

Root finding

$$g(x) = 0$$

$$\underline{g(\underline{x})} = \underline{0}$$

Newton's Method

1. Pick a guess x_0

→ 2. Iterations

$$x_1 = x_0 - \frac{g(x_0)}{g'(x_0)}$$

3. Go back

$$x_{k+1} = x_k - [g'(x_k)]^{-1} g(x_k)$$

$$\underline{x}_{k+1} = \underline{x}_k - \underline{J}(\underline{x}_k)^{-1} \underline{g}(\underline{x}_k)$$

$$x_0 \longrightarrow g(x_0), g'(x_0)$$

$$x_1 \xleftarrow{\quad} g(x_1), g'(x_1)$$

$$x_2 \xleftarrow{\quad}$$

$$\underline{x}_{k+1} = \underline{x}_k - \underline{J}(\underline{x}_k)^{-1} \underline{g}(\underline{x}_k)$$

$$\underline{J}(\underline{x}_k) \underline{x}_{k+1} = \underline{J}(\underline{x}_k) \underline{x}_k - \underline{J}(\underline{x}_k) \underline{J}(\underline{x}_k)^{-1} \underline{g}(\underline{x}_k)$$

$$\underline{J}(\underline{x}_k) (\underline{x}_{k+1} - \underline{x}_k) = - \underline{g}(\underline{x}_k)$$

$$\underline{J}(\underline{x}_k) \underline{\xi} = - \underline{g}(\underline{x}_k)$$

$$\Rightarrow \underline{\xi} \text{ by Gauss elim.}$$

$$\underline{\xi} = \underline{x}_{k+1} - \underline{x}_k \Rightarrow \underline{x}_{k+1} = \underline{\xi} + \underline{x}_k$$

Optimization

$$\min_{\underline{x}} f(\underline{x})$$



$$\max_{\underline{x}} -f(\underline{x})$$

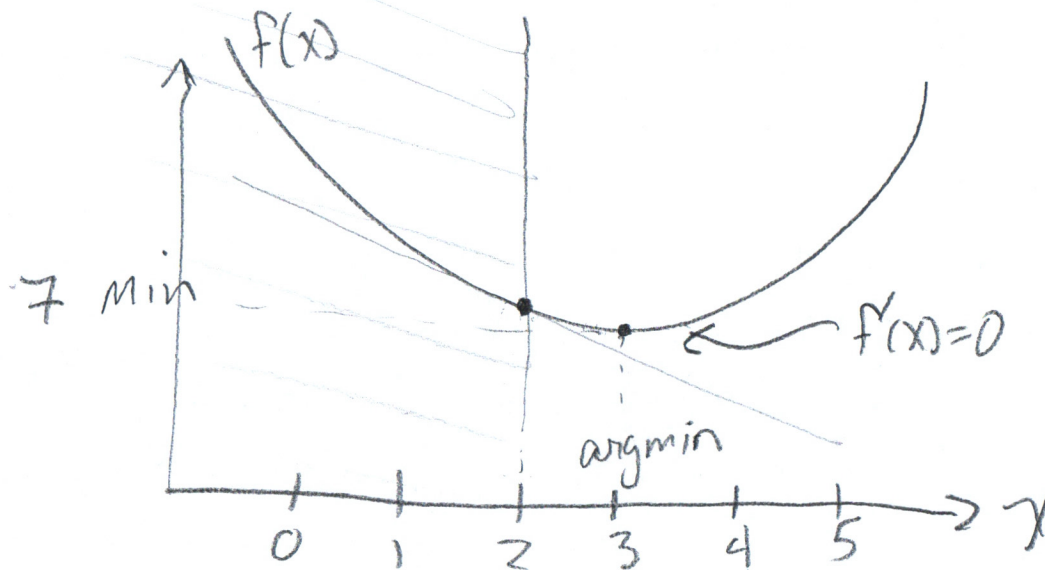
Root Finding

$$\underline{g}(\underline{x}) = \underline{0}$$

$$f(\underline{x}) = \|\underline{g}(\underline{x})\|$$

$$\min_{\underline{x}} f(\underline{x}) = \|\underline{g}(\underline{x})\|$$

Un-constrained vs. constrained opt.



