

Homework 3 solution

1. (Exercises from Beck Ch 2)

a. (Beck 2.17) Here $f(x_1, x_2) = 2x_2^3 - 6x_2^2 + 3x_1^2x_2$,

i. The gradient is

$$\nabla f(x) = \begin{bmatrix} 6x_1x_2 \\ 6x_2^2 - 12x_2 + 3x_1^2 \end{bmatrix},$$

There are two stationary points: $x^* = (0, 0)$ and $x^* = (0, 2)$.

ii. The Hessian is

$$\nabla^2 f(x) = \begin{bmatrix} 6x_2 & 6x_1 \\ 6x_1 & 12x_2 - 12 \end{bmatrix}$$

At $x^* = (0, 0)$,

$$\nabla^2 f([0 \ 0]) = \begin{bmatrix} 0 & 0 & 0 & -12 \end{bmatrix}$$

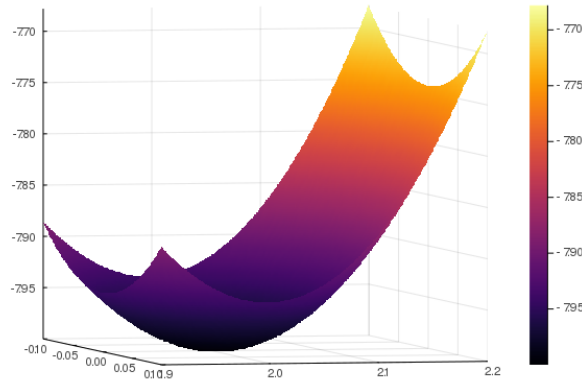
which is negative semidefinite. (Diagonal with all non-positive values, and one 0.) We cannot tell if it is a local minimum or maximum or saddle point. At $x^* = (0, 2)$,

$$\nabla^2 f([0 \ 2]) = \begin{bmatrix} 12 & 0 & 0 & 12 \end{bmatrix}$$

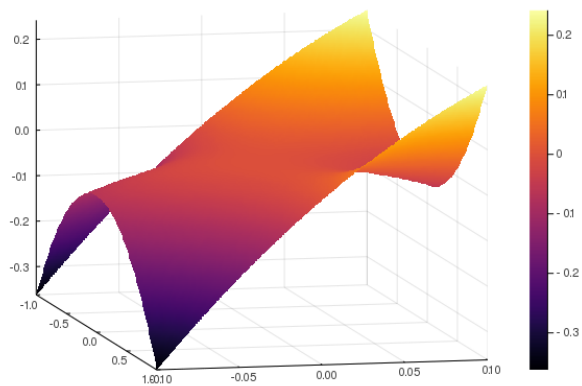
which is positive definite. (Diagonal with all strictly positive values).

This point must be a strict local minima.

iii. At $x = (0, 2)$, it is clearly a strict local minimum.



At $x = (0, 0)$, it is a saddle point.



- b. (Beck 2.19) We first show that forward implication. Since $\nabla^2 f(x) = A \succeq 0$ for all x , if we find any point in which $\nabla f(x) = 0$, then we have found a global minimizer of this function. If $b \in \mathbf{range}(A)$, then there exists a y where $Ay = b$. Taking $x^* = -y$ gives the stationary point we need.

Now assume that $b \notin \mathbf{range}(A)$. Then, this means that $b = u + v$ where $u \in \mathbf{range}(A)$ and $v \in \mathbf{null}(A^T) = \mathbf{null}(A)$ where $v \neq 0$. Now take any $x = \gamma v$ for any scalar c . Then

$$f(\gamma v) = \frac{\gamma^2}{2} \underbrace{v^T A v}_{=0} + \gamma \underbrace{b^T v}_{=v^T v} + c = \gamma \|v\|_2^2 + c.$$

Picking $\gamma \rightarrow -\infty$ shows that $f(\gamma v) \rightarrow -\infty$ is unbounded below.

