

The Art of Differentiating Computer Programs using Algorithmic Differentiation (AD)

Uwe Naumann

$\frac{\partial}{\partial x}$ void f(int n, double* x,
int m, double* y) { ... }



LuFG Informatik 12

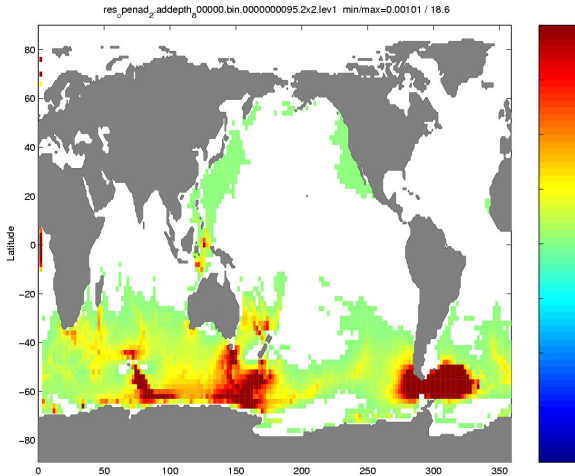
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Motivation: Numerical Simulation

e.g., MITgcm



Given: Numerical simulation program

$$F : \mathbb{R}^n \rightarrow \mathbb{R}^m, \quad \mathbf{y} = F(\mathbf{x})$$

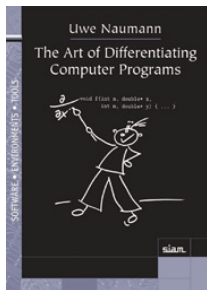
Wanted: Sensitivity of outputs $\mathbf{y} \in \mathbb{R}^m$ on inputs $\mathbf{x} \in \mathbb{R}^n$ (Jacobian $\nabla F(\mathbf{x})$)

$$\nabla F(\mathbf{x}) \equiv \left(\frac{\partial y_j}{\partial x_i} \right)_{\substack{j=0,\dots,m-1 \\ i=0,\dots,n-1}}$$

$y = f(x)$; effect of perturbation in x depending on $y' \equiv \frac{\partial y}{\partial x}$

- ▶ for large $y' > 0 \rightarrow$ large increase in y (instable)
- ▶ for small $y' > 0 \rightarrow$ small increase in y (stable)
- ▶ for large $y' < 0 \rightarrow$ large decrease in y (instable)
- ▶ for small $y' < 0 \rightarrow$ small decrease in y (stable)
- ▶ for $y' = 0 \rightarrow$ invariant

- ▶ 3 lectures
- ▶ 2 tutorials
- ▶ see tutorial sheet for contents



U. Naumann:

The Art of Differentiating Computer Programs.
An Introduction to Algorithmic Differentiation
Number 24 of Software, Environments, and
Tools Series, SIAM, 2012.

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- ▶ Computational Differentiation (V3Ü1, Ba, WS)
- ▶ Combinatorial Problems in Scientific Computing (V2Ü2, Ma, SS)

For a given numerical simulation program, e.g.,

```
void f(int n, double *x, int m, double *y) {
    y[0]=x[0]*(x[0]+x[1]);
    y[1]=sin(x[1]);
}
```

build a program that can be used to compute the sensitivities of all outputs with respect to all inputs (Jacobian matrix).

Specific Objective: Tangent-Linear Code

$$\dot{\mathbf{y}} = \nabla F(\mathbf{x}) \cdot \dot{\mathbf{x}}$$

$$\mathbf{y} = F(\mathbf{x})$$

```
void f(int n, double *x, int m, double *y)
```

becomes

```
void df(int n, double *x, double *dx,
        int m, double *y, double *dy)
```

and computes product of the Jacobian with $\dot{\mathbf{x}}$ in $\dot{\mathbf{y}}$; not the Jacobian itself.

```
void f(int n, double *x, int m, double *y) {
    y[0]=x[0]*( x[0]+x[1]);
    y[1]=sin(x[1]);
}
```

