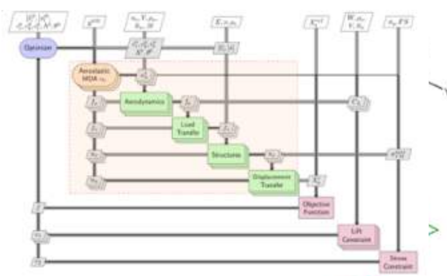
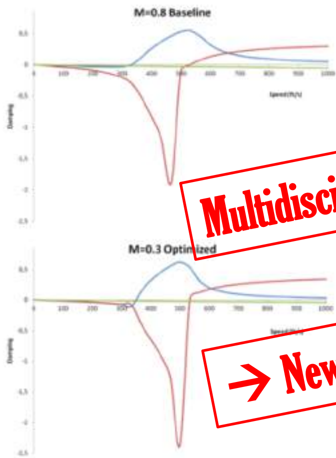
MDO, GP, ROM WHAT ELSE?

Prof.Joseph Morlier, MLclass 2019

My Research Group (Joint research with ONERA on MDO)

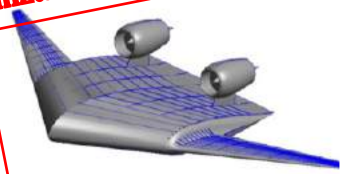
- 4 PhDs, 1 postdoc, 1 research assistant, 4 MsCs





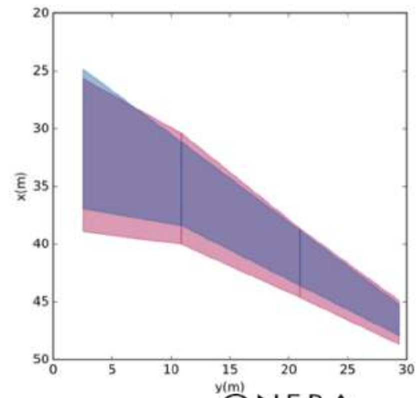
Multidisciplinary Design Optimization

→ New Aircraft Concept

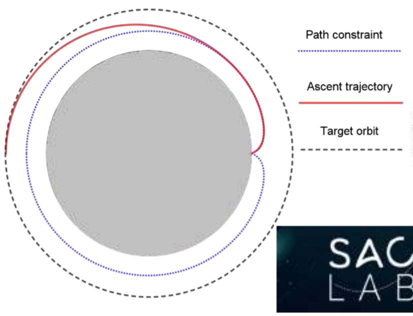


AIRBUS

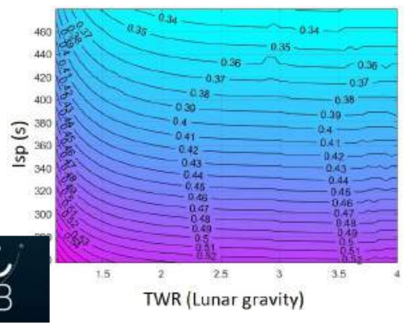
CHAIR FOR ECO DESIGN OF AIRCRAFT



ONERA
THE FRENCH AEROSPACE LAB



SAC LAB



→ New disciplines such as trajectory or control

minimize $f(x) = w_1 k_h + w_2 \bar{h}_{max}(t, V_f^{CL})$

with $x = (k_h, Q, R)^{[4]}$

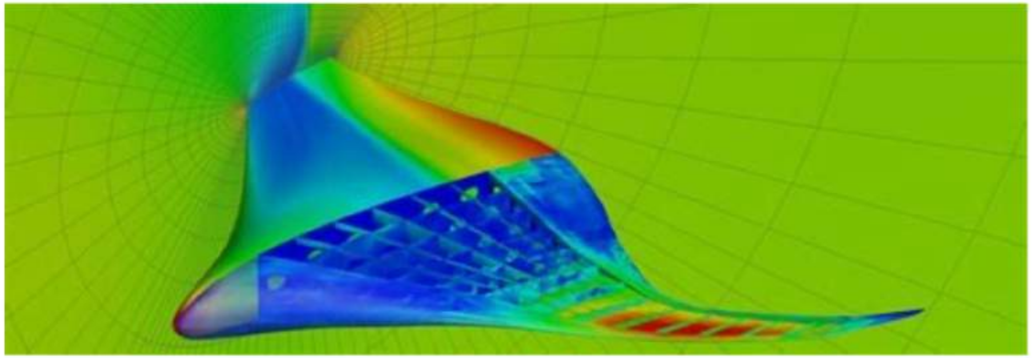
subject to
$$\begin{cases} V_f^{CL} > 1.2\, V_{f\,x_0}^{OL} \\ \left|\beta_{max}(t, V_f^{CL})\right| < \beta_{ref} \\ f_{max}^{i} < 3 f_{max\,x_0}^{i} \end{cases}$$

where V_f^{CL} is the open loop (OL) or closed loop (CL) flutter
β_{ref} is the maximum control surface deflection
f_{max}^{i} is the maximum frequency of mode i
$V_{f\,x_0}^{OL}$ is the open-loop flutter velocity at the starting point
Q, R are the LQR weight matrix to compute K

AIRBUS

Popularization for our common research ONERA-SUPAERO

https://www.linkedin.com/pulse/optimization-mdo-connecting-people-joseph-morlier/



http://mdolab.engin.umich.edu

Optimization [MDO] for connecting people?

Publié le 14 février 2019 | Modifier l'article | Voir les stats

joseph morlier
Professor in Structural and Multidisciplinary Design Optimization, ... any idea?
2 articles

74 31 3 0

Outlines for today

multidisciplinary **Design** optimization generates **Data** (a lot)

multidisciplinary optimization

1. MDO
2. GP
3. ROM

RECIPES

- MDO+GP+ROM = Optimization of coupled (costly) simulation codes at fixed budget

MOPTA08 is a multidisciplinary design optimization (MDO) benchmark problem based on a real-life problem from the automotive industry.

It states a large-scale multidisciplinary mass optimization of a vehicle in a crash test simulation. Real simulation (HPC) can optimistically compute about **60 points/day**. It was highly desirable to solve the optimization problem **in ≤ 1 month (30 days).**

For you:

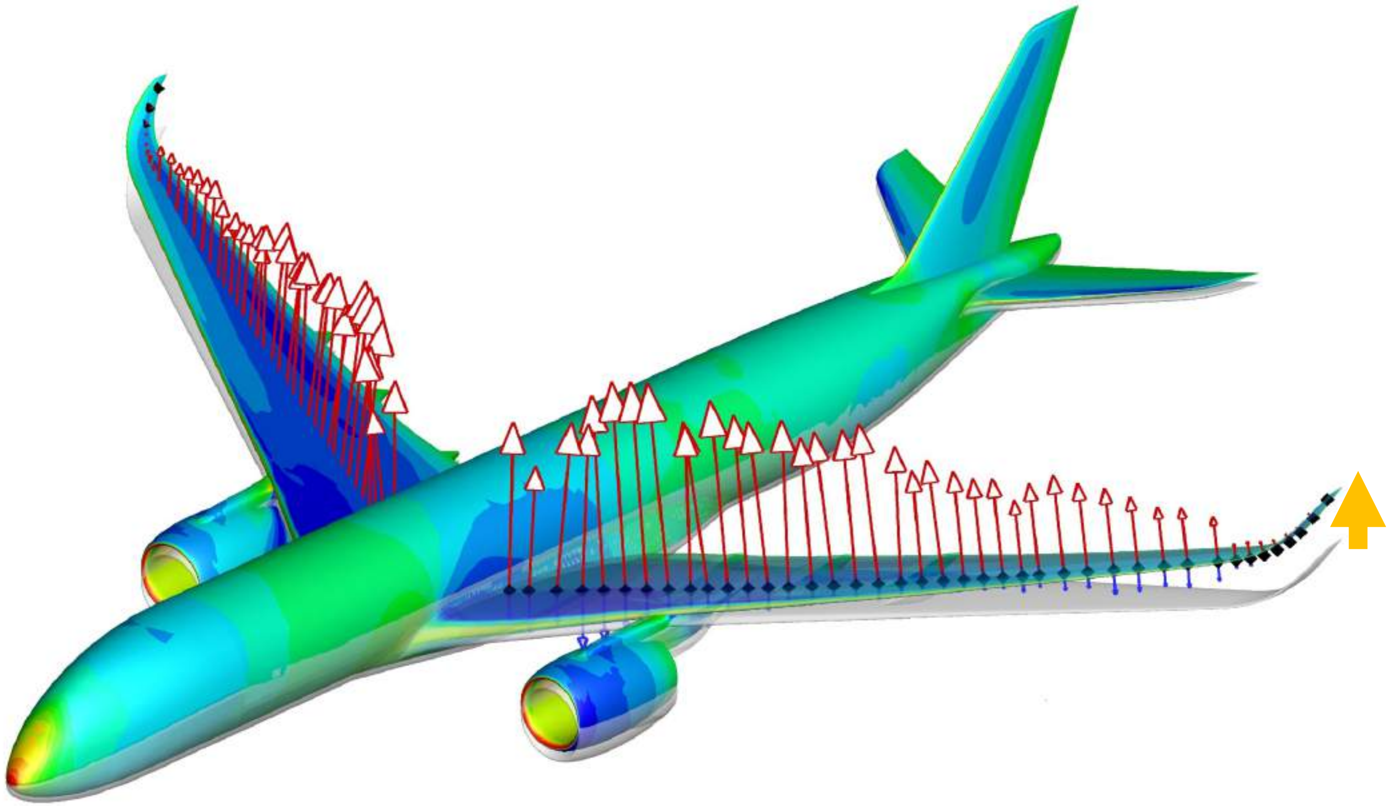
- 1 hour course (research oriented) 21/10 + 2H Python Practice 23/10

Outlines for today

1.MDO

2. GP
3. ROM

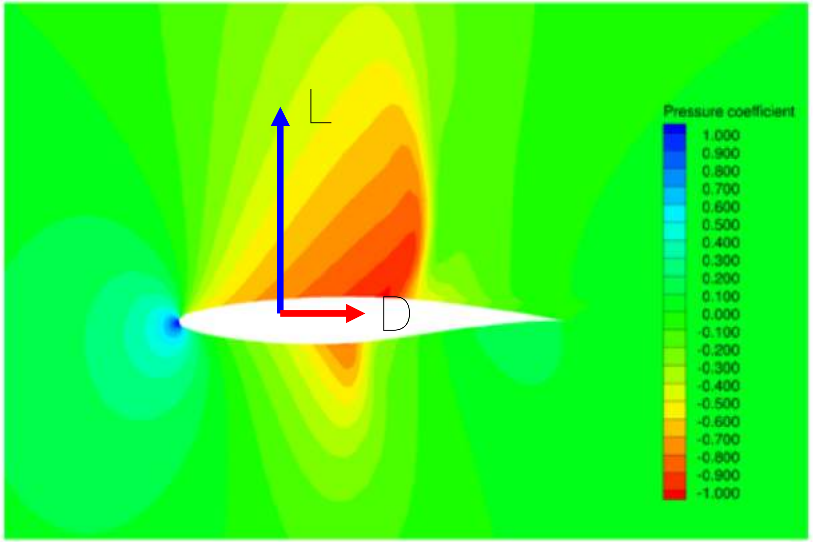
What is an MDA ? Static Aeroelasticity for example?



Source: DLR

But first, what is Disciplinary Optimization?

Example: Aerodynamics (L/D max)

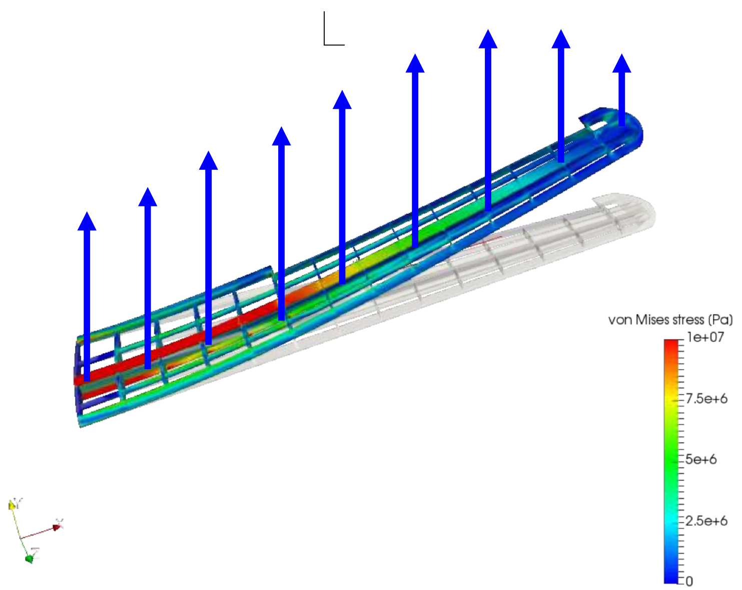


Source: NLR

Minimize D
w.r.t. shape, α
Subject to L = W

What is Disciplinary Optimization (2)?

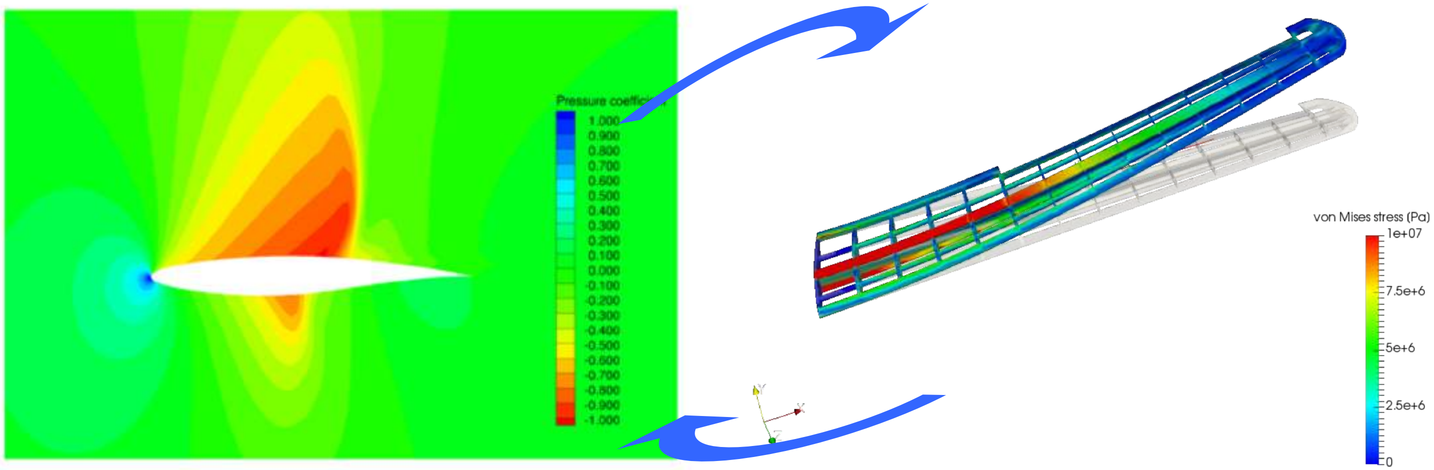
Another example: Structures



Source: simscale.com

Minimize Mass
w.r.t. thicknesses
Subject to $\sigma \leq \sigma y$

However… Disciplines are not isolated:



Structural deformation of wing → changes in the shape exposed to airflow

Changes in the shape exposed to airflow → changes in the aerodynamic loads

Then, how do we solve the complete system?

