# Nonlinear Optimization Lecture 18 Garrick Aden-Buie

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## **Quasi-Newton Method**

- Steepest Descent
- Newton's Method

$$x^{k+1} = \lambda_k d^k$$
$$d^k = -D_k \nabla f(x^k)$$
$$D_{k+1} = D_k + C_k$$

#### Davidon-Fletcher-Powell (DFP) Method

In the DFP method,  $D_k$  is updated via

$$C_k^{DFP} = \frac{p^k (p^k)^T}{(p^k)^T q^k} - \frac{D_k q^k (q^k)^T D_k}{(q^k)^T D_k q^k}$$

Where  $p^k = x^{k+1} - x^k$  and  $q^k = \nabla f(x^{k+1}) - \nabla f(x^k)$ .

#### **Broyden Family**

In this case,  $D_k$  is updated via

$$C_k^B = C_k^{DFP} + \frac{\phi \tau_k v_k (v_k)^T}{(p^k)^T q^k}$$

Where

$$v^k = p^k - \frac{1}{\tau_k} D_k q^k$$

 $\phi$ : a constant  $\phi \ge 0$ 

 $\tau_k$ : a constant, with  $C_k q^k = p^k - D_k q^k$ 

$$\tau_k = \frac{(q^k)^T D_k q^k}{(p^k)^T q^k} > 0$$

#### Broyden-Fletcher-Goldfarb-Shanno (BFGS)

Basically Broyden family when  $\phi = 1$ .

$$C_k^{BFGS} = C_k^B \big|_{\phi=1}$$

When  $\phi = 0$ ,  $C_k^B = C_k^{DFP}$ . Otherwise,  $C_k^B$  can be written as a convex combination of DFP and BFGS, when  $\phi \in (0,1)$ 

$$C_k^B = (1 - \phi)C_k^{DFP} + \phi C_k^{BFGS}$$

### Conjugate Directions

- $H: n \times n$  symmetric matrix
- Vectors  $d^1, \ldots, d^n$  are called H-conjugate if
  - They are linearly independent, and
  - $(d^i)^T H d^j = 0 \ \forall i \neq j$

Consider

$$\min \quad f(x) = c^t x + \frac{1}{2} x^t H x$$

for  $H: n \times n$  symmetric. Any  $x \in \mathbb{R}^n$ , x can be represented as

$$x = x^1 + \sum_{j=1}^{n} \lambda_j d^j$$

$$f(x) = F(\lambda) = c^T(x^1 + \sum \lambda_j d^j) + \frac{1}{2}(x^1 + \sum \lambda_j d^j)H(x^1 + \sum \lambda_j d^j)$$

Note that this function f(x) is not really a function of x but rather  $\lambda$ .

$$F(\lambda) = c^T x^1 + \sum_{j=1}^n \lambda_j c^T d^j + \sum_{j=1}^n \left[ \frac{1}{2} (x^1 + \lambda_j d^j)^T H (x^1 + \lambda_j d^j) \right]$$
$$\min F(\lambda) = \sum_{j=1}^n F_j(\lambda_j)$$
$$\min F_j(\lambda_j) = \lambda_j c^T d^j + \frac{1}{2} (x^1 + \lambda_j d^j)^T H (x^1 + \lambda_j d^j)$$

If H is PD, then we have a strictly convex problem.

$$\frac{\partial F_j}{\partial \lambda_j} = c^T d^j + (d^j)^T H(x^1 \lambda_j d^j) = 0$$

$$\Rightarrow \lambda_j = -\frac{c^t d^j + (d^j)^T H x^1}{(d^j)^T H d^j}$$

So, rather than solve the larger problem of  $F(\lambda)$ , we can just solve individual, easier, problems for each  $F_j(\lambda_j)$ . But, the tricky part of this method is that you need to find each of the  $d_i$ . Next class will discuss methods for finding these H-conjugate directions.