Optimization

Gursimran Singh Lnu, Yang Liu

Methods Implemented

- Gradient Descent
- Newton's Method
- Quasi-Newton (BFGS)
- Conjugate Gradient Descent
- Nelder-Mead Method

Problem for function 2

$$f(\mathbf{x}) = \mathbf{c}^T \mathbf{x} - \sum_{i=1}^m \log(b_i - \mathbf{a}_i^T \mathbf{x})$$
 where $m = 500$ and $n = 100$

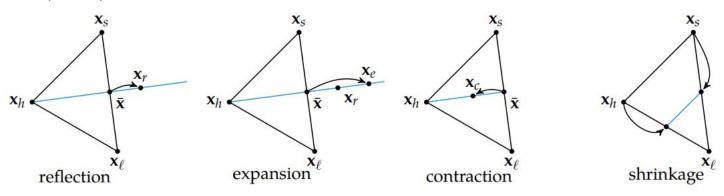
- Log can only accept positive values
- Optimization algorithm may step outside the domain.

Solution:

- Shrink the step size by half when such condition is met.

Nelder-Mead Method

Simplex operations



Nelder-Mead Method

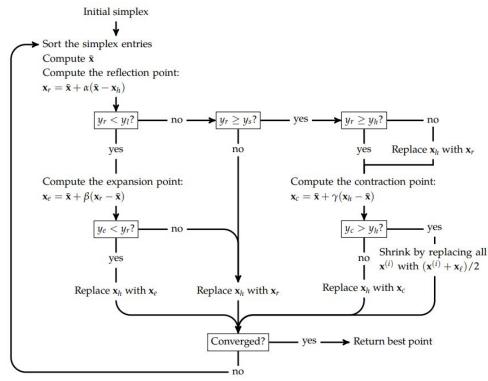
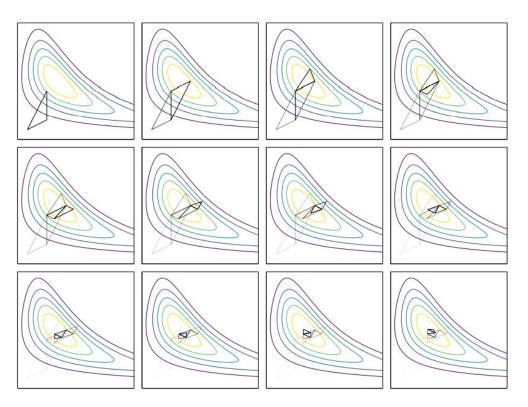


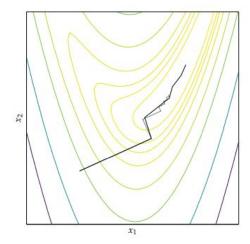
Figure 7.9. Flowchart for the Nelder-Mead algorithm.

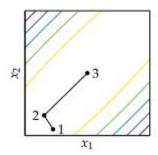
Nelder-Mead Method



Conjugate Gradient Descent

- Gradient Descent can perform poorly in narrow valleys.
- Similar to gradient descent, but differs in descent direction.
- It doesn't undo the previous steps, and optimizes in fewer steps.





Conjugate Gradient Descent

- The algorithm starts with the direction of steepest descent: d(1) = -g(1)
- We then use line search to find the next design point: $x(2) = x(1) + \alpha(1)d(1)$
- Subsequent iterations choose d (k+1) based on the next gradient and a contribution from the current descent direction: d (k+1) = -g (k+1) + β (k)d (k)

Conjugate Gradient Descent

Polak-Ribière:

$$\beta(k) = g(k)^{T} \cdot (g(k) - g(k-1)) / g(k-1)^{T}g(k-1)$$

• Fletcher-Reeves:

$$\beta$$
 (k) = g (k) T g (k) /g (k-1) T .g (k-1)

• Used to guarantee convergence - $\beta \leftarrow \max(\beta, 0)$

Summary

Functions	Function Type	Initial Values	Minimal value	Optimal solution	Achievable Algorithms
Fun 1	Convex	ones(100,1)	0	zeros(100,1)	Newton's, Nelder-mead
Fun 2	Non- Convex	zeros(100, 1)	-2.4432e3	[-1.1094 -1.0697 1.9717 -1.6617 0.4194]	Newton's, BFGS
Fun 3	Non- Convex	[3, 3]	2.2775e-16	[1 1]	Newton's (All other methods close but not exact)