Structure Analysis

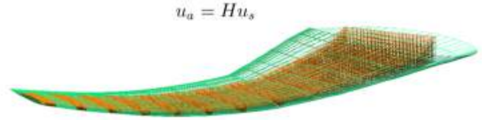
Nodal displacements

Radial Basis Function displacement interpolation (same for y and z)

$$u_x = \sum_{i=1}^{N_s} \alpha_i^x \phi(\|\mathbf{x} - \mathbf{x_i}\|) + \gamma_0^x + \gamma_x^x x + \gamma_y^x y + \gamma_z^x z$$

Displacement interpolation matrix

$$u_a = H u_s$$



Loads using principle of virtual work

$$f_s = H^T f_a$$

Aero grid displacements

Aerodynamic Analysis

Forces on aero grid points

Load Transfer

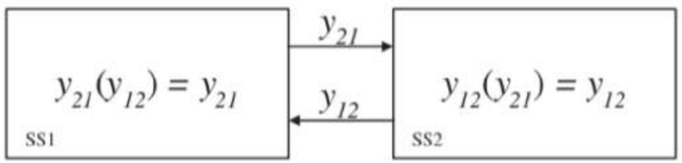
Rendall, T. C. S., & Allen, C. B. (2008). Unified fluid–structure interpolation and mesh motion using radial basis functions. International Journal for Numerical Methods in Engineering, 74(10), 1519-1559.

Nodal forces

The solution of the complete system is the set of displacements and forces that "satisfy" this loop

Multi-Disciplinary Analysis

- Computation of the state variables at equilibrium for given x and z
  - Generally computed using a fixed-point algorithm (Jacobi or Gauss-Seidel)
  - Or a root-finding method (Newton-Raphson)



(Step 0) choose initial guess y_{12}^0, set $i = 0$

(Step 1) $i = i + 1$

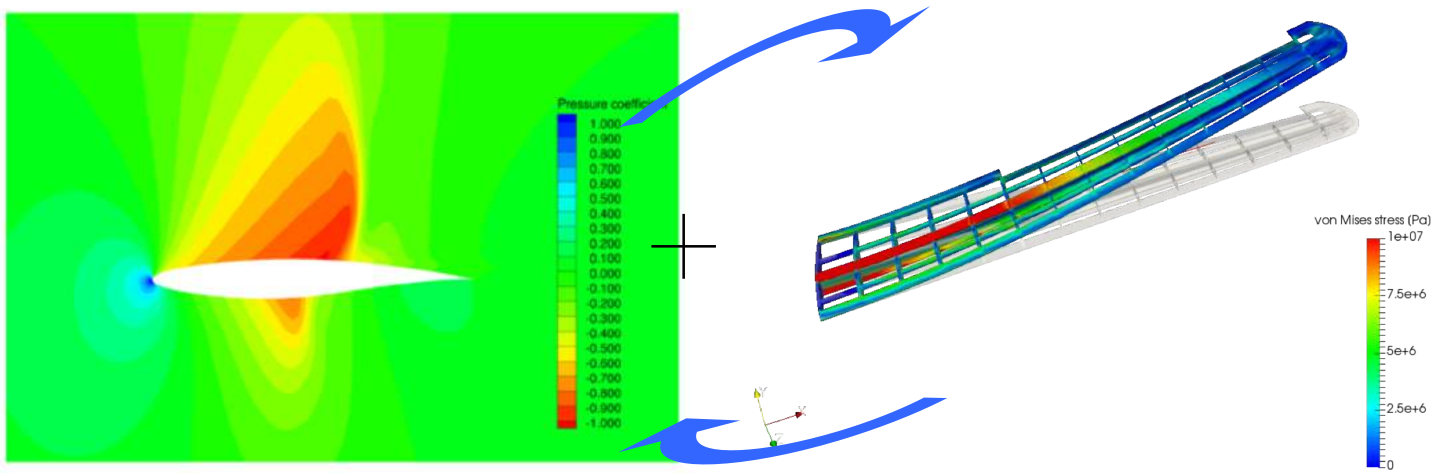
(Step 2) $y_{21}^i = y_{21}(y_{12}^{i-1})$

(Step 3) $y_{12}^i = y_{12}(y_{21}^i)$

(Step 4) if $|y_{12}^i - y_{12}^{i-1}| < \varepsilon$ stop, otherwise go to **(Step 1)**

Check the default tolerence

→we need to analyze BOTH disciplines at the SAME TIME



Minimize D, or Mass, or a combination of D and Mass
w.r.t. shape, α, thicknesses
Subject to:

$$L = W$$

$$\sigma \leq \sigma y$$

In practice, how do we solve that problem?

One possible approach: MultiDisciplinary Feasible (MDF, probably the most intuitive one…)

Steps:

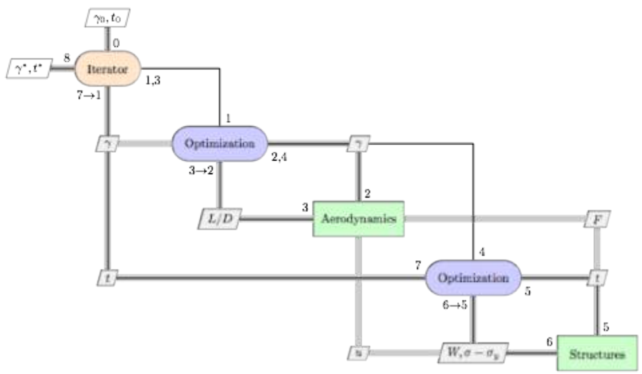
1. Start from a set of particular design variables: shape, α, thicknesses
2. Solve the complete system (with all the interactions) for these values
3. Evaluate objective function and constraints
4. From these values, the optimizer proposes a new set of design variables.

These steps are repeated until the optimum is reached.

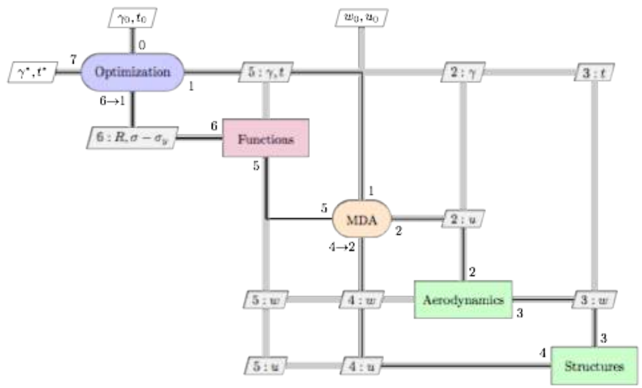
Next: MDO …The big picture

MDO optimizes all variables simultaneously, accounting for all the couplings

Sequential optimization



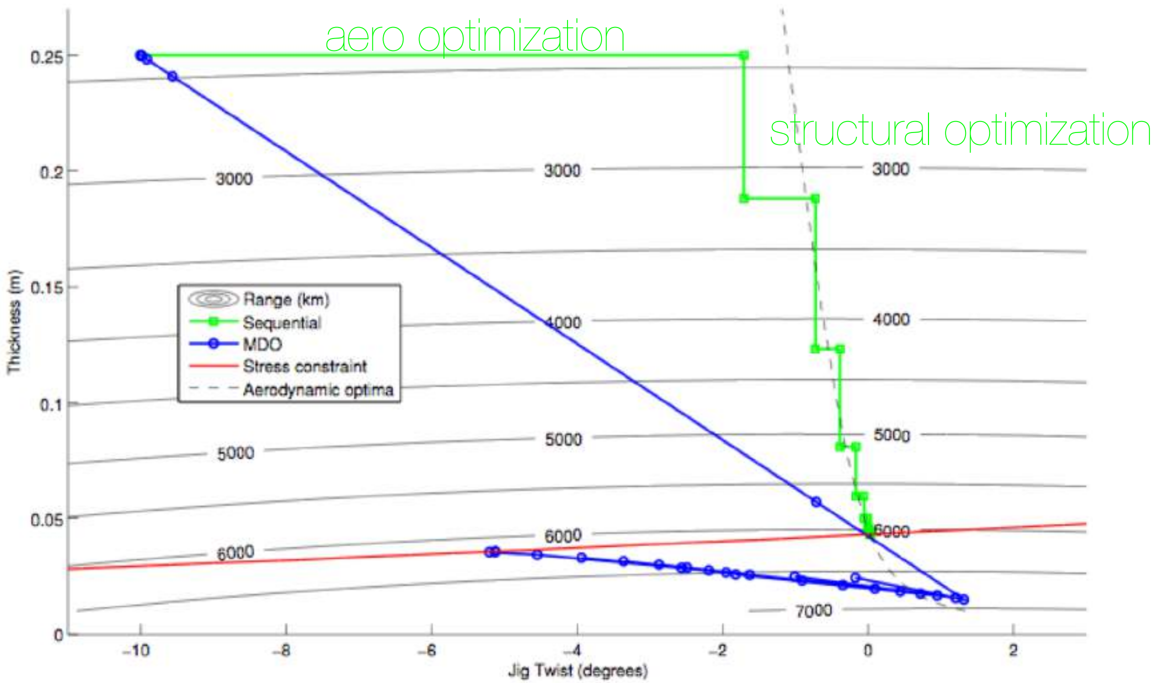
MDO



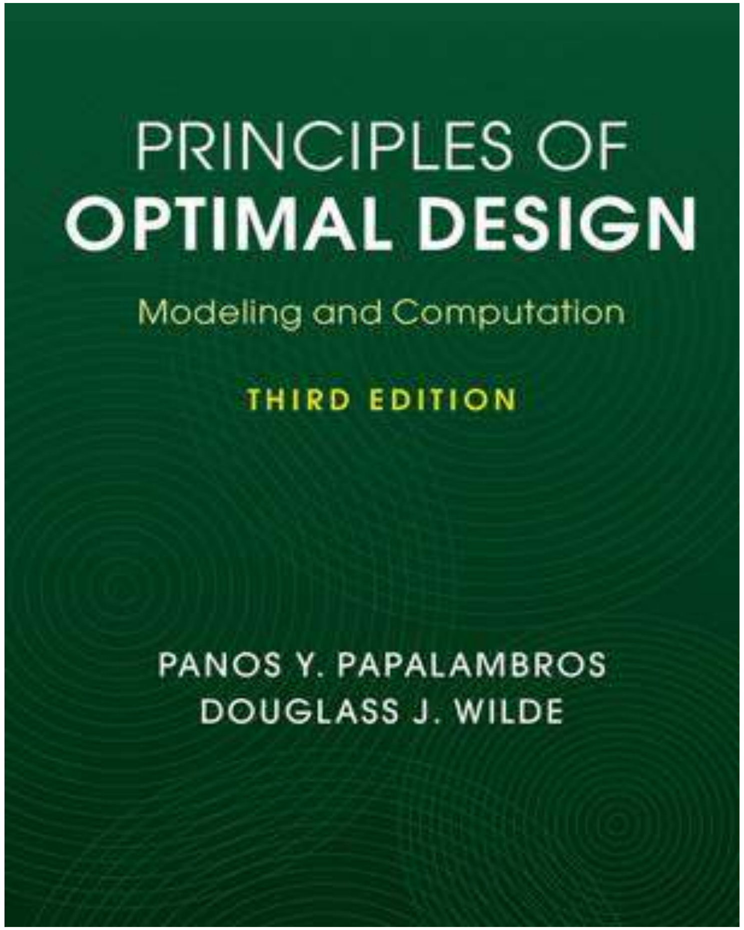
I. R. Chittick and J. R. R. A. Martins. An asymmetric suboptimization approach to aerostructural optimization. Optimization and Engineering, 10(1):133–152, Mar. 2009. doi:10.1007/s11081-008-9046-2.

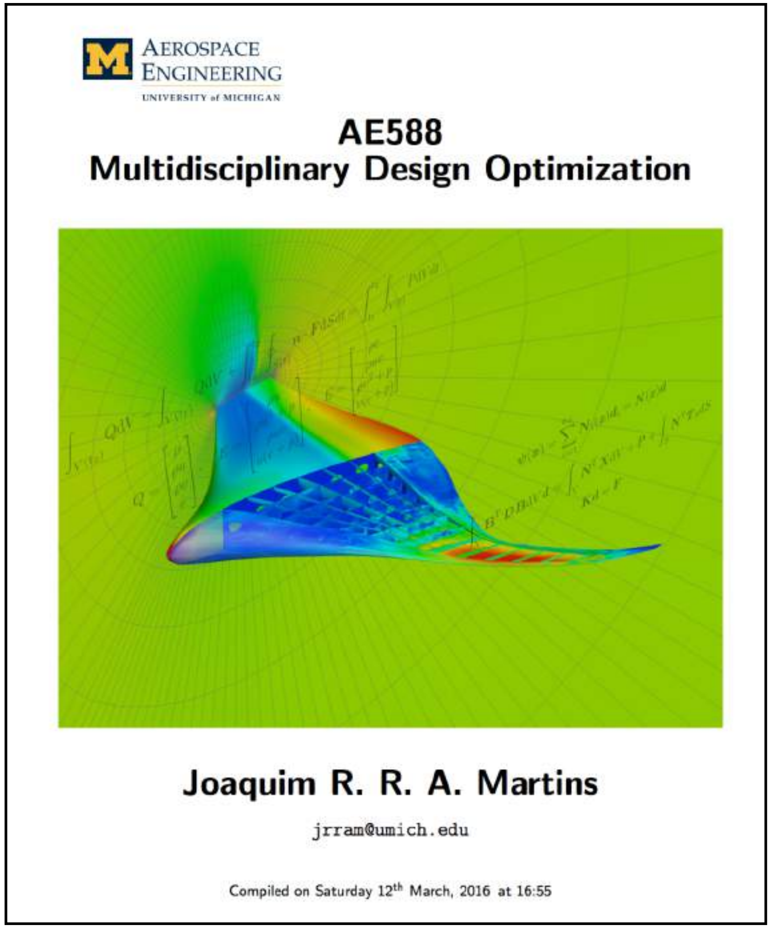
Sequential optimization fails to find the multidisciplinary optimum

Chittick, I. R., & Martins, J. R. (2008). Aero-structural optimization using adjoint coupled post-optimality sensitivities. Structural and Multidisciplinary Optimization, 36(1), 59-70.



