

Lecture 15

Global Constraints in calculus of Variations

ME 260 at the Indian Institute of Science, Bangalore

Structural Optimization: Size, Shape, and Topology

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Outline of the lecture

Global and local constraints

Dealing with global constraints

Euler-Lagrange equations with constraints; Lagrange multipliers

Inequality constraints

What we will learn:

How to identify a constraint as global as local

When is Lagrange multiplier a scalar

How to write Euler-Lagrange equations and boundary conditions for a problem with global constraints

Interpreting the Lagrange multipliers and understanding the complementarity conditions

Global vs. local constraints

Global vs. local here pertains to whether a constraint is imposed at each point in the domain or it is imposed on a quantity that pertains to the entire domain.

- Global constraints pertain to the entire domain.
- Local constraints are imposed at every point in the domain, individually.

Mathematically, it tells whether a constraint is a functional or a function.

- Global constraint is a functional
- Local constraint is a function. It can also be a differential equation.

It also has implications when we discretize.

- Upon discretization, a global constraint gives rise to only one constraint.
- A local constraint, on the other hand, gives as many constraints as the number of discretization points.

Examples of global and local constraints

Global constraints

Length of a curve

Area of a surface

Time of travel

Weight of a structure

Deflection at a particular point

Maximum stress

Buckling load

Natural frequency

Local constraints

Upper or lower bound on a curve

Bounds on the deflection of a structure

Bounds on stress

Governing differential equation

Bounds on the mode shape

It is important to understand this difference.

Global constraint: isoperimetric problem

$$\text{Min}_{y(x)} J = \int_{x_1}^{x_2} F(y(x), y'(x)) dx$$

Subject to

$$K = \int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* = 0$$

This problem statement means that we need to find $y(x)$ that minimizes J and satisfies the equality constraint, K .

It is a global constraint because K here depends on the entire domain. It is a functional. It is a single value.

A problem with a global constraint is also called **isoperimetric problem**. This is because the perimeter constraint is the historic global constraint.

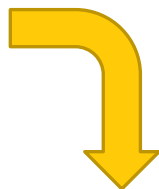
How do we solve this?

$$\text{Min}_{y(x)} J = \int_{x_1}^{x_2} F(y(x), y'(x)) dx$$

Subject to

$$K = \int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* = 0$$

Recall how we handled equality constraints in finite-variable optimization.



You may recall from that...

We linearized the constraint and used the first-order term to eliminate a variable and made the problem unconstrained.

We also came up with the concept of Lagrange multiplier.

Here too, we will follow the same idea.

