

# Introduction to Algorithmic Differentiation

AD by Hand (Tangent Code)

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- Sigmoidal Smoothing
- Newton's Method

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# Outline

## Recall

Sigmoidal Smoothing

Newton's Method

## Tangent Code Generation Rules

## Examples

Tangent Straight-Line Code

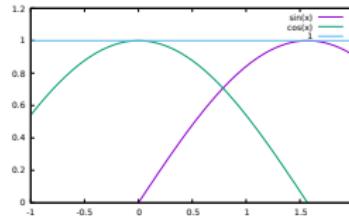
Tangent Intraprocedural Code

Tangent Interprocedural Code

## Sigmoidal Smoothing

Let  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  be defined as

$$f(x, p) = \begin{cases} f_1(x) & x < p \\ f_2(x) & x \geq p \end{cases}.$$



with differentiable univariate scalar  $f_1$  and  $f_2$ .

Depending on the choice of  $f_1$  and  $f_2$  the function  $f$  can be nondifferentiable or even discontinuous at  $x = p$ .

Examples:

- ▶  $f_1 = \cos, f_2 = \sin \Rightarrow$  discontinuous at  $x = p = 1$
- ▶  $f_1 = \cos, f_2 = \sin \Rightarrow$  nondifferentiable at  $x = p = \frac{\pi}{4}$
- ▶  $f_1 = 1, f_2 = \cos \Rightarrow$  differentiable at  $x = p = 0$

# Sigmoidal Smoothing

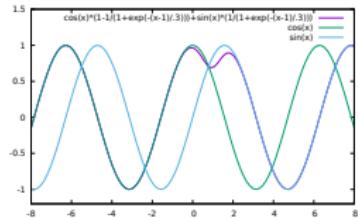
## Definition

Sigmoidal smoothing replaces  $f$  with  $\tilde{f} : \mathbb{R}^3 \rightarrow \mathbb{R}$  defined as

$$\tilde{f}(x, p, w) = (1 - \sigma(x, p, w)) \cdot f_1(x) + \sigma(x, p, w) \cdot f_2(x),$$

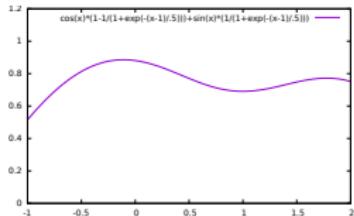
where

$$\sigma(x, p, w) = \frac{1}{1 + e^{-\frac{x-p}{w}}}.$$

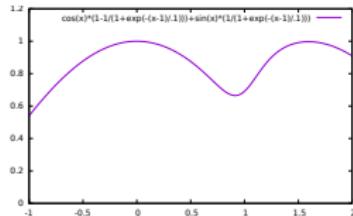


$$w = 0.3$$

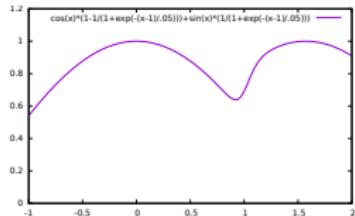
Example:  $f_1 = \cos, f_2 = \sin$  at  $x = p = 1$



$$w = 0.5$$



$$w = 0.1$$



$$w = 0.05$$

# Sigmoidal Smoothing

## Implementation

nondifferentiable

⇒

differentiable

```
1 #pragma once
2
3 #include <cmath>
4
5 template<typename T>
6 void g(T &x, const T &p)
7 {
8     if (x<p)
9         x=sin(x);
10    else
11        x=cos(x);
```

⇒

```
1 #pragma once
2
3 #include <cmath>
4
5 template<typename T>
6 void f(T &x, const T &p, const T &w) {
7     T f1=sin(x);
8     T f2=cos(x);
9     x=1./(1.+exp(-(x-p)/w));
10    x=f1*(1-x)+f2*x;
11 }
```

Consider a nonlinear equation  $y = f(x) = 0$  at some (starting) point  $x$ .