Good Starting Point (x0)

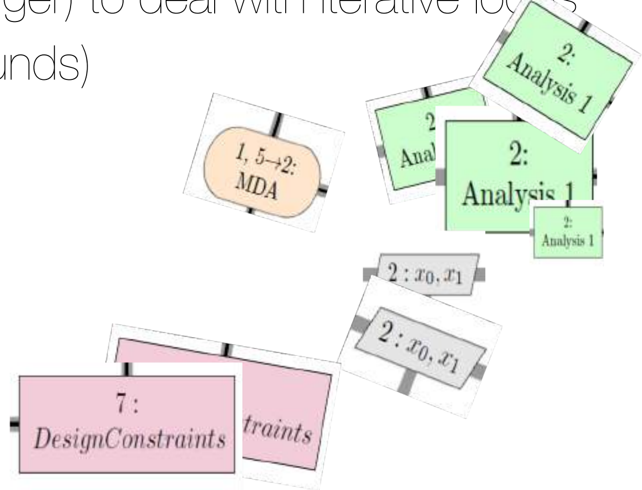




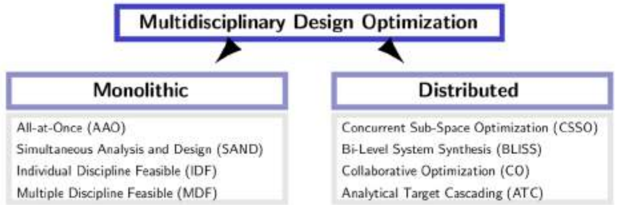
Assembling MDO systems

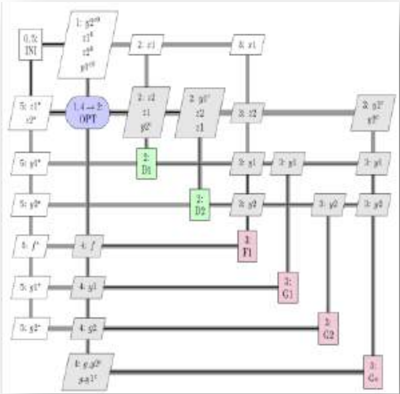
In order to assemble an MDO "architecture" we need a number of components:

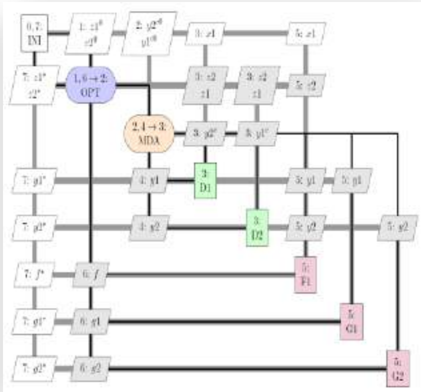
- One (or more) optimizers
- One (or more) objectives
- A number of disciplinary tools (or disciplines, or competences)
- Possibly some coordinator (or converger) to deal with iterative loops
- A bunch of design variables (with bounds)
- Some constraint specification

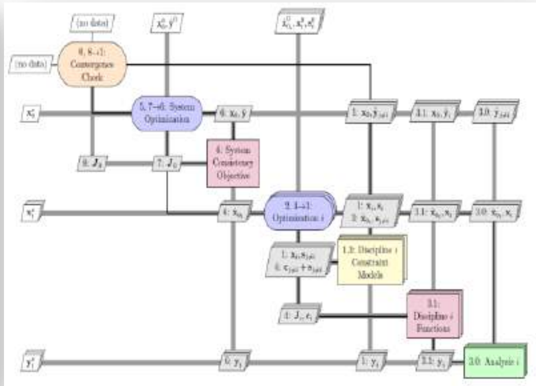


Assembling MDO systems

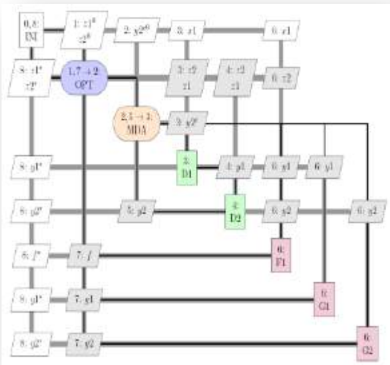


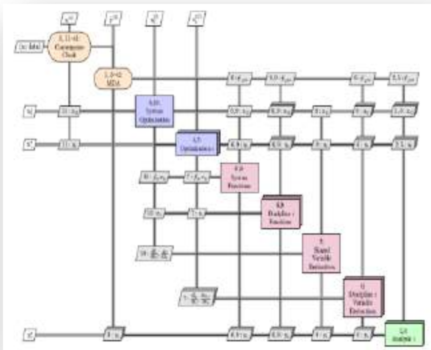


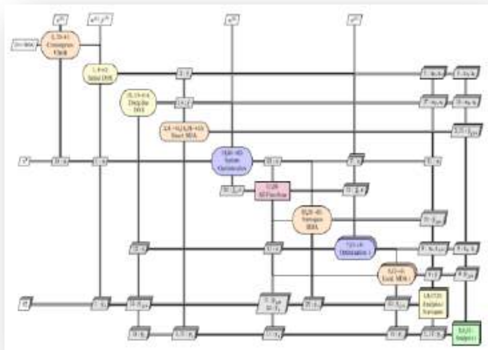




MDF Multidisciplinary Feasible approach—a complete analysis is performed at every optimization iteration. Also known as the All-in-One approach.







Illustrative example: the Sellar problem

2 disciplines involved

Variables: x_1, y_1, y_2, z_1, z_2

We'll see later what are the differences between these variables …

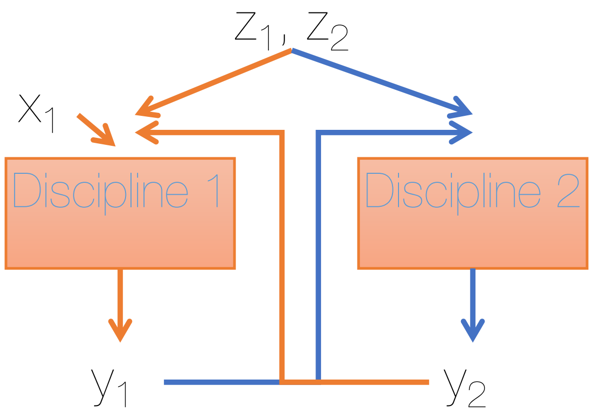
$$
\begin{gathered}
\text{minimize } x_1^2 + z_2 + y_1 + \exp(-y_2) \\
\text{with respect to } z, x \text{ or } (z_1,\ z_2,\ x_1) \\
\text{subject to:} \\
3.16 - y_1 \leqslant 0 \\
y_2 - 24 \leqslant 0 \\
-10 \leqslant z_1 \leqslant 10 \\
0 \leqslant z_2 \leqslant 10 \\
0 \leqslant x_1 \leqslant 10
\end{gathered}
$$

$$
\begin{gathered}
\text{Discipline 1}: y_1(z_1, z_2, x_1, y_2) = z_1^2 + x_1 + z_2 - 0.2y_2 \\
\text{Discipline 2}: y_2(z_1, z_2, y_2) = \sqrt{y_1} + z_1 + z_2
\end{gathered}
$$

Sellar, R. S., Batill, S. M., and Renaud, J. E., "Response Surface Based, Concurrent Subspace Optimization for Multidisciplinary System Design", 34th Aerospace Sciences Meeting and Exhibit, Aerospace Sciences Meetings, 1996.

Illustrative example: the Sellar problem

- Design variables: z_1, z_2, x_1 to minimize the objective
- Shared (or global) variables: z_1, z_2
- Local variable: x_1
- Coupling variables: y_1, y_2



$$\boxed{\begin{array}{c}\text{minimize } x_1^2 + z_2 + y1 + e^{-y_2}\\ \text{with respect to } z_1, z_2, x_1\end{array}}$$

$$\begin{array}{c}\text{subject to:}\\ \frac{y_1}{3.16} - 1 \geq 0\\ 1 - \frac{y_2}{24} \geq 0\\ -10 \leq z_1 \leq 10\\ 0 \leq z_2 \leq 10\\ 0 \leq x_1 \leq 10\end{array}$$

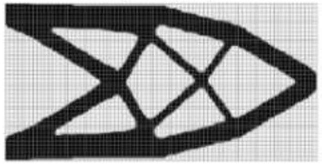
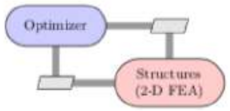
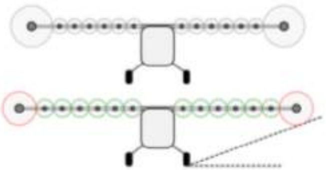
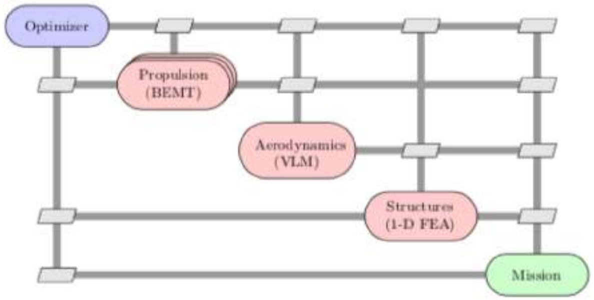
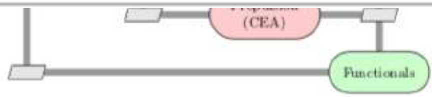
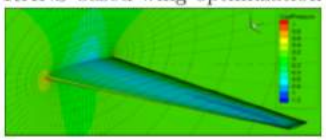
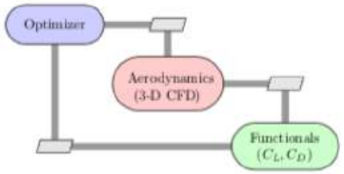
$$\boxed{\begin{array}{c}\text{Discipline 1: } y_1(z_1, z_2, x_1, y_2) = z_1^2 + x_1 + z_2 - 0.2y_2\\ \text{Discipline 2: } y_2(z_1, z_2, y_1) = \sqrt{y_1} + z_1 + z_2\end{array}}$$

Multidisciplinary analysis (MDA) consists in solution of the following equations

$R_1 = 0$ ➔ y_1 and y_2 solutions

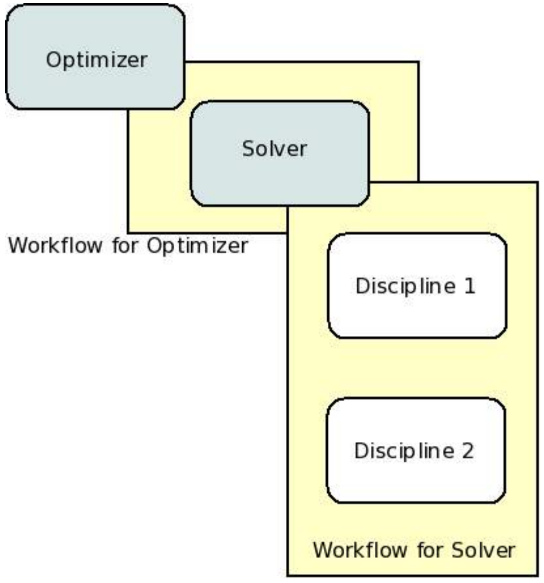
$R_2 = 0$

J. S. Gray, J. T. Hwang, J. R. R. A. Martins, K. T. Moore, and B. A. Naylor, "OpenMDAO: An Open-Source Framework for Multidisciplinary Design, Analysis, and Optimization," Structural and Multidisciplinary Optimization, 2019.

