# Math 171B: Numerical Optimization: Nonlinear Problems 

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Solutions for Homework Assignment \#1

Exercise 1.1. If $x$ is an eigenvector of $A$, show that $\beta x$ is also an eigenvector for any $\beta \neq 0$. What is the associated eigenvalue? Use this result to show that the unit vector $x /\|x\|$ formed from an eigenvector $x$ is also an eigenvector of $A$ corresponding to the same eigenvalue as that of $x$.
If $A x=\lambda x$, then clearly $A(\beta x)=\beta(A x)=\beta(\lambda x)=\lambda(\beta x)$ holds, simply by the properties of scalar-vector and scalar-matrix multiplication, and by the definition of an eigenpair. Therefore, if $x$ is an eigenvector then so is $\beta x$, and both have the same eigenvalue. Moreover, if $x$ is an eigenvector, we know that $x \neq 0$, so that $\|x\| \neq 0$ (property of the norm), so that taking $\beta=1 /\|x\|$ is well-defined. Therefore, if $x$ is an eigenvector, so is $x /\|x\|$, for the same eigevalue.

Exercise 1.2. Let $(x, y): V \mapsto \mathbb{R}$ be an inner-product on a vector space $V$ with associated scalar field $\mathbb{R}$. We know that $(x, y)$ must satisfy the three properties of an inner-product:

1. $(x, x) \geq 0, \quad \forall x \in V, \quad(x, x)=0 i f f x=0$.
2. $(x, y)=(y, x), \quad \forall x, y \in V$.
3. $(\alpha x+\beta y, z)=\alpha(x, z)+\beta(y, z), \quad \forall \alpha, \beta \in \mathbb{R}, \quad \forall x, y, z \in V$.

Use these three properties to show that the induced norm $\|x\|=(x, x)^{1 / 2}$ satisfies the three properties of a norm:

1. $\|\alpha x\|=|\alpha|\|x\|, \quad \forall \alpha \in \mathbb{R}, \quad \forall x \in V$.
2. $\|x\| \geq 0, \quad \forall x \in V, \quad\|x\|=0$ iff $x=0$.
3. $\|x+y\| \leq\|x\|+\|y\|, \quad \forall x, y \in V$.

Hint: Showing the first two properties is very easy; to show the last property (triangle inequality), assume the Cauchy-Schwarz inequality holds: $|(x, y)| \leq\|x\|\|y\|$.
Property 1 By properties 2 and 3 of the inner-product we have $\|\alpha x\|=(\alpha x, \alpha x)^{1 / 2}=\left\{\alpha^{2}(x, x)\right\}^{1 / 2}=$ $|\alpha|\|x\|$.

Property 2 By property 1 of the inner-product $\|x\|=(x, x)^{1 / 2} \geq 0 \forall x \in V$, and $\|x\|=(x, x)^{1 / 2}=0$ iff $x=0$.
Property 3 By properties 2 and 3 of the inner-product, and by the Cauchy-Schwarz inequality, it holds that:

$$
\begin{aligned}
\|x+y\|^{2} & =(x+y, x+y) \\
& =(x, x)+2(x, y)+(y, y) \\
& \leq(x, x)+2|(x, y)|+(y, y) \\
& \leq(x, x)+2\|x\|\|y\|+(y, y) \\
& =\|x\|^{2}+2\|x\|\|y\|+\|y\|^{2} \\
& =(\|x\|+\|y\|)^{2},
\end{aligned}
$$

which gives $\|x+y\| \leq\|x\|+\|y\|$.
Exercise 1.3. Let $F(x)$ denote a twice-differentiable function of one variable. Assuming only the meanvalue theorem of integral calculus: $F(b)=F(a)+\int_{a}^{b} F^{\prime}(t) d t$, derive the following variants of the Taylor-series expansion with integral remainder:
(a) $F(x+h)=F(x)+\int_{x}^{x+h} F^{\prime}(t) d t$.

This follows from the mean-value theorem on substituting $a=x$ and $b=x+h$.
(b) $F(x+h)=F(x)+h \int_{0}^{1} F^{\prime}(x+\xi h) d \xi$.