Building on the assumption that  $f(x + \Delta x) \approx f(x) + f'(x) \cdot \Delta x$  the root finding problem for  $f$  can be replaced locally by the root finding problem for the linearization

$$\bar{f}(\Delta x) = f(x) + f'(x) \cdot \Delta x .$$

The right-hand side is a straight line intersecting the  $y$ -axis in  $(\Delta x = 0, \bar{f}(\Delta x) = f(x))$ .

Solution of

$$\bar{f}(\Delta x) = f(x) + f'(x) \cdot \Delta x = 0$$

for  $\Delta x$  yields

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

implying  $f(x + \Delta x) \approx 0$ .

If the new iterate is not close enough to the root of the nonlinear function, i.e.,  $|f(x + \Delta x)| > \epsilon$  for some measure of accuracy of the numerical approximation  $\epsilon > 0$ , then it becomes the starting point for the next iteration yielding the recurrence

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

Convergence of this method is not guaranteed in general. **Damping** of the magnitude of the next step may help.

$$x = x - \alpha \cdot \frac{f(x)}{f'(x)} \quad \text{for } 0 < \alpha \leq 1 .$$

The damping parameter  $\alpha$  is often determined by **line search** (e.g, recursive bisection yielding  $\alpha = 1, 0.5, 0.25, \dots$ ) such that decrease in absolute function value is ensured.

The following iteration terminates if the residual is close enough to zero or if a given number (`maxit`) of iterations was performed.

```
1 template<typename T, typename PT>
2 void newton(T &x, const T &p, const PT
3             &eps, const unsigned int maxit) {
4     unsigned int it=0;
5     T f=pow(x,2)-p;
6     do {
7         T dfdx=2*x;
8         x-=f/dfdx;
9         f=pow(x,2)-p;
10        if (++it==maxit) break;
11    } while(fabs(f)>eps);
12 }
```

```
1 template<typename T, typename PT>
2 T f(T &x, const PT &p) {
3     return pow(x,2)-p;
4 }
5
6 template<typename T, typename PT>
7 T dfdx(T &x, const PT &) { return 2*x; }
8
9 template<typename T, typename PT>
10 void newton(T &x, const T &p, const PT
11             &eps, const unsigned int maxit) {
12     unsigned int it=0;
13     T y=f(x,p);
14     do {
15         x-=y/dfdx(x,p);
16         y=f(x,p);
17         if (++it==maxit) break;
18     } while(fabs(y)>eps);
19 }
```

Alternatively, ...

We consider **differentiable numerical programs**

$$\begin{pmatrix} y \\ \tilde{y} \end{pmatrix} = F(x, \tilde{x}) : \mathbf{R}^n \times \mathbf{R}^{\tilde{n}} \rightarrow \mathbf{R}^m \times \mathbf{R}^{\tilde{m}}$$

mapping **active** ( $x \in \mathbf{R}^n$ ) and **passive** ( $\tilde{x} \in \mathbf{R}^{\tilde{n}}$ ) inputs onto active ( $y \in \mathbf{R}^m$ ) and passive ( $\tilde{y} \in \mathbf{R}^{\tilde{m}}$ ) outputs. The active output  $y$  is assumed to be differentiable with respect to  $x$  with

$$F' \equiv F'(x, \tilde{x}) = \frac{dy}{dx}.$$

The corresponding (first-order) tangent program computes

$$\begin{pmatrix} y \\ \tilde{y} \\ y^{(1)} \end{pmatrix} = F^{(1)}(x, \tilde{x}, x^{(1)}) \equiv \begin{pmatrix} F(x, \tilde{x}) \\ F' \cdot x^{(1)} \end{pmatrix}.$$

## Example: Sigmoidal Smoothing

- ▶ all arguments active for  $\frac{dx}{d(x \ p \ w)^T}$  or  $\frac{dx}{d(p \ w)^T}$

```
1 | template<typename T>
2 | void f_t(T &x, T &x_t, const T &p, const T &p_t, const T &w, const T &w_t) {
3 |   ...
4 | }
```