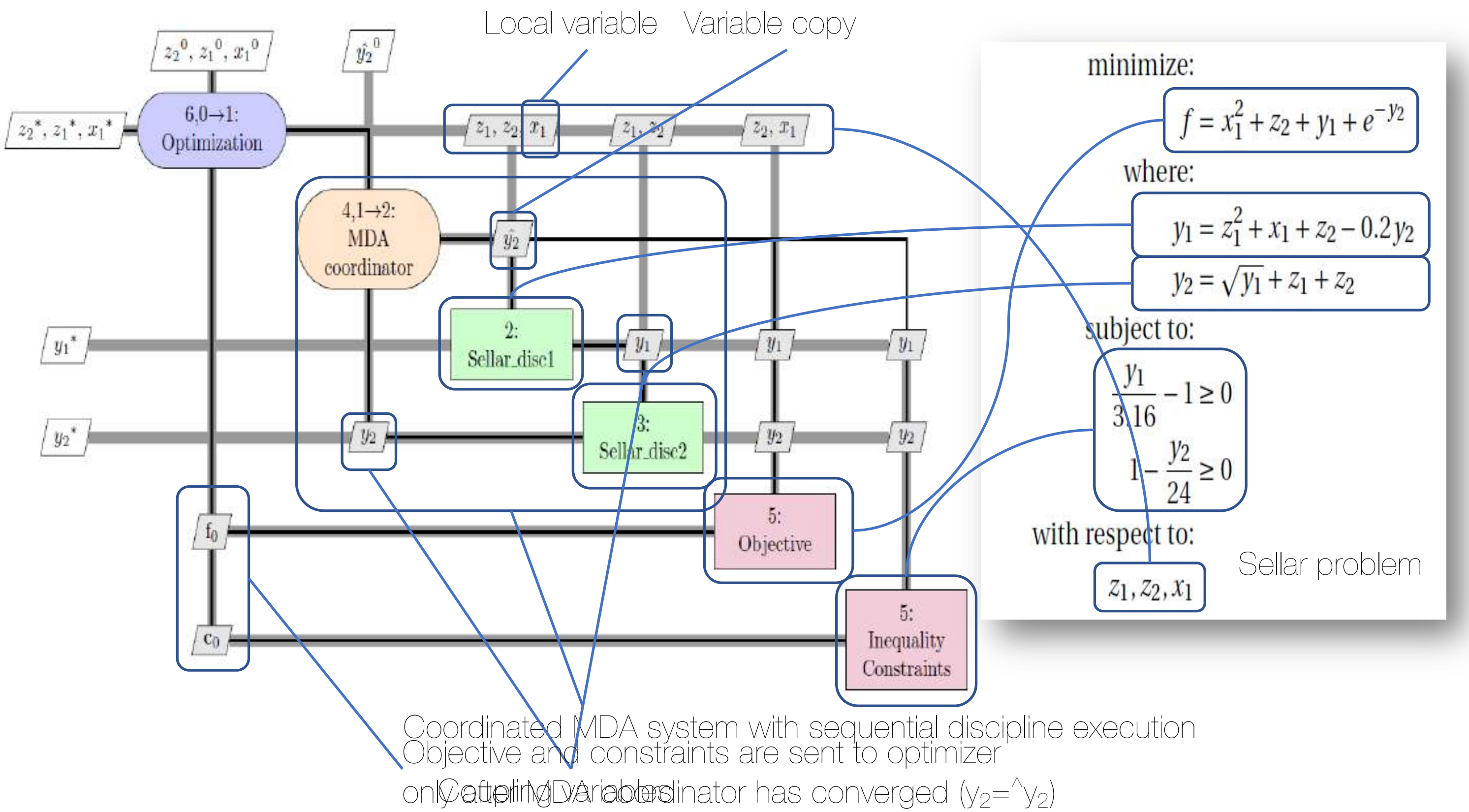
Problem	Model structure	Design variables	Objective	Constraints
Structural topology optimization 		Element densities	Compliance	Mass fraction
CTOL electric aircraft MDO 		Altitude prof., velocity prof., prop RPM profs., prop chord, prop twist, prop diam., wing twist, beam thickness	Range	Average speed, eqs. of motion, max. power, min. torque, ground clear., tip speed, wing failure
				
RANS-based wing optimization 		Shape	Drag coefficient	Lift coefficient

Multidisciplinary Feasible (MDF)

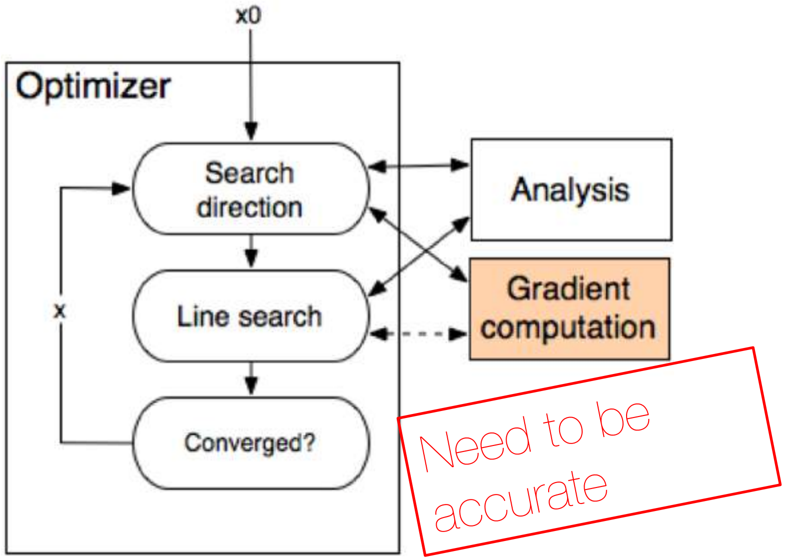
- The MDF architecture is the most intuitive for engineers
- The optimization problem formulation is identical to the single discipline case, except the disciplinary analysis is replaced by an MDA



MDF illustration on the Sellar problem:
MDF – Gauss-Seidel variant



Optimizer solver



- Requirements
- Problem to solve $\begin{cases} \min f(x) \\ wrt\ x \in R^d \\ st\ g_i(x) \leq 0 \text{ for } i = 1, \dots m \end{cases}$

- Derivative Fee Optimizer (DFO)
- Evolutionnary Strategies (ES)
- **Surrogate based Optimizer (SBO) or Bayesian Optimization (BO)**
- ...
- Gradient based Optimizer

→Computation of the derivatives of $f(x)$ and $g_i(x)$ to iterate and satisfy the KKT optimality conditions

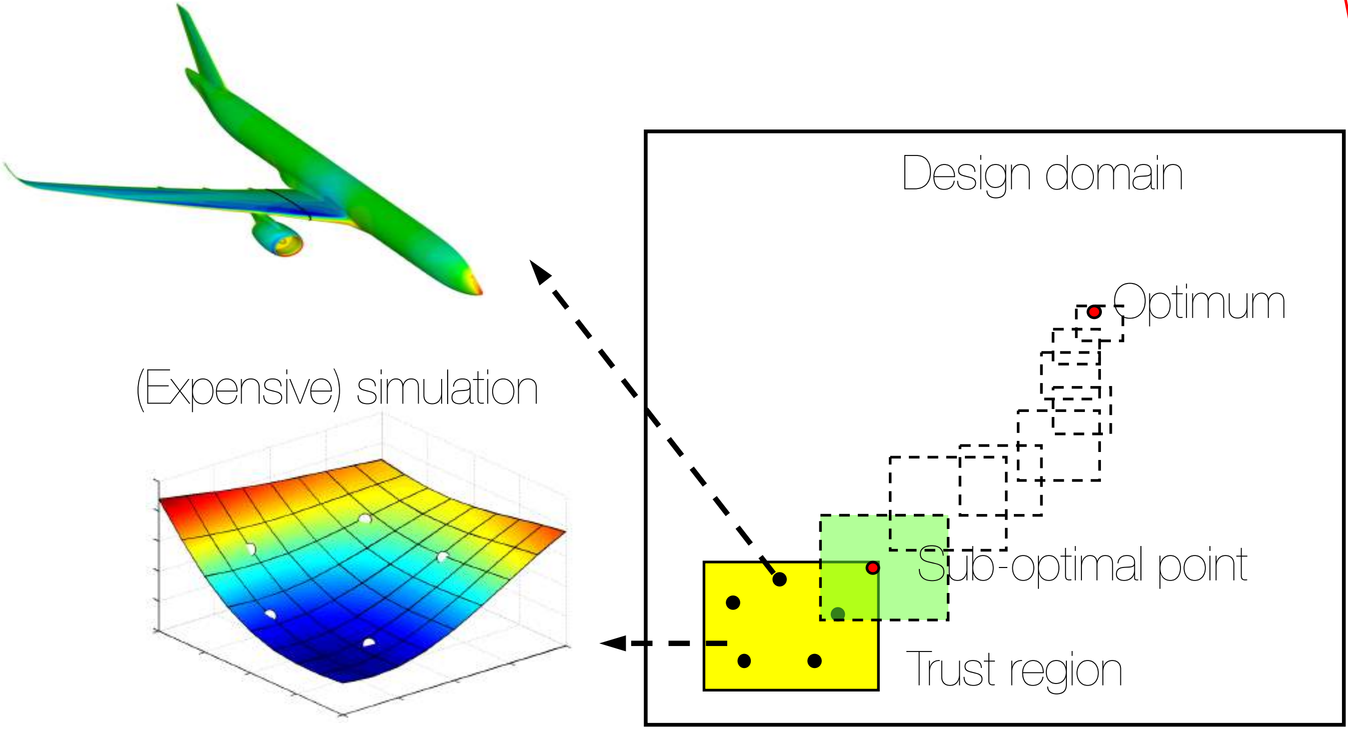
➔ OpenMDAO focus on computation of sensitivities (adjoint vs direct)

$$\frac{\partial f}{\partial x_i}, \frac{\partial g}{\partial x_i}, \frac{\partial h}{\partial x_i}$$

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.

But HOW?



Response surfaces, metamodels, surrogate models etc…

Outlines for today

1. MDO

2. GP

3. ROM

A bit of History

Kriging (Pionneer)	Gaussian Processes (link with AI)
Developed by Daniel Krige – 1951; formalized by Georges Mathéron in the 60's (Mines Paris)	Neural network with infinite neurons tend to Gaussian Process 1994
Evaluation: minimize error variance	Evaluation: Marginal Likelihood

Krige, D. G., 1951, A statistical approach to some basic mine valuation problems on the Witwatersrand: J. Chem. Metal. Min. Soc. South Africa, v. 52, p. 119-139.

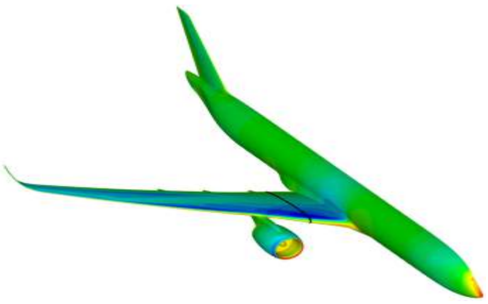
Matheron, G., 1963b, Principles of geostatistics: Economic Geol., v. 58, p. 1246-1266.

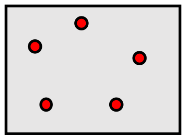
Neal, R. Priors for infinite networks. Tech. rep., University of Toronto, 1994.

Williams, C. K. I., and Rasmussen, C. E. Gaussian processes for regression. *Advances in Neural Information Processing Systems 8* (1996), 514–520.

http://extrapolated-art.com

Surrogate modeling Recipes

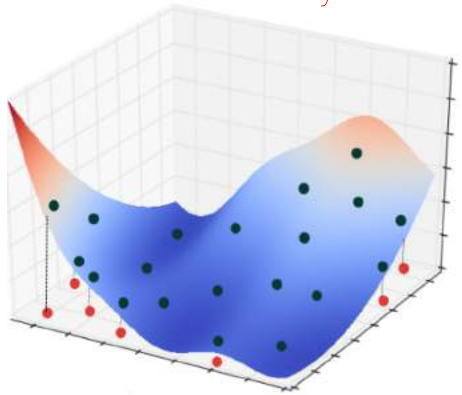


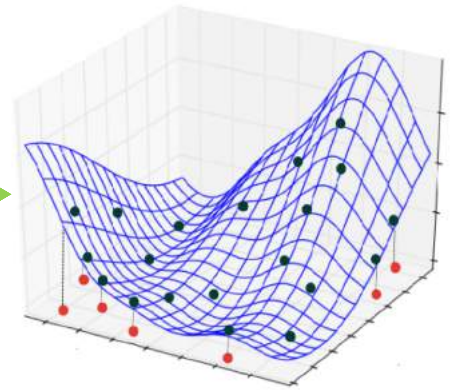


DOE

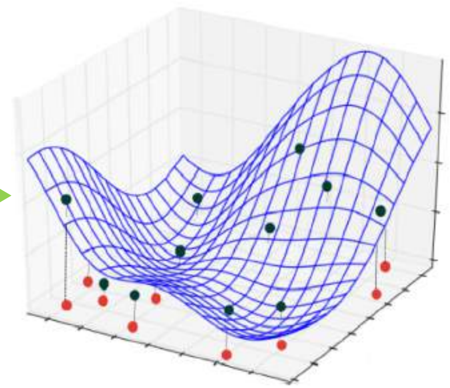
True Function Evaluation

This is costly!





Interpolant model



Regression model

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

$$LOF = \frac{MSE}{Var(y)}$$

$\boldsymbol{n}$ is the number of samples

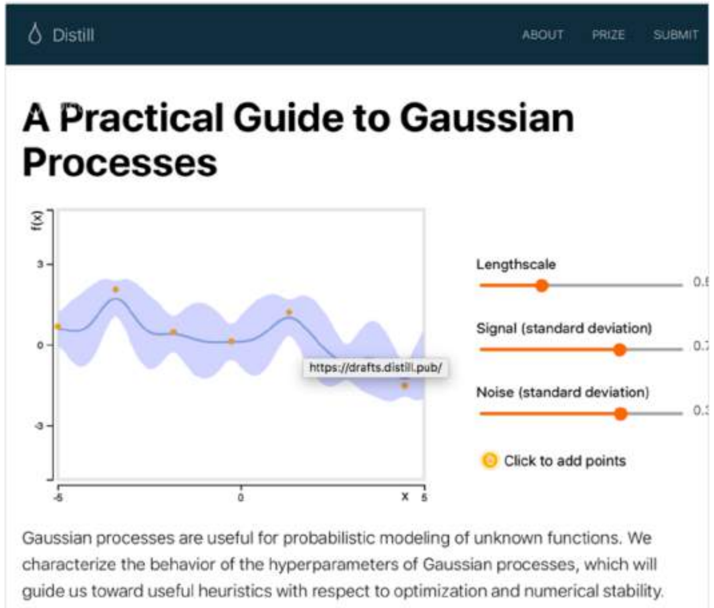
$\hat{\boldsymbol{y}}$ is the predictions of the n samples

$\boldsymbol{y}$ is the true outputs of the n samples

A good starting point x_0=Rasmussen's book (ML)

A good starting point x_0=Forrester's book (Aerospace)

- https://drafts.distill.pub/gp/



C. E. Rasmussen & C. K. I. Williams, Gaussian Processes for Machine Learning, the MIT Press, 2006, ISBN 026218253X. © 2006 Massachusetts Institute of Technology. www.GaussianProcess.org/gpml

Gaussian Processes for Machine Learning

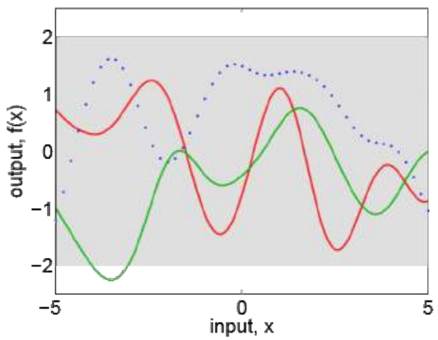
Engineering Design via Surrogate Modelling

