

# Sensitivity

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- Definition
  - Rate of change of a dependent quantity with respect to an independent quantity
- Numerical applications
  - Critical in gradient based optimization
  - Used to construct surrogate models
  - Useful in modeling uncertainties

$f(p, g(p)) = \{f_1 \quad f_2 \quad \dots \quad f_l\}^T : \begin{cases} \text{explicitly dependent on a scalar parameter } p \text{ and} \\ \text{implicitly on it via a vector function } g = \{g_1 \quad g_2 \quad \dots \quad g_m\}^T \end{cases}$

$$f' \equiv \frac{df}{dp} \equiv \frac{\partial f}{\partial p} + (\nabla_g f) \frac{\partial g}{\partial p} \equiv \nabla_p f + (\nabla_g f) g'$$

$$\text{If } p = \{p_1 \quad p_2 \quad \dots \quad p_m\}^T \rightarrow f^{(k)\prime} \equiv \nabla_{p_k} f + (\nabla_g f) g^{(k)}$$

# Sensitivity of Spatial Functions

- Assumption: spatial variables ( $x, y, z$ ) are independent of the parameter  $p$ , spatial domain is unaffected by  $p$

$$\left( \frac{\partial f}{\partial x} \right)' = \frac{\partial(f')}{\partial x} \rightarrow \nabla(f') = (\nabla f)'$$

$$\nabla_p f = \begin{Bmatrix} \frac{\partial f_1}{\partial p} & \frac{\partial f_2}{\partial p} & \dots & \frac{\partial f_l}{\partial p} \end{Bmatrix}^T : \text{partial derivative}$$

$$\nabla_g f = \begin{Bmatrix} \frac{\partial f_1}{\partial g_1} & \frac{\partial f_1}{\partial g_2} & \dots & \frac{\partial f_1}{\partial g_m} \\ \frac{\partial f_2}{\partial g_1} & \frac{\partial f_2}{\partial g_2} & \dots & \frac{\partial f_2}{\partial g_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_l}{\partial g_1} & \frac{\partial f_l}{\partial g_2} & \dots & \frac{\partial f_l}{\partial g_m} \end{Bmatrix} : \text{functional partial derivative}$$

# Sensitivity of Algebraic Systems

- Sensitivity of solution

$$Au = f \xrightarrow{(Au)' = A'u + Au'} Au' = f' - A'u \rightarrow Au^{(k)'} = f^{(k)'} - A^{(k)'}u$$

- Sensitivity of performance measures

$$\varphi(p, u(p)) \rightarrow \varphi' = \nabla_p \varphi + (\nabla_u \varphi) u' \rightarrow \varphi^{(k)'} = \nabla_{p_k} \varphi + (\nabla_u \varphi) u^{(k)'}$$

- Sensitivity of performance measures via adjoint

increased effort to compute  $u^{(k)'}$  when  $k$  becomes large !!!

$$\varphi^{(k)'} = \nabla_{p_k} \varphi + (\nabla_u \varphi) u^{(k)'} \xrightarrow{A^T \lambda = (\nabla_u \varphi)^T} \varphi^{(k)'} = \nabla_{p_k} \varphi + (\lambda^T A) u^{(k)'} \rightarrow \varphi^{(k)'} = \nabla_{p_k} \varphi + \lambda^T (f^{(k)'} - A^{(k)'}u)$$

- Sensitivity of performance measures via Lagrangian

$$L = \varphi + \lambda^T (f - Au) \xrightarrow{\nabla_p \lambda = \nabla_p u = 0} \nabla_p L = \nabla_p \varphi + \lambda^T (f' - A'u) = \varphi' \rightarrow \varphi^{(k)'} = \nabla_{p_k} L$$

# Size Sensitivity of BVP

- Assumption:  $\Omega$  does not depend on  $p$
- Sensitivity of  $u$  with respect to a parameter  $p$

$$\begin{aligned} \text{strong form } & \begin{cases} -\nabla \cdot k \nabla u + cu = f & \text{in } \Omega \\ u = \hat{u} & \text{in } \Gamma_D \\ -k \nabla u \cdot \hat{n} = q & \text{on } \Gamma_N \end{cases} \\ \text{weak form } & \begin{cases} \text{Find } u \in H^1 \text{ such that} \\ \int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} fv d\Omega - \int_{\Gamma_N} vq d\Gamma \quad \forall v \in H_0^1 \end{cases} \end{aligned}$$

- For  $s$  a non-negative integer and  $\Omega \subset \mathbb{R}^n$ , the Sobolev space  $H^s(\Omega)$  contains  $L^2$  functions whose weak derivatives of order up to  $s$  are also  $L^2$ . The inner product in  $H^s(\Omega)$  is

$$\langle f, g \rangle = \int_{\Omega} f(x) \bar{g}(x) dx + \int_{\Omega} Df \cdot D\bar{g}(x) dx + \cdots + \int_{\Omega} D^s f \cdot D^s \bar{g}(x) dx$$

$$\int_{\Omega} [-\nabla \cdot k \nabla u + cu - f] v d\Omega = 0$$

$$\int_{\Omega} [-v \nabla \cdot k \nabla u + cuv - fv] d\Omega = 0 \xrightarrow{\nabla \cdot (vk \nabla u) = v \nabla \cdot (k \nabla u) + \nabla v \cdot k \nabla u}$$

$$\int_{\Omega} [-\nabla \cdot (vk \nabla u) + \nabla v \cdot k \nabla u + cuv - fv] d\Omega = 0 \xrightarrow{\text{divergence theorem: } \int_{\Omega} \nabla \cdot (h) d\Omega = \int_{\partial\Omega} h \cdot n d\Gamma}$$

$$\int_{\Omega} [\nabla v \cdot k \nabla u + cuv - fv] d\Omega - \int_{\Gamma_N} (vk \nabla u) \cdot n d\Gamma = 0$$

$$\int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega - \int_{\Omega} fv d\Omega = \int_{\Gamma_N} (vk \nabla u) \cdot n d\Gamma$$

$$\int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} fv d\Omega - \int_{\Gamma_N} v q d\Gamma$$

Find  $u$  where  $u = \hat{u}$  on  $\Gamma_D$  and

$$\int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} fv d\Omega - \int_{\Gamma_N} v q d\Gamma \quad \forall v, v = 0 \text{ on } \Gamma_D$$

$$H^1 = \left\{ w \mid w, \nabla w \in C^1, w = \hat{u} \text{ on } \Gamma_D \right\}, H_0^1 = \left\{ w \mid w, \nabla w \in C^1, w = 0 \text{ on } \Gamma_D \right\}$$

# Sensitivity of Solution

$$\left. \begin{array}{l} -\nabla \cdot k \nabla u + cu = f \quad \text{in } \Omega \\ u = \hat{u} \quad \text{in } \Gamma_D \\ -k \nabla u \cdot \hat{n} = q \quad \text{on } \Gamma_N \end{array} \right\} \xrightarrow{\text{differentiate}} \begin{cases} -\nabla \cdot k \nabla u' - \nabla \cdot k' \nabla u + cu' + c'u = f' \quad \text{in } \Omega \\ \rightarrow -\nabla \cdot k \nabla u' + cu' = (f' + \nabla \cdot k' \nabla u - c'u) \quad \text{in } \Omega \\ u' = 0 \quad \text{in } \Gamma_D \\ -k \nabla u' \cdot \hat{n} - k' \nabla u \cdot \hat{n} = q' \quad \text{in } \Gamma_N \\ \rightarrow -k \nabla u' \cdot \hat{n} = k' \nabla u \cdot \hat{n} + q' \quad \text{on } \Gamma_N \end{cases}$$

Find  $u \in H^1$  such that

$$\int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} fvd\Omega - \int_{\Gamma_N} vqd\Gamma \quad \forall v \in H_0^1 \quad \xrightarrow{\text{differentiate}}$$

$$\int_{\Omega} [\nabla v \cdot k' \nabla u + \nabla v \cdot k \nabla u' + c'uv + cu'v] d\Omega = \int_{\Omega} f'vd\Omega - \int_{\Gamma_N} vq'd\Gamma$$

Find  $u' \in H_0^1$  such that

$$\int_{\Omega} [\nabla v \cdot k \nabla u' + cu'v] d\Omega = \int_{\Omega} f'vd\Omega - \int_{\Omega} [\nabla v \cdot k' \nabla u + c'uv] d\Omega - \int_{\Gamma_N} vq'd\Gamma \quad \forall v \in H_0^1$$

# Example: 1-D tension bar

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- Consider a 1-D problem that governs the deflection  $u(x)$  of a tensile bar (of possibly varying cross-section and Young's modulus) hanging due to its own weight, and fixed at  $x=0$  and free at  $x=L$
- Continuum sensitivity
  - Let the parameter  $p$  be the cross-sectional area  $A$ , i.e., a size parameter
  - Let the parameter  $p$  be the Young's modulus  $E$ , i.e., a material parameter

$$-\frac{d}{dx} \left( EA \frac{du}{dx} \right) = \rho g A, \quad 0 < x < L, \quad u(0) = 0, \quad \left. \frac{du}{dx} \right|_{x=L} = 0$$

$$-\frac{d}{dx} \left( EA \frac{du}{dx} \right) = \rho g A, \quad 0 < x < L, \quad u(0) = 0, \quad \left. \frac{du}{dx} \right|_{x=L} = 0$$

$$\rightarrow \int_0^L EA \frac{dv}{dx} \frac{du}{dx} dx = \int_0^L \rho g A v dx, \forall v \in H_0^1([0, L])$$