- ▶ p passive for  $\frac{dx}{d(x \ w)^T}$  or  $\frac{dx}{dw}$

```
1 | template<typename T>
2 | void f_t(T &x, T &x_t, const T &p, const T &w, const T &w_t) {
3 |   ...
4 | }
```

- ▶ w passive for  $\frac{dx}{d(x \ p)^T}$  or  $\frac{dx}{dp}$

```
1 | template<typename T>
2 | void f_t(T &x, T &x_t, const T &p, const T &p_t, const T &w) {
3 |   ...
4 | }
```

For given values of the inputs  $x = (x_i)_{i=0}^{n-1}$  and  $\tilde{x}$  the active section

$$y = (y_k)_{k=0}^{m-1} = y(x, \tilde{x})$$

of a differentiable program  $F(x, \tilde{x})$  decomposes into a sequence of  $q = p + m$  differentiable **elemental functions**  $\varphi_j$  evaluated as a **single assignment code**

$$v_j = \varphi_j(v_k)_{k \prec j} \quad \text{for } j = n, \dots, n + q - 1$$

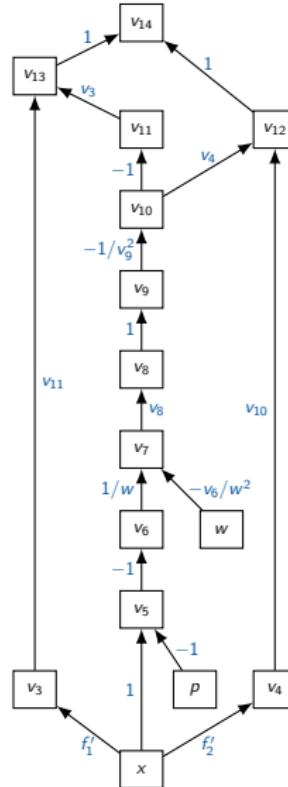
over active variables  $v_j$ ,  $j = 0, \dots, n + q - 1$  and where  $v_i = x_i$  for  $i = 0, \dots, n - 1$ ,  $y_k = v_{n+p+k}$  for  $k = 0, \dots, m - 1$ .

The notation  $k \prec j$  ( $j \succ k$ ) marks  $v_k$  as an argument of  $\varphi_j$ .

# Single Assignment Code

## Example: Sigmoidal Smoothing

```
1 template<typename T>
2 void f(T &x, const T &p, const T &w) {
3     std::vector<T> v(15);
4     v[0]=x;
5     v[1]=p,
6     v[2]=w;
7     v[3]=sin(v[0]);
8     v[4]=cos(v[0]);
9     v[5]=v[0]-v[1];
10    v[6]=-v[5];
11    v[7]=v[6]/v[2];
12    v[8]=exp(v[7]);
13    v[9]=1.0+v[8];
14    v[10]=1.0/v[9];
15    v[11]=1.0-v[10];
16    v[12]=v[3]*v[11];
17    v[13]=v[4]*v[10];
18    v[14]=v[12]+v[13];
19    x=v[14];
20 }
```



Assuming differentiability of all elemental functions the differentiation of

$$v_k = \varphi_k(v_j(v_i, (v_\mu)_{i \neq \mu \prec j}), v_i, (v_\nu)_{\{i,j\} \neq \nu \prec k})$$

with respect to  $v_i$  yields

$$\frac{dv_k}{dv_i} = \frac{dv_k}{dv_j} \cdot \frac{dv_j}{dv_i} + \frac{\partial v_k}{\partial v_i}$$

where  $v_j = \varphi_j(v_i, (v_\mu)_{i \neq \mu \prec j})$ .

