

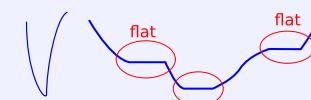
Relationships between different classes of functions

Quasiconvex

$$\forall x_1, x_2 \in S, \lambda \in (0, 1) : f(\lambda x_1 + (1 - \lambda)x_2) \leq \max\{f(x_1), f(x_2)\}$$

"either monotonic, or unimodal"

"all level sets are convex"



Semistrictly** quasiconvex

$$\forall x_1, x_2 \in S : f(x_1) \neq f(x_2); \lambda \in (0, 1) : f(\lambda x_1 + (1 - \lambda)x_2) < \max\{f(x_1), f(x_2)\}$$

"no flatlands anywhere but optimum"

"local min = global min"

"but global min is not necessarily unique*** -- see -->"

e.g.:

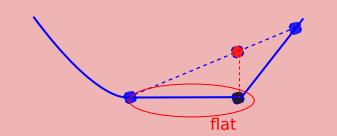
-
- semistrictly quasiconvex, but not quasiconvex

Convex

$$\forall x_1, x_2 \in S, \lambda \in (0, 1) : f(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda f(x_1) + (1 - \lambda)f(x_2)$$

Note: a convex function is continuous over int S

"any point on the line segment (red) is above the graph (black)"



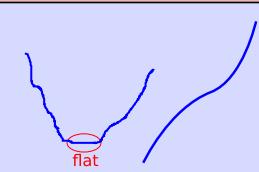
Pseudoconvex*

$$\forall x_1, x_2 \in S, \nabla^T f(x_1)(x_2 - x_1) \geq 0 \rightarrow f(x_2) \geq f(x_1)$$

$$\forall x_1, x_2 \in S, f(x_2) < f(x_1) \rightarrow \nabla^T f(x_1)(x_2 - x_1) < 0$$

"zero gradient implies global min (not necessarily unique)"

"minus gradient points towards min"



Strictly*** quasiconvex

$$\forall x_1 \neq x_2 \in S, \lambda \in (0, 1) : f(\lambda x_1 + (1 - \lambda)x_2) < \max\{f(x_1), f(x_2)\}$$

"now local min = **unique****** global min (if exists)"

Strictly convex

$$\forall x_1, x_2 \in S, \lambda \in (0, 1) : f(\lambda x_1 + (1 - \lambda)x_2) < \lambda f(x_1) + (1 - \lambda)f(x_2)$$

Differentiable strictly convex

Strictly pseudoconvex*

$$\forall x_1, x_2 \in S, x_1 \neq x_2, \nabla^T f(x_1)(x_2 - x_1) \geq 0 \rightarrow f(x_2) > f(x_1)$$

$$\forall x_1, x_2 \in S, x_1 \neq x_2, f(x_2) \leq f(x_1) \rightarrow \nabla^T f(x_1)(x_2 - x_1) < 0$$

"now flatlands are prohibited"

(note that const. is not strictly pseudoconvex)

"zero gradient implies **unique****** global min"

All **lower-semi-continuous** Strictly QC functions
+ maybe some non-lower-semi-continuous Strictly quasiconvex functions

Notes: S is assumed to be a convex set;

[!] phrases in "quotes" are rather mnemonic rules --
watch out for formal definitions and theorems!

Main source: Bazaraa, Sherali, Shetty "Nonlinear Programming", 3rd ed.

- * -- two equivalent formulations are provided
- ** -- "strictly quasiconvex" in terms of Bazaraa et al.
- *** -- "strongly convex" in terms of Bazaraa et al.
- **** -- that is why it is rather "semi"-strictly
- ***** -- hence, "strictly"