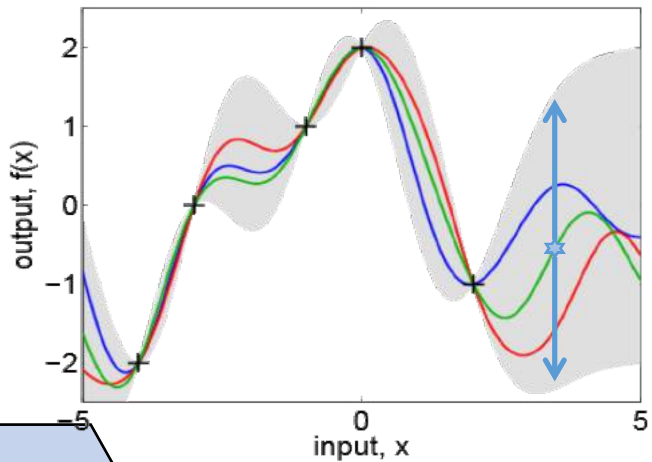
A Practical Guide

Alexander I. J. Forrester, András Sóbester and Andy J. Keane
University of Southampton, UK

Gaussian Process (aka Kriging)

Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/





Prior
f|x
$GP(0, K)$

X

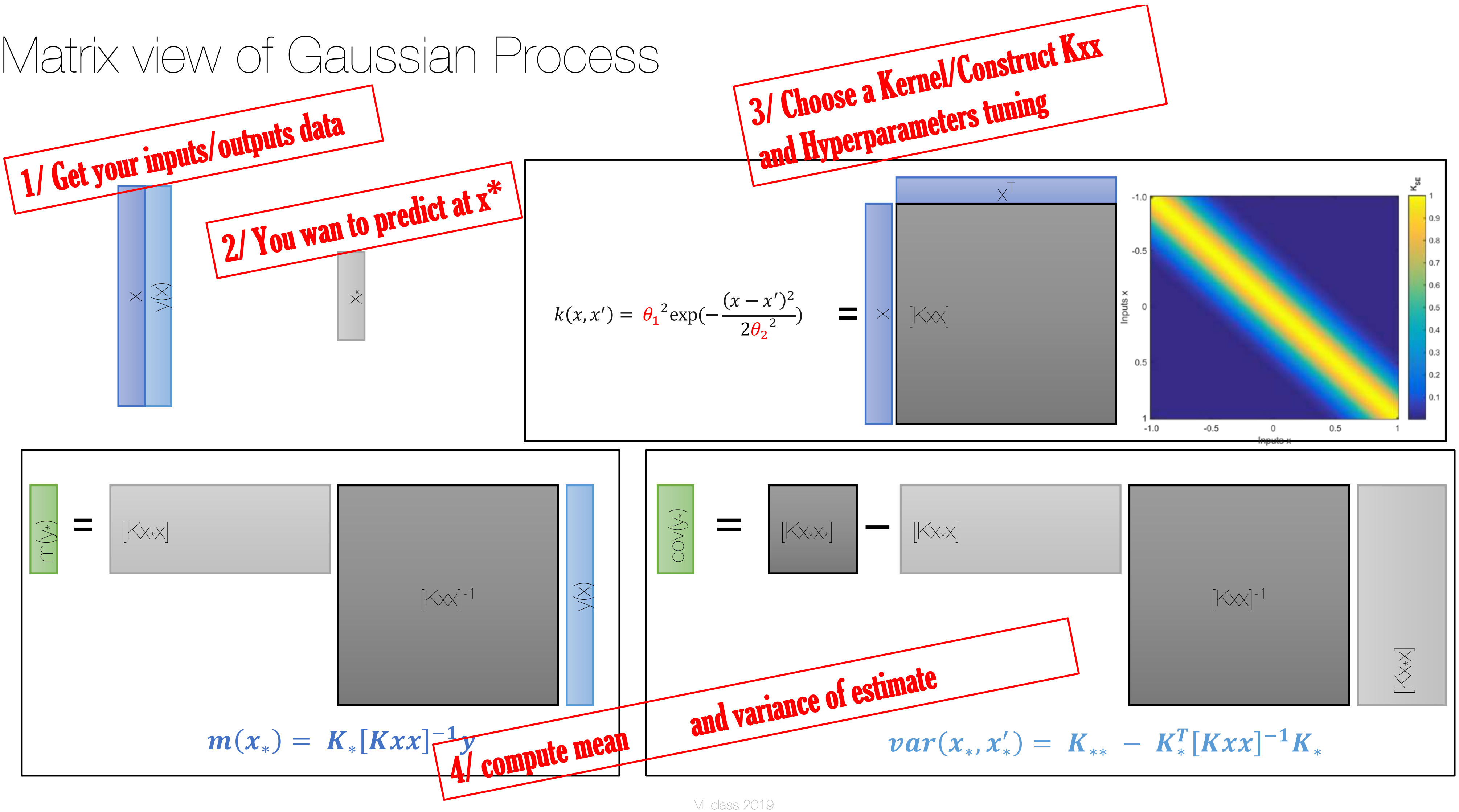
Y

Training
y|x
$GP(0, K + \sigma_n^2 I)$
Optimize: for a better hyperparameters and better prior

Posterior on y
$\boldsymbol{y}^* | \boldsymbol{x}^*, \boldsymbol{y}, \boldsymbol{x}$

GP $\mathbf{(}\ K_* [K + \sigma_n{}^2 I]^{-1}$y,
$K_{**} + \sigma_n^2 I\ -\ K_*^T [K + \sigma_n{}^2 I]^{-1} K_*)$

Matrix view of Gaussian Process

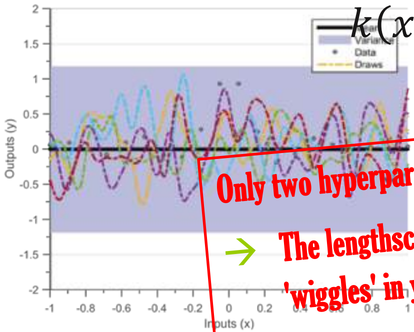


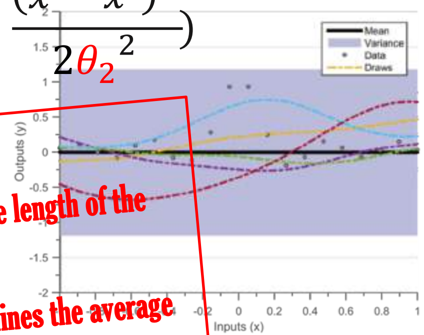
Optimizing Marginal Likelihood (ML)

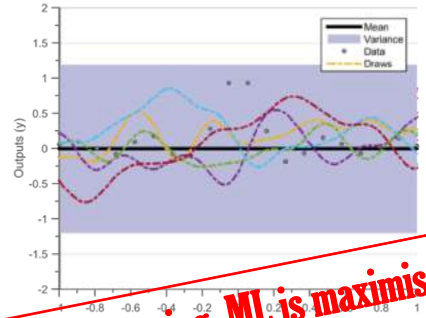
$$\text{ML} = log\big(p(y|X,\theta)\big) = -\frac{1}{2}y^T K^{-1} y \; - \; \frac{1}{2}log|K| \; - \frac{n}{2}log(2\pi)$$

- It is a combination of data-fit term, a complexity penalty term and a normalization term

$$k(x, x') = {\theta_1}^2 \exp\left(-\frac{(x-x')^2}{2{\theta_2}^2}\right)$$







Only two hyperparameters:

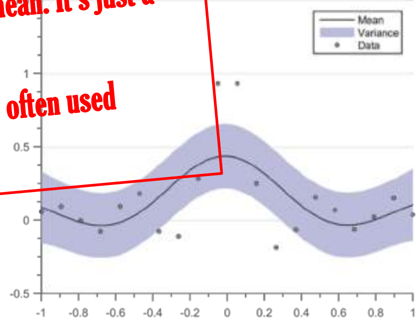
→ **The lengthscale θ_2 or ℓ determines the length of the 'wiggles' in your function.**

→ **The output variance ${\theta_1}^2$ or σ^2 determines the average distance of your function away from its mean. It's just a scale factor.**

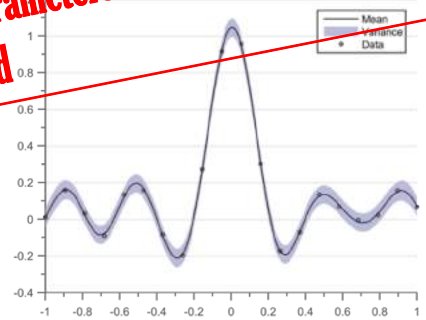
→ **A third hyperparameter θ_3 or σ_n^2 is often used (noise) $GP(0, K + \sigma_n^2 I)$**

3/ Hyperparameters tuning. ML is maximised, θ^* is found

ML = -8.2



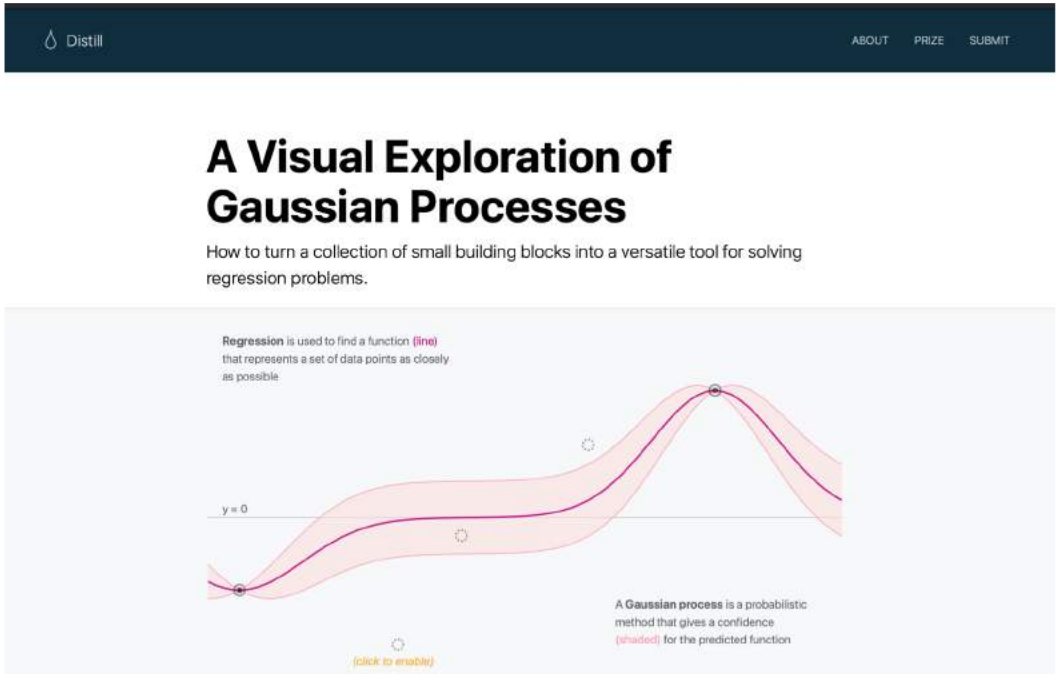
ML = -35.3



ML = 6,04

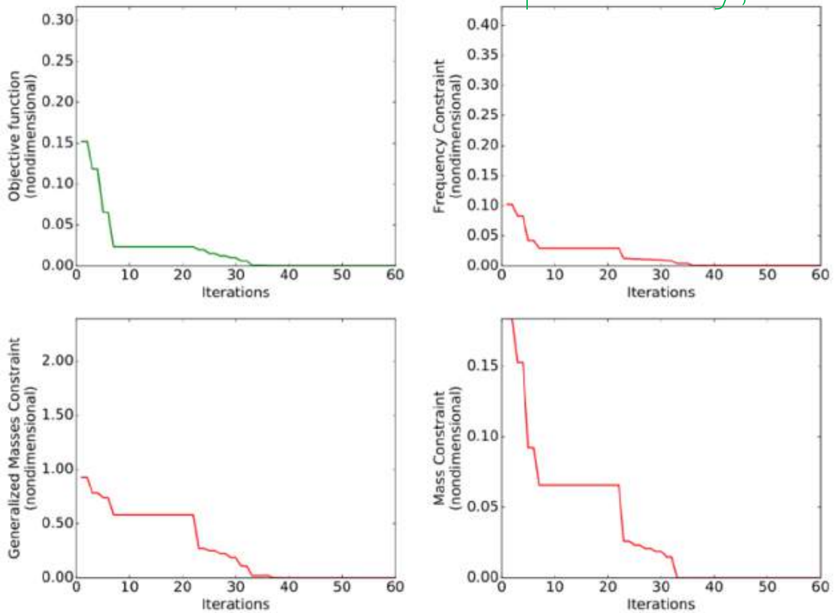
Need a demo ?

https://distill.pub/2019/visual-exploration-gaussian-processes/

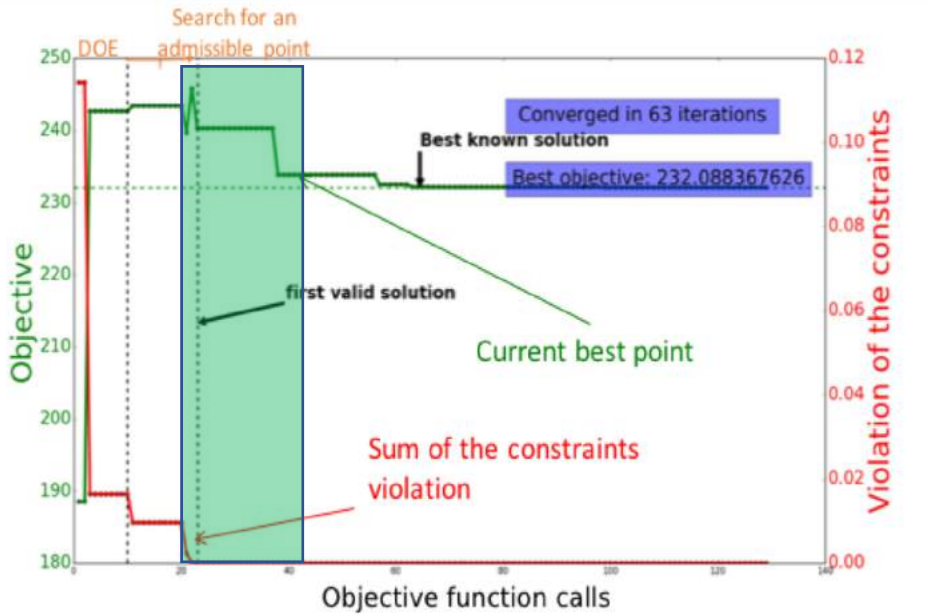


New paradigm for Surrogate Based Optimization (SBO)