The idea is to transform the variable of integration in part (a). Consider the new variable $\xi$ such that $t=x+h \xi$. As $t$ varies between the limits of integration $x$ and $x+h$, we find that $\xi$ varies between 0 and 1. Substituting for $t$ in part (a) and using $d t=h d \xi$ gives the result.
(c) $F(x+h)=F(x)+h F^{\prime}(x)+h \int_{0}^{1}\left[F^{\prime}(x+\xi h)-F^{\prime}(x)\right] d \xi$.

From part (b) we have

$$
\begin{aligned}
F(x+h) & =F(x)+h \int_{0}^{1} F^{\prime}(x+\xi h) d \xi \\
& =F(x)+h F^{\prime}(x)-h F^{\prime}(x)+h \int_{0}^{1} F^{\prime}(x+\xi h) d \xi
\end{aligned}
$$

Since $h F^{\prime}(x)$ is independent of $\xi$, the variable of integration, we may take it under the integral sign to give

$$
F(x+h)=F(x)+h F^{\prime}(x)+h \int_{0}^{1}\left[F^{\prime}(x+\xi h)-F^{\prime}(x)\right] d \xi
$$

as required.
(d) $F(x+h)=F(x)+h F^{\prime}(x)+h^{2} \int_{0}^{1} F^{\prime \prime}(x+\xi h)(1-\xi) d \xi$. (Hint: Try expanding $F^{\prime}(x+h)$ using a formula analogous to part (b) and differentiate with respect to $h$ using the chain rule.)
Since $F^{\prime}(x)$ is differentiable, we can apply the formula of part (b) to the function $F^{\prime}$, giving

$$
\begin{equation*}
F^{\prime}(x+h)=F^{\prime}(x)+h \int_{0}^{1} F^{\prime \prime}(x+\xi h) d \xi \tag{1.1}
\end{equation*}
$$

Another expression for $F^{\prime}(x+h)$ can be found by considering the result of part (b):

$$
\begin{equation*}
F(x+h)=F(x)+h \int_{0}^{1} F^{\prime}(x+\xi h) d \xi \tag{1.2}
\end{equation*}
$$

For fixed $x$ we can differentiate $F(x+h)$ with respect to $h$. Applying the chain-rule for differentiation gives

$$
\begin{equation*}
\frac{d F(x+h)}{d h}=F^{\prime}(x+h)=\int_{0}^{1} F^{\prime}(x+\xi h) d \xi+h \int_{0}^{1} F^{\prime \prime}(x+\xi h) \xi d \xi \tag{1.3}
\end{equation*}
$$

Combining (1.1), (1.2) and (1.3), so that the terms $F^{\prime}(x+h)$ and $\int_{0}^{1} F^{\prime}(x+\xi h) d \xi$ are eliminated, we obtain the required identity. In particular, taking $2 \times(1.2)-h \times(1.3)+h \times(1.1)$ gives the result.

Exercise 1.4. Find the gradient vector $F(x)=\nabla f(x)$ of the following functions, and then find the Jacobian matrix of $F(x)$. (The Jacobian matrix of $F(x)=\nabla f(x)$ is the same as the Hessian matrix $\nabla^{2} f(x)$ of $f(x)$ ).
(a) $f(x)=2\left(x_{2}-x_{1}^{2}\right)^{2}+\left(x_{1}-3\right)^{2}$.

First we form the row vector $f^{\prime}(x)$ by forming the first partials with respect to each variable. This gives

$$
f^{\prime}(x)=\left(-8 x_{1}\left(x_{2}-x_{1}^{2}\right)+2\left(x_{1}-3\right) \quad 4\left(x_{2}-x_{1}^{2}\right)\right) .
$$

The gradient of $f$ is just the transpose of this vector, giving

$$
g(x)=\left(f^{\prime}(x)\right)^{T}=\binom{-8 x_{1}\left(x_{2}-x_{1}^{2}\right)+2\left(x_{1}-3\right)}{4\left(x_{2}-x_{1}^{2}\right)}
$$

The Hessian matrix is defined as the derivative of the gradient $g$, so that

$$
H(x)=\left(\begin{array}{cc}
-8\left(x_{2}-x_{1}^{2}\right)+16 x_{1}^{2}+2 & -8 x_{1} \\
-8 x_{1} & 4
\end{array}\right)
$$

Since the Hessian is always a symmetric matrix (if the second partials are continuous), you can use this as a check on your work: if you work out the off-diagonal partial derivatives separately, they should come out to be the same value.
(b) $f(x)=\left(2 x_{1}+x_{2}\right)^{2}+4\left(x_{2}-x_{3}\right)^{4}$.