$$\begin{aligned} \min_x f(x) \\ \text{s.t. } x \leq 2 \end{aligned}$$

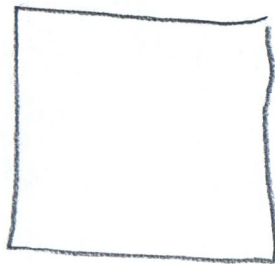
Unconst. $\rightarrow f'(x) = 0$

Const. \rightarrow Either $f'(x) = 0$ (x feasible)
OR x at boundary

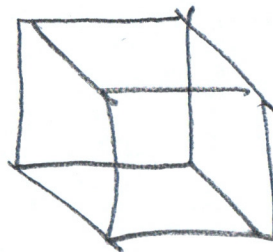
1D



2D

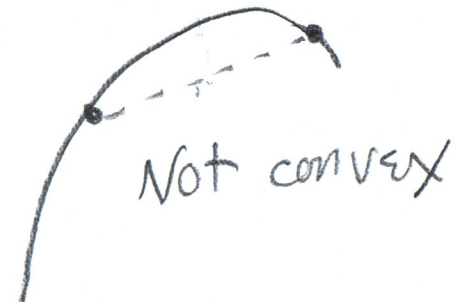
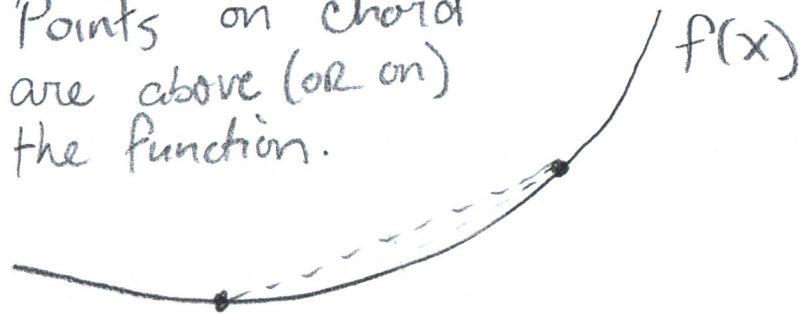


3D



Convex functions

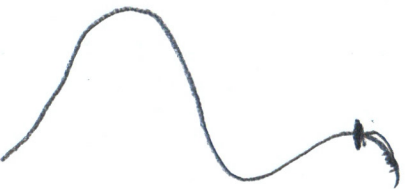
Points on chord
are above (or on)
the function.



When Minimizing a convex function
over a convex set, all
local minima are global minima.

Solution: walk downhill

1. Reach a valley
 2. Hit the boundary
- local minima



Convexity

1. Convex Sets

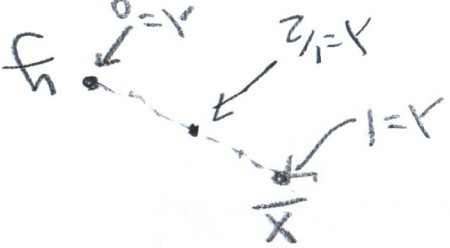
2. Convex functions.

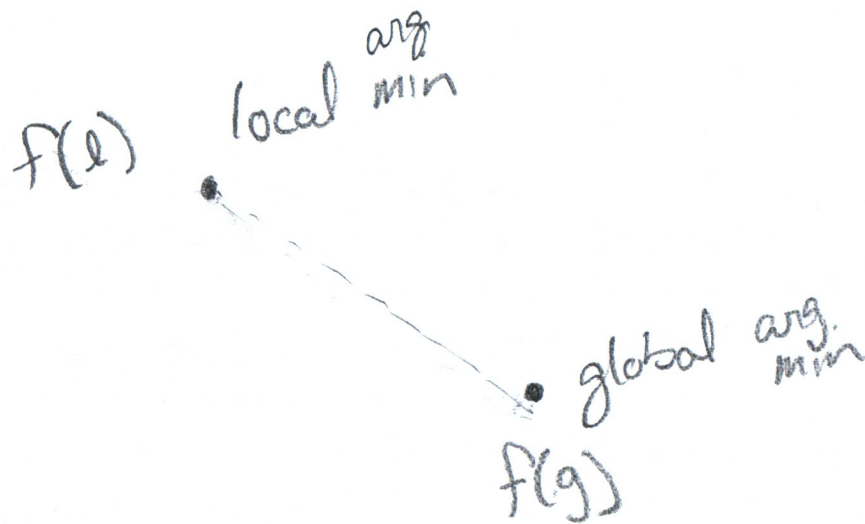
Convex combination

$$\bar{x} \text{ and } y$$

$$\lambda \bar{x} + (1-\lambda)y, \quad 0 \leq \lambda \leq 1$$

$$\frac{1}{2}\bar{x} + \frac{1}{2}y$$





$$f(g) < f(l)$$

Linear systems are convex.

$$\left. \begin{array}{l} \min_{\underline{x}} f(\underline{x}) \\ \text{s.t. } \underline{A} \underline{x} = \underline{b} \end{array} \right\} \text{convex set}$$