

Matrix Secant Methods

Optimization

Broyden Updates

Given $g : \mathbb{R}^n \rightarrow \mathbb{R}^n$ solve $g(x) = 0$.

Algorithm: Broyden's Method

Initialization: $x^0 \in \mathbb{R}^n$, $B_0 \in \mathbb{R}^{n \times n}$

Having (x^k, B_k) compute (x^{k+1}, B_{k+1}) as follows:

Solve $B_k s^k = -g(x^k)$ for s^k and set

$$x^{k+1} : = x^k + s^k$$

$$y^k : = g(x^k) - g(x^{k+1})$$

$$B_{k+1} : = B_k + \frac{(y^k - B_k s^k) s^{kT}}{s^{kT} s^k}.$$

Broyden Updates

Algorithm: Broyden's Method (Inverse Updating)

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Having (x^k, B_k) compute (x^{k+1}, B_{k+1}) as follows:

Solve $s^k = -J_k g(x^k)$ for s^k and set

$$\begin{aligned} x^{k+1} &: = x^k + s^k \\ y^k &: = g(x^k) - g(x^{k+1}) \\ J_{k+1} &: = J_k + \frac{(s^k - J_k y^k) s^{kT} J_k}{s^{kT} J_k y^k}. \end{aligned}$$

MSE for Optimization

$$\mathcal{P} : \underset{x \in \mathbb{R}^n}{\text{minimize}} \ f(x) ,$$

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The MSE becomes

$$M_{k+1} s^k = y^k ,$$

where

$$s^k := x^{k+1} - x^k \text{ and } y^k := \nabla f(x^{k+1}) - \nabla f(x^k).$$

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This is unsatisfactory for two reasons:

1. Since M_k approximates $\nabla^2 f(x^k)$ it must be symmetric.
2. Since we are minimizing, then M_k must be positive definite to insure that $s^k = -M_k^{-1} \nabla f(x^k)$ is a direction of descent for f at x^k .

SR1 Update

The Broyden class of updates is

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$$v = (y^k - M_k s^k)$$

giving

$$M_{k+1} = M_k + \frac{(y^k - M_k s^k)(y^k - M_k s^k)^T}{(y^k - M_k s^k)^T s^k}.$$

The corresponding inverse update (by SMW) is

$$H_{k+1} = H_k + \frac{(s^k - H_k y^k)(s^k - H_k y^k)^T}{(s^k - H_k y^k)^T y^k}.$$

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But this update may not be positive definite.



Positive Definite Updating

Basic Problem:

Let $M \in \mathbb{R}^{n \times n}$ be a given symmetric positive definite (spd) matrix. Given $s, y \in \mathbb{R}^n$ find an spd matrix M_+ such that $M_+s = y$ and M_+ is “close” to M .

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Let's try another approach that combines the Broyden update with yet another important property of symmetric matrices.

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Similarly, if M_+ exists, then there must be a nonsingular matrix J such that $M_+ = JJ^T$.

Positive Definite Updating

So $M = LL^T$ and $M_+ = JJ^T$ with $M_+s = y$.

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But then $v = \alpha L^T s$ for some $\alpha \in \mathbb{R}$.

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Hence

$$\alpha^2 = \left[\frac{s^T y}{s^T M s} \right].$$

Broyden-Fletcher-Goldfarb-Shanno (BFGS) Updating

Therefore, this update only exists if $s^T y > 0$ in which case

$$J = L + \frac{(y - \alpha Ms)s^T L}{\alpha s^T Ms},$$

with

$$\alpha = \left[\frac{s^T y}{s^T Ms} \right]^{1/2},$$

yielding

$$M_+ = M + \frac{yy^T}{y^T s} - \frac{Mss^T M}{s^T Ms}.$$

This is called the BFGS update. It is currently viewed as the best MSE update available for optimization due to its outstanding performance in practise.

BFGS Updating

In addition, we note that the M_+ can be obtained directly from the matrices J .

If the QR factorization of J^T is $J^T = QR$, we can set $L_+ = R$ yielding

$$M_+ = JJ^T = R^T Q^T QR = L_+ L_+^T.$$

Inverse BFGS Updating

Sherman-Morrison-Woodbury formula again gives the inverse update

$$H_+ = H + \frac{(s + Hy)^T y s s^T}{(s^T y)^2} - \frac{Hys^T + sy^T H}{s^T y},$$

where $H = M^{-1}$.

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Recall that

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Hence

$$\begin{aligned} y^k{}^T s^k &= \nabla f(x^{k+1})^T s^k - \nabla f(x^k)^T s^k \\ &= t_k (\nabla f(x^k + t_k d^k)^T d^k - \nabla f(x^k)^T d^k), \end{aligned}$$

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Therefore, to get $s^k{}^T y^k > 0$ we must show $t_k > 0$ can be chosen so that

$$\nabla f(x^k + t_k d^k)^T d^k \geq \beta \nabla f(x^k)^T d^k$$

for some $\beta \in (0, 1)$ since in this case

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But this precisely the second condition in the weak Wolfe conditions with $\beta = c_2$. Hence a successful BFGS update can always be obtained.