Forming the gradient vector as in part (a), we get

$$
g(x)=\left(\begin{array}{c}
8 x_{1}+4 x_{2} \\
4 x_{1}+2 x_{2}+16\left(x_{2}-x_{3}\right)^{3} \\
-16\left(x_{2}-x_{3}\right)^{3}
\end{array}\right)
$$

The Hessian matrix is just the "Jacobian" of this column vector. Plugging away at it gives the Hessian matrix $H(x)$ as

$$
\left(\begin{array}{ccc}
8 & 4 & 0 \\
4 & 2+48\left(x_{2}-x_{3}\right)^{2} & -48\left(x_{2}-x_{3}\right)^{2} \\
0 & -48\left(x_{2}-x_{3}\right)^{2} & 48\left(x_{2}-x_{3}\right)^{2}
\end{array}\right)
$$

Exercise 1.5. Find $f^{\prime}(x), \nabla f(x)$ and $\nabla^{2} f(x)$ for the following functions of $n$ variables.
(a) $f(x)=\frac{1}{2} x^{T} H x$, where $H$ is an $n \times n$ constant matrix.

The trick is to and work out the derivatives without getting too buried in lots of indices. First, we write $H$ in terms of its columns $\left\{h_{j}\right\}$,

$$
H=\left(\begin{array}{cccc}
h_{1} & h_{2} & \cdots & h_{n}
\end{array}\right), \text { where } h_{j}=\left(\begin{array}{c}
h_{1 j} \\
h_{2 j} \\
\vdots \\
h_{n j}
\end{array}\right) .
$$

This partition of $H$ allows us to write $f(x)$ as

$$
f(x)=\frac{1}{2} x^{T} H x=\frac{1}{2} x^{T}\left(\sum_{j=1}^{n} h_{j} x_{j}\right)=\frac{1}{2} \sum_{j=1}^{n}\left(x^{T} h_{j}\right) x_{j} .
$$

Taking the partial derivative with respect to $x_{i}$, and using standard rules about differentiating products, we obtain

$$
\frac{\partial f(x)}{\partial x_{i}}=\frac{1}{2} \sum_{j=1}^{n} \frac{\partial\left(x^{T} h_{j}\right)}{\partial x_{i}} x_{j}+\frac{1}{2} \sum_{j=1}^{n}\left(x^{T} h_{j}\right) \frac{\partial x_{j}}{\partial x_{i}}=\frac{1}{2} \sum_{j=1}^{n} \frac{\partial\left(x^{T} h_{j}\right)}{\partial x_{i}} x_{j}+\frac{1}{2} x^{T} h_{i}
$$

The first term under the summation can be written as

$$
\frac{\partial\left(x^{T} h_{j}\right)}{\partial x_{i}}=\frac{\partial}{\partial x_{i}} \sum_{k=1}^{n} x_{k} h_{k j}=h_{i j}
$$

Since $x^{T} h_{i}=\sum_{j=1}^{n} h_{j i} x_{j}$, it follows that

$$
\frac{\partial f(x)}{\partial x_{i}}=\frac{1}{2} \sum_{j=1}^{n} h_{i j} x_{j}+\frac{1}{2} \sum_{j=1}^{n} h_{j i} x_{j}
$$

and $\partial f(x) / \partial x_{i}$ is half the sum of the $i$ th elements of $H x$ and $H^{T} x$, with

$$
f^{\prime}(x)=\frac{1}{2} x^{T}\left(H+H^{T}\right)
$$

The gradient $\nabla f(x)$ is the transpose of $f^{\prime}(x)$, giving

$$
\nabla f(x)=\frac{1}{2}\left(H^{T}+H\right) x
$$

The Hessian matrix $\nabla^{2} f(x)$ is defined as the first derivative (i.e., Jacobian) of the gradient vector. Hence

$$
\nabla^{2} f(x)=(\nabla f(x))^{\prime}=\frac{1}{2}\left(\left(H^{T} x\right)^{\prime}+(H x)^{\prime}\right)
$$

Given any constant matrix $A$, the Jacobian of $A x$ is $A$, which implies that

$$
\nabla^{2} f(x)=\frac{1}{2}\left(H^{T}+H\right)
$$

Notice that the Hessian is a symmetric matrix, even though $H$ is not symmetric.
(b) $f(x)=b^{T} A x-\frac{1}{2} x^{T} A^{T} A x$, where $A$ is an $m \times n$ constant matrix and $b$ is a constant $m$-vector.