Gradient based Optimality, Feasibility



SBO Exploration, Exploitation



Stopping criteria: tolfun, tolx, maxiter

Stopping criteria: Max Budget (Function calls)

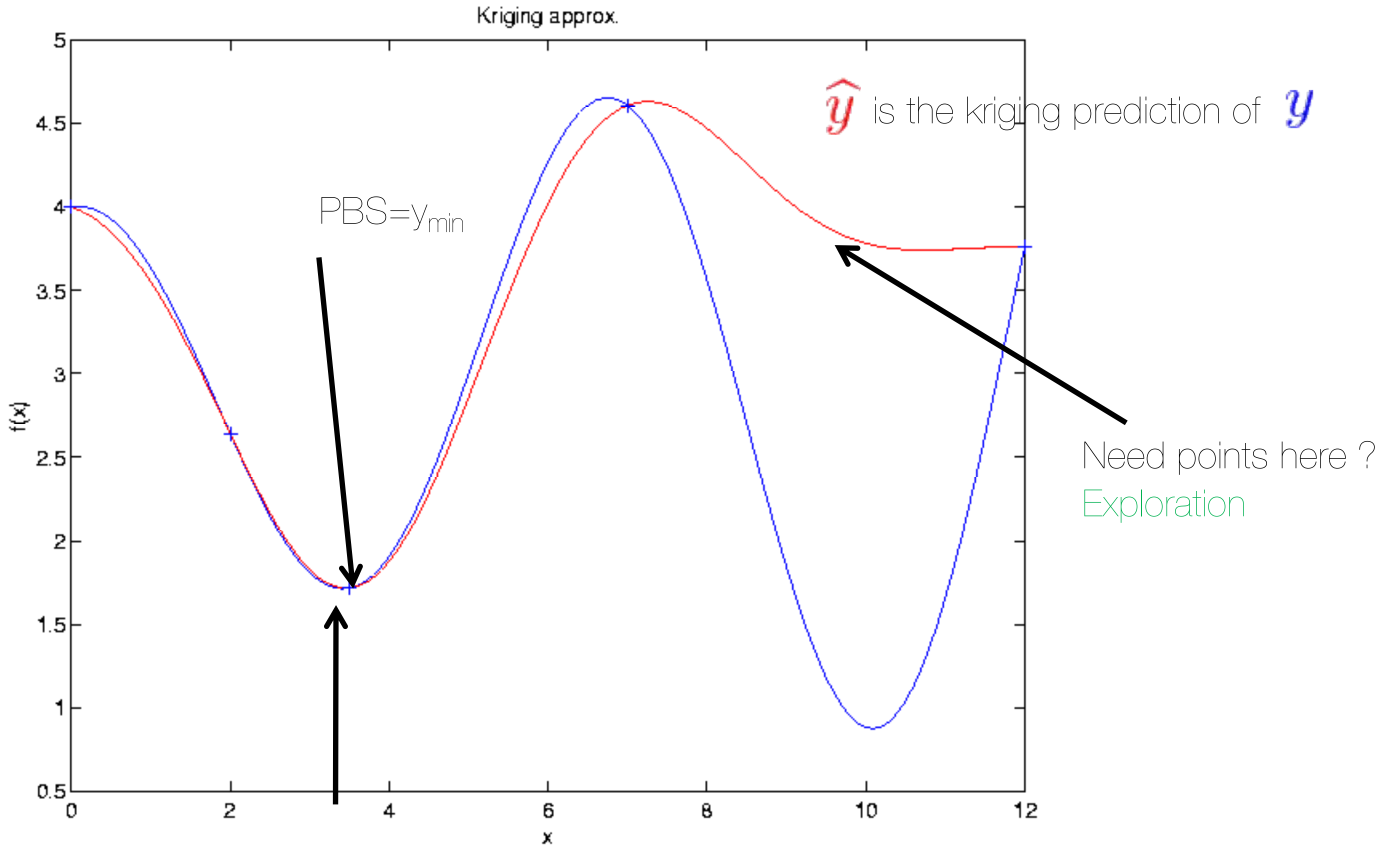
The goal is: find min of f(x) by sampling + and Kriging updating

Where do I need to update my sampling?

We note the present best solution (PBS=y_{min})

At every x there is some chance of improving on the PBS.

Then we ask: Assuming an improvement over the PBS, where is it likely be largest?

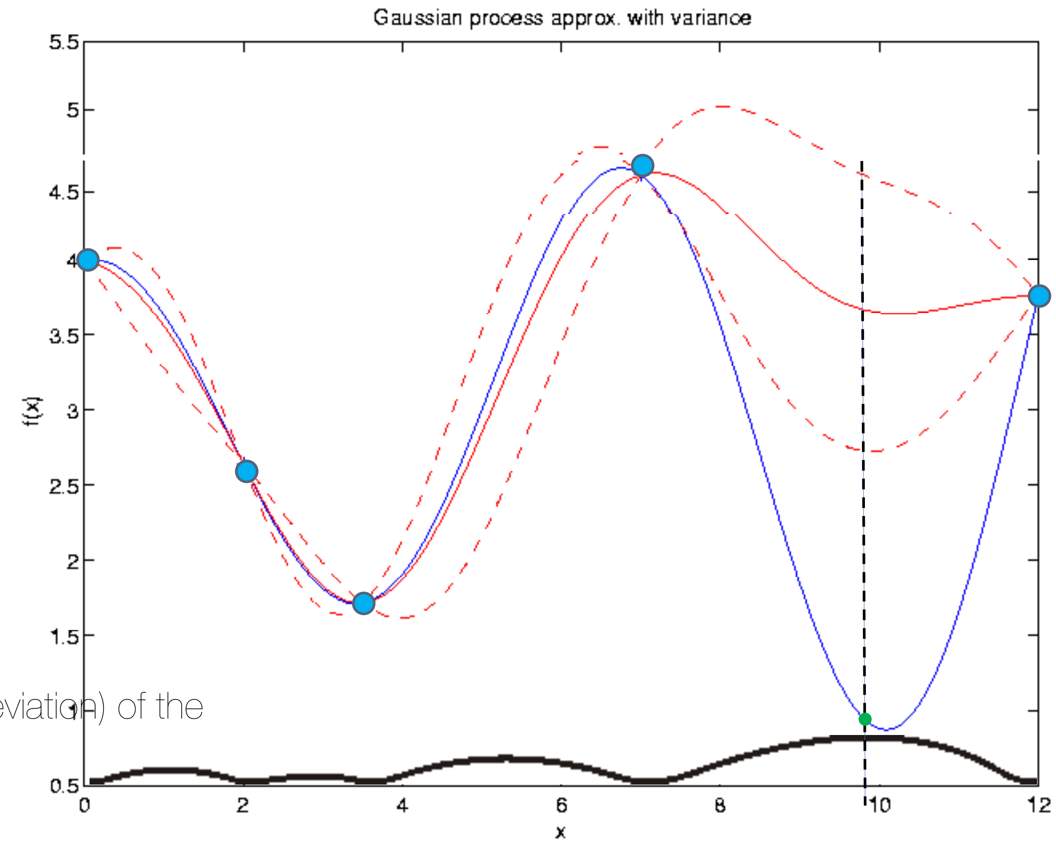


Exploitation may drive the optimization to a local optimum

In supervised mode … have a look to max(RMSE)

Impossible to compute the error: we don't know for each x the true value of the function

But…. Can we use GP properties ?

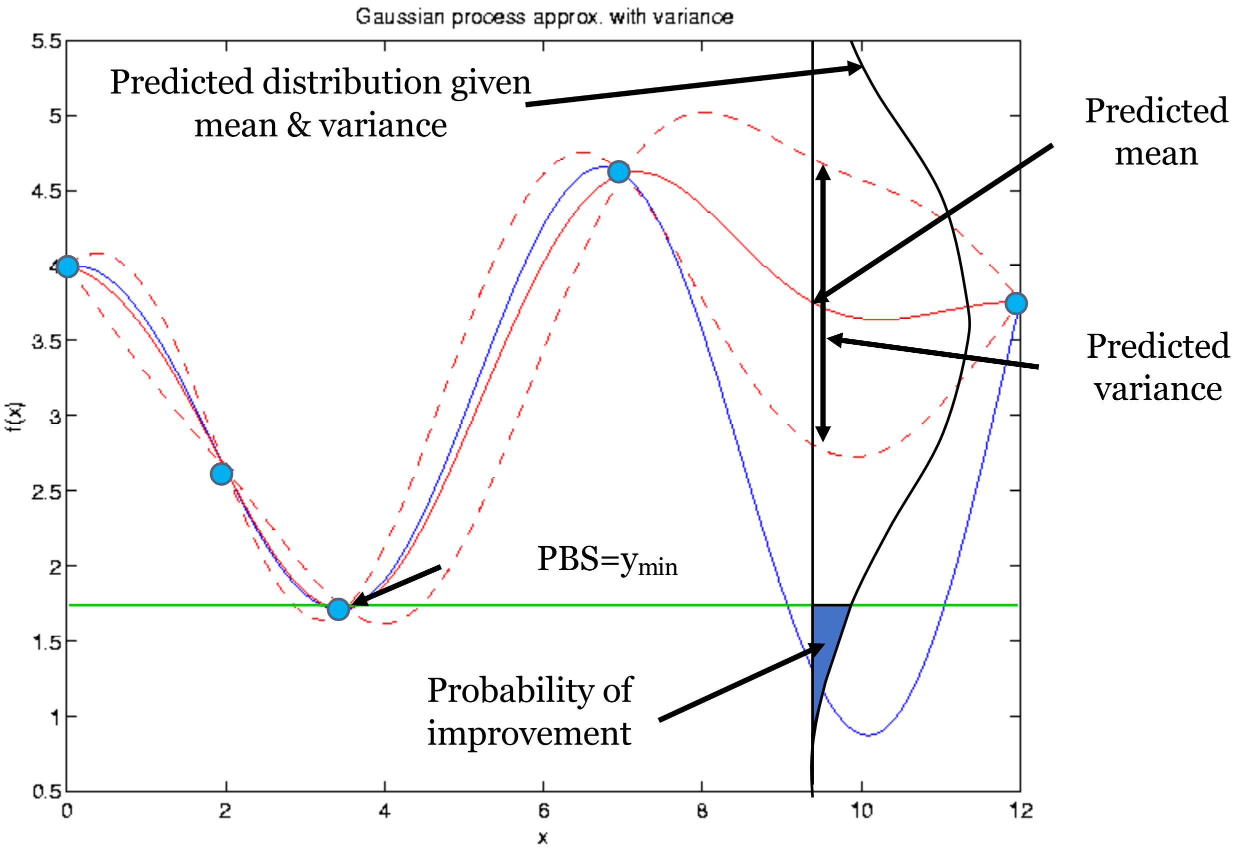


$\hat{y}$ is the kriging prediction of y

$\hat{s}$ is the estimation error (standard deviation) of the prediction (often noted σ_y)

PBS=y_{min}

Probability of improvement



Improvement … explicitely

- *Improvement* : $I(\mathbf{x}) = \max\left(y_{min} - \hat{Y}(\mathbf{x}), 0\right)$
- *Expected Improvement* :

$$\boxed{\mathrm{EI}(x) = \mathrm{E}[\max(0, y_{\min} - \hat{y}(x))]}$$

$$E[I(\mathbf{x})] = \int_{-\infty}^{y_{min}} (y_{min} - \hat{y})\varphi\left(\frac{y_{min} - \mu_{\hat{Y}}(\mathbf{x})}{\sigma_{\hat{Y}}(\mathbf{x})}\right) d\hat{y}$$

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

Exploitation

Exploration

global optimum can be found because *P[I(x)] = 0 when s = 0 so that there is no probability of improvement* at a point which has already been sampled → guarantees global convergence

Φ: cumulative distribution function $\mathcal{N}(0,1)$ ϕ: probability density function $\mathcal{N}(0,1)$

*Jones, D. R., Schonlau, M., & Welch, W. J. (1998). Efficient global optimization of expensive black-box functions. Journal of Global optimization, 13(4), 455-492.

Infill Criteria : max(Expected improvement)

