

Quasi-Newton Methods

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Quasi-Newton Methods

- Quasi-Newton methods (like steepest descent), **require only the gradient** of the objective function to be supplied at each iterate.
- By measuring the changes in gradients, they **construct a model** of the objective function that is good enough to produce **super-linear convergence**.
- The **improvement** over steepest descent is **dramatic**, especially on **difficult problems**.
- Moreover, since **second derivatives** are not required (unlike Newton's), quasi-Newton methods are sometimes more efficient than Newton's method.
- Today, optimization software libraries contain a variety of quasi-Newton algorithms for solving unconstrained, constrained, and large-scale optimization problems.

THE BFGS METHOD

- BFGS method, named for its discoverers Broyden, Fletcher, Goldfarb, and Shanno.
- Consider the following **quadratic model** of the objective function at the current iterate x_k :

$$m_k(p) = f_k + \nabla f_k^T p + \frac{1}{2} p^T B_k p. \quad (1)$$

B_k is a $n \times n$ symmetric positive definite matrix that will be **revised or updated at every iteration**.

- As the model is first-order accurate the function value f_k and the gradient ∇f_k , both match at $p = 0$.
- The **minimiser** of this model is

$$p_k = -B_k^{-1} \nabla f_k, \quad (2)$$

THE BFGS METHOD

- p_k is used as the search direction, and the new iterate is

$$x_{k+1} = x_k + \alpha_k p_k \quad (3)$$

where the step length α_k is chosen to satisfy the Wolfe conditions.

- Instead of computing B_k afresh at every iteration, **Davidon** proposed to update it in a simple manner to account for the curvature measured during the (most recent) previous step.
- Suppose that we have generated a new iterate x_{k+1} and wish to construct a new quadratic model, of the form

$$m_{k+1}(p) = f_{k+1} + \nabla f_{k+1}^T p + \frac{1}{2} p^T B_{k+1} p. \quad (4)$$

- What **requirements** should we impose on B_{k+1} , based on the **knowledge** gained during the **latest step**?

THE BFGS METHOD

- One reasonable requirement is that the **gradient of m_{k+1}** should **match** the **gradient** of the objective function **f** at the latest **two iterates x_k and x_{k+1}** , i.e.

$$\nabla m_{k+1}(0) = \nabla f_{k+1} \quad (\text{condition at the second point is satisfied})$$

- The first condition can be written mathematically as

$$\nabla m_{k+1}(-\alpha_k p_k) = \nabla f_{k+1} - \alpha_k B_{k+1} p_k = \nabla f_k$$

- By rearranging we get

$$B_{k+1} \alpha_k p_k = \nabla f_{k+1} - \nabla f_k \quad (5)$$

THE BFGS METHOD

- Introduce the notations

$$s_k = x_{k+1} - x_k = \alpha_k p_k$$

$$y_k = \nabla f_{k+1} - \nabla f_k$$

- With the above notation (5) becomes

$$B_{k+1} s_k = y_k \tag{6}$$

which is called the secant equation.

- Given the displacements s_k and the change of gradients y_k , the secant equation requires that the symmetric positive definite matrix B_{k+1} map s_k into y_k .