Equivalent of first-order term of a functional

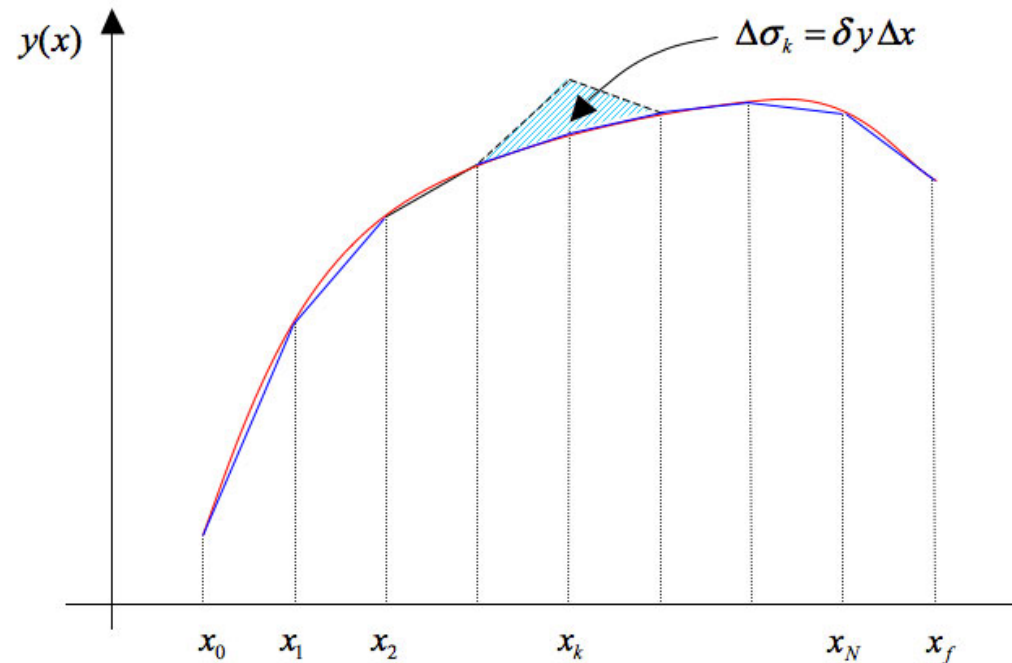
From Eq. (6) in Slide 26 of Lecture 9

$$\Delta J = J(y + h) - J(y) = \left\{ \frac{\delta J}{\delta y} \Big|_{x=\hat{x}} + \varepsilon \right\} \Delta \sigma$$

$$\frac{\delta J}{\delta y} = F_y - \frac{d}{dx}(F_{y'})$$

Variational derivative,
which is the expression in
the Euler-Lagrange
equation.

(first-order approximation
of a perturbed functional)



First-order term of the global constraint

$$K = \int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* = 0$$

$$\Delta K = K(y + h) - K(y) = \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=\hat{x}} + \varepsilon \right\} \Delta \sigma$$

$$\frac{\delta K}{\delta y} = G_y - \frac{d}{dx}(G_{y'})$$

The first-order term shows that the constraint has non-zero value whenever we perturb the function at a point. So, it won't satisfy the equality constraint anymore.

So, we will perturb $y(x)$ at two points...

Two perturbations of the global constraint

$$\Delta K_a = K(y+h) - K(y) = \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \Delta \sigma_a \quad \Delta \sigma_a = \delta y_a \Delta x_a$$

$$\Delta K_b = K(y+h) - K(y) = \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_b} + \varepsilon_b \right\} \Delta \sigma_b \quad \Delta \sigma_b = \delta y_b \Delta x_b$$

We choose x_a and x_b such that the first-order changes due to the two perturbations cancel each other and we retain the feasibility of the constraint.

$$\Delta K_a + \Delta K_b = 0$$

$$\Rightarrow \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \Delta \sigma_a + \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_b} + \varepsilon_b \right\} \Delta \sigma_b = 0$$

One perturbation of the function in terms of the other

$$\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\} \Delta \sigma_a + \left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\} \Delta \sigma_b = 0$$

$$\Rightarrow \Delta \sigma_b = - \frac{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\}}{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\}} \Delta \sigma_a$$

In order to divide like this, we require that there should be at least one point x where the variational derivative is not zero. This is the equivalent of constraint qualification of finite-variable optimization. See Slide 13 of Lecture 5.

Perturbation of the objective functional at the same two points by the same amounts

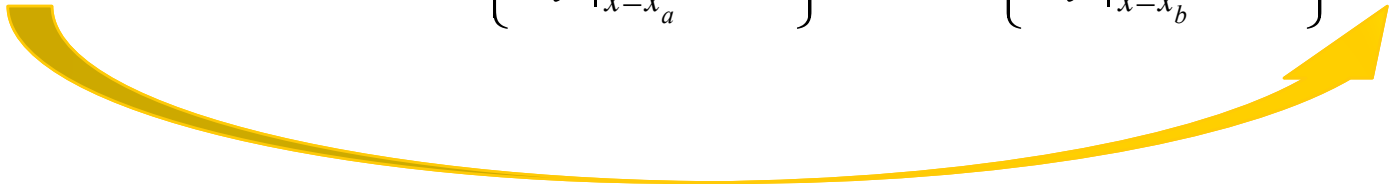
$$\Delta J_a = J(y+h) - J(y) = \left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \Delta \sigma_a \quad \Delta \sigma_a = \delta y_a \Delta x_a$$

$$\Delta J_b = J(y+h) - J(y) = \left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_b} + \varepsilon_b \right\} \Delta \sigma_b \quad \Delta \sigma_b = \delta y_b \Delta x_b$$

$$\Delta J_a + \Delta J_b = \Delta J_{a+b}$$

$$\Rightarrow \left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \Delta \sigma_a + \left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_b} + \varepsilon_b \right\} \Delta \sigma_b = \Delta J_{a+b}$$

Eliminating one perturbation...

$$\Delta\sigma_b = -\frac{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\}}{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\}} \Delta\sigma_a \quad \Delta J_{a+b} = \left\{ \frac{\delta J}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\} \Delta\sigma_a + \left\{ \frac{\delta J}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\} \Delta\sigma_b$$


$$\Delta J_{a+b} = \left\{ \frac{\delta J}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\} \Delta\sigma_a - \left\{ \frac{\delta J}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\} \frac{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_a} + \varepsilon_a \right\}}{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\}} \Delta\sigma_a$$

Defining a multiplier...

$$\Delta J_{a+b} = \left[\left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \left\{ \begin{array}{c} \left. \frac{\delta J}{\delta y} \right|_{x=x_b} + \varepsilon_b \\ \left. \frac{\delta K}{\delta y} \right|_{x=x_b} + \varepsilon_b \end{array} \right\} \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \right] \Delta \sigma_a$$

$$\Delta J_{a+b} = \left[\left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} + \Lambda \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \right] \Delta \sigma_a$$

First order change in the objective functional

$$\Delta J_{a+b} = \left[\left\{ \left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} + \Lambda \left\{ \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon_a \right\} \right] \Delta \sigma_a$$

$$\Rightarrow \Delta J_{a+b} = \left[\left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \Lambda \left. \frac{\delta K}{\delta y} \right|_{x=x_a} + \varepsilon \right] \Delta \sigma_a = 0$$

This is zero because now it is the first-order term due to one arbitrary feasible perturbation because the other one is eliminated.

$$\left. \frac{\delta J}{\delta y} \right|_{x=x_a} + \Lambda \left. \frac{\delta K}{\delta y} \right|_{x=x_a} = 0 \quad \text{because } \Delta \sigma_a \neq 0$$

and $\varepsilon \Delta \sigma_a = 0$ (the second order term)

Putting things together...

$$-\frac{\left\{ \frac{\delta J}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\}}{\left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\}} = \Lambda \Rightarrow \left\{ \frac{\delta J}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\} + \Lambda \left\{ \frac{\delta K}{\delta y} \Big|_{x=x_b} + \varepsilon_b \right\} = 0$$

From Slide 13...

$$\Rightarrow \frac{\delta J}{\delta y} \Big|_{x=x_b} + \Lambda \frac{\delta K}{\delta y} \Big|_{x=x_b} = 0$$

From Slide 14...

$$\frac{\delta J}{\delta y} \Big|_{x=x_a} + \Lambda \frac{\delta K}{\delta y} \Big|_{x=x_b} = 0$$

Since x_a and x_b are arbitrary, the following should be true for any x . And Λ must be a constant.

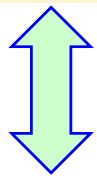
$$\frac{\delta J}{\delta y} + \Lambda \frac{\delta K}{\delta y} = 0$$

Lagrangian can now be defined.

$$\text{Min}_{y(x)} J = \int_{x_1}^{x_2} F(y(x), y'(x)) dx$$

Subject to

$$K = \int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* = 0$$



$$\text{Min}_{y(x)} L = \left\{ \int_{x_1}^{x_2} F(y(x), y'(x)) dx \right\} + \Lambda \left\{ \int_{x_1}^{x_2} G(y(x), y'(x)) dx \right\}$$

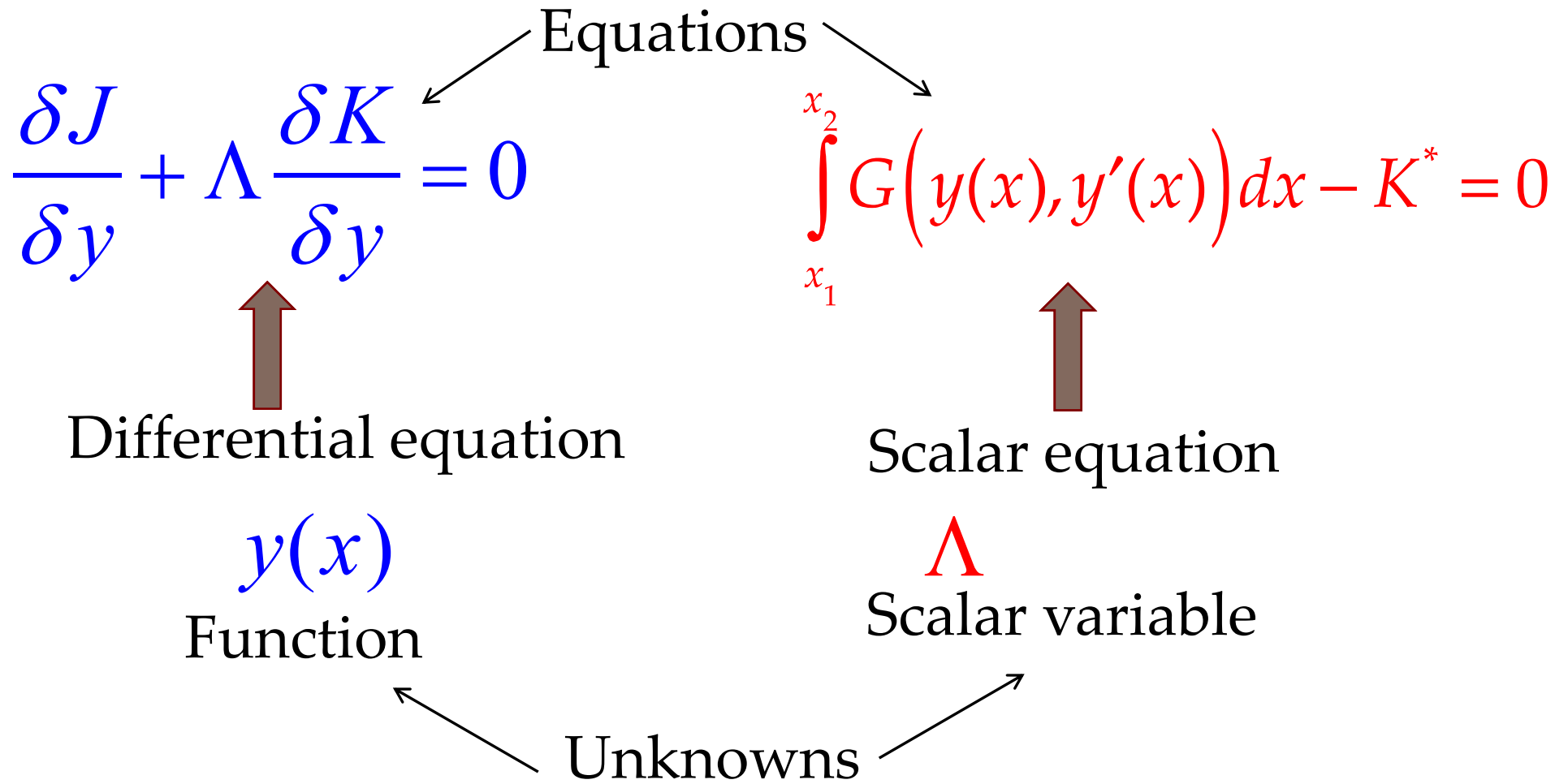
$$\frac{\delta J}{\delta y} + \Lambda \frac{\delta K}{\delta y} = 0$$

Necessary condition

$$\int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* = 0$$

Feasibility condition

Necessary conditions



What if we have an inequality constraint?

$$\text{Min}_{y(x)} J = \int_{x_1}^{x_2} F(y(x), y'(x)) dx$$

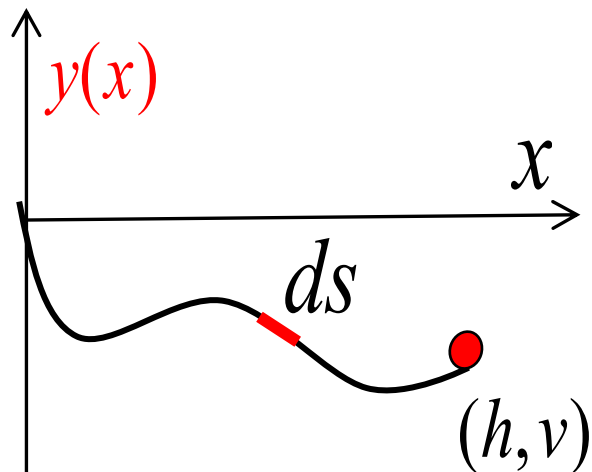
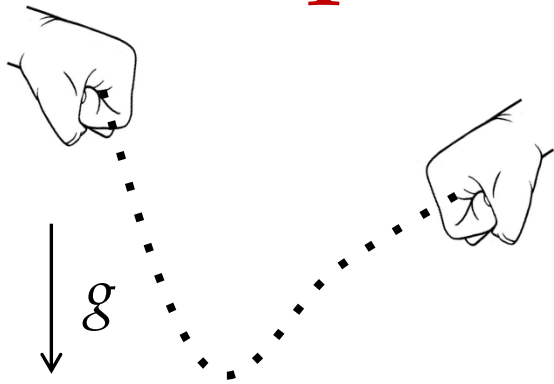
Subject to

$$K = \int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* \leq 0$$

$$\Lambda \left(\int_{x_1}^{x_2} G(y(x), y'(x)) dx - K^* \right) = 0$$
$$\Lambda \geq 0$$

We introduce **complementarity condition** and require **non-negativity of the Lagrange multiplier**... just as we did in finite-variable optimization. The same argument applies here too.

Example 1: hanging chain problem



Mass per unit
 $\rho =$ length of the
 chain

$$\text{Min}_{y(x)} PE = \int_0^h (\rho g y) ds = \int_0^h \rho g y \sqrt{1 + y'^2} dx$$

Subject to

$$\int_0^h \left(\sqrt{1 + y'^2} \right) dx - L = 0$$

Data : $L, y(0) = 0, h, y(h) = v, \rho, g$

$$\text{Min}_{y(x)} L = \int_0^h \rho g y \sqrt{1 + y'^2} dx + \Lambda \left(\int_0^h \left(\sqrt{1 + y'^2} \right) dx - L \right)$$

Data : $L, y(0) = 0, h, y(h) = v, \rho, g$

Necessary conditions for the hanging chain problem

$$\text{Min}_{y(x)} L = \int_0^h \rho g y \sqrt{1 + y'^2} dx + \Lambda \left(\int_0^h \left(\sqrt{1 + y'^2} \right) dx - L \right)$$

Data : $L, y(0) = 0, h, y(h) = v, \rho, g$

$$\delta_y L = 0$$

$$\int_0^h \left(\sqrt{1 + y'^2} \right) dx - L = 0$$

$$\delta_y L = \frac{\partial L}{\partial y} - \frac{d}{dx} \left(\frac{\partial L}{\partial y'} \right) = 0$$

Differential equation

Example 2: Stiffest beam of given volume

$$\text{Min}_{b(x)} SE = \int_0^L \left\{ \frac{1}{2} \frac{Ebd^3}{12} \left(\frac{d^2 w}{dx^2} \right)^2 \right\} dx$$

Subject to

$$\frac{d^2}{dx^2} \left(Ebd^3 \frac{d^2 w}{dx^2} \right) + q = 0$$

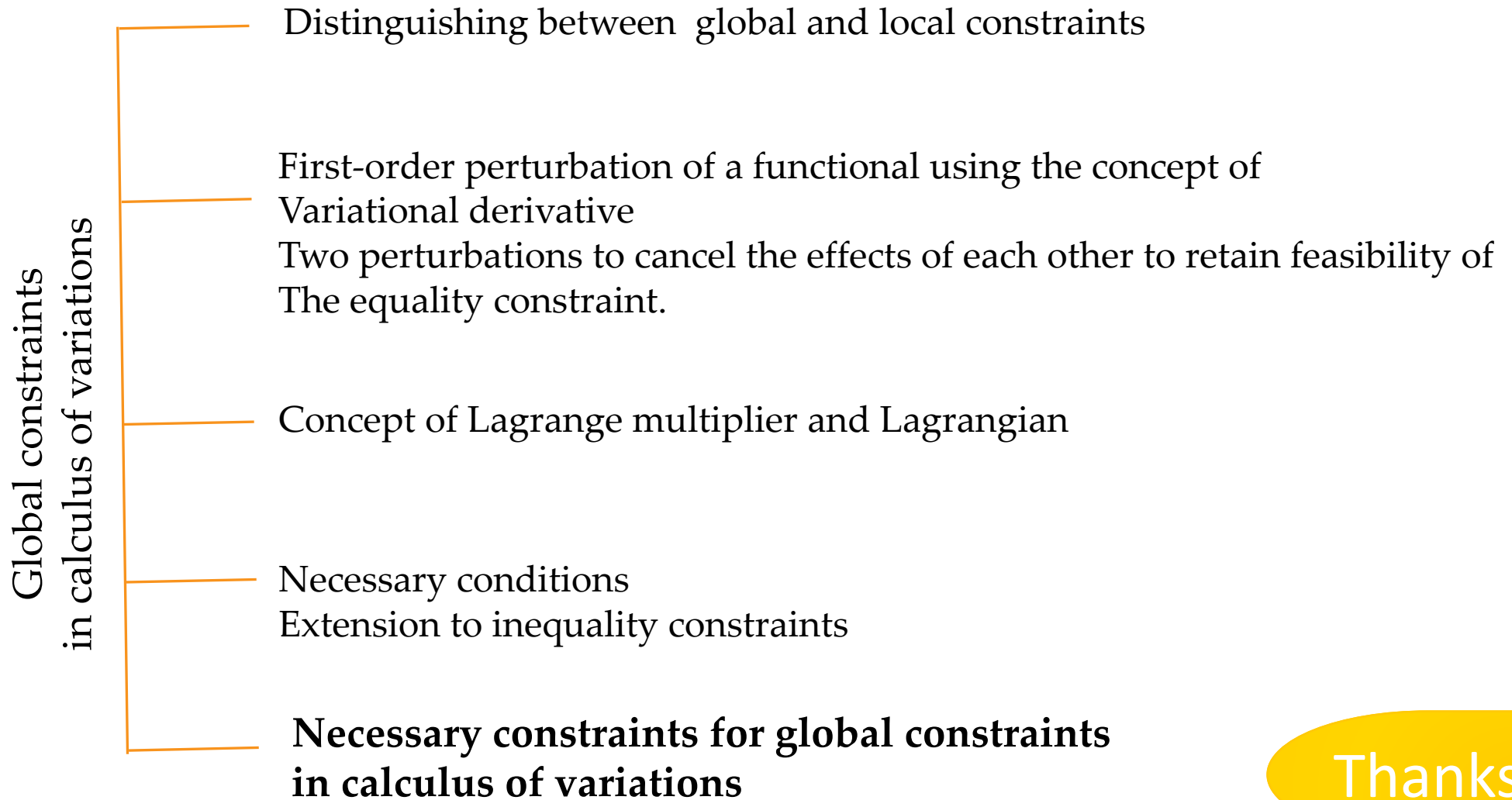
This is a local constraint; it is valid at every point in the domain.

$$\int_0^L bd \, dx - V^* \leq 0$$

We now know how to deal with this global constraint

Data : $L, q(x), d, V^*, E$

The end note



Thanks