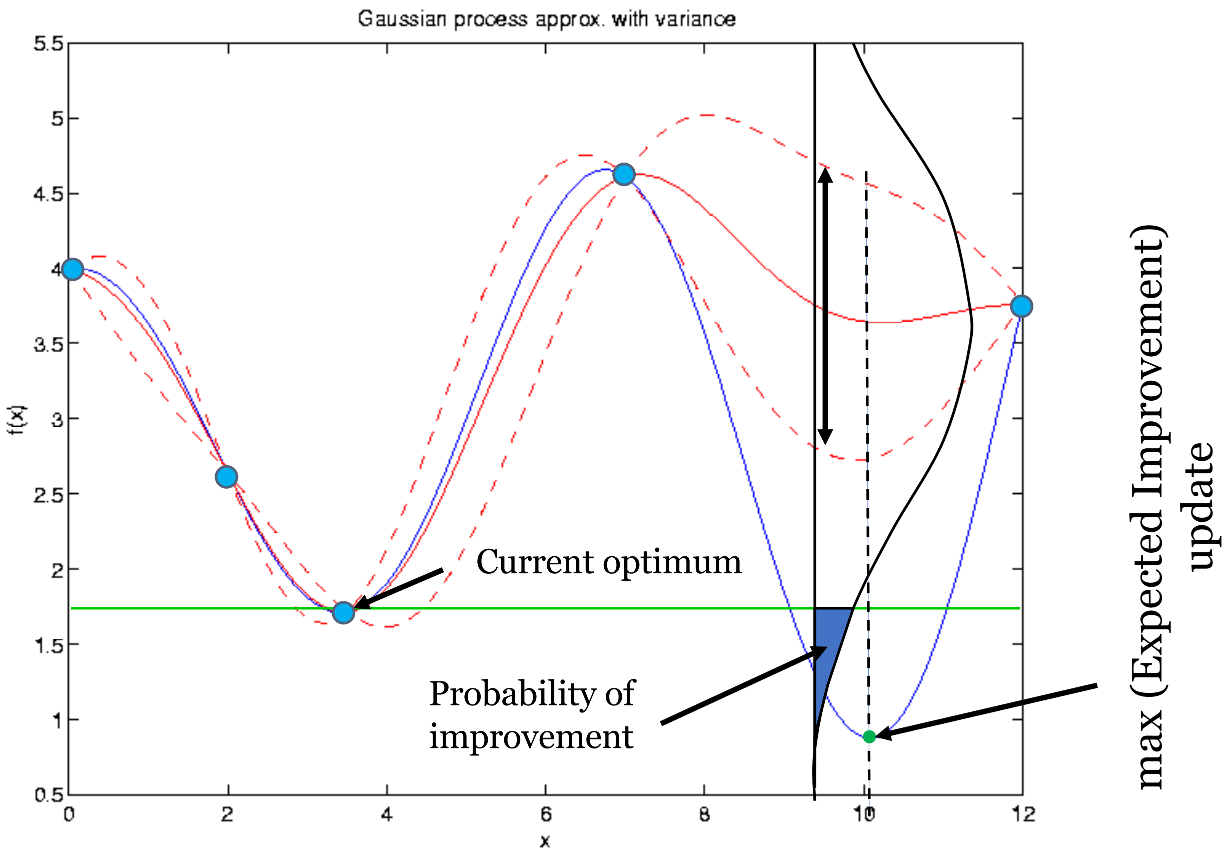
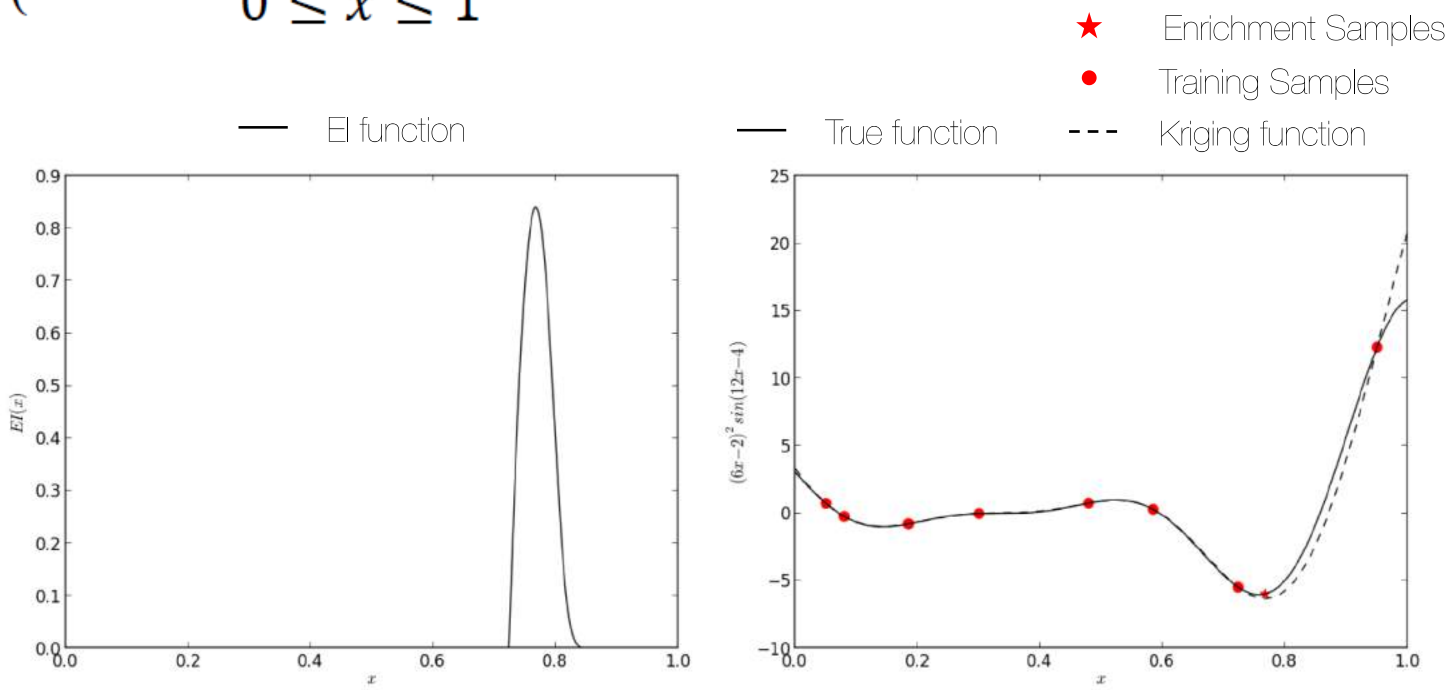
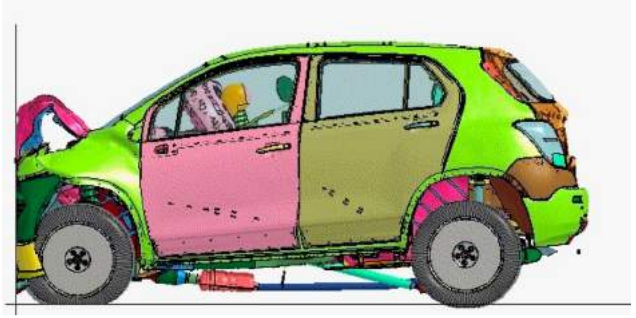


Illustration on 1D example

$$\begin{cases} \min \ (6x-2)^2 \sin(12x-4) \\ s.t. \\ 0 \le x \le 1 \end{cases}$$



MOPTA



Problem formulation:

1 objective function to be minimized - mass

124 variables normalized to [0,1]

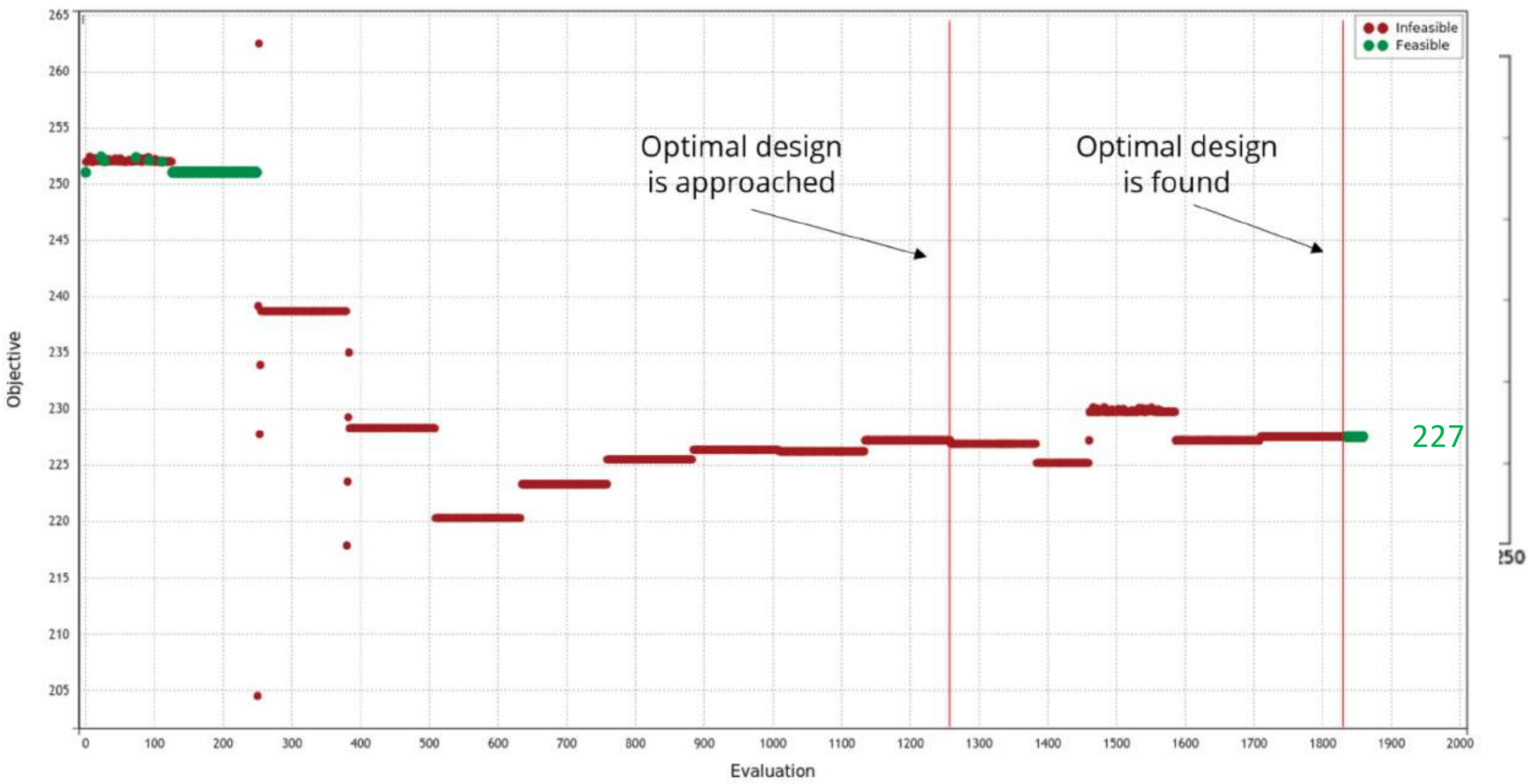
68 inequality constraints of form $g_i(x) \le 0$

Constraints well normalized: 0.05 means 5% over requirement, etc.

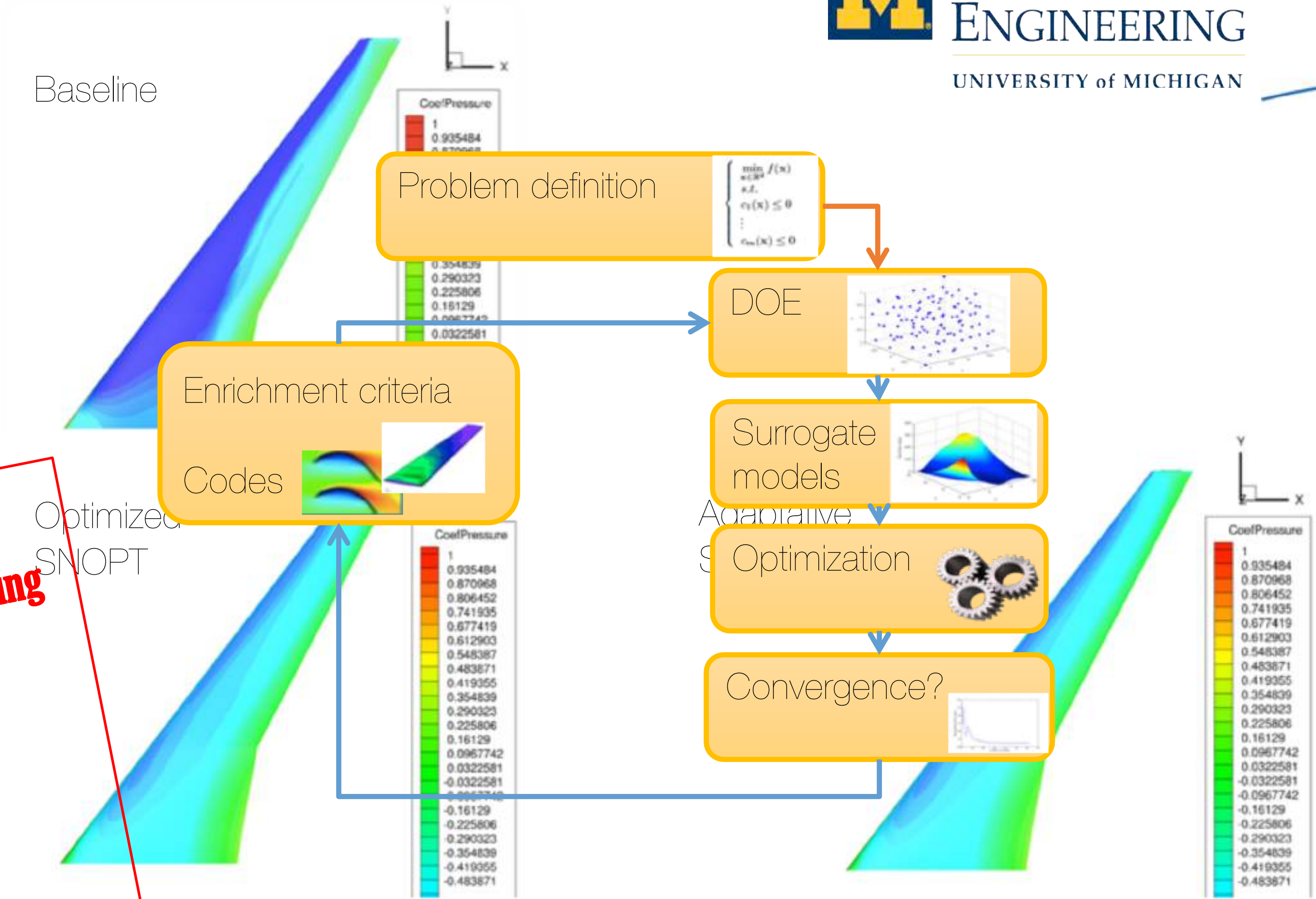
Test problem comes with the initial feasible point with objective ~251.07

A good performance would be comparable or better than derivative-free optimization algorithm - Powell's COBYLA:
Number of evaluations = ~ 15 x Number of variables
Fully feasible solution (no constraint violations)
Objective function value ≤ 228 (at least 80% of potential reduction)
"Anything better is exciting" - states Don Jones, the author of this benchmark.

MOPTA08 optimization history BO vs pSeven



SBO



Use SMT for surrogate modeling !

No baseline…

No need of derivatives…

Surrogate Model Toolbox: SMT

AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN
NASA
isae SUPAERO
ONERA
THE FRENCH AEROSPACE LAB

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SMT: Surrogate Modeling Toolbox

The surrogate model 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.

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

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

where $\mathbf{xt} \in \mathbb{R}^{nt \times nx}$ contains the training inputs, $\mathbf{yt} \in \mathbb{R}^{nt}$ contains the training outputs, $\mathbf{x} \in \mathbb{R}^{nx}$ contains the prediction inputs, and $y \in \mathbb{R}$ contains the prediction outputs. There are three types of derivatives of interest in SMT:

1. Derivatives (dy/dx): derivatives of predicted outputs with respect to the inputs at which the model is evaluated.
2. Training derivatives (dyt/dxt): derivatives of training outputs, given as part of the training data set, e.g., for gradient-enhanced kriging.
3. Output derivatives (dy/dyt): derivatives of predicted outputs with respect to training outputs, representing how the prediction changes if the training outputs change and the surrogate model is re-trained.