- ▶ Single Assignment Code (SAC)
- ▶ Directed Acyclic Graph (AST, DAG)
- ▶ Linearized SAC
- ▶ Linearized AST, DAG
- ▶ Local Tangent-Linear Code
- ▶ Chain Rule

Jacobian

Computation and Validation

```
void f(int n, double *x, int m, double *y) {  
    y[0]=x[0]*(x[0]+x[1]);  
    y[1]=sin(x[1]);  
}
```

- ▶ driver for tangent-linear code
- ▶ validation by finited differences

Validation through Approximation

Forward Finite Differences

Let $D \subseteq \mathbb{R}^n$ be an open domain and $F : D \rightarrow \mathbb{R}^m$ such that

$$F = \begin{pmatrix} F_0 \\ \vdots \\ F_{m-1} \end{pmatrix} .$$

A *forward finite difference* approximation of the i th column of the Jacobian ∇F at point $\mathbf{x}^0$ is computed as

$$\frac{\partial F}{\partial x_i}(\mathbf{x}^0) \equiv \begin{pmatrix} \frac{\partial F_0}{\partial x_i}(\mathbf{x}^0) \\ \vdots \\ \frac{\partial F_{m-1}}{\partial x_i}(\mathbf{x}^0) \end{pmatrix} \approx_1 \frac{F(\mathbf{x}^0 + \mathbf{e}_i \cdot h) - F(\mathbf{x})}{h} \quad (1)$$

The i th Cartesian basis vector in $\mathbb{R}^n$ is denoted by $\mathbf{e}_i$.

Consider the approximation of the first derivative of $y = f(x) = x$ in single precision IEEE floating-point arithmetic on a 64 bit machine at $x = 10^6$ by the forward finite quotient

$$\nabla f(x) \approx \frac{f(x+h) - f(x)}{h}$$

with $h = 0.1$. Obviously, $\nabla f(x) = 1$ independent of x . The code

```
...
float x=1e6, h=1e-1;
cout << "(f(x+h)-f(x))/h=" << (x+h-x)/h << endl;
...
```

returns 1.25.

Tangent-Linear Code by Forward Mode AD

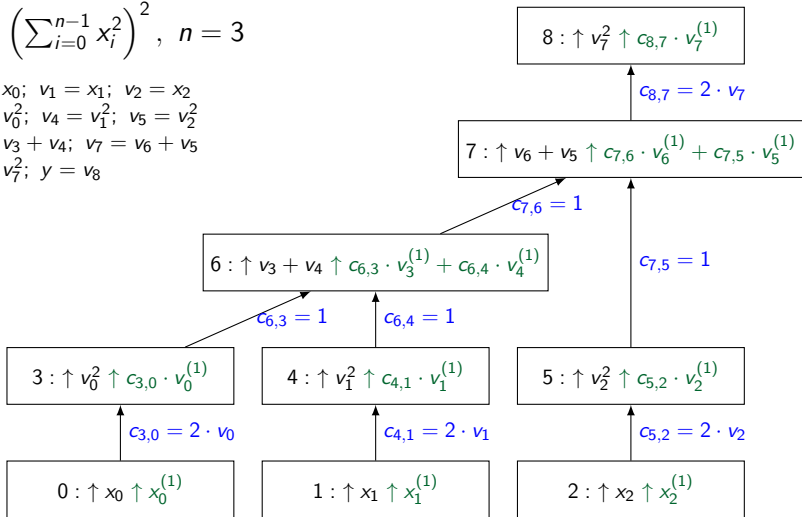
$$y = \left(\sum_{i=0}^{n-1} x_i^2 \right)^2, \quad n = 3$$

$$v_0 = x_0; \quad v_1 = x_1; \quad v_2 = x_2$$

$$v_3 = v_0^2; \quad v_4 = v_1^2; \quad v_5 = v_2^2$$

$$v_6 = v_3 + v_4; \quad v_7 = v_6 + v_5$$

$$v_8 = v_7^2; \quad y = v_8$$



Further Motivation

Nonlinear Optimization

Consider the nonlinear programming problem (NLP)