$\xrightarrow{\text{differentiate}}$

$$\begin{cases} \text{w.r.t. } A : -\frac{d}{dx} \left( EA \frac{du'}{dx} \right) = \rho g + \frac{d}{dx} \left( E \frac{du}{dx} \right), \quad u'(0) = 0, \quad \left. \frac{du'}{dx} \right|_{x=L} = 0 \\ \text{w.r.t. } E : -\frac{d}{dx} \left( EA \frac{du'}{dx} \right) = \frac{d}{dx} \left( A \frac{du}{dx} \right), \quad u'(0) = 0, \quad \left. \frac{du'}{dx} \right|_{x=L} = 0 \end{cases}$$

$$E = 1, \quad A(x) = 1, \quad \rho g = 1 \rightarrow -\frac{d^2 u}{dx^2} = 1 \rightarrow \frac{du}{dx} = -x + c_1 \rightarrow u(x) = -\frac{x^2}{2} + Lx$$

$$\begin{cases} \text{w.r.t. } A : -\frac{d}{dx} \left( \frac{du'}{dx} \right) = 1 + \frac{d}{dx} \left( \frac{du}{dx} \right) = 2, \quad u'(0) = 0, \quad \left. \frac{du'}{dx} \right|_{x=L} = 0 \rightarrow \frac{du'}{dx} = -2x + c_1 \rightarrow u' = -x^2 + 2Lx \\ \text{w.r.t. } E : -\frac{d}{dx} \left( \frac{du'}{dx} \right) = 1, \quad u'(0) = 0, \quad \left. \frac{du'}{dx} \right|_{x=L} = 0 \rightarrow \frac{du'}{dx} = -x + c_1 \rightarrow u' = -\frac{x^2}{2} + Lx \end{cases}$$

# Sensitivity of Performance Measures

$$\varphi = \int_{\Omega} g(u, \nabla u; p) d\Omega \Rightarrow \begin{cases} \varphi = \frac{1}{L} \int_0^L u(x) dx : \text{average deflection} \\ \varphi = \frac{1}{L} \int_0^L E \frac{du}{dx} dx : \text{average stress} \\ \varphi = \frac{1}{meas(\Omega)} \int_{\Omega} u d\Omega : \text{average temperature} \\ \varphi = \int_{\Omega} [u^2 + (\nabla u)^T \nabla u] d\Omega \\ \varphi = - \int_{\Gamma} k \nabla u \cdot \hat{n} d\Gamma : \text{flux} \end{cases}$$
$$\rightarrow \varphi' = \int_{\Omega} [\nabla_p g + (\nabla_u g u' + \nabla_{\nabla u} g \nabla u')] d\Omega$$

# Example

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$$\varphi = \int_{\Omega} \left[ pu^2 + (\nabla u)^T \nabla u \right] d\Omega$$

$p$ : independent parameter

$$\left. \begin{array}{l} \nabla_p g = u^2 \\ \nabla_u g = 2pu \\ \nabla_{\nabla u} g = 2\nabla u \end{array} \right\} \rightarrow \varphi' = \int_{\Omega} \left[ u^2 + 2puu' + 2(\nabla u)^T \nabla u' \right] d\Omega$$

# Sensitivity of Performance Measures via Adjoint

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$$\begin{aligned}
 & \left\{ \begin{array}{l} \text{Find } u \in H^1 \text{ such that} \\ \int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} f v d\Omega - \int_{\Gamma_N} v q d\Gamma \quad \forall v \in H_0^1 \end{array} \right. \\
 & \left\{ \begin{array}{l} \text{Find } u' \in H_0^1 \text{ such that} \\ \int_{\Omega} [\nabla v \cdot k \nabla u' + cu'v] d\Omega = \int_{\Omega} f' v d\Omega - \int_{\Omega} [\nabla v \cdot k' \nabla u + c'u v] d\Omega - \int_{\Gamma_N} v q' d\Gamma \quad \forall v \in H_0^1 \end{array} \right. \\
 \xrightarrow{\text{Adjoint Weak Form}} & \left\{ \begin{array}{l} \text{Find } \lambda \in H_0^1 \text{ such that} \\ \int_{\Omega} [\nabla v \cdot k \nabla \lambda + c\lambda v] d\Omega = \int_{\Omega} (\nabla_u g v + \nabla_{\nabla u} g \nabla v) d\Omega \quad \forall v \in H_0^1 \end{array} \right. \\
 \xrightarrow{v, u' \in H_0^1} & \int_{\Omega} [\nabla u' \cdot k \nabla \lambda + c\lambda u'] d\Omega = \int_{\Omega} (\nabla_u g u' + \nabla_{\nabla u} g \nabla u') d\Omega \\
 \xrightarrow{v, \lambda \in H_0^1} & \int_{\Omega} [\nabla \lambda \cdot k \nabla u' + cu'\lambda] d\Omega = \int_{\Omega} f' \lambda d\Omega - \int_{\Omega} [\nabla \lambda \cdot k' \nabla u + c'u \lambda] d\Omega - \int_{\Gamma_N} \lambda q' d\Gamma \\
 \rightarrow \varphi' = & \int_{\Omega} [\nabla_p g + (\nabla_u g u' + \nabla_{\nabla u} g \nabla u')] d\Omega \\
 = & \int_{\Omega} \nabla_p g d\Omega + \int_{\Omega} [f' \lambda - (\nabla \lambda \cdot k' \nabla u + c'u \lambda)] d\Omega - \int_{\Gamma_N} \lambda q' d\Gamma
 \end{aligned}$$

# Sensitivity of Performance Measures via Lagrangian

$$L = \underbrace{(\text{performance measure})}_{\varphi} + \underbrace{(\text{weak form: } v \leftrightarrow \lambda)}_{\int_{\Omega} [\nabla v \cdot k \nabla u + c u v] d\Omega = \int_{\Omega} f v d\Omega - \int_{\Gamma_N} v q d\Gamma}$$

$$L = \int_{\Omega} g d\Omega + \int_{\Omega} [f \lambda - (\nabla \lambda \cdot k \nabla u + c u \lambda)] d\Omega - \int_{\Gamma_N} \lambda q d\Gamma$$

$$\nabla_p u = \nabla_p \lambda = 0, \nabla_p f = f', \nabla_p q = q', \nabla_p k = k', \nabla_p c = c'$$

$$\nabla_p L = \int_{\Omega} \nabla_p g d\Omega + \int_{\Omega} [f' \lambda - (\nabla \lambda \cdot k' \nabla u + c' u \lambda)] d\Omega - \int_{\Gamma_N} \lambda q' d\Gamma$$

$$\varphi' = \nabla_p L$$

# Shape Sensitivity of BVP

- Shape parameter  $p$  influence the shape, size and location of  $\Omega$
- Assumption:  $p$  does not influence the coefficients  $k, f, q$
- Sensitivity of  $u$  with respect to a parameter  $p$

strong form 
$$\begin{cases} -\nabla \cdot k \nabla u + cu = f & \text{in } \Omega \\ u = \hat{u} & \text{in } \Gamma_D \\ -k \nabla u \cdot \hat{n} = q & \text{on } \Gamma_N \end{cases}$$

weak form 
$$\begin{cases} \text{Find } u \in H^1 = \{w \mid w = \hat{u} \text{ on } \Gamma_D\} \text{ such that} \\ \int_{\Omega} [\nabla v \cdot k \nabla u + cuv] d\Omega = \int_{\Omega} fv d\Omega - \int_{\Gamma_N} vq d\Gamma \quad \forall v \in H_0^1 = \{w \mid w = 0 \text{ on } \Gamma_D\} \end{cases}$$

# Material to Spatial Domain Transformation

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- Reference or material domain  $\Omega_0$ 
  - Independent of  $p$
- Spatial domain  $\Omega$

$$T(p) : \underbrace{\Omega_0(X, Y, Z)}_{u(X, Y, Z; p)} \rightarrow \underbrace{\Omega(x, y, z)}_{u(x, y, z; p) \rightarrow u}$$

# Spatial and Material Sensitivity (1)

- Spatial sensitivity
  - derivative of the spatial representation  $u$  with respect to  $p$ , where the spatial variables ( $x,y,z$ ) are considered fixed
- Material sensitivity
  - derivative of the material representation  $u(X,Y,Z; p)$  with respect to  $p$ , where the material variables ( $X,Y,Z$ ) are considered fixed

$$u' \equiv \frac{du}{dp} \Big|_{(x,y,z) \text{ fixed}}$$
$$i \equiv \frac{du(X,Y,Z; p)}{dp} \Big|_{(X,Y,Z) \text{ fixed}}$$

# Spatial and Material Sensitivity (2)

compute  $\dot{u}$  directly from  $u$

$$u = u(x; p) = u(x(X, p); p)$$

$$\dot{u} = \frac{du(x(X, p); p)}{dp} \Big|_{X \text{ fixed}} = \frac{du(x; p)}{dp} \Big|_{x \text{ fixed}} + \frac{\partial u}{\partial x} \frac{dx}{dp} = u' + \frac{\partial u}{\partial x} \frac{dx}{dp}$$

$$3D: \dot{u} = u' + \left\{ \frac{du}{dx} \quad \frac{du}{dy} \quad \frac{du}{dz} \right\} \left\{ \frac{dx}{dp} \quad \frac{dy}{dp} \quad \frac{dz}{dp} \right\}^T$$

$$V = \left\{ \frac{dx}{dp} \quad \frac{dy}{dp} \quad \frac{dz}{dp} \right\}^T : \text{design velocity}$$

$$\dot{u} = u' + \nabla u \cdot V$$

$$u_V \equiv \nabla u \cdot V: \text{projected gradient}$$

$$\dot{u} = u' + u_V: \text{relating spatial and material sensitivities}$$

# Sensitivity of Spatial Gradient

$$\text{spatial sensitivity: } (\nabla f)' \equiv \frac{d(\nabla f)}{dp} \Big|_{x \text{ fixed}} = \nabla \frac{df}{dp} \Big|_{x \text{ fixed}} \equiv \nabla f'$$

•

$$\begin{aligned}\text{material sensitivity: } (\nabla f)' &= (\nabla f)' + \underbrace{(\nabla_H^2 f) V}_{f_{ij}} = \nabla f' + (\nabla_H^2 f) V \\ &= \dot{\nabla f} - (\nabla V) \nabla f\end{aligned}$$

$$\dot{\nabla f} = \nabla(f' + \nabla f \cdot V) = \nabla f' + \nabla(\nabla f \cdot V): \text{ gradient of material sensitivity}$$

$$\begin{aligned}\nabla(\nabla f \cdot V) &= (f_{,i} V_i)_{,j} = (f_{,ij} V_i + f_{,i} V_{i,j}) = (\nabla_H^2 f) V + (\nabla V) \nabla f \\ \rightarrow \dot{\nabla f} &= \nabla f' + (\nabla_H^2 f) V + (\nabla V) \nabla f\end{aligned}$$

# Example

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- Find the material sensitivity of (1) spatial variable and (2) spatial gradient

$$\Omega_0 = [0 \quad 1] \text{ with } x = X(1 + p)$$

$$u = 1 + x^2 p + x e^p$$

# Example: Solution (1)

$$\Omega_0 = \begin{bmatrix} 0 & 1 \end{bmatrix} \text{ with } x = X(1+p)$$

$$u = 1 + x^2 p + x e^p \xleftarrow{x=X(1+p)} u(X; p) = 1 + X^2 (1+p)^2 p + X(1+p)e^p$$

$$u' \equiv \frac{du}{dp} \Bigg|_{(x,y,z) \text{ fixed}} = x^2 + x e^p$$

[1] material representation  $\rightarrow$  differentiate w.r.t.  $X$   $\rightarrow$  spatial representation

$$\dot{u}(X; p) = X^2 \left[ 2(1+p)p + (1+p)^2 \right] + X \left[ e^p + (1+p)e^p \right]$$

$$\xrightarrow{X=\frac{x}{1+p}} \dot{u} = x^2 \left[ \frac{2p}{1+p} + 1 \right] + x e^p \left[ \frac{1}{1+p} + 1 \right]$$

[2] using design velocity

$$V(X; p) = x_{,p} = X = \frac{x}{1+p}$$

$$\nabla u(x; p) = 2xp + e^p$$

$$\dot{u} = u' + \nabla u \cdot V = \left( x^2 + x e^p \right) + \left( 2xp + e^p \right) \frac{x}{1+p}$$

# Example: Solution (2)

$$\Omega_0 = \begin{bmatrix} 0 & 1 \end{bmatrix} \text{ with } x = X(1+p)$$

$$u = 1 + x^2 p + x e^p \xleftarrow{x=X(1+p)} u(X; p) = 1 + X^2 (1+p)^2 p + X(1+p)e^p$$

$$\nabla u(x; p) = 2xp + e^p \rightarrow (\nabla u)' = 2x + e^p$$

$$u' \equiv \frac{du}{dp} \Bigg|_{(x,y,z) \text{ fixed}} = x^2 + xe^p \rightarrow \nabla(u') = 2x + e^p$$

$$[1] \quad \begin{cases} \nabla u(x; p) = 2xp + e^p \xleftarrow{x=X(1+p)} \nabla u(X; p) = 2X(1+p)p + e^p \\ \dot{(\nabla u)}(X; p) = 2Xp + 2X(1+p) + e^p \xrightarrow{X=\frac{x}{1+p}} \dot{(\nabla u)}(x; p) = 2x + \frac{2xp}{1+p} + e^p \end{cases}$$

$$[2] \quad \begin{cases} \dot{u} = u' + \nabla u \cdot V = (x^2 + xe^p) + \frac{(2xp + e^p)x}{1+p} \rightarrow \nabla \dot{u} = (2x + e^p) + \frac{4xp + e^p}{1+p} \\ \dot{(\nabla u)} = \nabla \dot{u} - (\nabla V) \nabla u = (2x + e^p) + \frac{4xp + e^p}{1+p} - \left( \frac{1}{1+p} \right) (2xp + e^p) = 2x + e^p + \frac{2xp}{1+p} \end{cases}$$

# Volume Integral Transformation

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- Sensitivity of a domain integral: derivative w.r.t.  $p$
- Spatial domain  $\Omega$  is dependent on  $p \rightarrow$  change the domain of integration to the material domain  $\Omega_0$  that is independent of  $p$

$$dx = \frac{\partial x}{\partial X} dX + \frac{\partial x}{\partial Y} dY + \frac{\partial x}{\partial Z} dZ \rightarrow \begin{Bmatrix} dx \\ dy \\ dz \end{Bmatrix} = \begin{bmatrix} \frac{\partial x}{\partial X} & \frac{\partial x}{\partial Y} & \frac{\partial x}{\partial Z} \\ \frac{\partial y}{\partial X} & \frac{\partial y}{\partial Y} & \frac{\partial y}{\partial Z} \\ \frac{\partial z}{\partial X} & \frac{\partial z}{\partial Y} & \frac{\partial z}{\partial Z} \end{bmatrix} \begin{Bmatrix} dX \\ dY \\ dZ \end{Bmatrix} \rightarrow \begin{Bmatrix} dx \\ dy \\ dz \end{Bmatrix} = J(X; p) \begin{Bmatrix} dX \\ dY \\ dZ \end{Bmatrix}$$

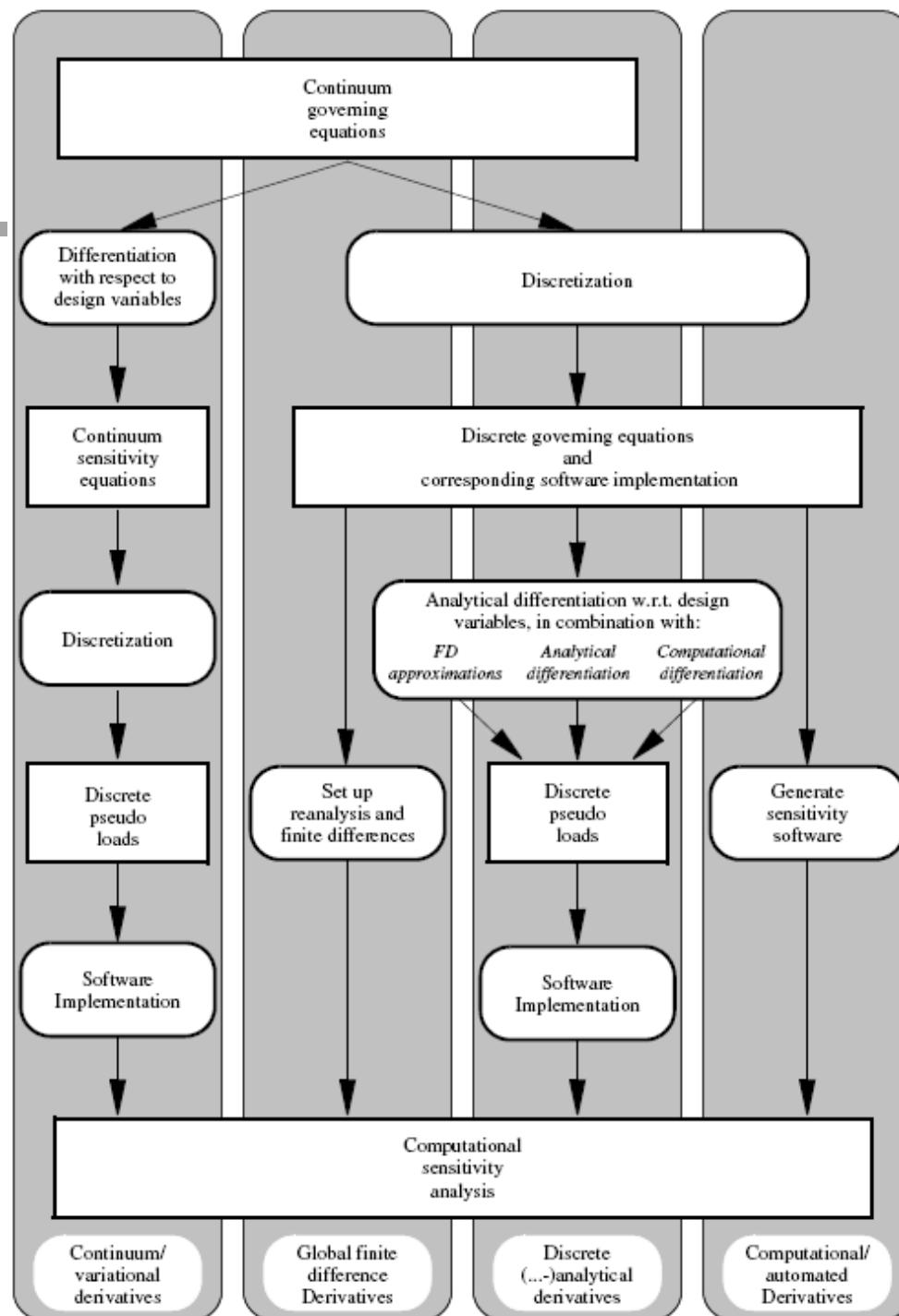
$$J(X; p) \equiv \frac{\partial(x, y, z)}{\partial(X, Y, Z)} \equiv \begin{bmatrix} \frac{\partial x}{\partial X} & \frac{\partial x}{\partial Y} & \frac{\partial x}{\partial Z} \\ \frac{\partial y}{\partial X} & \frac{\partial y}{\partial Y} & \frac{\partial y}{\partial Z} \\ \frac{\partial z}{\partial X} & \frac{\partial z}{\partial Y} & \frac{\partial z}{\partial Z} \end{bmatrix} : \text{ Jacobian}$$

$$dxdydz = \underbrace{|J(X; p)|}_{\det J(X; p)} dXdYdZ \rightarrow d\Omega = |J(X; p)| d\Omega_0$$

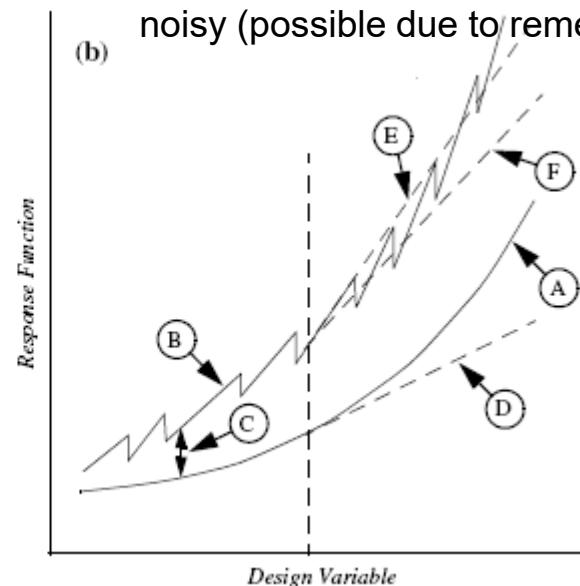
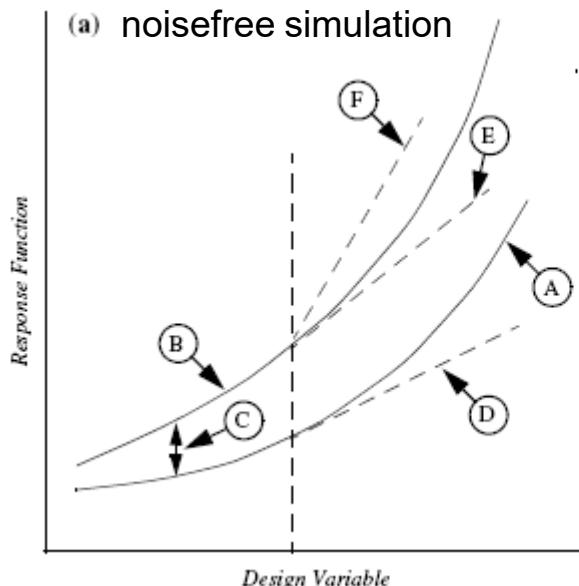
$$\int_{\Omega} f d\Omega = \int_{\Omega_0} f(X; p) |J(X; p)| d\Omega_0 \rightarrow \frac{d \left( \int_{\Omega} f d\Omega \right)}{dp}$$

# Overview

F. Keulen, R.T. Haftka, N.H. Kim,  
Review on options for structural  
design sensitivity analysis.  
Part 1: Linear systems, Comput.  
Methods Appl. Mech. Engrg. 194  
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- Categories
  - Overall finite differences
  - Direct derivatives
  - Continuum derivatives
  - Computational or automatic differentiation
- Criteria
  - Accuracy
  - Consistency
  - Computational cost and implementation effort



- A: exact solution of the governing continuum equations
- B: computational counterpart
- C: modeling error
- D: exact derivatives
- E: consistent derivatives
- F: non-exact and non-consistent computed derivatives

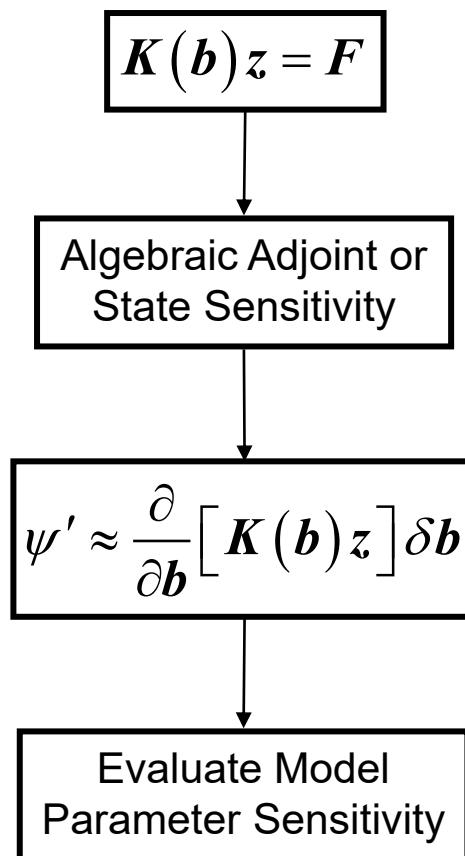
# Approaches to Design Sensitivity Analysis

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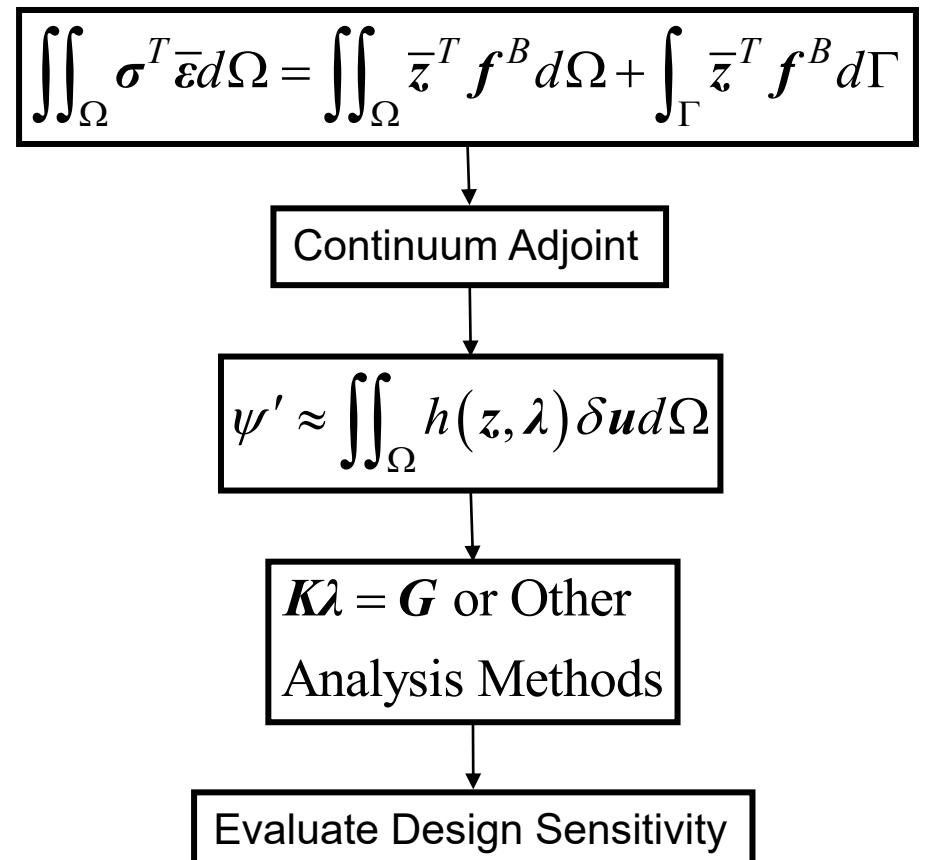
- Approximation approach
  - Forward finite difference
  - Central finite difference
- Discrete approach
  - Semi-analytical method
  - Analytical method
- Continuum approach
  - Continuum-discrete method
  - Continuum-continuum method

# Design Sensitivity Analysis Method

- Discrete Model



- Continuum Model



# Sensitivity of Discrete Systems

- Sensitivity: derivatives of response w.r.t. a design variable
  - Major computational cost of the optimization process
  - Statistical variation in the response of the structure
  - Discretization → differentiate (ch.7)
  - Differentiate the continuum equations → discretization (ch.8)

spatial discretization of the continuum equations



algebraic equations (static response)  
algebraic eigenvalue problems (vibration/buckling)  
ordinary differential equations (transient response)

# Finite Difference Approximation

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- Popular, computationally expensive, easy to implement, accuracy problem
  - Forward-difference approximation

$$u(x + \Delta x) = u(x) + \Delta x u'(x) + \frac{(\Delta x)^2}{2!} u''(x) + \dots \rightarrow u'(x) = \frac{u(x + \Delta x) - u(x)}{\Delta x} - \frac{\Delta x}{2} u''(x) - \dots$$
$$\frac{\Delta u}{\Delta x} = \frac{u(x + \Delta x) - u(x)}{\Delta x} + O(\Delta x)$$

- Central-difference approximation

$$u(x + \Delta x) = u(x) + \Delta x u'(x) + \frac{(\Delta x)^2}{2!} u''(x) + \frac{(\Delta x)^3}{3!} u'''(x) + \dots \quad \left. \right\}$$
$$u(x - \Delta x) = u(x) - \Delta x u'(x) + \frac{(\Delta x)^2}{2!} u''(x) - \frac{(\Delta x)^3}{3!} u'''(x) + \dots \quad \left. \right\}$$
$$\rightarrow u'(x) = \frac{u(x + \Delta x) - u(x - \Delta x)}{2\Delta x} - \frac{(\Delta x)^2}{6} u'''(x) + \dots$$
$$\frac{\Delta u}{\Delta x} = \frac{u(x + \Delta x) - u(x - \Delta x)}{2\Delta x} + O[(\Delta x)^2]$$

# Accuracy and Step Size

- Truncation error
  - Due to neglected terms in the Taylor series expansion

$$u(x + \Delta x) = u(x) + \Delta x \frac{du}{dx}(x) + \frac{(\Delta x)^2}{2!} \frac{d^2 u}{dx^2}(x + \varsigma \Delta x), \quad 0 \leq \varsigma \leq 1$$

$$\left\{ \begin{array}{l} \text{forward difference: } e_T(\Delta x) = \frac{\Delta x}{2} \frac{d^2 u}{dx^2}(x + \varsigma \Delta x) = \frac{\Delta x}{2} |s_b|, \quad 0 \leq \varsigma \leq 1 \\ \quad s_b : \text{bound on the second derivative in } [x, x + \Delta x] \\ \text{central difference: } e_T(\Delta x) = \frac{(\Delta x)^2}{6} \frac{d^3 u}{dx^3}(x + \varsigma \Delta x), \quad -1 \leq \varsigma \leq 1 \end{array} \right.$$

- Condition error
  - Round-off error, ill-conditioned numerical process

$$\text{forward-difference: } e_C(\Delta x) = \frac{2}{\Delta x} \varepsilon_u, \quad \varepsilon_u: \text{absolute error bound } (10^{-16})$$

# Optimal Step Size for Forward Difference

---

- Formula:  $\frac{\Delta u}{\Delta x} = \frac{u(x + \Delta x) - u(x)}{\Delta x}$
- Bound for total error: step size dilemma

$$e = \frac{\Delta x}{2} |s_b| + \frac{2}{\Delta x} \varepsilon_u$$

- Optimal step size

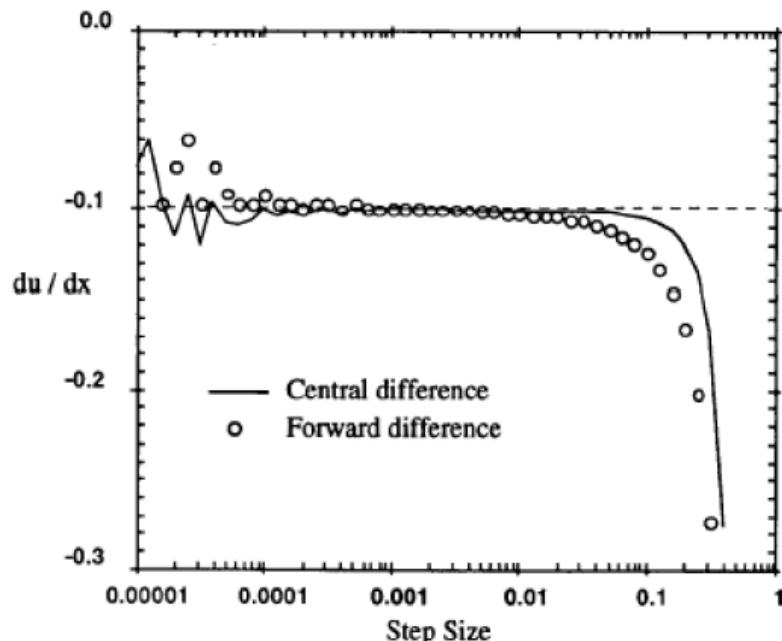
$$\frac{de}{d(\Delta x)} = \frac{|s_b|}{2} - \frac{2}{(\Delta x)^2} \varepsilon_u = 0 \rightarrow (\Delta x)_{opt} = 2 \sqrt{\frac{\varepsilon_u}{|s_b|}}$$

# Example 7.1.1

$$\begin{aligned} \left. \begin{aligned} 101u + xv = 10 \\ xu + 100v = 10 \end{aligned} \right\} \rightarrow u = \frac{\begin{vmatrix} 10 & x \\ 10 & 100 \end{vmatrix}}{\begin{vmatrix} 101 & x \\ x & 100 \end{vmatrix}} = \frac{-10x + 1000}{10100 - x^2} \end{aligned}$$

→ derivative @  $x = 100$

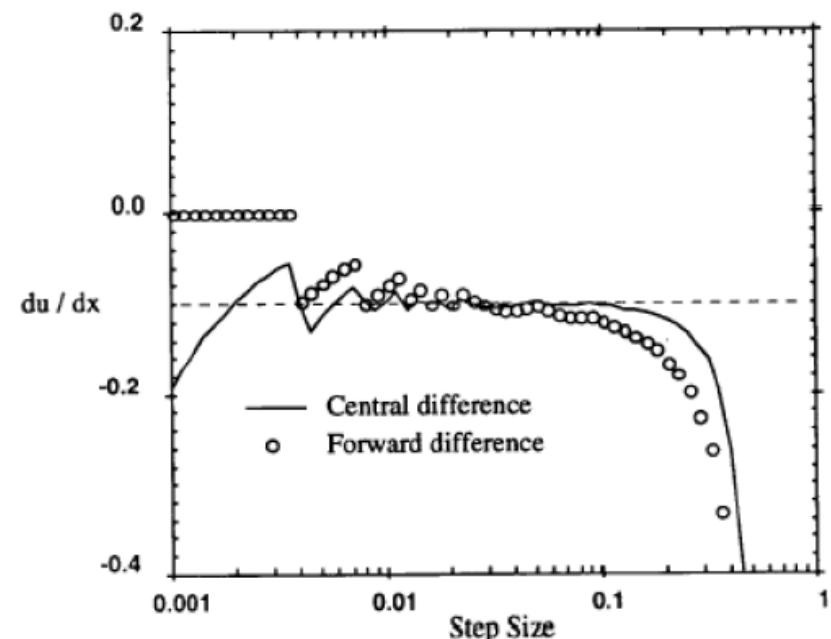
$$\frac{du}{dx} = \frac{30x^2 - 2000x - 101000}{(10100 - x^2)^2}$$



with poorer conditioning

$$\begin{aligned} 10001u + xv = 1000 \\ xu + 10000v = 1000 \end{aligned} \left. \right\}$$

→ derivative @  $x = 10,000$



# Effect of derivative magnitude

---

- Large derivatives are easier to estimate than small ones
- What does it mean that derivative is large?
- Accuracy measure
  - Logarithmic derivative: percentage change in  $u$  due to a percent change in  $x$

$$\frac{d_l u}{dx} = \frac{d(\log u)}{d(\log x)} = \frac{du/u}{dx/x} = \frac{du}{dx} \frac{x}{u} \xrightarrow{\text{change in sign}} \frac{d_{lm} u}{dx} = \frac{du/u_t}{dx/x_t}$$

$$\begin{cases} \frac{d_l u}{dx} > 1: \text{the derivative to be large} \\ \frac{d_l u}{dx} < 1: \text{the derivative to be small} \end{cases} \rightarrow \text{difficult to evaluate it accurately using FDM}$$

# Example: $y = 10 + (x - 5)^2$

- compare the accuracy of forward difference derivatives with a step size of one at  $x=10$  and  $x=6$ 
  - What does it mean to have a logarithmic derivative equal to one?

$$y = 10 + (x - 5)^2 \rightarrow \left\{ \begin{array}{l} \text{exact: } \frac{dy}{dx} = 2(x - 5) \\ \text{forward difference: } \frac{\Delta y}{\Delta x} = \frac{y(x_0 + 1) - y(x_0)}{1} \end{array} \right\} \rightarrow \frac{d_l y}{dx} \Big|_{x=x_0} = \frac{dy}{dx} \frac{x_0}{y_0}$$

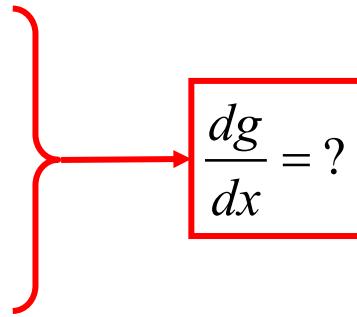
$$@x = 10: \left\{ \begin{array}{l} \text{exact: } \frac{dy}{dx} = 2(x - 5) = 10 \\ \text{forward difference: } \frac{\Delta y}{\Delta x} = \frac{y(x_0 + 1) - y(x_0)}{1} = \frac{46 - 35}{1} = 11 \end{array} \right\} \text{(10% error)} \rightarrow \frac{d_l y}{dx} \Big|_{x=10} = 10 \frac{10}{35} = 2.8$$

$$@x = 6: \left\{ \begin{array}{l} \text{exact: } \frac{dy}{dx} = 2(x - 5) = 2 \\ \text{forward difference: } \frac{\Delta y}{\Delta x} = \frac{y(x_0 + 1) - y(x_0)}{1} = \frac{14 - 11}{1} = 3 \end{array} \right\} \text{(50% error)} \rightarrow \frac{d_l y}{dx} \Big|_{x=6} = 2 \frac{6}{11} = 1.1$$

# Sensitivity for Static Problem (1)

- Governing equations
  - $K$ : normally large, banded, sparse and ill-conditioned, but positive definite

$$\begin{aligned} \mathbf{K}\mathbf{u} = \mathbf{f} &\xrightarrow{\text{Cholesky decomposition}} \mathbf{L} \mathbf{D} \mathbf{L}^T \mathbf{u} = \mathbf{f} \\ \mathbf{L}\mathbf{v} = \mathbf{f} &\rightarrow \mathbf{D}\mathbf{L}^T \mathbf{u} = \mathbf{v} \end{aligned}$$

- Analytical method
    - Direct method
    - Adjoint method
  - Semi-analytical method
- 
- $$\frac{dg}{dx} = ?$$

# Sensitivity for Static Problem (2)

- Direct method
  - Requires pseudo load calculation and solution for each design variable
  - Pseudo load can be calculated outside of finite element program
  - Requires only forward and backward substitution
  - Minimal effort with new constraints

equations for displacement vector:  $\mathbf{K}\mathbf{u} = \mathbf{f}$   $\xrightarrow{\text{differentiate}}$   $\mathbf{K} \frac{d\mathbf{u}}{dx} = \underbrace{\frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u}}_{\text{pseudo load}}$

response quantity of interest:

$$g(\mathbf{u}, x) \geq 0 \xrightarrow{\text{differentiate}} \frac{dg}{dx} = \frac{\partial g}{\partial x} + \frac{\partial g}{\partial \mathbf{u}} \frac{d\mathbf{u}}{dx} \xrightarrow{z_i = \frac{\partial g}{\partial u_i}} \frac{dg}{dx} = \frac{\partial g}{\partial x} + z^T \frac{d\mathbf{u}}{dx}$$

$$\frac{d\mathbf{u}}{dx} \rightarrow z^T \frac{d\mathbf{u}}{dx} \quad (\text{number of design variables})$$

# Sensitivity for Static Problem (3)

- Adjoint method (dummy-load method)
  - Requires solution for each new g and pseudo load calculation for each design variable

$$\mathbf{K} \frac{d\mathbf{u}}{dx} = \underbrace{\frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u}}_{\text{pseudo load}} \rightarrow \frac{d\mathbf{u}}{dx} = \mathbf{K}^{-1} \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} \right)$$

$$\frac{dg}{dx} = \frac{\partial g}{\partial x} + \mathbf{z}^T \frac{d\mathbf{u}}{dx} \rightarrow \frac{dg}{dx} = \frac{\partial g}{\partial x} + \mathbf{z}^T \mathbf{K}^{-1} \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} \right)$$

$$\mathbf{z}^T \mathbf{K}^{-1} = \boldsymbol{\lambda}^T \rightarrow \mathbf{K}\boldsymbol{\lambda} = \underbrace{\mathbf{z}}_{\text{dummy load}} \quad (\text{number of constraints})$$

$$\frac{dg}{dx} = \frac{\partial g}{\partial x} + \mathbf{z}^T \frac{d\mathbf{u}}{dx} = \frac{\partial g}{\partial x} + \boldsymbol{\lambda}^T \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} \right)$$

# Sensitivity for Static Problem (4)

- Adjoint method in general
  - Adding the derivative of the equations of equilibrium multiplied by a Lagrange multiplier to the derivative of the constraint

$$\mathbf{K}\mathbf{u} = \mathbf{f} \rightarrow \mathbf{K} \frac{d\mathbf{u}}{dx} = \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u}$$

$$\frac{dg}{dx} = \frac{\partial g}{\partial x} + \mathbf{z}^T \frac{d\mathbf{u}}{dx} + \boldsymbol{\lambda}^T \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} - \mathbf{K} \frac{d\mathbf{u}}{dx} \right) = \frac{\partial g}{\partial x} + (\mathbf{z}^T - \boldsymbol{\lambda}^T \mathbf{K}) \frac{d\mathbf{u}}{dx} + \boldsymbol{\lambda}^T \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} \right)$$

$$\xrightarrow{\mathbf{K}\boldsymbol{\lambda}=\mathbf{z}} \frac{dg}{dx} = \frac{\partial g}{\partial x} + \boldsymbol{\lambda}^T \left( \frac{d\mathbf{f}}{dx} - \frac{d\mathbf{K}}{dx} \mathbf{u} \right)$$

# Sensitivity for Static Problem (5)

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- Semi-analytical method
  - Analytical derivatives of stiffness matrices are burdensome especially in commercial software
  - Most resort to finite difference calculation of derivatives of stiffness matrix and force vector
  - Accuracy problem? central difference approximation

$$\frac{d\mathbf{K}}{dx} \approx \frac{\mathbf{K}(x + \Delta x) - \mathbf{K}(x)}{\Delta x}$$

$$\frac{df}{dx} \approx \frac{f(x + \Delta x) - f(x)}{\Delta x}$$

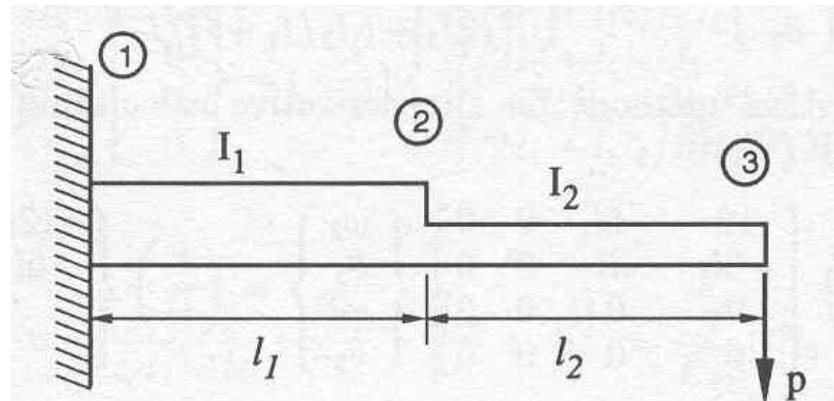
# Example 7.2.1+7.2.2

- Sensitivity of a constraint on the tip displacement of a stepped cantilever beam w.r.t. the moment of inertia  $I_1$  and length  $l_1$
- Errors associated with the finite-difference method and the semi-analytical method

$$w_{tip} = \frac{p}{3EI_1} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) + \frac{pl_2^3}{3EI_2}$$

$$g = c - w_{tip} \geq 0$$

$$\begin{cases} \frac{\partial g}{\partial I_1} = \frac{p}{3EI_1^2} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) \\ \frac{\partial g}{\partial l_1} = -\frac{p}{3EI_1} (3l_1^2 + 6l_1 l_2 + 3l_2^2) = -\frac{p}{EI_1} (l_1 + l_2)^2 \end{cases}$$



$$\begin{aligned}
U &= \int_0^{l_1} \frac{[p(l_1 + l_2 - x)]^2}{2EI_1} dx + \int_{l_1}^{l_2} \frac{[p(l_1 + l_2 - x)]^2}{2EI_2} dx = \frac{p^2}{2EI_1} \int_0^{l_1} (l_1 + l_2 - x)^2 dx + \frac{p^2}{2EI_2} \int_{l_1}^{l_2} (l_1 + l_2 - x)^2 dx \\
&= \frac{p^2}{2EI_1} \left( \frac{l_1^3}{3} + l_1^2 l_2 + l_1 l_2^2 \right) + \frac{p^2}{2EI_2} \left( \frac{l_2^3}{3} - \frac{l_1^3}{3} \right) \\
\delta &= \frac{\partial U}{\partial p} = \frac{p}{3EI_1} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) + \frac{p}{3EI_2} (l_2^3 - l_1^3) \\
&\xrightarrow{???} w_{tip} = \frac{p}{3EI_1} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) + \frac{pl_2^3}{3EI_2} \\
g &= c - w_{tip} \geq 0 \\
\begin{cases} \frac{\partial g}{\partial l_1} = \frac{p}{3EI_1^2} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) \\ \frac{\partial g}{\partial l_1} = -\frac{p}{3EI_1} (3l_1^2 + 6l_1 l_2 + 3l_2^2) = -\frac{p}{EI_1} (l_1 + l_2)^2 \end{cases}
\end{aligned}$$

# Solution for Displacement

$$\mathbf{K}_e = \frac{EI}{l^3} \begin{bmatrix} 12 & 6l & -12 & 6l \\ 6l & 4l^2 & -6l & 2l^2 \\ -12 & -6l & 12 & -6l \\ 6l & 2l^2 & -6l & 4l^2 \end{bmatrix}, \mathbf{u} = \begin{Bmatrix} w_2 \\ \theta_2 \\ w_3 \\ \theta_3 \end{Bmatrix}, \mathbf{f} = \begin{Bmatrix} 0 \\ 0 \\ p \\ 0 \end{Bmatrix}$$

$$\rightarrow E \begin{bmatrix} 12\frac{I_1}{l_1^3} & 6\frac{I_1}{l_1^2} & -12\frac{I_1}{l_1^3} & 6\frac{I_1}{l_1^2} \\ 6\frac{I_1}{l_1^2} & 4\frac{I_1}{l_1} & -6\frac{I_1}{l_1^2} & 2\frac{I_1}{l_1} \\ -12\frac{I_1}{l_1^3} & -6\frac{I_1}{l_1^2} & 12\frac{I_1}{l_1^3} + 12\frac{I_2}{l_2^3} & -6\frac{I_1}{l_1^2} + 6\frac{I_2}{l_2^2} \\ 6\frac{I_1}{l_1^2} & 2\frac{I_1}{l_1} & -6\frac{I_1}{l_1^2} + 6\frac{I_2}{l_2^2} & 4\frac{I_1}{l_1} + 4\frac{I_2}{l_2} \end{bmatrix} \begin{Bmatrix} w_1 \\ \theta_1 \\ w_2 \\ \theta_2 \\ w_3 \\ \theta_3 \end{Bmatrix} = \begin{Bmatrix} 0 \\ 0 \\ 0 \\ p \\ 0 \\ 0 \end{Bmatrix} \rightarrow \mathbf{u} = \begin{Bmatrix} w_2 \\ \theta_2 \\ w_3 \\ \theta_3 \end{Bmatrix} = \frac{p}{E} \begin{Bmatrix} \frac{2l_1^3 + 3l_1^2 l_2}{6I_1} \\ \frac{l_1^2 + 2l_1 l_2}{2I_1} \\ \frac{l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2}{3I_1} + \frac{l_2^3}{3I_2} \\ \frac{l_1^2 + 2l_1 l_2}{2I_1} + \frac{l_2^2}{2I_2} \end{Bmatrix}$$

# Direct Method

---

$$\frac{\partial \mathbf{u}}{\partial I_1} = \mathbf{K}^{-1} \left( \frac{\partial \mathbf{f}}{\partial I_1} - \frac{\partial \mathbf{K}}{\partial I_1} \mathbf{u} \right) \rightarrow \frac{\partial g}{\partial I_1} = -\frac{\partial w_3}{\partial I_1}$$

$$\frac{\partial \mathbf{K}}{\partial I_1} \mathbf{u} = \frac{E}{l_1^3} \begin{bmatrix} 12 & -6l_1 & 0 & 0 \\ -6l_1 & 4l_1^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} w_2 \\ \theta_2 \\ w_3 \\ \theta_3 \end{bmatrix} = \frac{E}{l_1^3} \begin{bmatrix} 12w_2 - 6l_1\theta_2 \\ -6l_1w_2 + 4l_1^2\theta_2 \\ 0 \\ 0 \end{bmatrix} = \frac{p}{I_1} \begin{bmatrix} 1 \\ l_2 \\ 0 \\ 0 \end{bmatrix}$$

$$\rightarrow \frac{\partial \mathbf{u}}{\partial I_1} = \frac{\partial}{\partial I_1} \begin{bmatrix} w_2 \\ \theta_2 \\ w_3 \\ \theta_3 \end{bmatrix} = \mathbf{K}^{-1} \begin{bmatrix} \frac{p}{I_1} \\ \frac{pl_2}{I_1} \\ 0 \\ 0 \end{bmatrix} = -\frac{p}{EI_1^2} \begin{bmatrix} \frac{l_1^2 l_2 + l_1^3}{2} \\ l_1 l_2 + \frac{l_1^2}{2} \\ l_1^2 l_2 + l_1 l_2^2 + \frac{l_1^3}{3} \\ l_1 l_2 + \frac{l_1^2}{2} \end{bmatrix}$$

# Adjoint Method

---

$$\boldsymbol{\lambda} = \mathbf{K}^{-1} \mathbf{z} = \mathbf{K}^{-1} \frac{\partial g}{\partial \mathbf{u}} = \mathbf{K}^{-1} \begin{Bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{Bmatrix} \rightarrow \frac{\partial g}{\partial I_1} = \frac{\partial g}{\partial I_1} + \boldsymbol{\lambda}^T \left( \frac{d\mathbf{f}}{dI_1} - \frac{d\mathbf{K}}{dI_1} \mathbf{u} \right) = -\boldsymbol{\lambda}^T \frac{\partial \mathbf{K}}{\partial I_1} \mathbf{u}$$

$$\mathbf{z}^T = -\frac{\partial w_{tip}}{\partial \mathbf{u}} = \begin{Bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{Bmatrix}, \quad \boldsymbol{\lambda} = \mathbf{K}^{-1} \mathbf{z} = \mathbf{K}^{-1} \begin{Bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{Bmatrix} = -\frac{1}{E} \begin{Bmatrix} \frac{2l_1^3 + 3l_1^2 l_2}{6I_1} \\ \frac{l_1^2 + 2l_1 l_2}{2I_1} \\ \frac{l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2}{3I_1} + \frac{l_2^3}{3I_2} \\ \frac{l_1^2 + 2l_1 l_2}{2I_1} + \frac{l_2^2}{2I_2} \end{Bmatrix}$$

$$\rightarrow \frac{\partial g}{\partial I_1} = -\boldsymbol{\lambda}^T \frac{\partial \mathbf{K}}{\partial I_1} \mathbf{u} = \frac{p}{EI_1} \left( \frac{2l_1^3 + 3l_1^2 l_2}{6I_1} + \frac{l_1^2 + 2l_1 l_2}{2I_1} l_2 \right) = \frac{p}{EI_1^2} \left( l_1^2 l_2 + l_1 l_2^2 + \frac{l_1^3}{3} \right)$$

# Example 7.2.2

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finite difference method:

$$\begin{cases} e_T(\Delta I_1) = \frac{\Delta I_1}{2} \frac{\partial^2 g}{\partial I_1^2} (I_1 + \zeta \Delta I_1) = -\frac{\partial^2 w_{tip}}{\partial I_1^2} \frac{\Delta I_1}{2} = -\frac{p}{3EI_1^3} (l_1^3 + 3l_1^2 l_2 + 3l_1 l_2^2) \Delta I_1 = -\frac{\partial g}{\partial I_1} \frac{\Delta I_1}{I_1} \rightarrow \frac{e_T}{\partial g} = -\frac{\Delta I_1}{I_1} \\ e_T(\Delta l_1) = -\frac{\partial^2 w_{tip}}{\partial l_1^2} \frac{\Delta l_1}{2} = -\frac{p}{EI_1} (l_1 + l_2) \Delta l_1 = \frac{\partial g}{\partial l_1} \frac{\Delta l_1}{l_1 + l_2} \rightarrow \frac{e_T}{\partial g} = \frac{\Delta l}{l_1 + l_2} \end{cases}$$

semi-analytical method:  $\frac{\partial g}{\partial x} \approx \lambda^T \frac{K(x + \Delta x) - K(x)}{\Delta x} u$

$$\begin{cases} e_T(\Delta I_1) = \frac{\Delta I_1}{2} \frac{\partial^2 g}{\partial I_1^2} = \frac{\Delta I_1}{2} \lambda^T \frac{\partial^2 K}{\partial I_1^2} u = 0 \\ e_T(\Delta l_1) = \frac{\Delta l_1}{2} \frac{\partial^2 g}{\partial l_1^2} = \frac{\Delta l_1}{2} \lambda^T \frac{\partial^2 K}{\partial l_1^2} u = \frac{p \Delta l_1}{EI_1 l_1} (3l_1^2 + 7l_1 l_2 + 4l_2^2) \rightarrow \frac{e_T}{\partial g} = \frac{3l_1^2 + 7l_1 l_2 + 4l_2^2}{(l_1 + l_2)^2} \frac{\Delta l}{l_1} \end{cases}$$

# Sensitivity for Eigenvalue Problem (1)

- Undamped vibration and linear buckling

	$\mathbf{K}\mathbf{u} - \mu\mathbf{M}\mathbf{u} = 0 \quad (\mathbf{u}^T \mathbf{M} \mathbf{u} = 1)$	
problem	Undamped vibration	Linear buckling
K	Stiffness	Stiffness
M	Mass	Geometric stiffness
u	Mode shape	Mode shape
$\mu$	Square of the frequency	Buckling load factor

# Sensitivity for Eigenvalue Problem (2)

(for the case of distinct eigenvalue s)

$$\begin{cases} \mathbf{K}\mathbf{u} - \mu\mathbf{M}\mathbf{u} = 0 \rightarrow (\mathbf{K} - \mu\mathbf{M})\frac{d\mathbf{u}}{dx} - \frac{d\mu}{dx}\mathbf{M}\mathbf{u} = -\left(\frac{d\mathbf{K}}{dx} - \mu\frac{d\mathbf{M}}{dx}\right)\mathbf{u} \rightarrow \frac{d\mu}{dx} = \frac{\mathbf{u}^T \left( \frac{d\mathbf{K}}{dx} - \mu \frac{d\mathbf{M}}{dx} \right) \mathbf{u}}{\mathbf{u}^T \mathbf{M} \mathbf{u}} \\ \mathbf{u}^T \mathbf{W} \mathbf{u} = 1 \rightarrow \mathbf{u}^T \mathbf{W} \frac{d\mathbf{u}}{dx} = -\frac{1}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u} \end{cases}$$
$$\rightarrow \begin{bmatrix} \mathbf{K} - \mu\mathbf{M} & -\mathbf{M}\mathbf{u} \\ \mathbf{u}^T \mathbf{W} & 0 \end{bmatrix} \begin{Bmatrix} \frac{d\mathbf{u}}{dx} \\ \frac{d\mu}{dx} \end{Bmatrix} = \begin{Bmatrix} -\left(\frac{d\mathbf{K}}{dx} - \mu\frac{d\mathbf{M}}{dx}\right)\mathbf{u} \\ -\frac{1}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u} \end{Bmatrix}$$

# Sensitivity for Eigenvalue Problem (3)

- Nelson's method
  - Largest component of the eigenvector be equal to one

$$\mathbf{u}^T \mathbf{W} \mathbf{u} = 1 \rightarrow \mathbf{u} = u_m \bar{\mathbf{u}} \left( \text{re-normalization: } \bar{u}_m = 1 \text{ and } \frac{d\bar{u}_m}{dx} = 0 \right)$$

$$\frac{d\mathbf{u}}{dx} = \frac{du_m}{dx} \bar{\mathbf{u}} + u_m \frac{d\bar{\mathbf{u}}}{dx}$$

$$\mathbf{u}^T \mathbf{W} \frac{d\mathbf{u}}{dx} = -\frac{1}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u} \rightarrow \mathbf{u}^T \mathbf{W} \left( \frac{du_m}{dx} \bar{\mathbf{u}} + u_m \frac{d\bar{\mathbf{u}}}{dx} \right) = -\frac{1}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u}$$

$$\rightarrow \mathbf{u}^T \mathbf{W} \frac{\mathbf{u}}{u_m} \frac{du_m}{dx} = -u_m \mathbf{u}^T \mathbf{W} \frac{d\bar{\mathbf{u}}}{dx} - \frac{1}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u} \rightarrow \frac{du_m}{dx} = -u_m^2 \mathbf{u}^T \mathbf{W} \frac{d\bar{\mathbf{u}}}{dx} - \frac{u_m}{2} \mathbf{u}^T \frac{d\mathbf{W}}{dx} \mathbf{u}$$

- Modal technique

$$\frac{d\mathbf{u}^k}{dx} = \sum_{j=1}^l c_{kj} \mathbf{u}^j \quad \text{where } c_{kj} = \frac{(\mathbf{u}^j)^T \left( \frac{d\mathbf{K}}{dx} - \mu_k \frac{d\mathbf{M}}{dx} \right) \mathbf{u}^k}{(\mu_k - \mu_j) (\mathbf{u}^j)^T \mathbf{M} \mathbf{u}^j}, \quad k \neq j$$

# Derivatives of Repeated Eigenvalues

---

- Assume  $m$  repeated eigenvectors
- To find eigenvalue derivatives need to solve a second eigenvalue problem

$$\mathbf{u} = \sum_{i=1}^m q_i \mathbf{u}_i = U\mathbf{q}$$

$$\mathbf{K}\mathbf{u} - \mu \mathbf{M}\mathbf{u} = 0 \rightarrow (\mathbf{K} - \mu \mathbf{M}) \frac{d\mathbf{u}}{dx} - \frac{d\mu}{dx} \mathbf{M}\mathbf{u} = - \left( \frac{d\mathbf{K}}{dx} - \mu \frac{d\mathbf{M}}{dx} \right) \mathbf{u}$$

$$U^T \left[ (\mathbf{K} - \mu \mathbf{M}) \frac{d(U\mathbf{q})}{dx} - \frac{d\mu}{dx} \mathbf{M}(U\mathbf{q}) \right] = -U^T \left[ \left( \frac{d\mathbf{K}}{dx} - \mu \frac{d\mathbf{M}}{dx} \right) (U\mathbf{q}) \right]$$

$$U^T \left( \frac{d\mathbf{K}}{dx} - \mu \frac{d\mathbf{M}}{dx} \right) U\mathbf{q} - \frac{d\mu}{dx} U^T \mathbf{M} U\mathbf{q} = 0$$

$$\frac{U^T \left( \frac{d\mathbf{K}}{dx} - \mu \frac{d\mathbf{M}}{dx} \right) U = \mathbf{A}, U^T \mathbf{M} U = \mathbf{B}}{\longrightarrow \left( \mathbf{A} - \frac{d\mu}{dx} \mathbf{B} \right) \mathbf{q} = 0}$$

# Constraints on Transient Response

$$g(\mathbf{u}, x, t) \geq 0, \quad 0 \leq t \leq t_f \rightarrow g_i(\mathbf{u}, x, t_i) \geq 0, \quad i = 1, \dots, n_t$$

- Remove the time dependence of the constraint
  - Equivalent integrated constraint
    - Blurring effect

$$\bar{g}(\mathbf{u}, x) = \left[ \frac{1}{t_f} \int_0^{t_f} \langle -g(\mathbf{u}, x, t) \rangle^2 dt \right]^{1/2}$$

$$\bar{g}(\mathbf{u}, x) = -\frac{1}{\rho} \ln \left[ \sum_{i=1}^{n_t} e^{-\rho g_i} dt \right] \rightarrow \bar{g} = g_{\min} - \frac{1}{\rho} \ln \left[ \sum_{i=1}^{n_t} e^{-\rho(g_i - g_{\min})} dt \right]$$

- Critical point constraint

$$g(\mathbf{u}, x, t_{mi}) \geq 0, \quad i = 1, 2, \dots \rightarrow \frac{dg(t_{mi})}{dx} = \frac{\partial g}{\partial x} + \frac{\partial g}{\partial \mathbf{u}} \frac{d\mathbf{u}}{dx} + \frac{\partial g}{\partial t} \frac{dt_{mi}}{dx}$$

# Sensitivity of Constraints

$$\bar{g}(\mathbf{u}, x) = \int_0^{t_f} p(\mathbf{u}, x, t) dt \geq 0 \quad \text{where } p(\mathbf{u}, x, t) = g(\mathbf{u}, x, t) \delta(t - t_{mi})$$

$$\rightarrow \frac{d\bar{g}}{dx} = \int_0^{t_f} \left( \frac{\partial p}{\partial x} + \frac{\partial p}{\partial \mathbf{u}} \frac{d\mathbf{u}}{dx} \right) dt$$

$A\dot{\mathbf{u}} = f(\mathbf{u}, x, t), \quad \mathbf{u}(0) = \mathbf{u}_0$

- Direct method

$$A \frac{d\dot{\mathbf{u}}}{dx} = \mathbf{J} \frac{d\mathbf{u}}{dx} - \frac{dA}{dx} \dot{\mathbf{u}} + \frac{\partial f}{\partial x}, \quad \frac{d\mathbf{u}(0)}{dx} = 0 \quad \left( J_{ij} = \frac{\partial f_i}{\partial u_j} \right)$$

- Adjoint method

$$\begin{aligned} \frac{d\bar{g}}{dx} &= \int_0^{t_f} \left( \frac{\partial p}{\partial x} + \frac{\partial p}{\partial \mathbf{u}} \frac{d\mathbf{u}}{dx} \right) dt + \int_0^{t_f} \boldsymbol{\lambda}^T \left( A \frac{d\dot{\mathbf{u}}}{dx} - \mathbf{J} \frac{d\mathbf{u}}{dx} - \frac{\partial f}{\partial x} + \frac{dA}{dx} \dot{\mathbf{u}} \right) dt \\ &= \int_0^{t_f} \left\{ \frac{\partial p}{\partial x} - \boldsymbol{\lambda}^T \left( \frac{\partial f}{\partial x} - \frac{dA}{dx} \dot{\mathbf{u}} \right) + \left[ \frac{\partial p}{\partial \mathbf{u}} - \boldsymbol{\lambda}^T (\dot{\mathbf{A}} + \mathbf{J}) - (\dot{\boldsymbol{\lambda}})^T A \right] \frac{d\mathbf{u}}{dx} \right\} dt + \boldsymbol{\lambda}^T A \frac{d\mathbf{u}}{dx} \Big|_0^{t_f} \\ \rightarrow \frac{d\bar{g}}{dx} &= \int_0^{t_f} \left[ \frac{\partial p}{\partial x} - \boldsymbol{\lambda}^T \left( \frac{\partial f}{\partial x} - \frac{dA}{dx} \dot{\mathbf{u}} \right) \right] dt \\ \frac{\partial p}{\partial \mathbf{u}} - \boldsymbol{\lambda}^T (\dot{\mathbf{A}} + \mathbf{J}) - (\dot{\boldsymbol{\lambda}})^T A &= 0 \rightarrow A^T \dot{\boldsymbol{\lambda}} + (J^T + \dot{A}^T) \boldsymbol{\lambda} = \left( \frac{\partial p}{\partial \mathbf{u}} \right)^T, \quad \boldsymbol{\lambda}(t_f) = 0 \end{aligned}$$