

Problem 1 [BV 9.8]

By definition we have:

$$\begin{aligned}\Delta x_{nsd} &= \arg \min \{ \nabla f(x)^T v \mid \|v\|_\infty \leq 1 \} \\ &= \arg \min \{ \nabla f(x)^T v \mid \max\{|v_1|, \dots, |v_n|\} \leq 1 \} \\ &= \arg \min \{ \frac{\partial f}{\partial x_1}(x)v_1 + \dots + \frac{\partial f}{\partial x_n}(x)v_n \mid \max\{|v_1|, \dots, |v_n|\} \leq 1 \}\end{aligned}$$

since each $-1 \leq v_i \leq 1$, if we choose $v_i = -\frac{\frac{\partial f}{\partial x_i}(x)}{|\frac{\partial f}{\partial x_i}(x)|}$ when $\frac{\partial f}{\partial x_i}(x) \neq 0$ and $v_i = 0$ otherwise, the objective function will be minimized. In other words, v_i is always the negative of the sign of the i^{th} element of the gradient.

On the other hand, since the dual of l_∞ -norm is l_1 -norm, we have:

$$\begin{aligned}\Delta x_{sd} &= \|\nabla f(x)\|_1 \Delta x_{nsd} \\ &= \left(\sum_{i=1}^n \left| \frac{\partial f}{\partial x_i}(x) \right| \right) \Delta x_{nsd}\end{aligned}$$

where elements of Δx_{nsd} are in $\{-1, 0, 1\}$. This choice of steepest direction always points to a direction negative of the direction (sign) of gradient on each coordinate, unless the gradient is zero in that coordinate.

Problem 2 [BV 9.10]

(a)

$$\begin{aligned}f(x) &= \log(e^x + e^{-x}) \\ f'(x) &= \frac{e^x - e^{-x}}{e^x + e^{-x}} \\ f''(x) &= \frac{4}{(e^x + e^{-x})^2} \\ x^+ &= x - \frac{1}{f''(x)} f'(x)\end{aligned}$$

The Newton's updates with different initial points are reported below, it shows that

in this case of fixed step size, a small deviation in the initial point could lead to non-convergence of the algorithm:

| iteration (k) | 0 | 1 | 2 | 3 | 4 | 5 |
|-------------------|---|---------|--------|---------|-------------------------|---------------------------|
| $x^{(k)}$ | 1 | -0.8134 | 0.4094 | -0.0473 | 7.0602×10^{-5} | -2.3470×10^{-13} |
| $f(x^{(k)})$ | 1 | 0.9928 | 0.7747 | 0.6942 | 0.6931 | 0.6931 |

| iteration (k) | 0 | 1 | 2 | 3 | 4 | 5 |
|-------------------|---------|---------|--------|---------|--------|-------------|
| $x^{(k)}$ | 1.1 | -1.1285 | 1.2341 | -1.6951 | 5.7153 | -23021.3564 |
| $f(x^{(k)})$ | 1.00468 | 1.2280 | 1.3154 | 1.7283 | 5.7153 | 23021.3564 |

(b)

$$f(x) = -\log x + x$$

$$f'(x) = -\frac{1}{x} + 1$$

$$f''(x) = \frac{1}{x^2}$$

$$x^+ = x - \frac{1}{f''(x)} f'(x)$$

In this case after a single iteration, the Newton's update get outside of the domain of function.

| iteration (k) | 0 | 1 | 2 | 3 | 4 | 5 |
|-------------------|--------|-------------|---|---|---|---|
| $x^{(k)}$ | 3 | -3 | - | - | - | - |
| $f(x^{(k)})$ | 1.9013 | not defined | - | - | - | - |

Problem 3 [BV 9.11]

1. Gradient Method.

$$\nabla g(x) = \phi'(f(x)) \nabla f(x)$$

Since ϕ is increasing ($\phi'(f(x)) \geq 0$), then the gradient of g is always in the same direction as the gradient of f . Therefore both of them will have the same search

direction and when the exact line search is used, minimizing both of the will have the same iterations.

2. Newton Method.

$$\begin{aligned}
& \nabla^2 g(x)^{-1} \nabla g(x) \\
&= [\phi'' \nabla f(x) \nabla f(x)^T + \phi' \nabla^2 f(x)]^{-1} \nabla g(x) \\
&= \left[\frac{1}{\phi'} \nabla^2 f^{-1} - \frac{1}{\phi'} \nabla^2 f^{-1} \phi'' \nabla f (I + \frac{1}{\phi'} \nabla f^T \nabla^2 f^{-1} \phi'' \nabla f)^{-1} \nabla f^T \frac{1}{\phi'} \nabla^2 f^{-1} \right] \nabla g(x) \\
&= \left[\frac{1}{\phi'} \nabla^2 f^{-1} - \frac{1}{\phi'} \nabla^2 f^{-1} \phi'' \nabla f (I + \frac{\phi''}{\phi'} p)^{-1} \nabla f^T \frac{1}{\phi'} \nabla^2 f^{-1} \right] \nabla g(x) \\
&= \left[\frac{1}{\phi'} \nabla^2 f^{-1} - \frac{\phi''}{\phi'(\phi' + p\phi'')} \nabla^2 f^{-1} \nabla f \nabla f^T \nabla^2 f^{-1} \right] \phi' \nabla f \\
&= \nabla^2 f^{-1} \left[I - \frac{\phi''}{\phi' + p\phi''} \nabla f \nabla f^T \nabla^2 f^{-1} \right] \nabla f \\
&= \nabla^2 f^{-1} \left[\nabla f - \frac{\phi''}{\phi' + p\phi''} \nabla f \nabla f^T \nabla^2 f^{-1} \nabla f \right] \\
&= \nabla^2 f^{-1} \nabla f \left[I - \frac{\phi''}{\phi' + p\phi''} \nabla f^T \nabla^2 f^{-1} \nabla f \right] \\
&= \nabla^2 f^{-1} \nabla f \left[I - \frac{\phi''}{(\phi' + p\phi'')} p \right] \\
&= \nabla^2 f^{-1} \nabla f \left[\frac{\phi'}{\phi' + p\phi''} \right]
\end{aligned}$$

where the second equality follows from Matrix Inversion Lemma (C.4.3) and $p := \nabla f^T \nabla^2 f^{-1} \phi'' \nabla f$ is a nonnegative scalar, as f is a convex function. Since ϕ is increasing and convex, the coefficient $\frac{\phi'}{\phi' + p\phi''}$ is non-negative. Therefore both of f and g will have the same Newton search direction and when the exact line search is used, minimizing both of them will result in same iterations.