If we use $H=A^{T} A$ in part (a) we have

$$
f^{\prime}(x)=b^{T} A-\frac{1}{2} x^{T}\left(A^{T} A+\left(A^{T} A\right)^{T}\right)=b^{T} A-x^{T} A^{T} A .
$$

the last equality following from the fact that $A^{T} A$ is symmetric. Forming the transpose for $g(x)$ gives

$$
\nabla f(x)=f^{\prime}(x)^{T}=A^{T} b-A^{T} A x=A^{T}(b-A x) .
$$

Finally, we have from part (a)

$$
\nabla^{2} f(x)=(\nabla f(x))^{\prime}=\frac{1}{2}\left(A^{T} A+\left(A^{T} A\right)^{T}\right)=A^{T} A .
$$

(c) $f(x)=\|x\|=\left(\sum_{i=1}^{n} x_{i}^{2}\right)^{1 / 2}$.

First we compute $\partial f / \partial x_{j}$ :

$$
\frac{\partial f(x)}{\partial x_{j}}=\frac{1}{2}\left(\sum_{i=1}^{n} x_{i}^{2}\right)^{-1 / 2} 2 x_{j}=\frac{1}{\|x\|} x_{j} .
$$

This implies that

$$
f^{\prime}(x)=\left(\begin{array}{llll}
\frac{1}{\|x\|} x_{1} & \frac{1}{\|x\|} x_{2} & \cdots & \frac{1}{\|x\|} x_{n}
\end{array}\right)=\frac{1}{\|x\|} x^{T},
$$

and $\nabla f(x)=x /\|x\|$.
Differentiating with respect to $x_{i}$ for $i \neq j$, we obtain

$$
\frac{\partial^{2} f(x)}{\partial x_{i} \partial x_{j}}=\frac{\partial}{\partial x_{i}}\left(\frac{\partial f(x)}{\partial x_{j}}\right)=\frac{\partial}{\partial x_{i}}\left(\frac{x_{j}}{\|x\|}\right)=-\frac{x_{i} x_{j}}{\|x\|^{3}} .
$$

Similarly, for $i=j$, we have

$$
\frac{\partial^{2} f(x)}{\partial x_{j}^{2}}=\frac{\partial}{\partial x_{j}}\left(\frac{\partial f(x)}{\partial x_{j}}\right)=\frac{\partial}{\partial x_{j}}\left(\frac{x_{j}}{\|x\|}\right)=\frac{\|x\|^{2}-x_{j}^{2}}{\|x\|^{3}} .
$$

Therefore, the Hessian of $f(x)$ may be written:

$$
\begin{aligned}
\nabla^{2} f(x) & =\frac{1}{\|x\|^{3}}\left(\begin{array}{cccc}
\|x\|^{2}-x_{1}^{2} & -x_{1} x_{2} & \cdots & -x_{1} x_{n} \\
-x_{2} x_{1} & \ddots & \vdots \\
\vdots & & \\
-x_{n} x_{1} & \cdots & \|x\|^{2}-x_{n}^{2}
\end{array}\right) \\
& =\frac{1}{\|x\|^{3}}\left(\|x\|^{2} I-x x^{T}\right)=\frac{1}{\|x\|}\left(I-\hat{x} \hat{x}^{T}\right),
\end{aligned}
$$

where $\hat{x}$ is the unit vector $x /\|x\|$.
Exercise 1.6.* Create a Matlab m-file of the form:

```
function [F,J] = D(x)
    F = [ a ; b ];
    J = [ c d ; e f ];
```

where the expressions for $a, b, c, d, e, f$ are chosen so that the function returns the $2 \times 1$-vector-valued function $F(x)$ and the $2 \times 2$ Jacobian matrix $J(x)$ for the function $F(x)$ from part (a) of Problem 1.4. Use this m-file to compute $F$ and $J$ at $x=(1,0)^{T}$; and $x=(1,1)^{T}$. Capture the output from the computation and turn it in with the homework.

See the TA for the solution to this problem.

