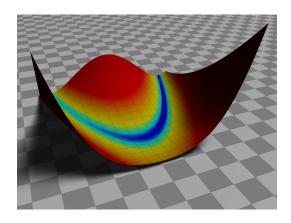
# Direct/Adjoint Methods

## Lecture 11



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## Outline

Analytic Sensitivity Equations

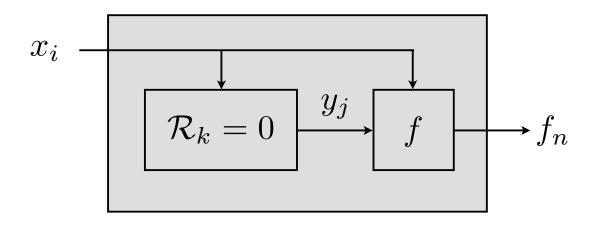
Direct/Adjoint

 $x_i$ : design variables

 $y_j$ : state variables

 $\mathcal{R}_k$  : residuals

 $f_n$ : outputs (objectives and constraints)



Our end goal is to get

$$\frac{df_n}{dx_i}$$

for all i and n.

$$f_n = f(x_i, y_j(x_i))$$

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} + \frac{\partial f_n}{\partial y_j} \frac{dy_j}{dx_i}$$

$$\mathcal{R}(x_i, y_j(x_i)) = 0$$

$$\frac{d\mathcal{R}_k}{dx_i} = \frac{\partial \mathcal{R}_k}{\partial x_i} + \frac{\partial \mathcal{R}_k}{\partial y_j} \frac{dy_j}{dx_i} = 0$$

## Two equations:

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} + \frac{\partial f_n}{\partial y_j} \left[ \frac{dy_j}{dx_i} \right]$$

$$\frac{d\mathcal{R}_k}{dx_i} = \frac{\partial \mathcal{R}_k}{\partial x_i} + \frac{\partial \mathcal{R}_k}{\partial y_j} \left[ \frac{dy_j}{dx_i} \right] = 0$$

## Rearrange second equation:

$$\frac{\partial \mathcal{R}_k}{\partial y_j} \frac{dy_j}{dx_i} = -\frac{\partial \mathcal{R}_k}{\partial x_i}$$

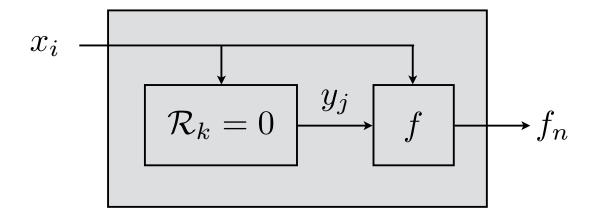
Sub into first:

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} - \frac{\partial f_n}{\partial y_j} \left[ \frac{\partial \mathcal{R}_k}{\partial y_j} \right]^{-1} \frac{\partial \mathcal{R}_k}{\partial x_i}$$

## **Analytic Sensitivity Equations**

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} - \frac{\partial f_n}{\partial y_j} \left[ \frac{\partial \mathcal{R}_k}{\partial y_j} \right]^{-1} \frac{\partial \mathcal{R}_k}{\partial x_i}$$

- Can get total derivatives from partial derivatives that are much more easily obtained.
- We don't actually invert a matrix. We often don't even store the factorization.
- Order of operations is extremely important (more on this next).



Two ways to solve. Partial derivatives are always the same, but order of operations is not.

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} - \underbrace{\frac{\partial f_n}{\partial y_j}}_{\Psi} \underbrace{\left[\frac{\partial \mathcal{R}_k}{\partial y_j}\right]^{-1}}_{-1} \underbrace{\frac{\partial \mathcal{R}_k}{\partial x_i}}_{\Psi}$$

Direct method:

$$\frac{\partial \mathcal{R}_k}{\partial y_j} \Phi_j = -\frac{\partial \mathcal{R}_k}{\partial x_i}$$

then:

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} + \frac{\partial f_n}{\partial y_j} \Phi_j$$

One linear solve for each input  $x_i$ , but can reuse for all outputs  $f_n$ 

Adjoint method:

$$\left[\frac{\partial \mathcal{R}_k}{\partial y_j}\right]^T \Psi_k = -\frac{\partial f_n}{\partial y_j}.$$

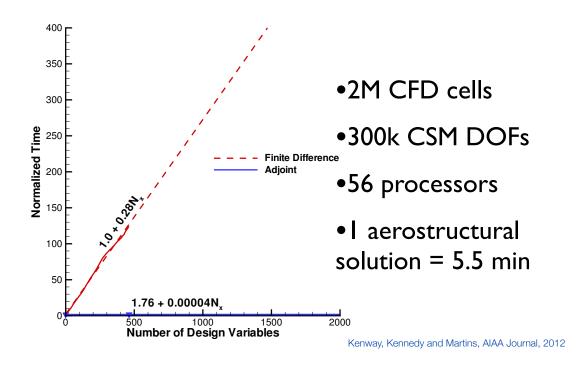
then

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} + \Psi_k^T \frac{d\mathcal{R}_k}{dx_i}$$

One linear solve for each output  $f_n$ , but can reuse for all inputs  $x_i$ 

Step	Direct	Adjoint
Matrix Factorization	same	same
Back-solve	$N_x$ times	$N_f$ times
Multiplication	same	same

Important implication: For the adjoint method, computing gradients is practically independent of the number of design variables.



