# Analysis of BFGS 

Giuseppe Giorgio Colabufo<br>giuseppe.colabufo@polytechnique.edu

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## BFGS Algorithm

1. Obtain a direction $d_{k}$ by $d_{k}=-B_{k}^{B F G S} \nabla f\left(x_{k}\right)$.
2. Perform a one-dimensional optimization (line search) to find an acceptable step-size $\alpha_{k}$ in the direction found in the first step, so $\alpha_{k}=\underset{\alpha}{\arg \min } f\left(x_{k}+\alpha d_{k}\right)$.
3. Set $p_{k}=\alpha_{k} d_{k}$ and update $x_{k+1}=x_{k}+p_{k}$.
4. $q_{k}=\nabla f\left(x_{k+1}\right)-\nabla f\left(x_{k}\right)$.
5. $B_{k+1}^{B F G S}=B_{k}^{B F G S}+\frac{\left(p_{k}^{T} q_{k}+q_{k}^{T} B_{k}^{B F G S} q_{k}\right)\left(p_{k} p_{k}^{T}\right)}{\left(p_{k}^{T} q_{k}\right)^{2}}-\frac{B_{k}^{B F G S} q_{k} p_{k}^{T}+p_{k} q_{k}^{T} B_{k}^{B F G S}}{p_{k}^{T} q_{k}}$.

We consider the update for the matrix $B$ as follows:

$$
B_{k+1}= \begin{cases}B_{k}+\frac{\left(p_{k}^{T} q_{k}+q_{k}^{T} B_{k} q_{k}\right)\left(p_{k} p_{k}^{T}\right)}{\left(p_{k}^{T} q_{k}\right)^{2}}-\frac{B_{k} q_{k} p_{k}^{T}+p_{k} q_{k}^{T} B_{k}}{p_{k}^{T} q_{k}} & p_{k} \neq 0  \tag{1}\\ B_{k} & p_{k}=0\end{cases}
$$

Remark 0.0.1. In the previous update we only consider the case in which $p_{k}=0$ because $p_{k}=\Longleftrightarrow q_{k}=0$.
Proof. If $p_{k}=0$ then $x_{k+1}=x_{k}$ and $\nabla f\left(x_{k+1}\right)=\nabla f\left(x_{k}\right)$, i.e. $q_{k}=0$.
On the other hand, if $q_{k}=0$, i.e. $\nabla f\left(x_{k+1}\right)=\nabla f\left(x_{k}+\alpha_{k} d_{k}\right)=\nabla f\left(x_{k}\right)$, there are two cases:

- $\alpha_{k}=0$ that means $p_{k}=0$.
- $\alpha_{k} \neq 0$, but since $\alpha_{k}=\arg \min \phi(\alpha)=\arg \min f\left(x_{k}+\alpha d_{k}\right)$ from the first
order condition

$$
\begin{aligned}
0 & =\phi^{\prime}\left(\alpha_{k}\right) \\
& =\nabla f\left(x_{k}+\alpha_{k} d_{k}\right)^{T} d_{k} \\
& =\nabla f\left(x_{k}\right)^{T} d_{k} \\
& =-\nabla f\left(x_{k}\right)^{T} B_{k} \nabla f\left(x_{k}\right) \leq 0
\end{aligned}
$$

we obtain $\nabla f\left(x_{k}\right)=0$ since $B_{k}$ is positive definite. But then $d_{k}=0$ and $p_{k}=0$.

In both cases we showed that $q_{k}=0 \Rightarrow p_{k}=0$.
This justifies the form of the update.