$$\min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x})$$

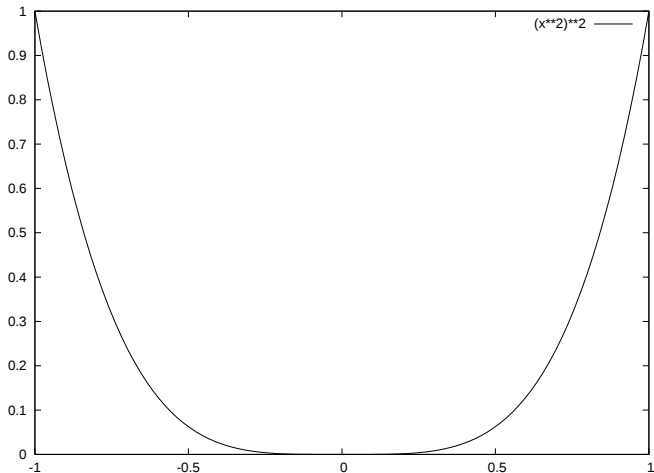
where, for example,

$$f(\mathbf{x}) = \left(\sum_{i=0}^{n-1} x_i^2 \right)^2 \quad (2)$$

is implemented as

```
void f(int n, double *x, double &y)
{
    y=0;
    for (int i=0; i<n; i++) y=y+x[i]*x[i];
    y=y*y;
}
```

The function has a global minimum at $\mathbf{x} = 0$.



... computes

$$\mathbf{x}^{k+1} = \mathbf{x}^k - \alpha_k \cdot \nabla f(\mathbf{x}^k) \quad .$$

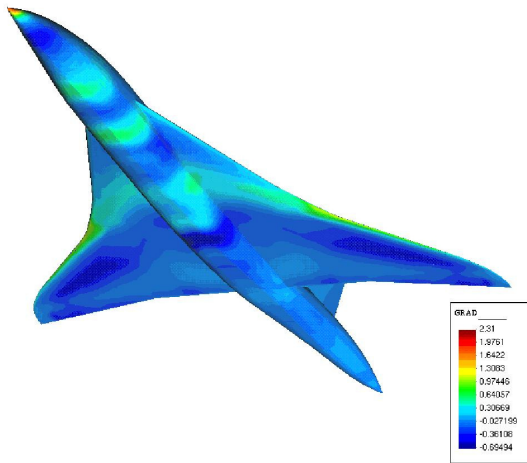
for some suitable starting value $\mathbf{x}^0 = (x_i^0)_{i=0,\dots,n-1}$ and with a step length $\alpha_k > 0$, where $\nabla f(\mathbf{x}^k)$ denotes the gradient of f at the current iterate.

The step length $\alpha_k > 0$ is, for example, chosen by recursive bisection on α_k starting from $\alpha_k = 1$ (0.5, 0.25, ...) and such that a decrease in the objective value is ensured

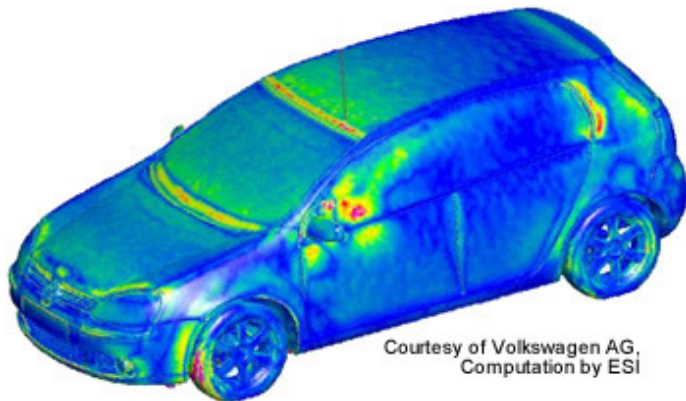
...



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www.siam.org/books/se24

for

- ▶ source
- ▶ use guide
- ▶ Windows version

It also works for, e.g.

```
void f(int n, double *x, double &y) {
    int i=0;
    while (i<n) {
        if (i==0) { y=x[i]*x[i]; }
        else { y=y+x[i]*x[i]; }
        i=i+1;
    }
    y=y*y;
}
```

as well as for interprocedural code etc.