## Example: Finite Element Analysis

Force-displacment relationship:

$$F = Ku$$

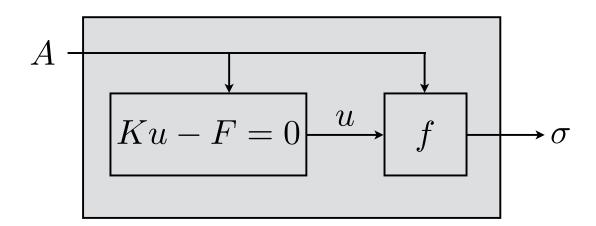
Residual form:

$$\mathcal{R}(u) = Ku - F = 0$$

Stress:

$$\sigma = Su$$

Can change cross-sectional areas of truss.



 $x_i$ : design variables

 $y_j$ : state variables

 $\mathcal{R}_k$  : residuals

 $f_n$ : outputs (objectives and constraints)

 $A: {\it design \ variables \ (cross-sectional \ areas)}$ 

 $y_j$ : state variables

 $\mathcal{R}_k$  : residuals

 $f_n$ : outputs (objectives and constraints)

A: design variables (cross-sectional areas)

u: state variables (deflections)

 $\mathcal{R}_k$ : residuals

 $f_n$ : outputs (objectives and constraints)

A: design variables (cross-sectional areas)

u: state variables (deflections)

Ku - F = 0: residuals (stiffness relationship)

 $f_n$ : outputs (objectives and constraints)

 $A: {\sf design\ variables\ (cross-sectional\ areas)}$ 

u: state variables (deflections)

Ku - F = 0: residuals (stiffness relationship)

 $\sigma$  : outputs (stress)

#### Partial derivatives:

$$\frac{\partial f}{\partial x} =$$

$$\frac{\partial f}{\partial y} =$$

$$\frac{\partial \mathcal{R}}{\partial x} =$$

$$\frac{\partial \mathcal{R}}{\partial y} =$$

Partial derivatives:

$$\frac{\partial f}{\partial x} = \frac{\partial \sigma}{\partial A} = 0$$

$$\frac{\partial f}{\partial y}$$

$$\frac{\partial \mathcal{R}}{\partial x}$$

$$\frac{\partial \mathcal{R}}{\partial y}$$

## Partial derivatives:

$$\frac{\partial f}{\partial x} = \frac{\partial \sigma}{\partial A} = 0$$

$$\frac{\partial f}{\partial y} = \frac{\partial \sigma}{\partial u} = S$$

$$\frac{\partial \mathcal{R}}{\partial x}$$

$$\frac{\partial \mathcal{R}}{\partial y}$$

Partial derivatives:

$$\frac{\partial f}{\partial x} = \frac{\partial \sigma}{\partial A} = 0$$

$$\frac{\partial f}{\partial y} = \frac{\partial \sigma}{\partial u} = S$$

$$\frac{\partial \mathcal{R}}{\partial x} = \frac{\partial \mathcal{R}}{\partial A} = \left[\frac{\partial K}{\partial A}\right] u$$

$$\frac{\partial \mathcal{R}}{\partial y}$$

#### Partial derivatives:

$$\frac{\partial f}{\partial x} = \frac{\partial \sigma}{\partial A} = 0$$

$$\frac{\partial f}{\partial y} = \frac{\partial \sigma}{\partial u} = S$$

$$\frac{\partial \mathcal{R}}{\partial x} = \frac{\partial \mathcal{R}}{\partial A} = \left[\frac{\partial K}{\partial A}\right] u$$

$$\frac{\partial \mathcal{R}}{\partial y} = \frac{\partial \mathcal{R}}{\partial u} = K$$

$$\frac{df_n}{dx_i} = \frac{\partial f_n}{\partial x_i} - \frac{\partial f_n}{\partial y_j} \left[ \frac{\partial \mathcal{R}_k}{\partial y_j} \right]^{-1} \frac{\partial \mathcal{R}_k}{\partial x_i}$$

$$\frac{d\sigma}{dA} = \frac{\partial\sigma}{\partial A} - \frac{\partial\sigma}{\partial u} \left[ \frac{\partial\mathcal{R}_k}{\partial u} \right]^{-1} \frac{\partial\mathcal{R}_k}{\partial A}$$

$$\frac{d\sigma}{dA_i} = -SK^{-1} \left[ \frac{\partial K}{\partial A_i} \right] u$$