Figure 1: A diagram summarizing the BFGS algorithm.
In the following we note $r_{k}=\nabla f\left(x_{k-1}\right)$ for each $k \geq 1$.
Lemma 0.1. The three following statement are equivalent:
(i) $\exists K \in \mathbb{N} \cup\{+\infty\} \forall m \geq K x_{m}=x^{*}$;
(ii) $\exists K \in \mathbb{N} \cup\{+\infty\} \forall m \geq K B_{m}=B^{*}$;
(iii) $\exists K \in \mathbb{N} \cup\{+\infty\} \forall m \geq K r_{m}=r^{*}$;

Proof. First suppose $K<+\infty$.
$(i) \Rightarrow(i i)$ If $(i)$ holds then $\forall m \geq K p_{m}=0$ and that means $B_{m}=B_{K}=B^{*}$ because of the update formula (1).
$(i) \Rightarrow(i i i)$ If $(i)$ holds, since $\forall m \geq K p_{m}=0$ then $q_{m}=0$, i.e. $\nabla f\left(x_{m}\right)=\nabla f\left(x^{*}\right)$ and $r_{m}=r^{*}$.
$(i i+i i i) \Rightarrow(i)$ It follows from the algorithm that $d_{m}=-B_{m} \nabla f\left(x_{m}\right)=-B^{*} r^{*}=: d^{*}$. Then $\alpha_{m}$ satisfies

$$
0=\nabla f\left(x_{m}+\alpha_{m} d^{*}\right)^{T} d^{*}=r^{* T} d^{*}
$$

which implies $r^{*}=0 \Rightarrow d^{*}=0$ and $p_{m}=0$ as before. This latter equation is equivalent to $(i)$.
If $K=+\infty$ then the sequence $x_{k}$ does not converge to $x^{*}$ in finite time: for all $m \in \mathbb{N}$ the stepsize $p_{m} \neq 0$ which in particularly implies $q_{m} \neq 0$ and this is equivalent to the fact that $r_{k}$ does not converge in finite time. The sequence $B_{k}$ does not converge either, otherwise the secant equation $B_{+} q=p$ would give a contraddiction. This proves the equivalence of the three statements in the case.

Remark 0.1.1. We can derive a lower bound on $\|B\|$ using a Taylor expansion on $r$ :

$$
\begin{aligned}
r_{k+1}-r_{k} & =\nabla f\left(x_{k}\right)-\nabla f\left(x_{k-1}\right) \\
& =H(\tau)\left(x_{k}-x_{k-1}\right) \\
& =\alpha_{k-1} H(\tau) p_{k-1} \\
& =\alpha_{k-1} H(\tau) B_{k} q_{k-1} \\
& =\alpha_{k-1} H(\tau) B_{k}\left(r_{k+1}-r_{k}\right)
\end{aligned}
$$

where $\tau$ is a point between $x_{k-1}$ and $x_{k}$. Taking the norms

$$
\left\|r_{k+1}-r_{k}\right\| \leq\left|\alpha_{k-1}\right|\|H(\tau)\|\left\|B_{k}\right\|\left\|r_{k+1}-r_{k}\right\|
$$

Now, if $r_{k+1} \neq r_{k}$ we derive the lower bound on $\left\|B_{k}\right\|$ :

$$
\left\|B_{k}\right\| \geq \frac{1}{\left|\alpha_{k-1}\right|\|H(\tau)\|}
$$

and if $r_{k+1}=r_{k}$ then the algorithm has converged (reasoning as in the proof of (Lemma 0.1)).

Remark 0.1.2. Without loss of generality we can impose $\alpha \geq 0$ in the algorithm, to require $p$ to be a descent direction. This means that $p_{k}^{T} \nabla f\left(x_{k}\right)<0$ for every $k \geq 0$. In particular yields $f\left(x_{k+1}\right) \leq f\left(x_{k}\right)$.

Remark 0.1.3. With the extra assumption $\alpha \geq 0$ and the update formula (1), we can conclude that the (BFGS Algorithm) converges to a stationary point $x^{*}$. If this happens in a finite number of steps $K<+\infty$, then, by (Lemma 0.1), the sequence of matrices $B_{k}$ converges as well and their dynamics is clearly stable: the sequence is modified for $K$ steps and after it becomes constant.