The corresponding contribution to the directional derivative (tangent) of  $v_k$  becomes equal to

$$\frac{dv_k}{dv_i} (v_i, (v_\mu)_{i \neq \mu \prec j}, (v_\nu)_{\{i,j\} \neq \nu \prec k}) \cdot v_i^{(1)}.$$

Example:  $v\_t[7] += v\_t[6]/v[2]$ ;  $v\_t[7] += -v[6]*v\_t[2]/\text{pow}(v[2],2)$ ;

As an immediate consequence of the chain rule the directional derivative (tangent) of

$$y = (y_k)_{k=0}^{m-1} = y(x, \tilde{x})$$

with respect to  $x = (x_i)_{i=0}^{n-1}$  in direction  $x^{(1)} = (x_i^{(1)})_{i=0}^{n-1}$  is computed for given  $v_i^{(1)} = x_i^{(1)}$  as

$$v_j^{(1)} = v_j^{(1)} + \frac{d\varphi_j}{dv_i}(v_k)_{k \prec j} \cdot v_i^{(1)} \quad \forall i \prec j$$

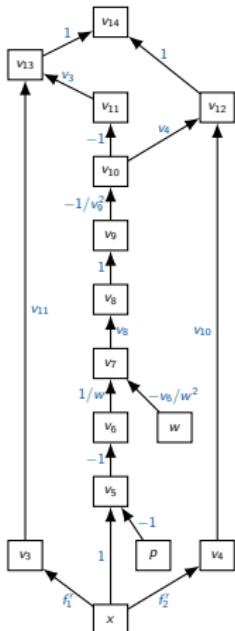
for  $j = n, \dots, n+q-1$  and all  $v_j^{(1)}$  equal to zero initially.

The directional derivative is returned through  $y^{(1)} = (y_k^{(1)})_{k=0}^{m-1}$  where  $y_k^{(1)} = v_{n+p+k}^{(1)}$ . Tangent arithmetic lends itself to implementation by overloading as a simple augmentation of the primal arithmetic with the computation of directional derivatives.

# Tangent Single Assignment Code

## Example: Sigmoidal Smoothing

```
1 template<typename T>
2 void f_t(T &x, T &x_t,
3           const T &p, const T &p_t, const T &w, const T &w_t) {
4     std::vector<T> v(15), v_t(15,0);
5     v[0]=x; v_t[0]=x_t;
6     v[1]=p, v_t[1]=p_t,
7     v[2]=w; v_t[2]=w_t;
8     v[3]=sin(v[0]); v_t[3]+=cos(v[0])*v_t[0];
9     v[4]=cos(v[0]); v_t[4]+=-sin(v[0])*v_t[0];
10    v[5]=v[0]-v[1]; v_t[5]+=v_t[0]; v_t[5]+=-v_t[1];
11    v[6]=-v[5]; v_t[6]+=-v_t[5];
12    v[7]=v[6]/v[2]; v_t[7]+=v_t[6]/v[2]; v_t[7]+=-v[6]*v_t[2]/pow(v[2],2);
13    v[8]=exp(v[7]); v_t[8]+=v[8]*v_t[7];
14    v[9]=1.0+v[8]; v_t[9]+=v_t[8];
15    v[10]=1.0/v[9]; v_t[10]+=-v_t[9]/pow(v[9],2);
16    v[11]=1.0-v[10]; v_t[11]+=-v_t[10];
17    v[12]=v[3]*v[11]; v_t[12]+=v_t[3]*v[11]; v_t[12]+=v[3]*v_t[11];
18    v[13]=v[4]*v[10]; v_t[13]+=v_t[4]*v[10]; v_t[13]+=v[4]*v_t[10];
19    v[14]=v[12]+v[13]; v_t[14]+=v_t[12]; v_t[14]+=v_t[13];
20    x=v[14]; x_t=v_t[14];
21 }
```



# Outline

## Recall

Sigmoidal Smoothing  
Newton's Method

## Tangent Code Generation Rules

## Examples

Tangent Straight-Line Code  
Tangent Intraprocedural Code  
Tangent Interprocedural Code

- TR1 **The active data segment must be duplicated.** Each active primal variable is matched by its tangent [of same type and shape].
- TR2 **Assignment-level tangent code must precede the respective primal assignments.** Local tangent single assignment code simplifies differentiation of complex expressions.
- TR3 **The tangent flow of control is equal to the primal flow of control.** Mind potential non-differentiability due to branching.
- TR4 **Calls to primal subprograms must be replaced with calls to the corresponding tangent subprograms.** This rule generalizes to polymorphism (overloading, class hierarchies).
- TR5 **Drivers are required,** e.g, for the accumulation of the gradient.

```
1 template<typename T>
2 void gradient(const std::vector<T> &x, T& y,
3                 std::vector<T> &grad) {
4     size_t n=x.size();
5     std::vector<T> x_t(n,0);
6     for (size_t i=0;i<n;i++) {
7         x_t[i]=1;
8         f_t(x,x_t,y,grad[i]);
9         x_t[i]=0;
10    }
11 }
```

- ▶ A driver is required to extract the appropriate derivatives from the tangent code in the given context; e.g, the gradient element-wise as directional derivatives in the Cartesian basis directions.
- ▶ Directional derivatives in other directions may be required.

```
1 void f(float x, float &y) {  
2     float z=x*x; y=sin(z);  
3 }  
4  
5 void f_t(float x, float x_t,  
6          float &y, float &y_t) {  
7     float z_t=2*x*x_t;  
8     float z=x*x;  
9     y_t=cos(z)*z_t;  
10    y=sin(z);  
11 }
```

- ▶ The signature is augmented with tangents  $x\_t$  and  $y\_t$  for the active arguments  $x$  and  $y$ .
- ▶  $x$  is passed by value; so is  $x\_t$  yielding two local variables of type **float**.
- ▶  $y$  is passed by reference; so is  $y\_t$  which needs to be declared outside of  $f\_t$ .
- ▶ The local variable  $z$  is augmented with its tangent  $z\_t$ .
- ▶ Both primal assignments are preceded by their (trivial) tangent assignments.

```
1 void f(float x, float &y) {  
2     y=sin(x*x);  
3 }  
4  
5 void f_t(float x, float x_t,  
6          float &y, float &y_t) {  
7     float v_t=2*x*x_t;  
8     float v=x*x;  
9     y_t=cos(v)*v_t;  
10    y=sin(v);  
11 }
```

- ▶ Each (one in this case) primal assignment is decomposed into a single assignment code augmented with its corresponding tangents.

- ▶ Optimization by *copy propagation* eliminates  $v_t$  yielding

```
T v=x*x;  
y_t=cos(v)*2*x*x_t;  
y=sin(v);
```

```
1 template<typename T>
2 void f_t(const std::vector<T> &x, const
3         std::vector<T> &x_t, T &y, T &y_t) {
4     T xTx_t=0, xTx=0;
5     for (size_t i=0;i<x.size();i++)
6         if (i==0) {
7             xTx_t=2*x[i]*x_t[i];
8             xTx=pow(x[i],2);
9         } else {
10            xTx_t+=2*x[i]*x_t[i];
11            xTx+=pow(x[i],2);
12        }
13    y_t=cos(xTx)*xTx_t; y=sin(xTx);
```

- ▶ For a given primal implementation of  $y = \sin(x^T \cdot x)$  as

```
template<typename T>
void f(const std::vector<T> &x, T &y)
{
    T xTx=0;
    for (size_t i=0;i<x.size();i++)
        if (i==0)
            xTx=pow(x[i],2);
        else
            xTx+=pow(x[i],2);
    y=sin(xTx);
```

we obtain the tangent code on the left.

- ▶ Special care must be taken if the flow of control yields **nondifferentiability**; e.g, (sigmoidal) smoothing. We focus on **differentiable** programs.

```
1 void g(float x, float &y) {  
2     y=x*x;  
3 }  
4  
5 void g_t(float x, float x_t,  
6          float &y, float &y_t) {  
7     y_t=2*x*x_t; y=x*x;  
8 }  
9  
10 void f(float x, float &y) {  
11     float z; g(x,z); y=sin(z);  
12 }  
13  
14 void f_t(float x, float x_t,  
15          float &y, float &y_t) {  
16     float z,z_t;  
17     g_t(x,x_t,z,z_t);  
18     y_t=cos(z)*z_t; y=sin(z);  
19 }
```

- ▶ Calls to primal subprograms need to be replaced by calls to their tangents.
- ▶ Potentially induced **nondifferentiability** (e.g, due to recursion) needs to be dealt with. We focus on **differentiable** programs.

# Outline

## Recall

Sigmoidal Smoothing  
Newton's Method

## Tangent Code Generation Rules

## Examples

Tangent Straight-Line Code  
Tangent Intraprocedural Code  
Tangent Interprocedural Code

In the following we apply the tangent code generation rules to “slightly more real-world” examples, namely the previously introduced implementations of

- ▶ sigmoidal smoothing to illustrate tangent straight-line code;
  - ▶ Newton's method to illustrate tangent
    - ▶ intraprocedural
    - ▶ interprocedural
- code.

```
1 template<typename T>
2 void f_t(T &x, T &x_t, const T &p, const T &p_t, const T &w, const T &w_t) {
3     T f1_t=cos(x)*x_t; T f1=sin(x);
4     T f2_t=-sin(x)*x_t; T f2=cos(x);
5     T aux=exp(-(x-p)/w);
6     x_t=-pow(1./(1.+aux),2)*aux*(-x_t/w+p_t/w+w_t*(x-p)/pow(w,2));
7     x=1./(1.+aux);
8     x_t=f1_t*(1-x)-f1*x_t+f2_t*x+f2*x_t;
9     x=f1*(1-x)+f2*x;
10 }
```

```
1 template<typename T, typename PT>
2 void f_t(T &x, T &x_t, const T &p, const T &p_t, const PT &eps, const unsigned int
3 maxit) {
4     unsigned int it=0;
5     T f_t=2*x*x_t-p_t;
6     T f=pow(x,2)-p;
7     do {
8         T dfdx_t=2*x_t;
9         T dfdx=2*x;
10        x_t-=f_t/dfdx-f*dfdx_t/pow(dfdx,2);
11        x-=f/dfdx;
12        f_t=2*x*x_t-p_t;
13        f=pow(x,2)-p;
14        if (++it==maxit) break;
15    } while(fabs(f)>eps);
}
```

## Example: Newton's Method

```
1 template<typename T, typename PT>
2 void f_t(T &x, T& x_t, const PT &p, const PT &p_t, T &r, T &r_t);
3
4 template<typename T, typename PT>
5 void dfdx_t(T &x, T &x_t, const PT &, const PT &, T &drdx, T& drdx_t);
6
7 template<typename T, typename PT>
8 void newton_t(T &x, T &x_t, const T &p, const T &p_t, const PT &eps, const unsigned
  int maxit) {
9     unsigned int it=0;
10    T y,y_t;
11    f_t(x,x_t,p,p_t,y,y_t);
12    do {
13        T dydx,dydx_t;
14        dfdx_t(x,x_t,p,p_t,dydx,dydx_t);
15        x_t-=y_t/dydx-y*dydx_t/pow(dydx,2);
16        x-=y/dydx;
17        f_t(x,x_t,p,p_t,y,y_t);
18        if (++it==maxit) break;
19    } while(fabs(y)>eps);
20 }
```

- ▶ association of tangents by address
- ▶ vector tangent mode
- ▶ assignment-level adjoint code
- ▶ lower-precision tangents

# Summary

## Recall

Sigmoidal Smoothing  
Newton's Method

## Tangent Code Generation Rules

## Examples

Tangent Straight-Line Code  
Tangent Intraprocedural Code  
Tangent Interprocedural Code