2. To compute $\mathbf{tr}(A^T B)$, we must first form the matrix product $A^T B$ which requires $O(n^2 m)$ flops and $O(n^2)$ storage. Then extracting the trace is an

additional $O(n)$ flops and $O(1)$ storage. So, in total, $O(n^2m + n)$ flops (or $O(n^2m)$ as the dominating term) and $O(n^2 + 1)$ storage (or just $O(n^2)$).

To compute the right and side, we do not need any additional storage, and just require $O(mn)$ flops.

Now if $m \gg n$, this is a significant reduction in storage, and if n is large is a significant reduction in flops. The key takeaway is that, for proper scalability, though many things are equivalent, how you implement it matters.

3. Here, $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a twice continuously differentiable function that has L -Lipschitz gradient.

a. The directional derivative of ∇f at x in the direction v is

$$\nabla^2 f(x)v = \lim_{t \searrow 0} \frac{\nabla f(x + tv) - \nabla f(x)}{t}. \quad (1)$$

So,

$$\|\nabla^2 f(x)v\|_2 = \left\| \lim_{t \searrow 0} \frac{\nabla f(x + tv) - \nabla f(x)}{t} \right\|_2 \quad (2)$$

$$= \lim_{t \searrow 0} \left\| \frac{\nabla f(x + tv) - \nabla f(x)}{t} \right\|_2 \quad (3)$$

$$\leq \lim_{t \searrow 0} \frac{L\|tv\|}{t} \quad (4)$$

$$= L\|v\|_2 \quad (5)$$

where second line follows from continuity of norms and third line follows from L -Lipschitz of gradient.

b. From above, we have that any fixed x satisfies the inequality

$$\|\nabla^2 f(x)v\| \leq L\|v\|_2 \text{ for all } v.$$

Fix x and let (λ_+, v_+) be the maximal eigen-pair of the matrix $\nabla^2 f(x)$. So, $\|\nabla^2 f(x)v\| \leq L\|v\|_2$ for all v gives $\lambda_+ \leq L$. Thus, all eigenvalues of

$\nabla^2 f(x)$ is bounded from above by L . As x is arbitrary, we get that for all x , the eigenvalues of $\nabla^2 f(x)$ is bounded from above by L .

c. Using Taylor's remainder theorem, we get

$$f(v) = f(w) - \nabla f(w)^\top (v - w) + \frac{1}{2} (v - w)^\top \nabla^2 f(\xi) (v - w),$$

where $v, w \in \mathbb{R}^n$ and $\xi \in [v, w]$. Since $\|\nabla^2 f(x)v\| \leq L\|v\|_2$ for all v and x , we also have $v^\top \nabla^2 f(x)v \leq L\|v\|_2^2$ all v and x . Thus,

$$f(v) = f(w) + \nabla f(w)^\top (v - w) + \frac{L}{2} \|v - w\|_2^2.$$

d. A gradient descent step is $x_{k+1} = x_k - \alpha \nabla f(x_k)$. Substituting $v = x_{k+1}$ and $w = x_k$, we get

$$f(x_{k+1}) = f(x_k) + \nabla f(x_k)^\top (x_{k+1} - x_k) + \frac{L}{2} \|x_{k+1} - x_k\|_2^2 \quad (6)$$

$$= f(x_k) - \alpha \nabla f(x_k)^\top \nabla f(x_k) + \frac{L\alpha^2}{2} \|\nabla f(x_k)\|_2^2 \quad (7)$$

$$= f(x_k) - \alpha \|\nabla f(x_k)\|_2^2 \left(1 - \frac{L\alpha}{2}\right) \quad (8)$$

Note that $\alpha \|\nabla f(x_k)\|_2^2 (1 - \frac{L\alpha}{2}) > 0$ if x_k is not a stationary point and $0 < \alpha < \frac{2}{L}$