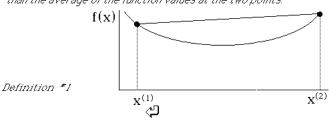


Convex Function

A function f(x) is *convex* if:

$$f(\lambda x^{(1)} + (1-\lambda)x^{(2)}) \le \lambda f(x^{(1)}) + (1-\lambda) f(x^{(2)}) \quad \forall \ \lambda \in [0,1]$$

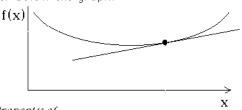
For example, if evaluated at the midpoint of two points is less than the average of the function values at the two points.



Convex Function

A differentiable function f(x) is convex if:

the tangent line (hyperplane) to the graph lies on or below the graph:

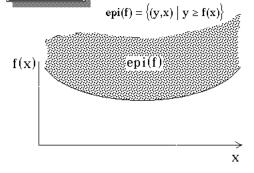


Property of convex function

Epigraph

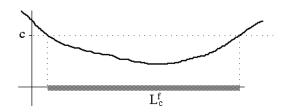
The epigraph of a function is the set

of



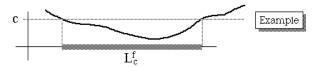
For any real value c, the Level Set the function f is the set

 $L_c^f = \{x \mid f(x) \le c\}$



If f is a convex function, then L_c^f is convex.

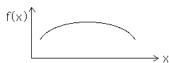
However, the convexity of the level sets does NOT imply convexity of the function.

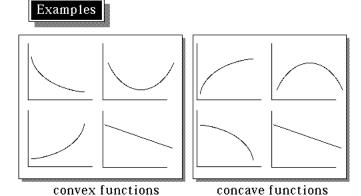


If all the level sets of a function are convex, then the function is *quasi* convex.



- its negative, (-f), is convex
- a chord between 2 points on the graph lies on or below the graph
- a tangent line (hyperplane) to the graph lies on or above the graph
- the hypergraph $\{(y,x) \mid y \le f(x)\}\$ is convex





A linear function is *both* convex and concave!

A function may be neither convex nor concave:



