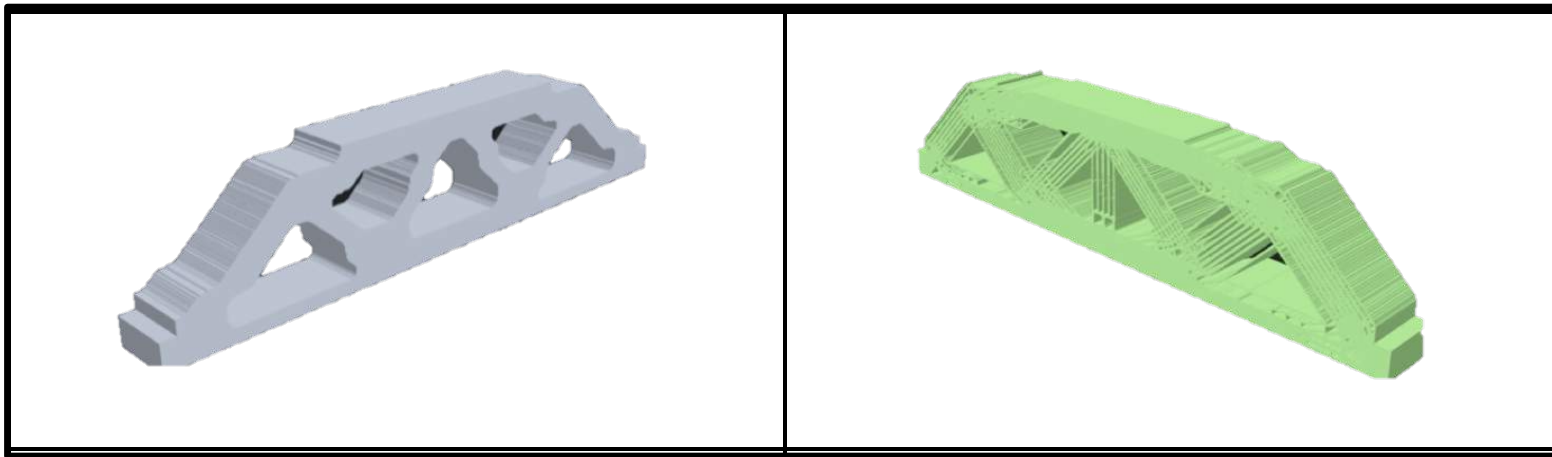


# AE4ASM521

- Additive Manufacturing



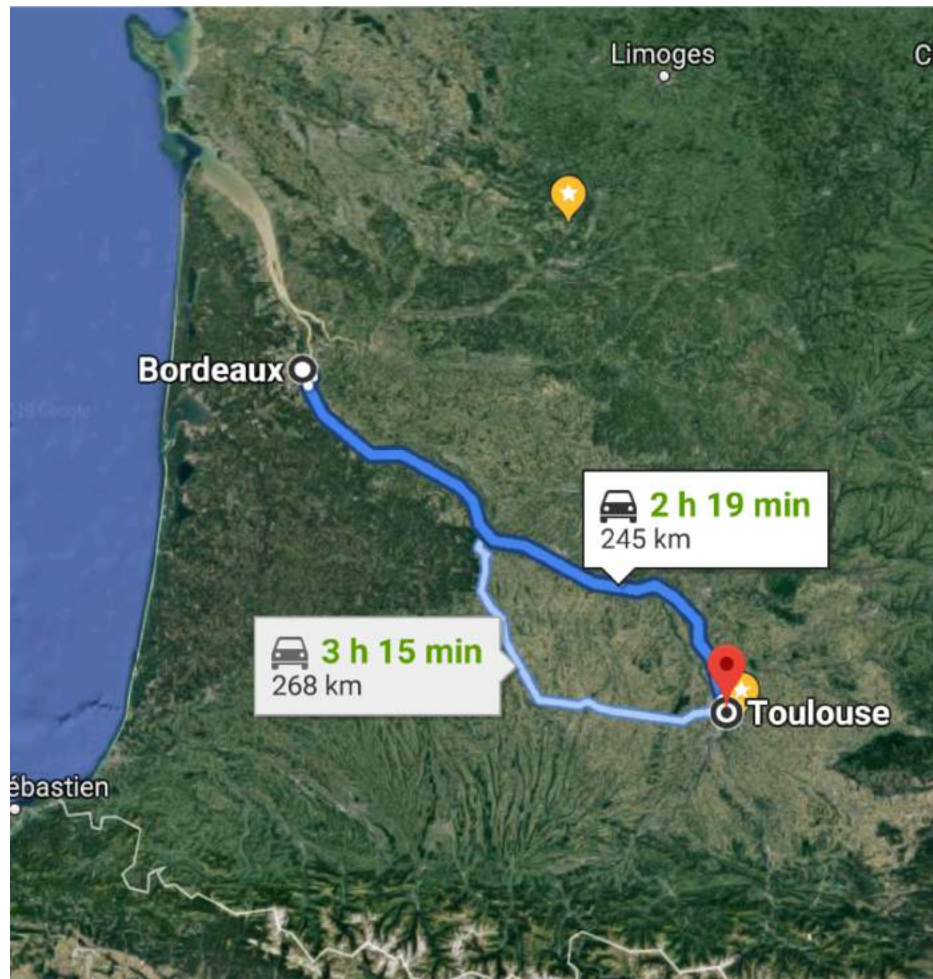
Professor Joseph Morlier  
ISAE-SUPAERO, FRANCE



<https://ica.cnrs.fr/en/author/jmorlier/>

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# PhD in Bordeaux then... Toulouse



# Au programme

Duration	Description	Agenda
15'	Design Optimization	Refresh
15'	Computing Derivatives	Mathematical Background
15'	Topopt review	Need a break ?
15'	Current CAD-CAE	Quiz
15'	GGP for ALM	Our research
15'	Ecodesign	That's new

Fondation  
**ISAE - SUPAERO**  
Reconnue d'utilité publique

AGENCE NATIONALE DE LA RECHERCHE  
**ANR**  
**PLAN D'ACTION 2021**

**CONSTRUCTION DE L'ESPACE EUROPEEN DE LA  
RECHERCHE ET ATTRACTIVITE INTERNATIONALE**

**Programme : « Montage de Réseaux Scientifiques  
Européens ou Internationaux »  
- Edition 2021, Vague 1 -**

Optimisation  
Promo Structures  
Fondation  
Gift 83 SUPAERO  
ISAE Class  
Aero  
Ecodesign  
Topologique

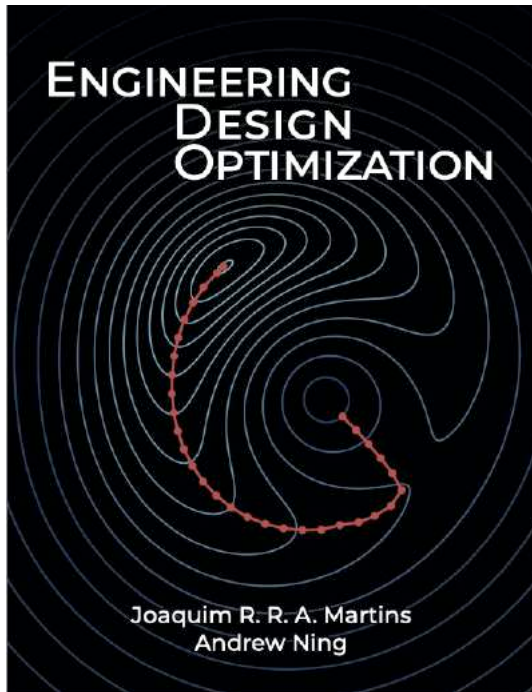


Au programme

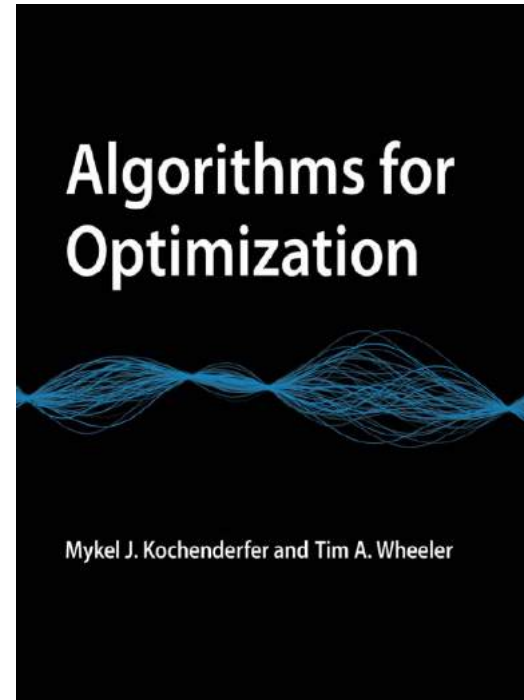
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15'	<b>Ecodesign</b>	<b>That's new</b>

**Design Optimization**

# Good Starting Point ( $x_0$ )



<https://github.com/mdobook/resources>

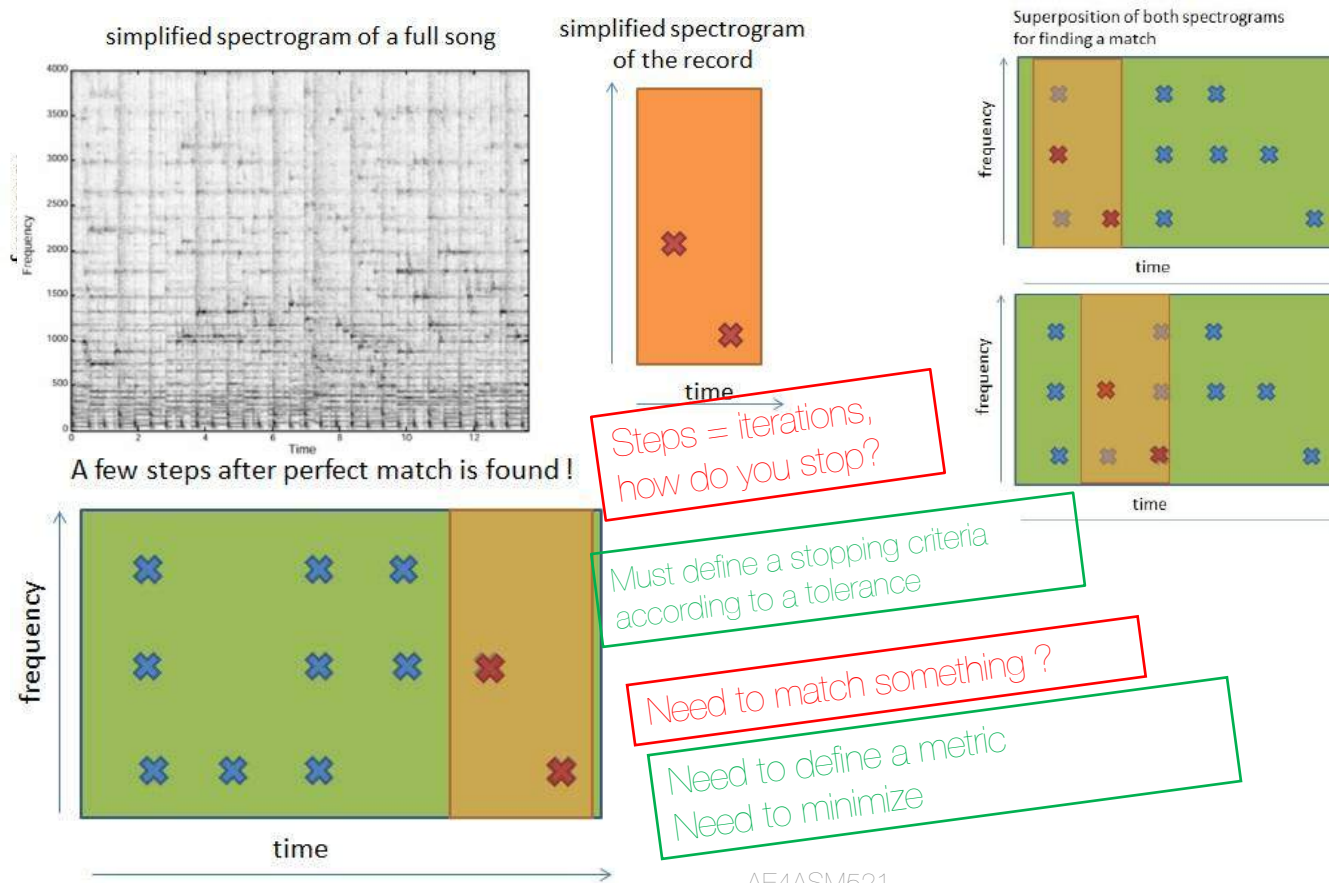


<https://github.com/sisl/algforopt-notebooks>



# Optimization is everywhere

<http://coding-geek.com/how-shazam-works/>



# Design Optimization Process

# On the road to design optimization

<https://medium.com/daptablog/on-the-road-to-design-optimisation-a3c9867f29b6>

- **optimization**

noun [ U ] (UK usually **optimisation**)

**the act of making something as good as possible**

([Cambridge Dictionary](#))

Do Better with Less

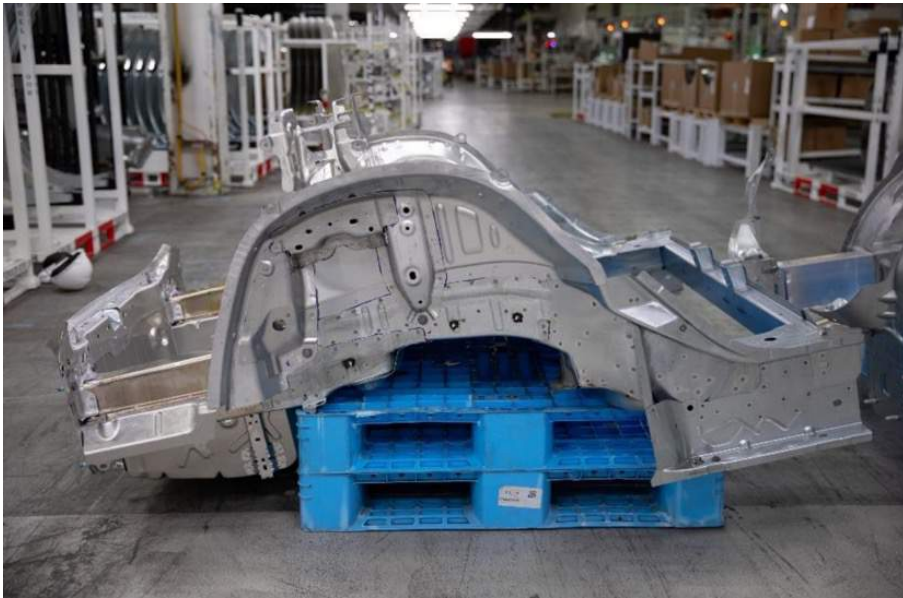
- Design optimization is an engineering design methodology **using a mathematical formulation of a design problem** to support selection of the optimal design among many alternatives. ([Wikipedia](#))



# Optimization is everywhere

<https://www.3dprintingmedia.network/tesla-shows-massive-generatively-designed-3d-printed-part-in-model-y-underbody>

@Tesla



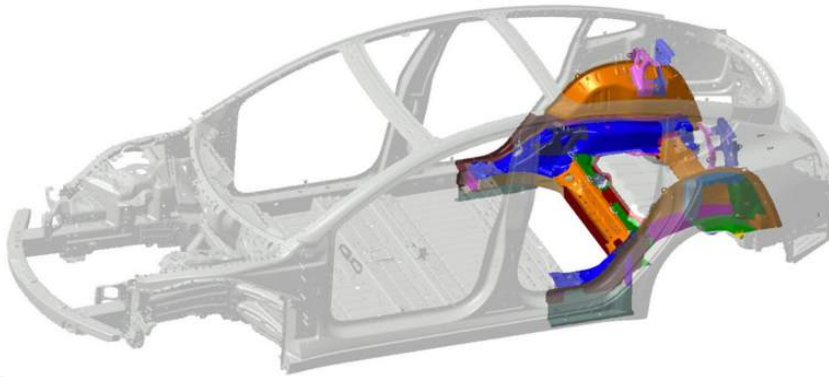
The current underbody part made of 70 different components



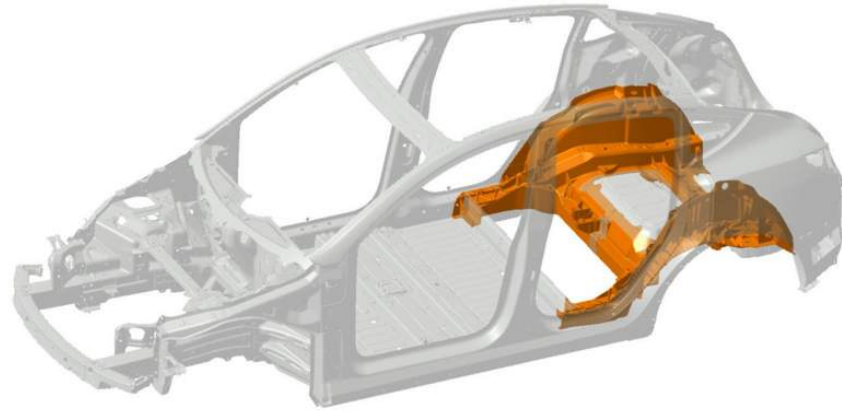
The generatively designed underbody, made of 2 and eventually 1 single piece.

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# Think different!



Model 3 rear underbody  
70 pieces of metal



Model Y rear underbody  
2 pieces of metal (eventually a single piece)

The use of 3D printing for sand casts such as that offered by voxeljet and ExOne for to enable the reduction of subassemblies (from 70 to 1) in a custom cast can bring about a significant transition even before metal AM can be used to produce such large metal parts directly. Producing a complex cast that can reduce the number of parts to this degree needs digital casting technology

# Optimization is everywhere

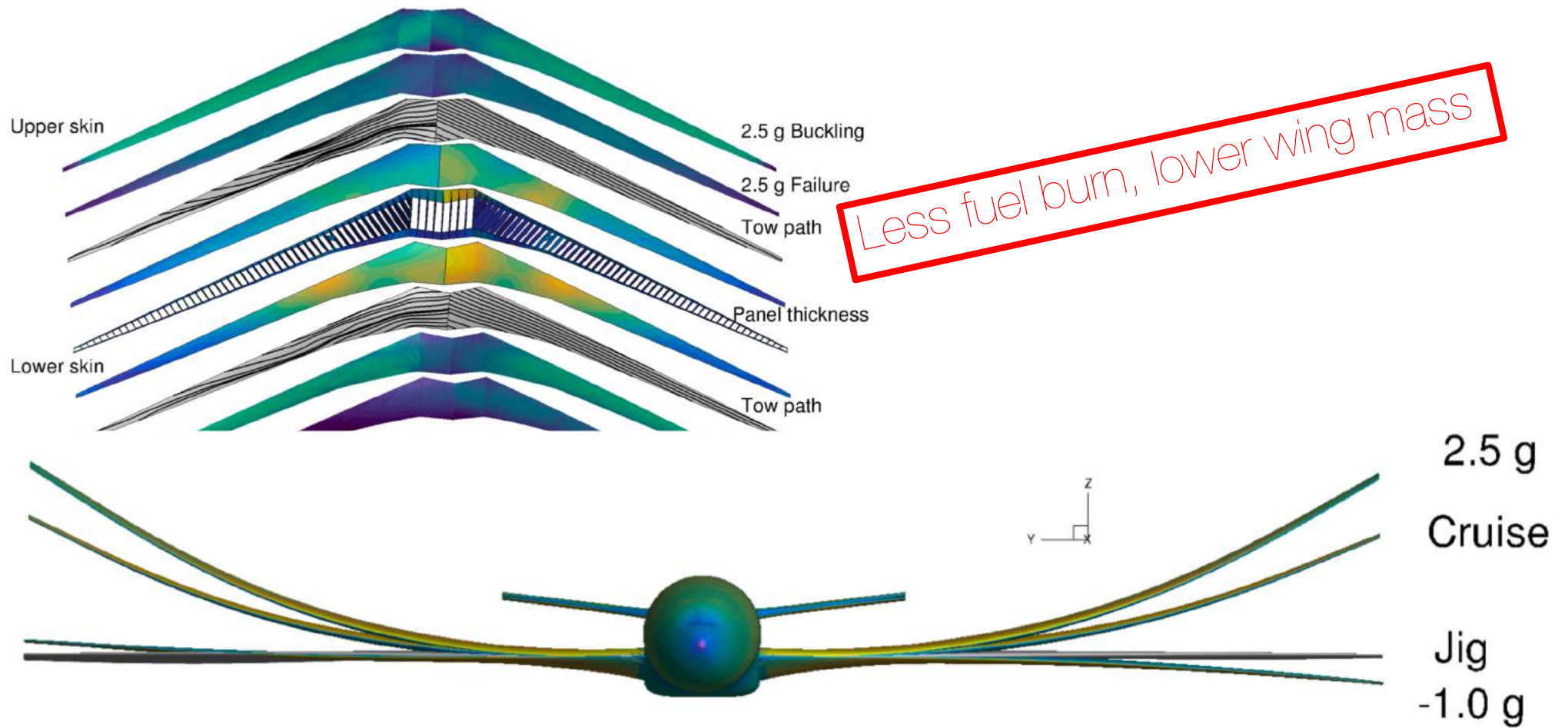
<https://www.compositesworld.com/articles/leveraging-motorsports-composites-for-next-gen-rotorcraft>



**Figure 17: AFP machine manufacturing the tow-steered optimized uCRM-13.5 wingbox (left; courtesy of Aurora Flight Sciences). Static test of the same wing (right; courtesy of NASA)**



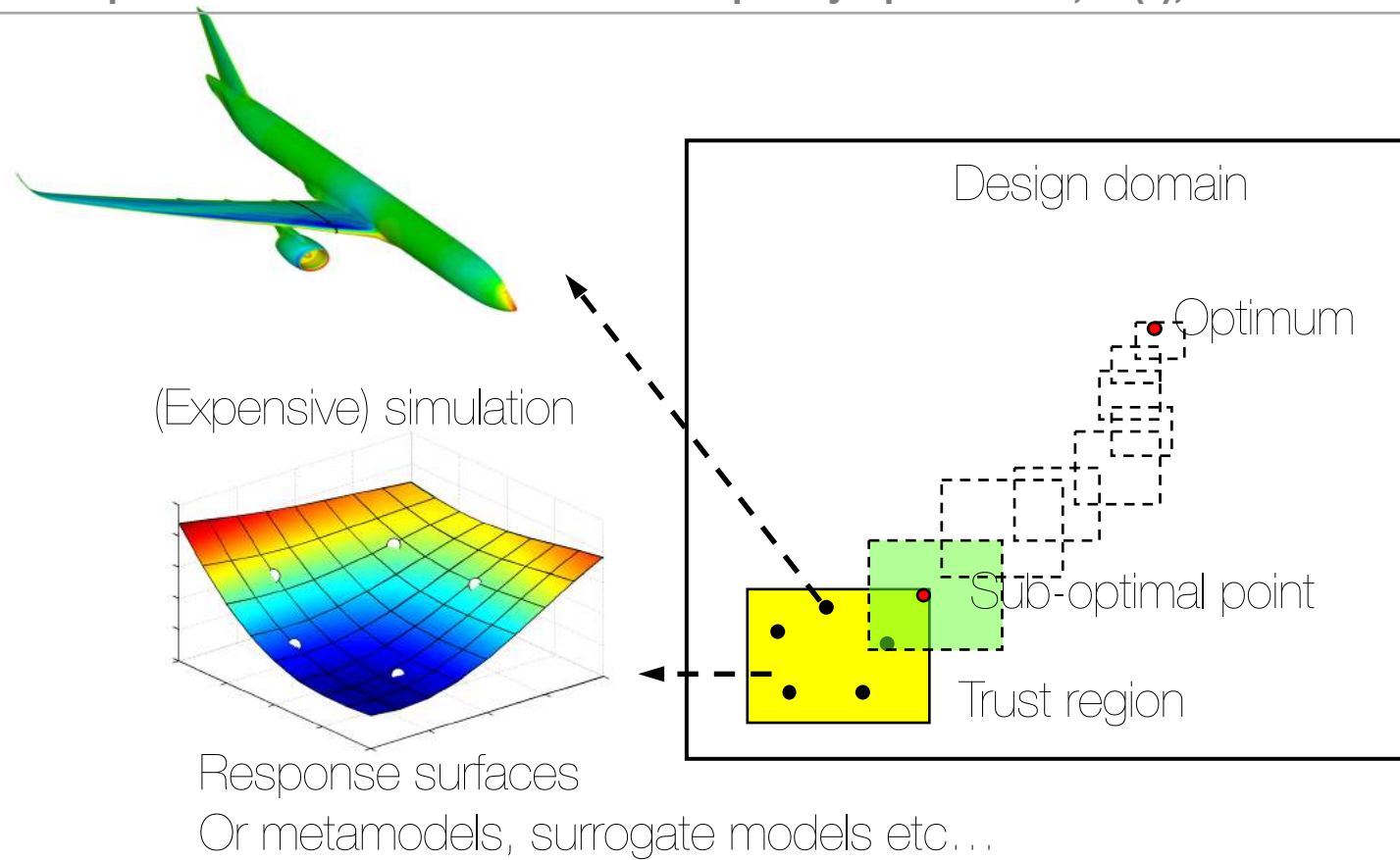
# Prof Martins 'sTow Steered Wing Structure Design



# SURROGATE MODELING

learning for Optimizing

**Jacobs, J. H., Etman, L. F. P., Van Keulen, F., & Rooda, J. E. (2004). Framework for sequential approximate optimization. Structural and Multidisciplinary Optimization, 27(5), 384-400.**



# Bayesian Optimization in 1-slide ?

Bartoli, N., Lefebvre, T., Dubreuil, S., Olivanti, R., Priem, R., Bons, N., ... & Morlier, J. (2019). Adaptive modeling strategy for constrained global optimization with application to aerodynamic wing design. *Aerospace Science and technology*, 90, 85-102.

Baseline  
{Not so Bad}

Optimized  
SNOPT

Problem definition

Same Results  
Same Performance  
but  
**WITHOUT BASELINE**

**infill Criteria??**

decide of the new point  
(exploitation-exploration tradeoff)

$$E[I(\mathbf{x})] = (y_{min} - \mu_{\hat{y}}(\mathbf{x}))\Phi\left(\frac{y_{min} - \mu_{\hat{y}}(\mathbf{x})}{\sigma_{\hat{y}}(\mathbf{x})}\right) + \sigma_{\hat{y}}(\mathbf{x})\varphi\left(\frac{y_{min} - \mu_{\hat{y}}(\mathbf{x})}{\sigma_{\hat{y}}(\mathbf{x})}\right)$$

infill Criteria  
EI (analytical)

DOE

GP  
SE Kernel

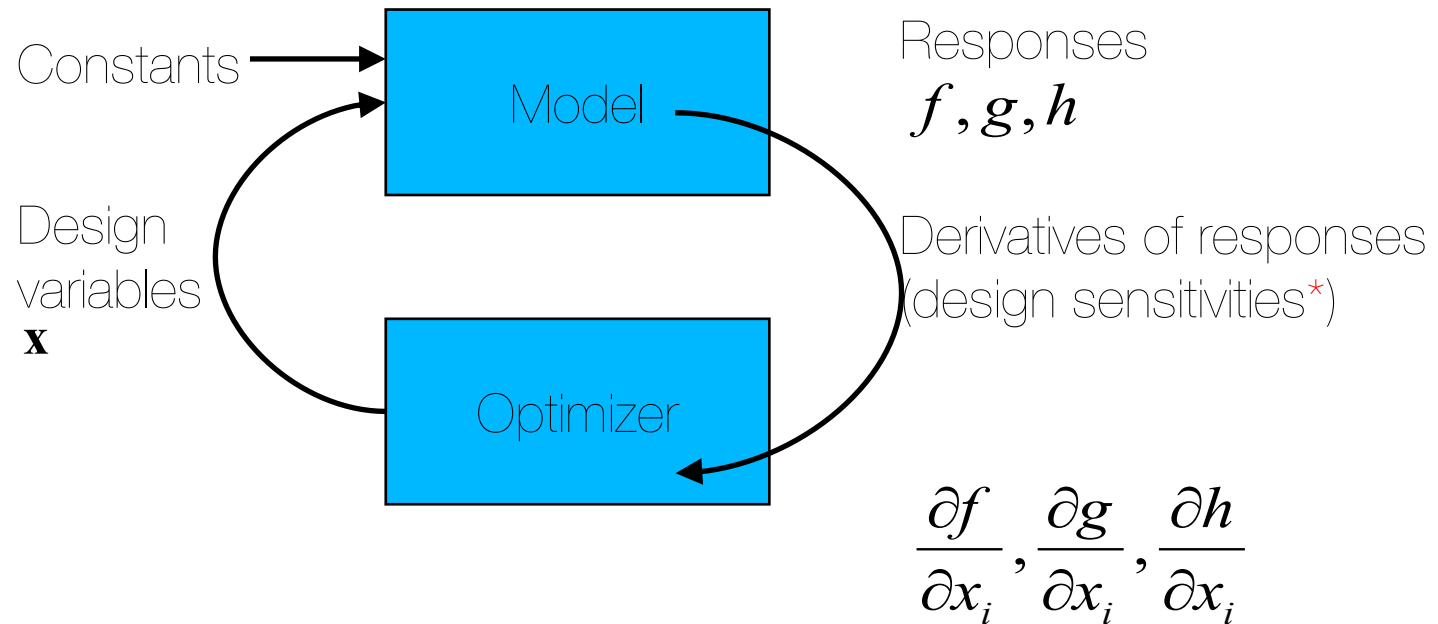
Gradient Based  
Optimization

Convergence?

Jones, D. R. (2001). A taxonomy of global optimization methods based on response surfaces. *Journal of global optimization*, 21(4), 345-383.

# Gradient Based Optimization

- Costly if Finite Differences is used for sensitivities
- Difficult to implement Adjoint in industrial code
- Sensitive to discontinuity
- Sensitive to  $X_0$

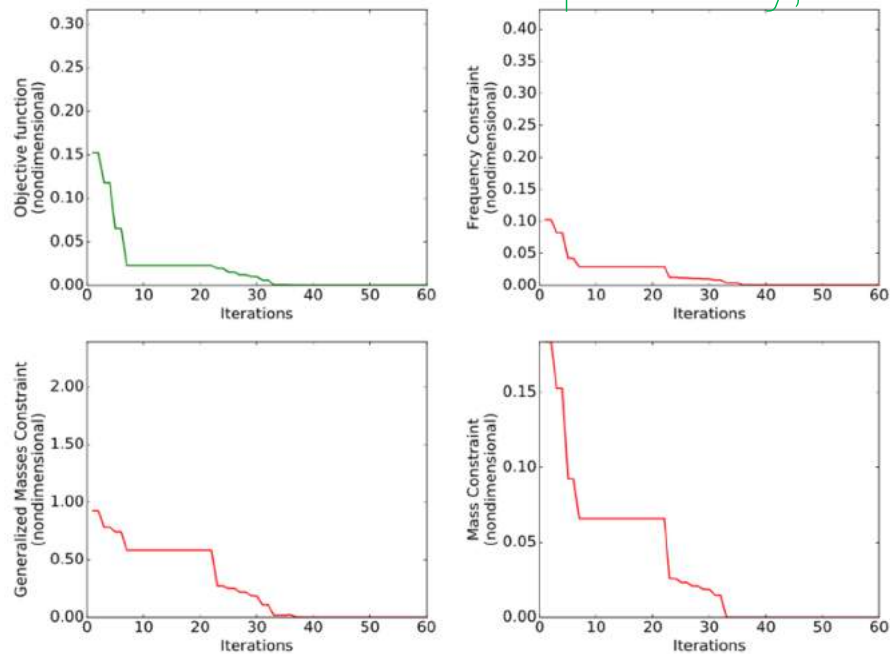


\*SOL200 in MSC Nastran for example

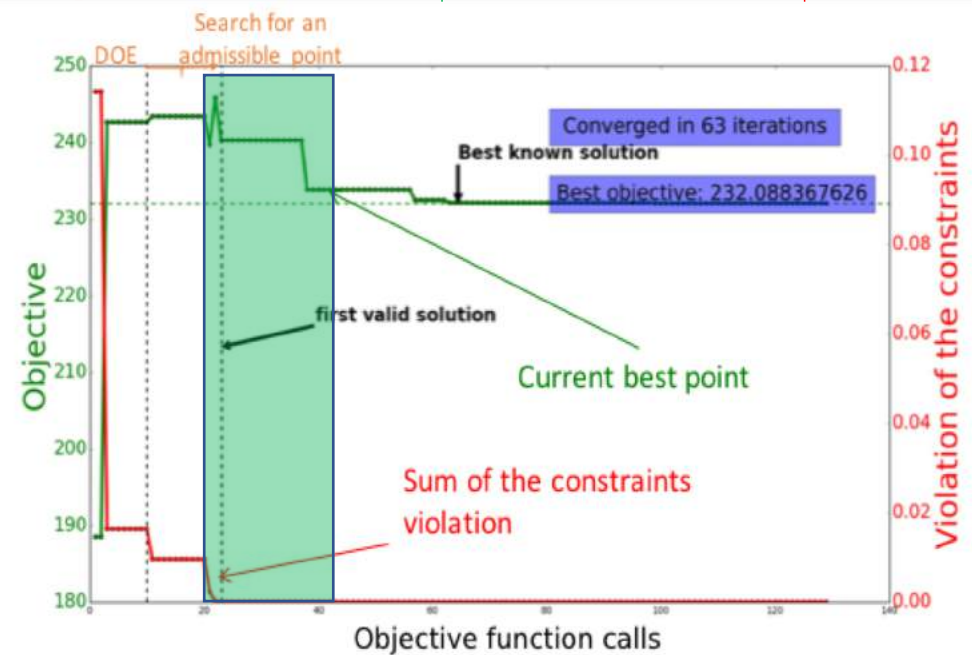


# New Graphs for BO

Gradient based Optimality, Feasibility SBO Exploration, Exploitation



Stopping criteria: tolfun, tolX, maxiter



Stopping criteria: Max Budget (Function calls)

X\_0

<https://smt.readthedocs.io/en/latest>

<https://github.com/SMTorg/smt>

SMT 0.8.0 documentation »




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SMT: Surrogate Modeling Toolbox

Cite us

Focus on derivatives

Documentation contents

- Indices and tables

Next topic

Getting started

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SMT: Surrogate Modeling Toolbox

The surrogate modeling toolbox (SMT) is an open-source Python package consisting of libraries of surrogate modeling methods (e.g., radial basis functions, kriging), sampling methods, and benchmarking problems. SMT is designed to make it easy for developers to implement new surrogate models in a well-tested and well-document platform, and for users to have a library of surrogate modeling methods with which to use and compare methods.

The code is available open-source on [GitHub](#).

Cite us

To cite SMT: M. A. Bouhlel and J. T. Hwang and N. Bartoli and R. Lafage and J. Morlier and J. R. R. A. Martins.

[A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 2019.](#)

```
@article{SMT2019,
  Author = {Mohamed Amine Bouhlel and John T. Hwang and Nathalie Bartoli and Rémi Lafage},
  Journal = {Advances in Engineering Software},
  Title = {A Python surrogate modeling framework with derivatives},
  pages = {102662},
  year = {2019},
  issn = {0965-9978},
  doi = {https://doi.org/10.1016/j.advengsoft.2019.03.005},
  Year = {2019}}
```

Focus on derivatives

SMT is meant to be a general library for surrogate modeling (also known as metamodeling, interpolation, and regression), but its distinguishing characteristic is its focus on derivatives, e.g., to be used for gradient-based optimization. A surrogate model can be represented mathematically as

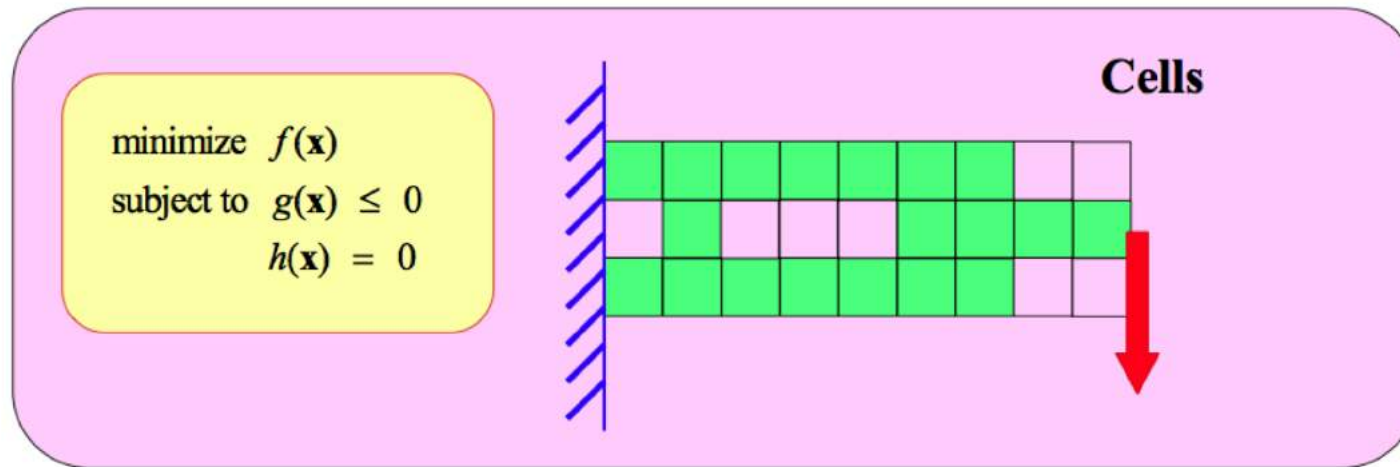
$$y = f(\mathbf{x}, \mathbf{x}_t, \mathbf{y}_t),$$

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17

# Topology Optimization

MIT Course Number ESD.77 / 16.888



minimize  $f(\mathbf{x})$   
subject to  $g(\mathbf{x}) \leq 0$   
 $h(\mathbf{x}) = 0$

**Design variables ( $\mathbf{x}$ )**

$\mathbf{x}$  : density of each cell

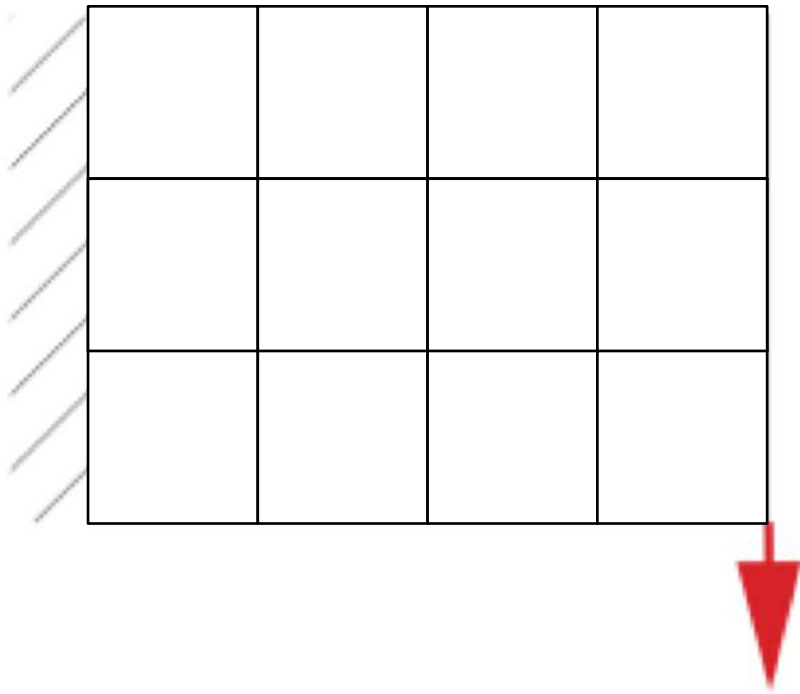
**Number of design variables (ndv)**

**ndv = 27**

$f(\mathbf{x})$  : compliance

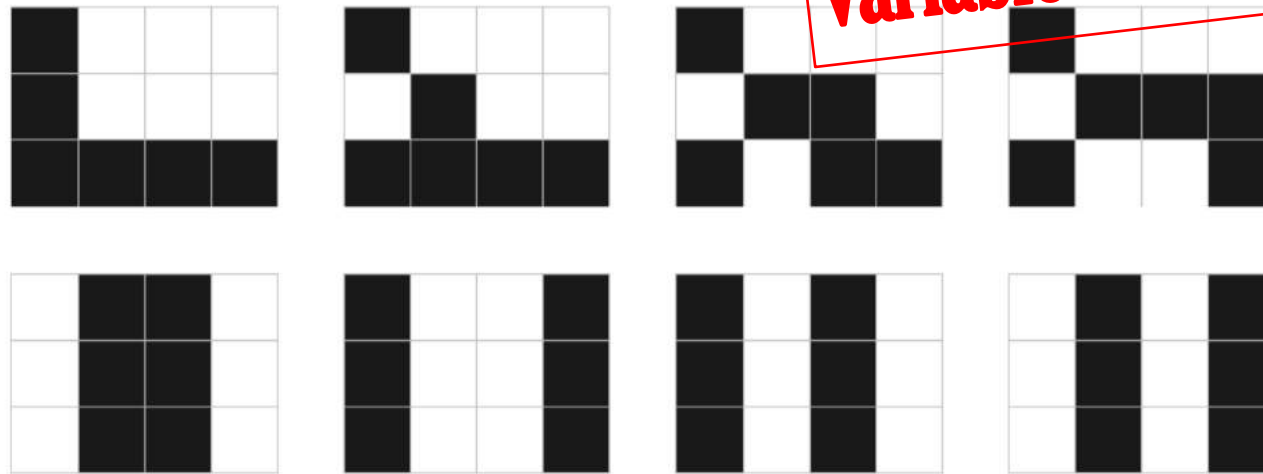
$g(\mathbf{x})$  : mass

Quiz ! draw material (black) or void (white)



**Goal: 50%  
gain in mass**

# Results



**discrete or continuous variables ?**

The legal (top) and some illegal (bottom) topologies with 4 by 3 elements

# Some Aerospace Parts



Airbus A320 nacelle  
hinge bracket by EADS  
and Airbus



A structural bracket for Eurostar  
E3000 satellites by Airbus  
Defense and Space in UK



An antenna  
bracket for a  
Sentinel-1 -Satellite  
by RUAG

Coupling  
TopOpt & ALM  
offer new possible feasible  
designs (see Jun Wu's course)

# Au programme

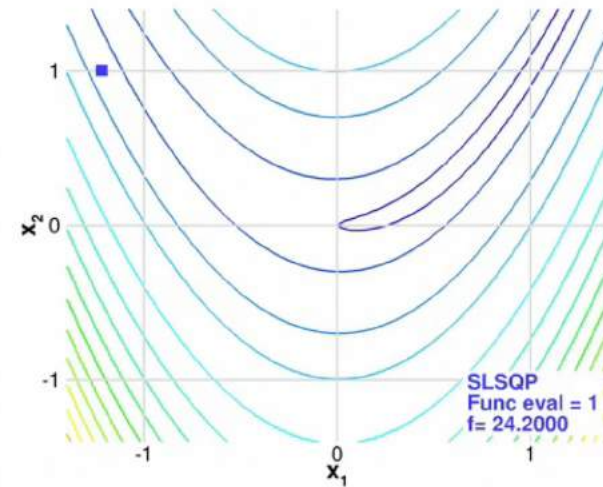
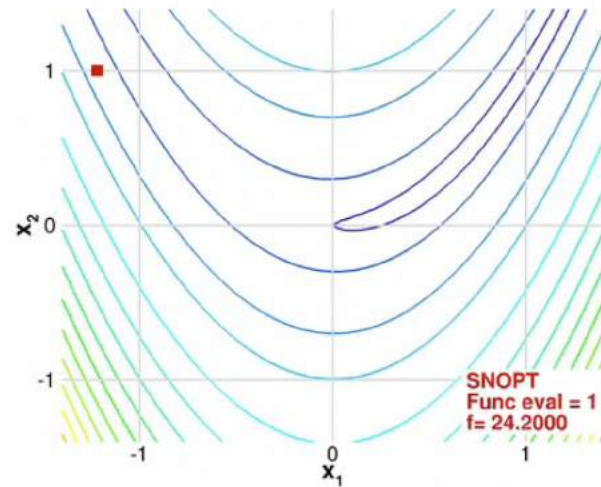
Duration	Description	Agenda
15'	Design Optimization	Refresh
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**Computing Derivatives**

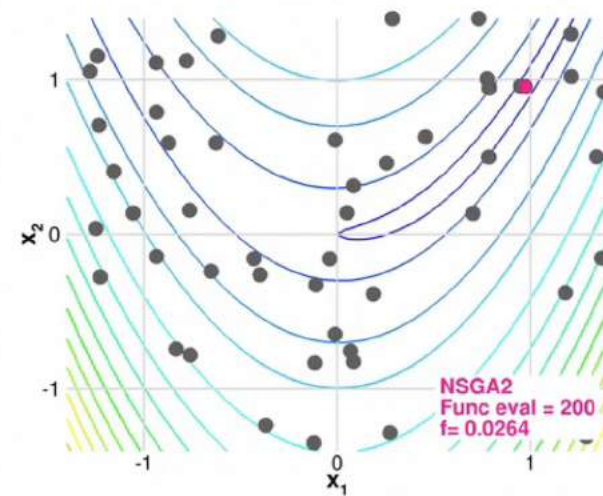
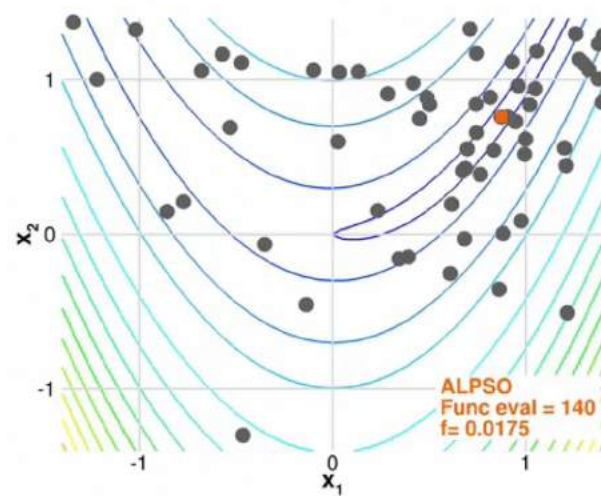


Gradient-based methods take a more direct path to ...  
the optimum

Gradient-based

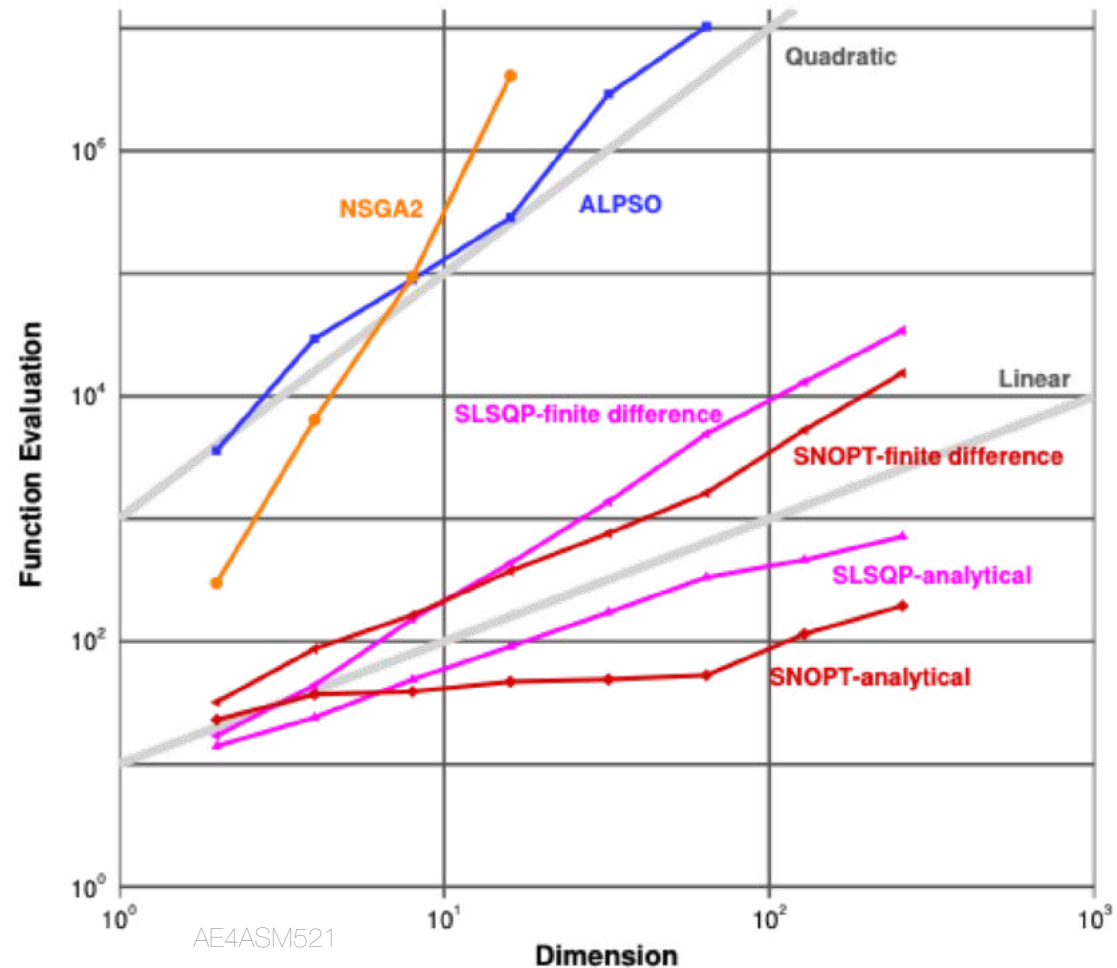


Gradient-free



**Gradient-based optimization** is the only hope  
for large numbers of design variables

**Need accurate  
derivative**



[Lyu et al. ICCFD8-2014-0203]

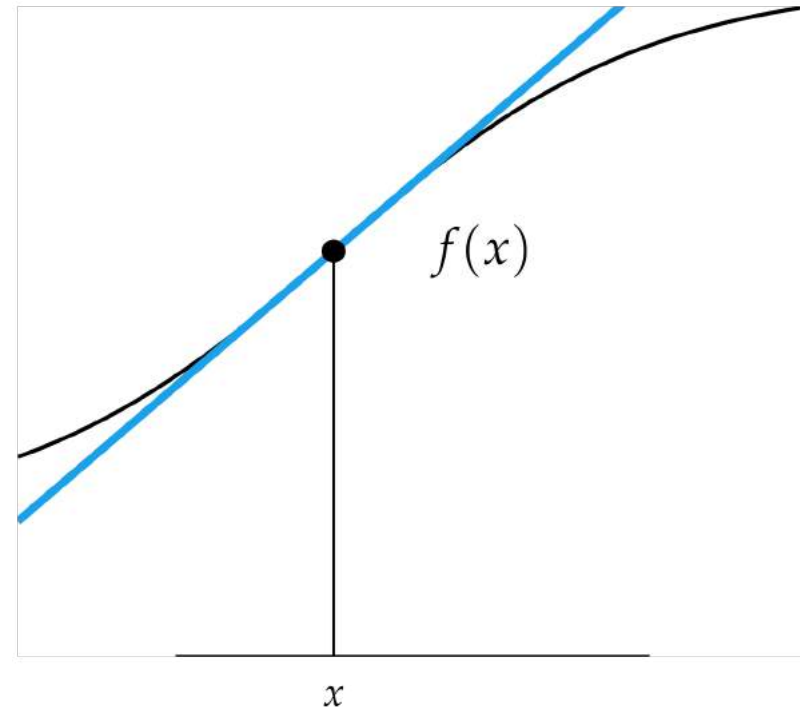
# Derivatives

- Derivatives tell us which direction to search for a solution

# Derivatives

- Slope of Tangent Line

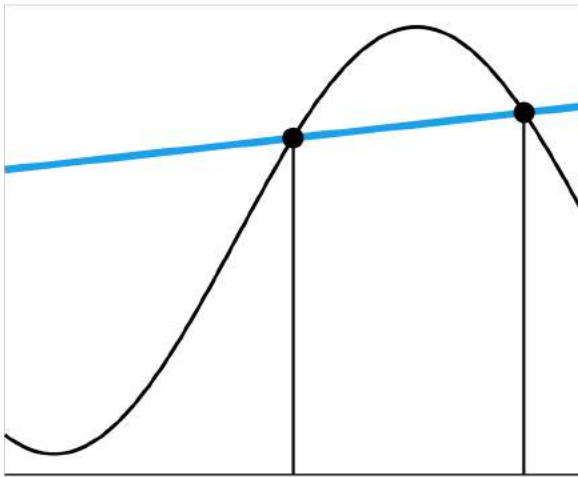
$$f'(x) \equiv \frac{df(x)}{dx}$$



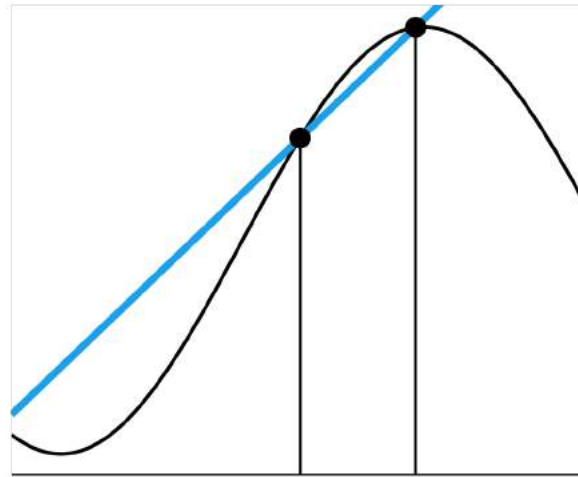
# Derivatives

$$f(x + \Delta x) \approx f(x) + f'(x)\Delta x$$

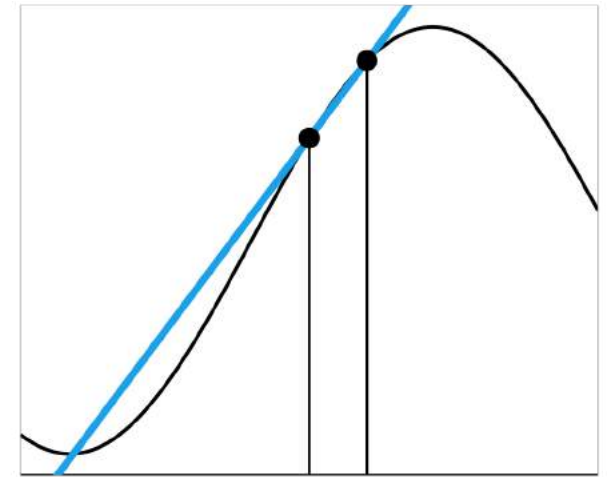
$$f'(x) = \frac{\Delta f(x)}{\Delta x}$$



$h$



$h$



$h$

# Derivatives in Multiple Dimensions

- Directional Derivative

$$\nabla_{\mathbf{s}} f(\mathbf{x}) \equiv \lim_{h \rightarrow 0} \underbrace{\frac{f(\mathbf{x} + h\mathbf{s}) - f(\mathbf{x})}{h}}_{\text{forward difference}}$$

$$= \lim_{h \rightarrow 0} \underbrace{\frac{f(\mathbf{x} + h\mathbf{s}/2) - f(\mathbf{x} - h\mathbf{s}/2)}{h}}_{\text{central difference}}$$

$$= \lim_{h \rightarrow 0} \underbrace{\frac{f(\mathbf{x}) - f(\mathbf{x} - h\mathbf{s})}{h}}_{\text{backward difference}}$$

# Numerical Differentiation: Finite Difference

- Error Analysis
  - Forward Difference:  $O(h)$
  - Central Difference:  $O(h^2)$



# Numerical Differentiation: Complex Step

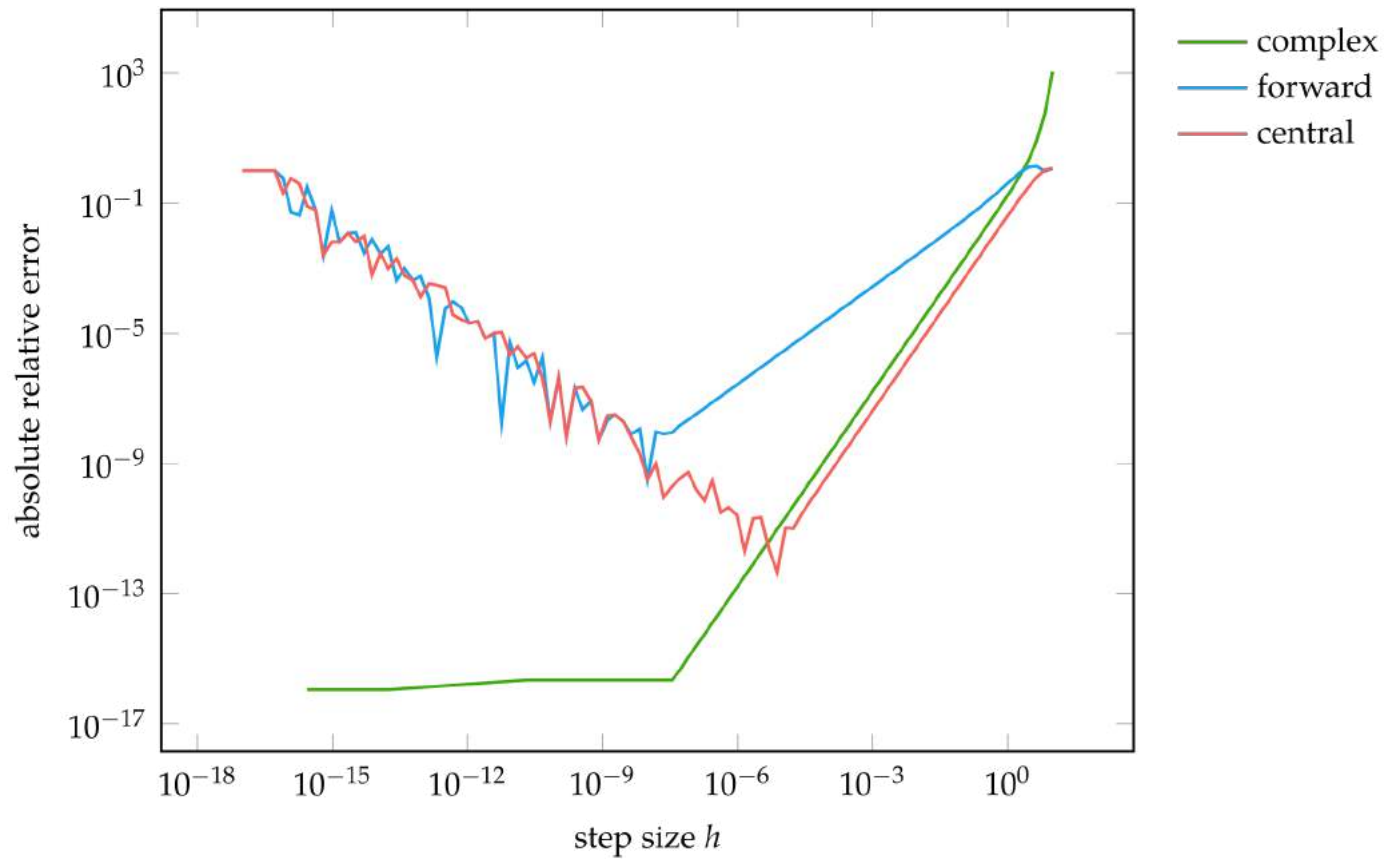
- Taylor series expansion using imaginary step

$$f(x + ih) = f(x) + ihf'(x) - h^2 \frac{f''(x)}{2!} - ih^3 \frac{f'''(x)}{3!} + \dots$$

$$f'(x) = \frac{\text{Im}(f(x + ih))}{h} + O(h^2) \text{ as } h \rightarrow 0$$

$$f(x) = \text{Re}(f(x + ih)) + O(h^2)$$

# Numerical Differentiation Error Comparison



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# Automatic Differentiation

- Evaluate a function and compute partial derivatives simultaneously using the chain rule of differentiation

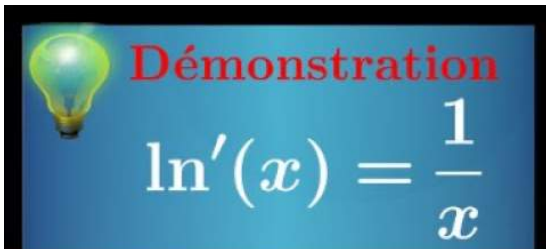
$$\frac{d}{dx}f(g(x)) = \frac{d}{dx}(f \circ g)(x) = \frac{df}{dg} \frac{dg}{dx}$$

# AD... is Computer Sciences

A program is composed of elementary operations like addition, subtraction, multiplication, and division.

Consider the function  $f(a, b) = \ln(ab + \max(a, 2))$ . If we want to compute the partial derivative with respect to  $a$  at a point, we need to apply the chain rule several times:<sup>9</sup>

$$\begin{aligned}\frac{\partial f}{\partial a} &= \frac{\partial}{\partial a} \ln(ab + \max(a, 2)) \\ &= \frac{1}{ab + \max(a, 2)} \frac{\partial}{\partial a} (ab + \max(a, 2)) \\ &= \frac{1}{ab + \max(a, 2)} \left[ \frac{\partial(ab)}{\partial a} + \frac{\partial \max(a, 2)}{\partial a} \right] \\ &= \frac{1}{ab + \max(a, 2)} \left[ \left( b \frac{\partial a}{\partial a} + a \frac{\partial b}{\partial a} \right) + \left( (2 > a) \frac{\partial 2}{\partial a} + (2 < a) \frac{\partial a}{\partial a} \right) \right] \\ &= \frac{1}{ab + \max(a, 2)} [b + (2 < a)]\end{aligned}$$



# One example

- Forward Accumulation is equivalent to expanding a function using the chain rule and computing the derivatives inside-out
- Requires n-passes to compute n-dimensional gradient

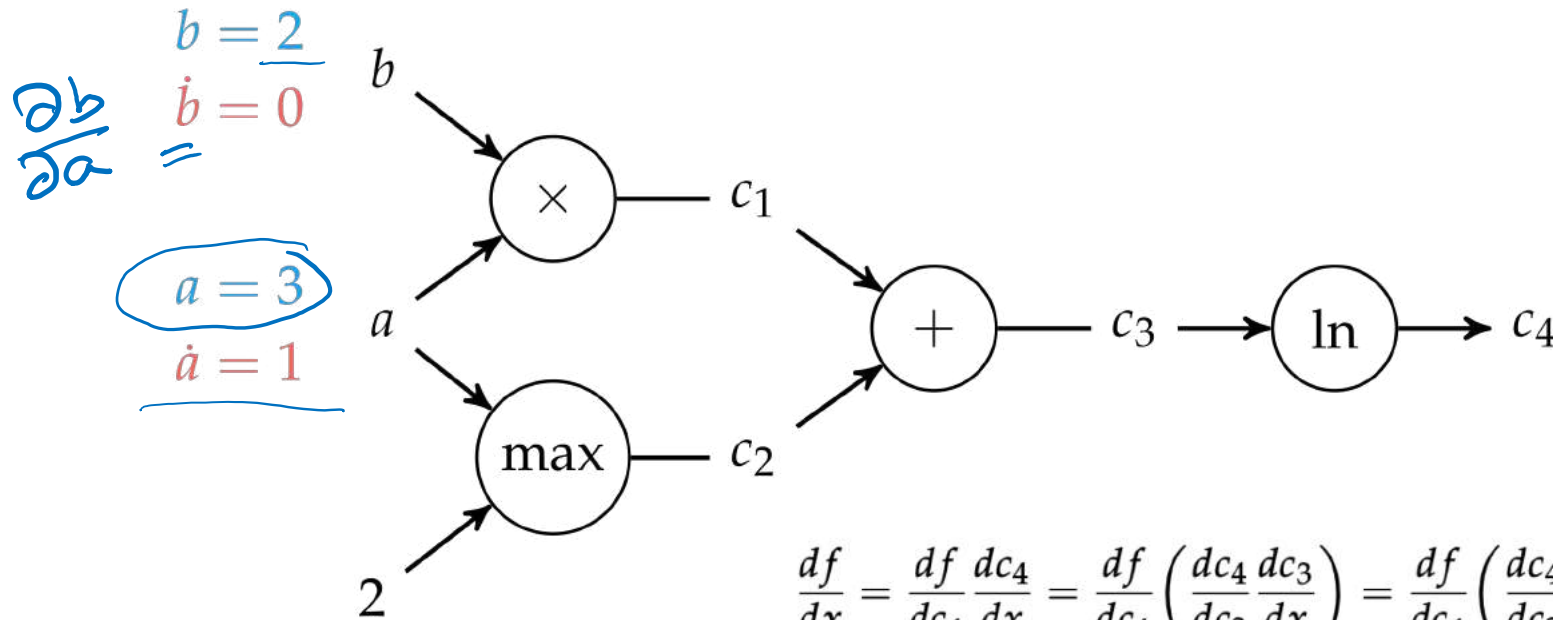
$$\frac{\partial f}{\partial a}(3,2) \quad f(a,b) = \ln(\underbrace{a}_{\leftarrow} \underbrace{b}_{\leftarrow} + \underbrace{\max(a, 2)}_{\leftarrow})$$

# AD computational graphs

$$\frac{\partial f(3,2)}{\partial a}$$

$$f(a,b) = \ln(ab + \max(a, 2))$$

- Forward Accumulation

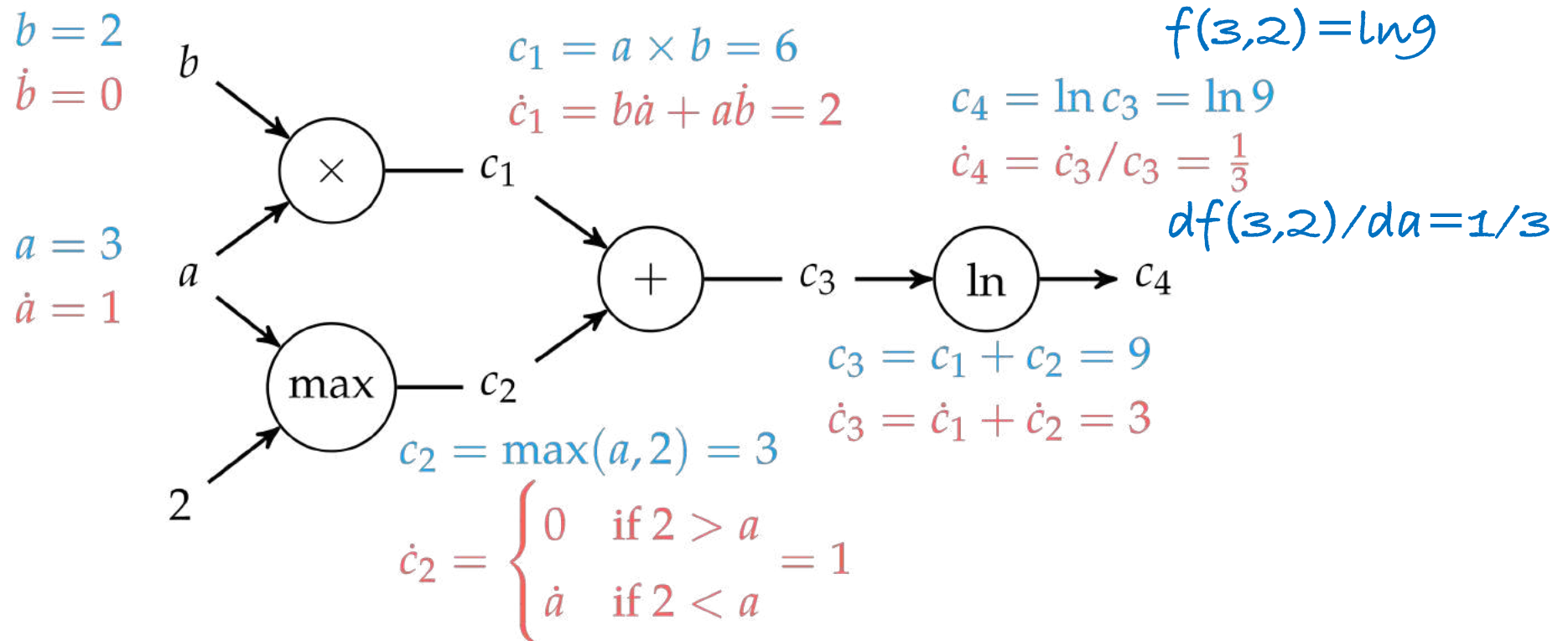


$$\frac{df}{dx} = \frac{df}{dc_4} \frac{dc_4}{dx} = \frac{df}{dc_4} \left( \frac{dc_4}{dc_3} \frac{dc_3}{dx} \right) = \frac{df}{dc_4} \left( \frac{dc_4}{dc_3} \left( \frac{dc_3}{dc_2} \frac{dc_2}{dx} + \frac{dc_3}{dc_1} \frac{dc_1}{dx} \right) \right)$$

# Automatic Differentiation

- Forward Accumulation

$$f(a,b) = \ln(ab + \max(a, 2))$$





# In Julia

The ForwardDiff.jl package supports an extensive set of mathematical operations and additionally provides gradients and Hessians.

```
julia> using ForwardDiff
julia> a = ForwardDiff.Dual(3,1);
julia> b = ForwardDiff.Dual(2,0);
julia> log(a*b + max(a,2))
Dual{Nothing}(2.1972245773362196, 0.3333333333333333)
```

# Au programme

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**Topopt review**

# History

- Homogenization of Microstructures was introduced by mathematics in the 1970s.
- First paper by Martin Bendsoe (Technical University of Denmark) and Noboru Kikuchi (University of Michigan) in 1988

A topology optimisation problem can be written in the general form of an optimization problem as

$$\min_{\rho} F = F(\mathbf{u}(\rho), \rho) = \int_{\Omega} f(\mathbf{u}(\rho), \rho) dV$$

subject to

- $\rho \in \{0, 1\}$
- $G_0(\rho) = \int_{\Omega} \rho(\mathbf{u}) dV - V_0 \leq 0$
- $G_j(\mathbf{u}(\rho), \rho) \leq 0$  with  $j = 1, \dots, m$

# TopOpt

*Je choisis un bloc de marbre et j'enlève tout ce dont je n'ai pas besoin..  
Auguste Rodin (1840-1917)*



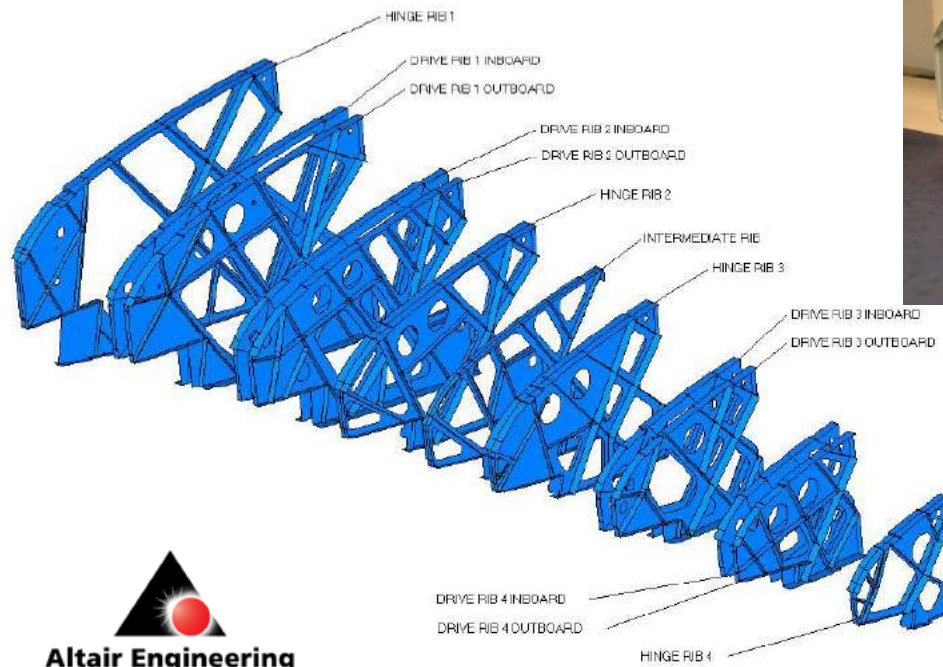
- Define the design space (marble block, fixed mesh)
- Apply loads & BCs
- Start optimization with hyper parameters
- Interpreting the results
- Optimal distribution of material (One can have an idea of the part to be reinforced, in addition to giving an excellent initial design ...)

Why is it so powerful?

→ There is a lot of possible redistribution of **INTERNAL FORCES**

## Airbus A380 example (cont.)

- Result: 500 kg weight savings!



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## Wing rib designs

The perforated plates were replaced by reinforced lattice structures  
(think of the path of preferential internal forces)

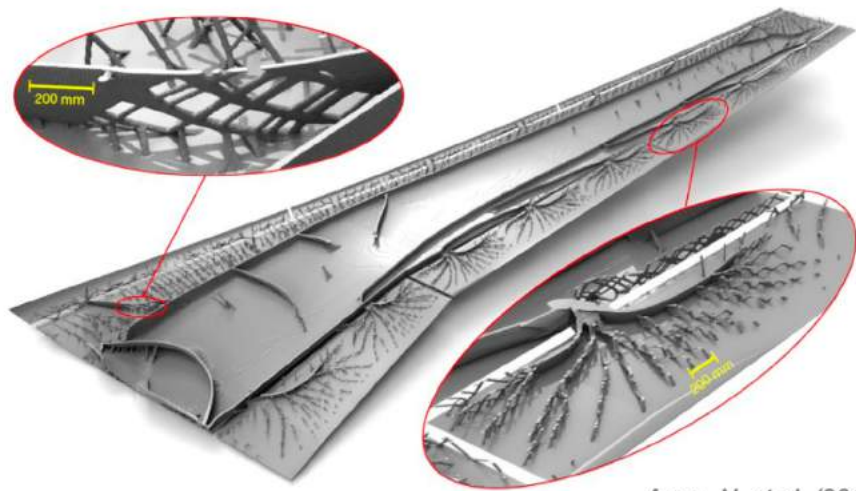
Is this totally new?

## Supermarine Southampton, 1925

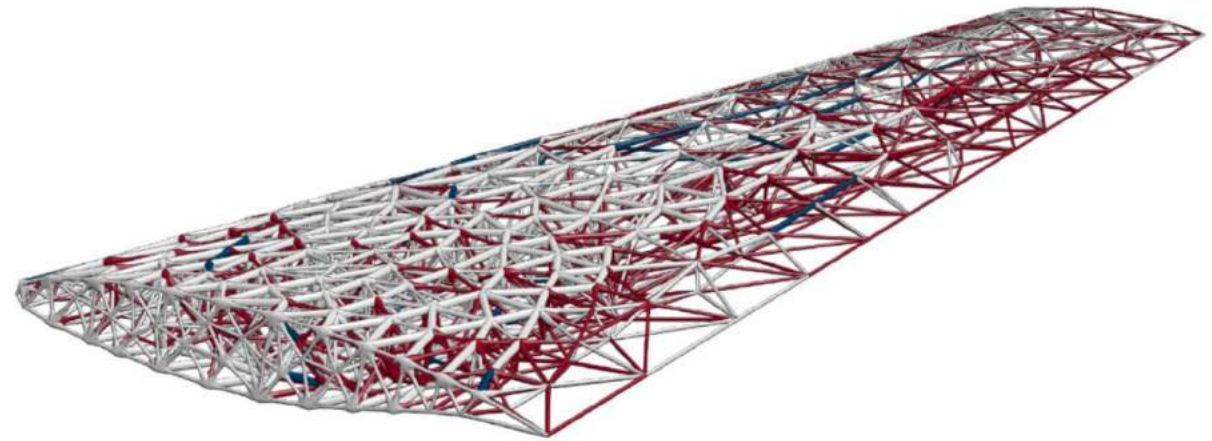


System approach automates the process!

## Concurrent method TOPOPT vs LAYOPT (continuous vs discrete)



*Aage, N. et al. (2017)*



*Opgenoord, M. M. and Willcox, K. E. (2018)*



# TopOpt



$$Ku = f$$

$$\text{Compliance } J = f^T u$$

$$\text{Compliance} = 1/\text{Stiffness}$$

1. Objective?
2. Constraints?
3. Method?

Minimize Compliance

Volume Constraint

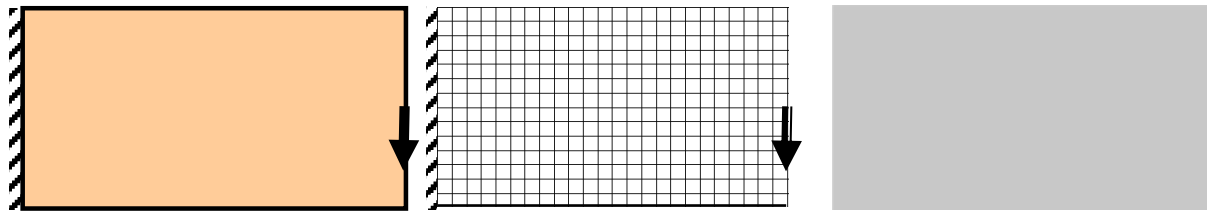
Minimize  $J$

$\text{Vol.Frac} \leq 0.5$

Method: Gradient based:  
Need sensitivities...

# SIMP

SIMP: Solid Isotropic Material with Penalization



*Min* Compliance  
 $v = 0.5v_0$

$0 < \rho_e \leq 1$  : 'PseudoDensity'

Where do we add  
 holes?

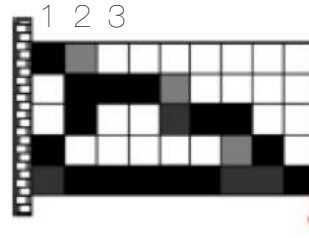
$$\begin{aligned} & \text{Min}_{\rho_e} \text{ Compliance} \\ & \sum \rho_e v_e = 0.5v_0 \end{aligned}$$

Pixels?



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# Intuitive Problem? Quadratic Form



$$\begin{aligned} x_1 &= 1 \\ x_2 &= 0.5 \\ x_3 &= 0 \\ &\dots \end{aligned}$$

- Objective function; Strain energy

$$\min c(\mathbf{x}) = \mathbf{U}^T \mathbf{F} = \mathbf{U}^T \mathbf{K} \mathbf{U} \quad \text{with} \quad x_e = \frac{\rho_e}{\rho_0} \quad (4)$$

with  $\mathbf{K} = \mathbf{K}_0 \sum_{e=1}^N x_e^p$  one can write:

$$\min c(\mathbf{x}) = \sum_{e=1}^N (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e \quad \text{Scalar} \quad (5)$$

- Constraints: mass target

$$\frac{V(\mathbf{x})}{V_0} = f = \text{const} \Leftrightarrow \sum_{e=1}^N V_e x_e - V_0 f = 0 = h(\mathbf{x}) \quad \text{Scalar}$$

$$0 < \rho_{\min} \leq \rho_e \leq 1$$

$$\min c(\mathbf{x}) = \sum_{e=1}^N (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

## Quadratic Form

$$\mathbf{x} \in \mathbb{R}^{m \times 1}, \mathbf{A} \in \mathbb{R}^{m \times m}$$


Quadratic form :  $\mathbf{x}^T \mathbf{A} \mathbf{x}$

$\mathbf{x}^T \mathbf{A} \mathbf{x}$  is a scalar value.

$$\begin{array}{c} \downarrow \quad \searrow \quad \searrow \\ (1 \times m) \times (m \times m) \times (m \times 1) \rightarrow 1 \times 1 \end{array}$$

K is linked through E and x<sub>e</sub>

Rozvany, G.I.N. , Zhou, M., and Gollub, M. (1989). Continuum Type Optimality Criteria Methods for Large Finite Element Systems with a Displacement Constraint, Part 1. Structural Optimization 1:47-72.


$$\mathbf{K} = \mathbf{K}_0 \sum_{e=1}^N x_e^p \quad x_e = \frac{\rho_e}{\rho_0}$$

- **But HOW ??**

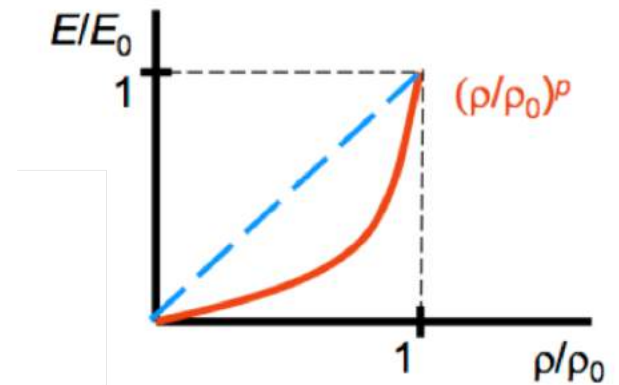
Avoid intermediate densities !

Solid Isotropic Material with Penalization (SIMP)

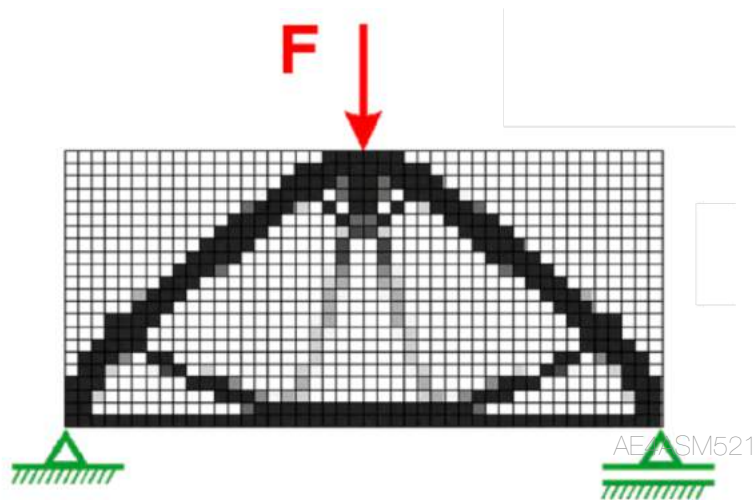
$$E(x) = E_{min} + (E_0 - E_{min})x^p$$

$p$  is the penalty parameter to push densities to black (1) and white (0).

$E_{min}$  is a small value that avoid stiffness matrix singularity



Penalization for altering stiffness locally

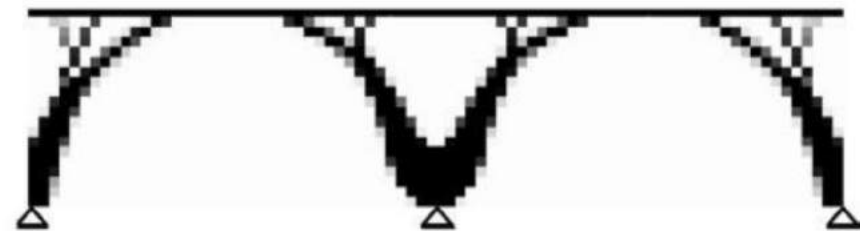
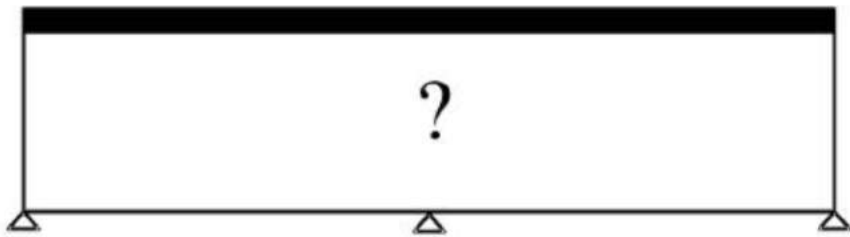


**Nice idea !**

1. Transform discrete variables **continuously (TO USE gradient-based algorithms)**
2. Find an objective function with "**cheap**" derivatives (we will see this later but you can also **use AD**)



Can you comment this ?  
1 problem; 3 optimizers

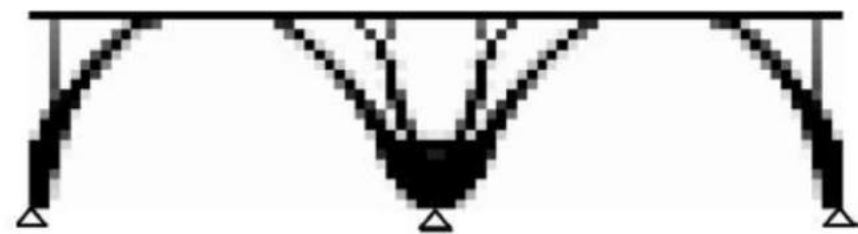


MMA

- **Local Optimum**

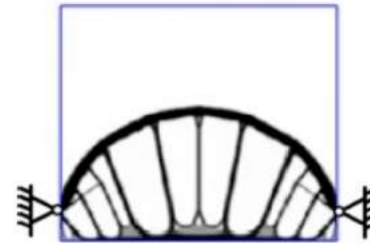
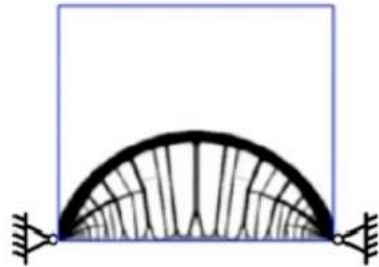


Conlin & GCMMA

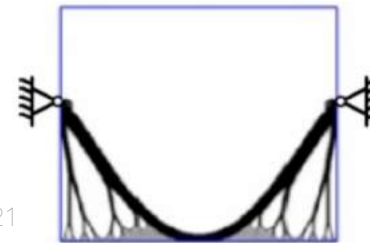
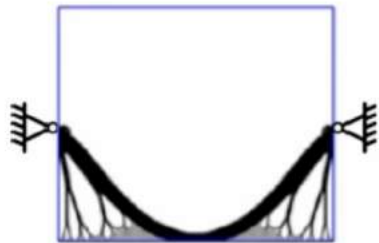


Can you comment this ?

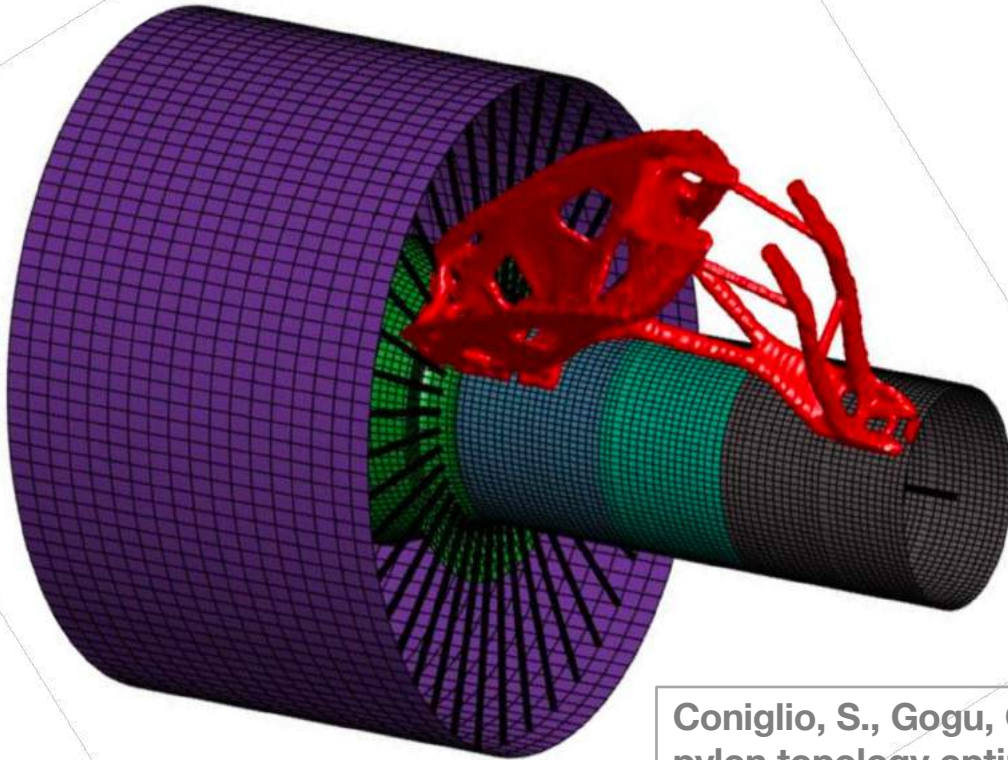
Small changes in BCs



...link to  
Uncertainty  
of modeling



# Pylon Design



Coniglio, S., Gogu, C., Amargier, R., & Morlier, J. (2019). Engine pylon topology optimization framework based on performance and stress criteria. *AIAA Journal*, 57(12), 5514-5526.

## History (1988, Bendsoe)

A topology optimization problem based on the power-law approach, where the objective is to minimize compliance can be written as

$$\left. \begin{array}{l} \min_{\mathbf{x}}: \quad c(\mathbf{x}) = \mathbf{U}^T \mathbf{K} \mathbf{U} = \sum_{e=1}^N (x_e)^p \mathbf{u}_e^T \mathbf{k}_e \mathbf{u}_e \\ \text{subject to:} \quad \frac{V(\mathbf{x})}{V_0} = f \\ \quad \quad \quad : \quad \mathbf{K} \mathbf{U} = \mathbf{F} \\ \quad \quad \quad : \quad \mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1} \end{array} \right\}, \quad (1)$$

where  $\mathbf{U}$  and  $\mathbf{F}$  are the global displacement and force vectors, respectively,  $\mathbf{K}$  is the global stiffness matrix,  $\mathbf{u}_e$  and  $\mathbf{k}_e$  are the element displacement vector and stiffness matrix, respectively,  $\mathbf{x}$  is the vector of design variables,  $\mathbf{x}_{\min}$  is a vector of minimum relative densities (non-zero to avoid singularity),  $N$  ( $= \text{nelx} \times \text{nely}$ ) is the number of elements used to discretize the design domain,  $p$  is the penalization power (typically  $p = 3$ ),  $V(\mathbf{x})$  and  $V_0$  is the material volume and design domain volume, respectively and  $f$  (`volfrac`) is the prescribed volume fraction.

## Compliance minimization self adjoint

- Compliance is the opposite of stiffness

$$\mathbf{C} = \mathbf{f}^T \mathbf{u} = \mathbf{u}^T \mathbf{K} \mathbf{u}$$

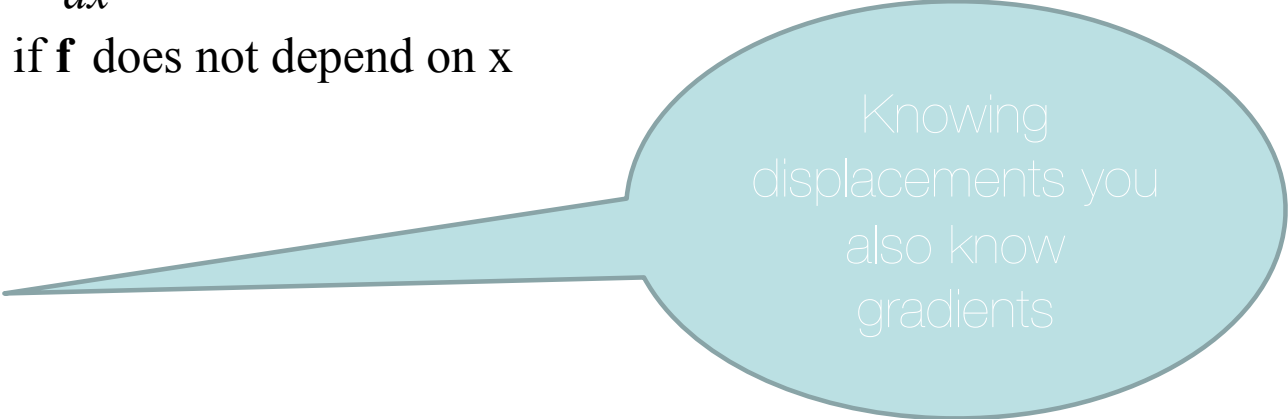
- Inexpensive derivatives (use chain rule)

$$\frac{dC}{dx} = 2\mathbf{u}^T \mathbf{K} \frac{d\mathbf{u}}{dx} + \mathbf{u}^T \frac{d\mathbf{K}}{dx} \mathbf{u}$$

But since  $\mathbf{K}\mathbf{u} = \mathbf{f}$  if  $\mathbf{f}$  does not depend on  $x$

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

$$\frac{dC}{dx} = -\mathbf{u}^T \frac{d\mathbf{K}}{dx} \mathbf{u}$$



Knowing  
displacements you  
also know  
gradients

## Density design variables

Need a DEMO ?

- Recall  $\frac{dC}{dx} = -\mathbf{u}^T \frac{dK}{dx} \mathbf{u}$
- For density variables

$$\frac{dC}{d\rho^e} \propto -\mathbf{u}^T \rho^{p-1} K^e \mathbf{u}$$

- Want to increase density of elements with high strain energy and vice versa
- To minimize compliance for given weight can use an optimality criterion method.

And for other responses?

$$0 = f(x, U)$$

$$\frac{\partial 0}{\partial x} = \frac{\partial f^T}{\partial U} \frac{\partial U}{\partial x}$$

$$KU = F$$

$$\frac{\partial K}{\partial x} U + K \frac{\partial U}{\partial x} = 0$$

$$\frac{\partial 0}{\partial x} = \frac{\partial f^T}{\partial U} \frac{\partial U}{\partial x} = -\frac{\partial f^T}{\partial U} K^{-1} \frac{\partial K}{\partial x} U = -\frac{\partial f^T}{\partial U} \delta$$

$$K\lambda = \frac{\partial f}{\partial U} \text{ Adjoint Method}$$

$$K\delta = \frac{\partial K}{\partial x} U \text{ Direct Method}$$

Either one solution per  
response

Either one solution per  
design variables

That's why Compliance!