Numerical Optimization  
Lecture Notes #16  
Calculating Derivatives — Finite Differencing

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Fall 2017
Outline

1. Non-Analytic Derivatives — Finite Differencing
   - Taylor’s Theorem \(\Rightarrow\) Finite Differencing
   - Finite Difference Gradient
   - Finite Difference Hessian

2. Finite Differencing — Sparsity and Symmetry

3. #include <std_project.h>
   - Default Project Milestone #2
Derivatives Needed!!!

As we have seen (and will see), algorithms for nonlinear optimization (and nonlinear equations) require knowledge of derivatives:

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Often it is quite trivial to provide the code which computes those derivatives, but in some cases the analytic expressions for the derivatives are not available and/or not practical to evaluate.

In those cases we need some other way to compute or **approximate** the derivatives.
Finite Differences — The Return of Taylor’s Theorem

We can get an approximation of the gradient $\nabla f(\bar{x})$ by evaluating the objective $f$ at $(n + 1)$ points, using the Forward Difference Formula

$$\frac{\partial f(\bar{x})}{\partial x_i} \approx \frac{f(\bar{x} + \epsilon \bar{e}_i) - f(\bar{x})}{\epsilon}, \quad i = 1, 2, \ldots, n,$$

where $\bar{e}_i$ is the $i$th unit vector, and $\epsilon > 0$ is small.

If $f$ is twice continuously differentiable, then by Taylor’s Theorem

$$f(\bar{x} + \bar{p}) = f(\bar{x}) + \nabla f(\bar{x})^T \bar{p} + \frac{1}{2} \bar{p}^T \nabla^2 f(\bar{x} + t\bar{p})\bar{p}, \quad t \in (0, 1),$$

with $\bar{p} = \epsilon \bar{e}_i$, i.e.

$$f(\bar{x} + \epsilon \bar{e}_i) = f(\bar{x}) + \epsilon \nabla f(\bar{x})^T \bar{e}_i + \frac{1}{2} \epsilon^2 \bar{e}_i^T \nabla^2 f(\bar{x} + t\epsilon \bar{e}_i)\bar{e}_i, \quad i = 1, 2, \ldots, n.$$
Forward Differences

With a bit of re-arrangement we see

\[
\nabla f(\bar{x})^T \bar{e}_i = \left( \frac{\partial f(\bar{x})}{\partial x_i} \right) = \frac{f(\bar{x} + \epsilon \bar{e}_i) - f(\bar{x})}{\epsilon} - \frac{1}{2} \epsilon \bar{e}_i^T \nabla^2 f(\bar{x} + t \epsilon \bar{e}_i) \bar{e}_i
\]

Finite Difference Approximation

Approximation Error

If the Hessian $\nabla^2 f(\bar{x})$ is bounded, i.e. $\|\nabla^2 f(\bar{x})\| \leq L_c$, then we have

\[
\frac{\partial f(\bar{x})}{\partial x_i} \approx \frac{f(\bar{x} + \epsilon \bar{e}_i) - f(\bar{x})}{\epsilon},
\]

where the approximation error is bounded by

\[
\frac{\epsilon L_c}{2}.
\]

Since the error is proportional to $\epsilon$, this is a **first-order approximation**.
Clearly, the smaller the $\epsilon$ the smaller the error. How small can we set $\epsilon$ in finite precision???

Let $\epsilon_{\text{mach}}$ denote value for machine epsilon, a.k.a. unit roundoff, it is essentially the largest value for which

$$((1.0 + \epsilon_{\text{mach}}) - 1.0) = 0, \quad \text{in finite precision}$$

$\epsilon_{\text{mach}} \approx 10^{-16}$ in double-precision arithmetic (IEEE 64-bit floating point: “C” `double`, and Matlab internals on typical Intel-based systems.)

$\epsilon_{\text{mach}}$ is a measure of how well (or badly) we can represent any number in finite precision, and in extension a measure of the (best case) quality of every computation.
If \( L_f \) is a bound on the value of \( f(\vec{x}) \), i.e. \( |f(\vec{x})| \leq L_f \), then in finite precision we have

\[
\| \text{computed}(f(\vec{x})) - f(\vec{x}) \| \leq \epsilon_{\text{mach}} L_f \\
\| \text{computed}(f(\vec{x} + \epsilon \vec{e}_i)) - f(\vec{x} + \epsilon \vec{e}_i) \| \leq \epsilon_{\text{mach}} L_f.
\]

Now, if we recall our finite difference approximation

\[
\frac{\partial f(\vec{x})}{\partial x_i} \approx \frac{f(\vec{x} + \epsilon \vec{e}_i) - f(\vec{x})}{\epsilon} + \text{error}(\epsilon),
\]

we find that the total error is

\[
\text{error}(\epsilon) \sim \frac{2\epsilon_{\text{mach}} L_f}{\epsilon} + \frac{\epsilon L_c}{2}.
\]

Floating Point Error Approximation Error
Selecting $\epsilon$

Now,

$$\frac{d}{d\epsilon} \text{error}(\epsilon) \sim -\frac{2\epsilon_{\text{mach}} L_f}{\epsilon^2} + \frac{L_c}{2} = 0 \quad \Rightarrow \quad \epsilon^2 = \frac{4\epsilon_{\text{mach}} L_f}{L_c},$$

gives us the optimal value for epsilon. Since $L_f$ and $L_c$ are unknown in general, most software packages tend to select

$$\epsilon^* = \sqrt{\epsilon_{\text{mach}}},$$

which is close to optimal in most cases.

Hence, the error in the approximated gradient is

$$\text{error}(\epsilon^*) \sim 2L_f \sqrt{\epsilon_{\text{mach}}} + \frac{L_c}{2} \sqrt{\epsilon_{\text{mach}}} \sim O(\sqrt{\epsilon_{\text{mach}}}).$$
At twice the cost, we can get about 2.67 extra digits of precision in the finite difference approximation, by using central differences.

More Taylor expansions...

\[
\begin{align*}
  f(\bar{x} + \epsilon \vec{e}_i) &= f(\bar{x}) + \epsilon \frac{\partial f}{\partial x_i} + \frac{1}{2} \epsilon^2 \frac{\partial^2 f}{\partial x_i^2} + O(\epsilon^3) \\
  f(\bar{x} - \epsilon \vec{e}_i) &= f(\bar{x}) - \epsilon \frac{\partial f}{\partial x_i} + \frac{1}{2} \epsilon^2 \frac{\partial^2 f}{\partial x_i^2} + O(\epsilon^3) \\
  f(\bar{x} + \epsilon \vec{e}_i) - f(\bar{x} - \epsilon \vec{e}_i) &= 2\epsilon \frac{\partial f}{\partial x_i} + \frac{\epsilon^3}{3} \frac{\partial^3 f}{\partial x_i^3} + O(\epsilon^5).
\end{align*}
\]

We get

Central Difference Formula, with Error Term

\[
\frac{\partial f(\bar{x})}{\partial x_i} = \frac{f(\bar{x} + \epsilon \vec{e}_i) - f(\bar{x} - \epsilon \vec{e}_i)}{2\epsilon} + \frac{\epsilon^2}{6} \frac{\partial^3 f}{\partial x_i^3} + O(\epsilon^4).
\]
Now, if we have a bound on the third derivative(s)

\[
\left| \frac{\partial^3 f}{\partial x_i^3} \right| \leq L_J,
\]

we can derive an optimal \( \epsilon \):

\[
\text{error}(\epsilon) \sim \frac{\epsilon_{\text{mach}} L_f}{\epsilon} + \frac{\epsilon^2 L_J}{6}.
\]

\[
\frac{d}{d\epsilon} \text{error}(\epsilon) \sim -\frac{\epsilon_{\text{mach}} L_f}{\epsilon^2} + \frac{\epsilon L_J}{3} = 0.
\]

\[
\Rightarrow \epsilon^* \sim \sqrt[3]{\frac{3 \epsilon_{\text{mach}} L_f}{L_J}} \sim \sqrt[3]{\epsilon_{\text{mach}}} \Rightarrow \text{error} \sim \mathcal{O} \left( \epsilon_{\text{mach}}^{2/3} \right).
\]
The easy case: Analytic Gradient given

If the analytic gradient is known, then we can get an approximation of the Hessian by applying forward or central differencing to each element of the gradient vector in turn. When the second derivatives exist and are Lipschitz continuous, Taylor’s theorem says

\[ \nabla f(\bar{x} + \bar{p}) = \nabla f(\bar{x}) + \nabla^2 f(\bar{x})\bar{p} + \mathcal{O}(\|\bar{p}\|^2). \]

Again, we let \( \bar{p} = \epsilon \bar{e}_i \), \( i = 1, 2, \ldots, n \) and get

\[ \nabla^2 f(\bar{x})\bar{e}_i \approx \frac{\nabla f(\bar{x} + \epsilon \bar{e}_i) - \nabla f(\bar{x})}{\epsilon} + \mathcal{O}(\epsilon), \text{ or} \]

\[ \nabla^2 f(\bar{x})\bar{e}_i \approx \frac{\nabla f(\bar{x} + \epsilon \bar{e}_i) - \nabla f(\bar{x} - \epsilon \bar{e}_i)}{2\epsilon} + \mathcal{O}(\epsilon^2). \]
It is worth noting that this is a column-at-a-time process, which does not — due to numerical roundoff and approximation errors — necessarily give a symmetric Hessian.

It is often necessary to **symmetrize the result**

\[
H_{\text{sym}} = \frac{1}{2} \left[ H_{\text{num}} + H_{\text{num}}^T \right].
\]
Special Case: In Newton-CG methods we do not require full knowledge of the Hessian. Each iteration requires the Hessian-vector product $\nabla^2 f(\bar{x})\bar{p}$, where $\bar{p}$ is the given search direction, this expression can be approximated

$$\nabla^2 f(\bar{x})\bar{p} \approx \frac{\nabla f(\bar{x} + \epsilon \bar{p}) - \nabla f(\bar{x} - \epsilon \bar{p})}{2\epsilon} + \mathcal{O}(\epsilon^2)$$

This approximation is very cheap — only one [two] extra gradient evaluation[s] is [are] needed.
The harder case: Analytic Gradient not given

When the analytic gradient is not given we must use a finite difference formula using only function values to approximate the Hessian.

The first order **forward difference** approximation is given by

\[
\frac{\partial^2 f(\bar{x})}{\partial x_i \partial x_j} \approx \frac{f(\bar{x} + \epsilon \bar{e}_i + \epsilon \bar{e}_j) - f(\bar{x} + \epsilon \bar{e}_i) - f(\bar{x} + \epsilon \bar{e}_j) + f(\bar{x})}{\epsilon^2}
\]
Approximating the Hessian

At a price of $\sim n^2$ additional function evaluations (an increase of 33%) we can use the second order central difference approximation

$$\frac{\partial^2 f(\bar{x})}{\partial x_i \partial x_j} \approx \frac{f(\bar{x} + \epsilon \bar{e}_i + \epsilon \bar{e}_j) - f(\bar{x} + \epsilon \bar{e}_i - \epsilon \bar{e}_j) - f(\bar{x} - \epsilon \bar{e}_i + \epsilon \bar{e}_j) + f(\bar{x} - \epsilon \bar{e}_i - \epsilon \bar{e}_j)}{4\epsilon^2}$$

**Figure:** The second order 4-point central difference approximation stencil for $\frac{\partial^2 f(\bar{x})}{\partial x_i \partial x_j}$ at the central point in the stencil — note that the value in that point is not part of the evaluation!
Now that we are paying $\sim 4$ function evaluations per entry in the Hessian matrix, it is worth taking sparsity and symmetry into account.

Ponder the extended Rosenbrock function:

```c
double function_rosenbrock( int n, double *x )
{
    double f = 0.0;
    int i;
    for( i=0; i<n/2; i++ )
        f += ( 10 * ( x[2*i+1] - x[2*i]*x[2*i] ) * 
                ( x[2*i+1] - x[2*i]*x[2*i] ) ) + 
                ( 1 - x[2*i] ) * ( 1 - x[2*i] );
    return(f);
}
```

Clearly, there is no “interaction” between coordinate-directions $\vec{e}_i$ and $\vec{e}_j$, where $|i - j| > 1$. 

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The fill-pattern of the Hessian of the extended Rosenbrock function consists of $2 \times 2$-diagonal blocks:

There are a lot of zero-entries in this Hessian. If somehow we have knowledge of the sparsity pattern, then we can exploit this by not computing/touching the zeros.
By using the fact that the Hessian is symmetric, we can save about half of the work,

\[ H_{ij} = H_{ji}, \quad j > i. \]

**Figure:** The entries to the left \( H_{ij}, \ j \leq i \) must be computed, but using symmetry we can fill in the missing ones \( H_{ij} = H_{ji}, \ j > i. \)
Add the following to your codebase:

fdhessg  Finite difference approximation to the Hessian using analytic gradient. (Executed when analgrad=TRUE, analhess=FALSE, cheapf=TRUE.)

fdjac  The core call from fdhessg, note that fvec in the pseudo-code corresponds to your analytic gradient.

fdgrad  Finite difference (forward) approximation to the gradient. (Executed when analgrad=FALSE.)

fdhessf  Finite difference approximation to the Hessian using only function values. (Executed when analgrad=FALSE, analhess=FALSE, cheapf=TRUE.)

**Compare:** Performance of analytic everything (from before) / analytic gradient (fdhessg+fdjac) / finite difference everything (fdhessf+fdgrad). Try optimal and non-optimal $\epsilon$. Use 2 test problems from Dennis-Schnabel, Appendix B.

**Add-on:** Central differencing strategies.
Due Friday 10/27/2017

Please let me know in the very near future what you are working on!!! A brief paragraph outlining your project is sufficient.
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