Not all surrogate modeling methods support or are required to support all three types of derivatives; all are optional.

pip install SMT

Before 23/10

https://github.com/SMTorg/SMT

Outlines for today

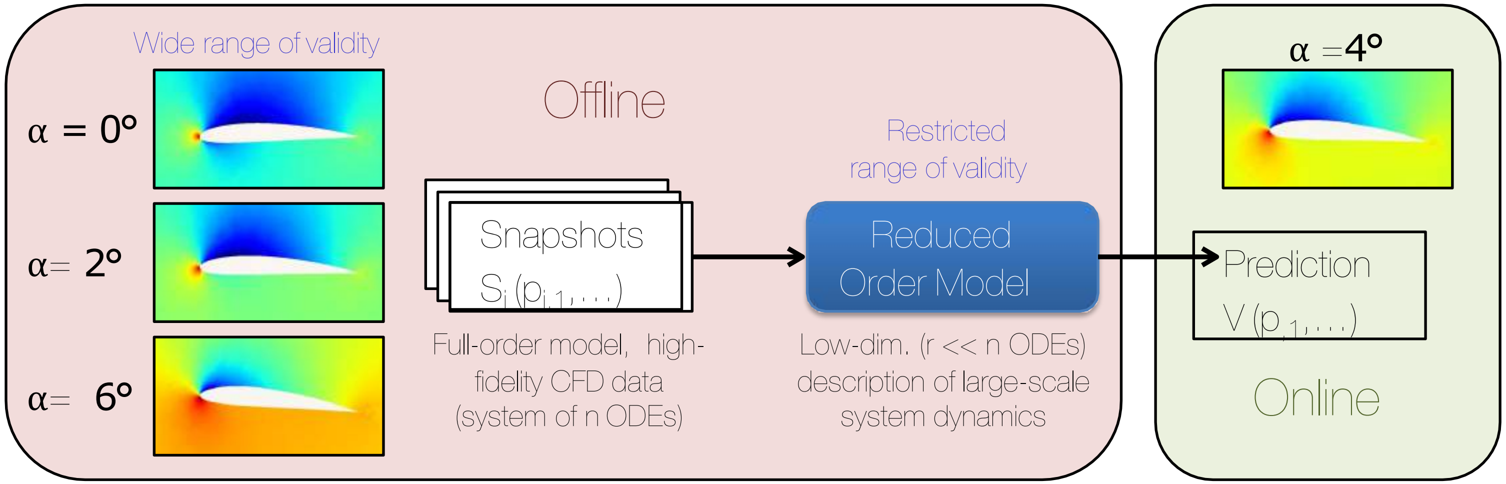
1. MDO
2. GP

3.ROM

How? Using POD (SVD, PCA, KLT)*

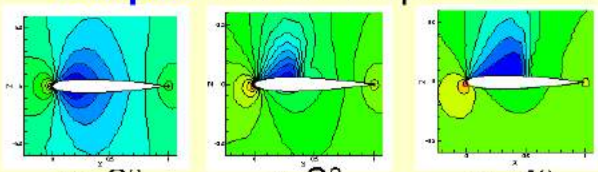
* eceweb1.rutgers.edu/~orfanidi/ece525/svd.pdf

- Reduced order models operate on parameterized generated data (snapshots)
  - scalar quantities: lift, drag and moment coefficients Cl, Cd, Cm
  - surface quantities: pressure and shear stress, volume quantities: primitive variables ρ, T
- Parameters can be related to the flow (e.g. angle of attack α , Mach number M or to the geometry

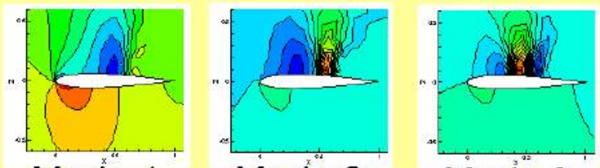


POD-based Reduced Order Modeling

1. Input: m CFD snaphots W^m



2. POD Basis: m Modes U^m



RIC>0.9999

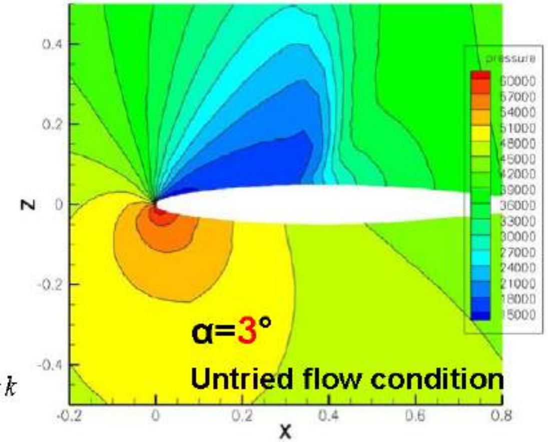
3. Order Reduction
Select $\widetilde{m}$ POD components with largest information content

4. Interpol./Optimization Step
Determine POD-ROM coefficients a_k such that defect of POD solution $W(a)$ to governing equations is minimized

$$\min_{a=(a_1,\dots,a_{\widetilde{m}})}! \left\|\mathrm{Res}(W(a))\right\|^2$$

$$W = \sum_{k=1}^{\widetilde{m}} a_k U^k$$

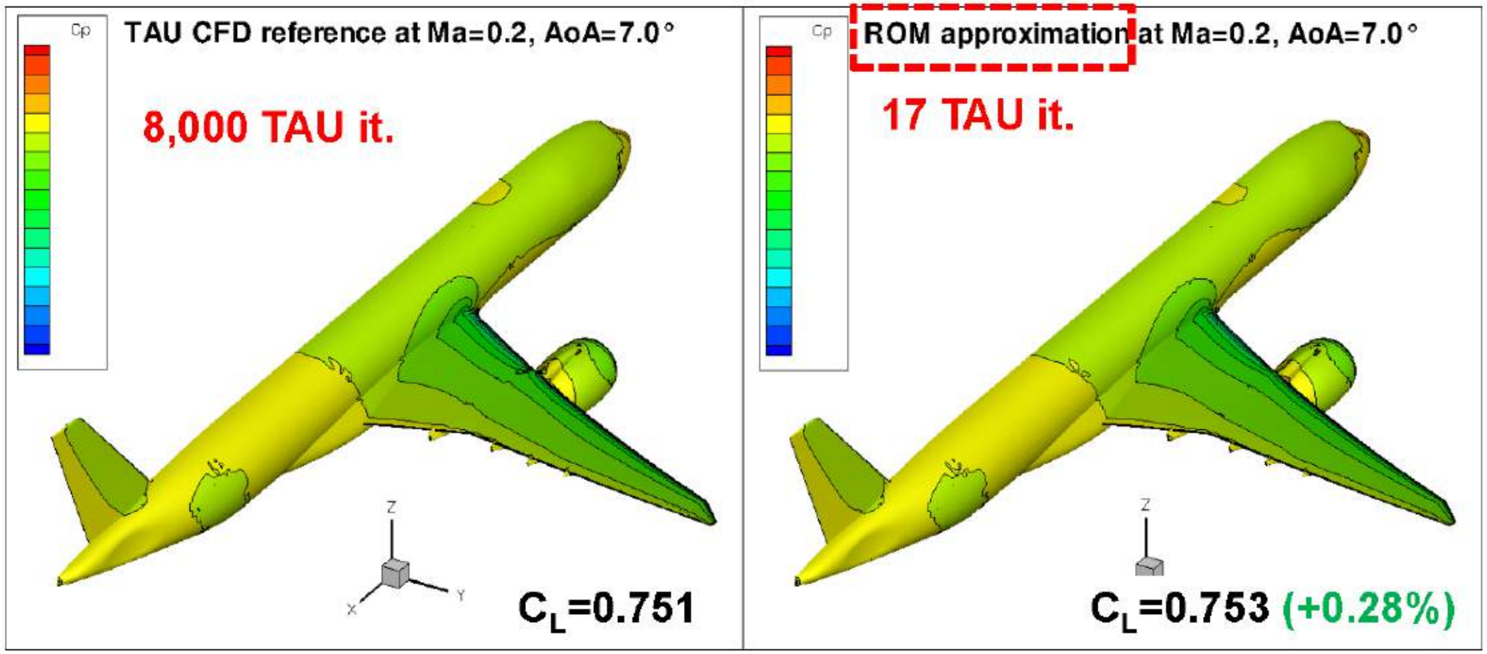
5. Output: approximated flow field



POD-based Reduced Order Modeling

Navier-Stokes ROM subsonic

- Industrial a/c config., grid size: 8898749
- 4 Snapshots at α = [-1°,0°,1°,2°] with TAU code
- Approximation at α = 7° (extrapolation)



ROM speed-up by factor: 470

DLR

Example from a recent PhD thesis …with your teacher Emmanuel Rachelson

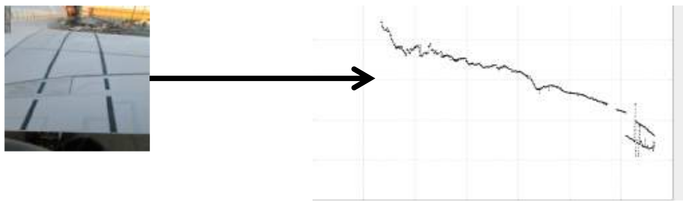
https://github.com/ankitchiplunkar/thesis_isae

A350-1000 : Interpolation of shock

- Measurements from Flight Tests Instrumentation, accessible real-time in telemetry thanks to EV tools

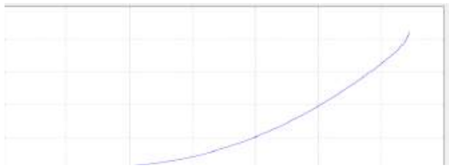
Pressure measurements from MEMS on the right wing, wing deformation from inclinometers on right wing spars

MEMS

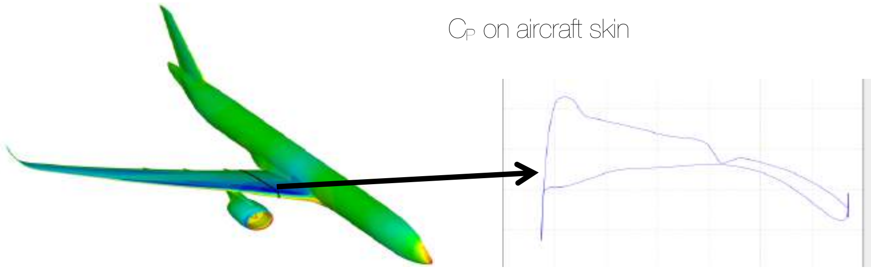


- CFD/CSM simulations representing the aircraft design intent as we understand it

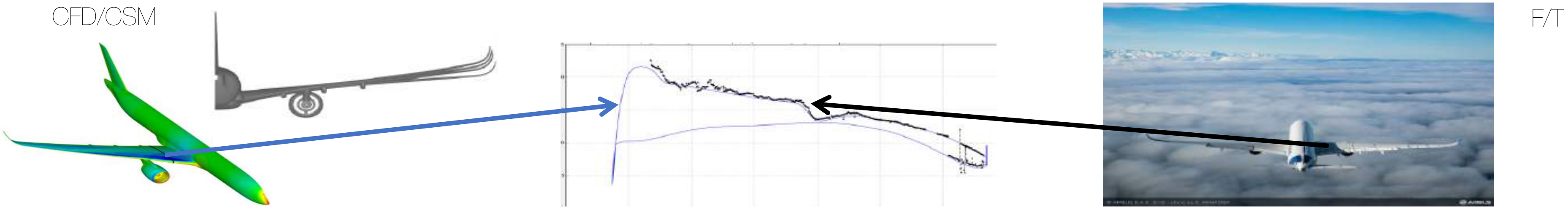
Wing deformation (bend, twist)



C_P on aircraft skin



A350-1000 flight test analysis



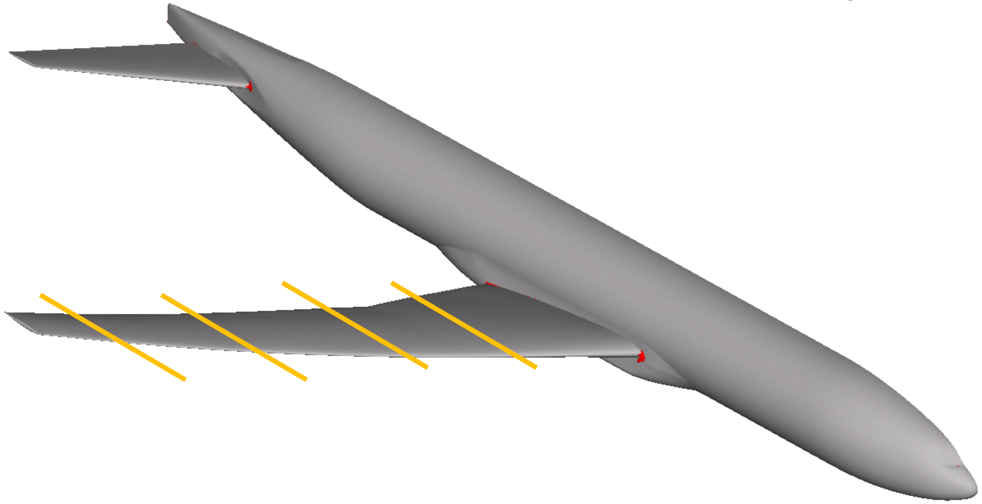
- Comparing these two sources of data during flight tests enables us to check that the A/C behaves as expected, and that our understanding of its physics (aerodynamics, loads, wing shape) is correct.

- By doing this comparison live in telemetry, we can interact with the ongoing flight test, and optimize configurations (VC/DFS) if needed, for bringing the A/C behaviour as close as possible to design intent.

- These comparisons between CFD/CSM and Flight Test measurements have to be done at identical values of flight parameters : Mach, Alpha, Flight level, VC configuration… so we need to be able to plot instantly the CFD/CSM data for any given combination of these parameters.

Experimental dataset

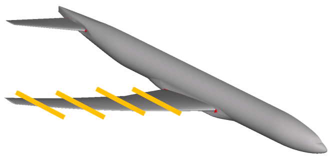
- https://commonresearchmodel.larc.nasa.gov/

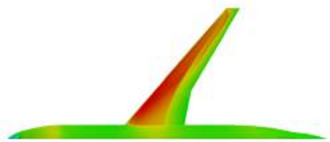


- Simulations run using : Elsa – kOmega-SST
- Same as the one proposed during drag prediction workshop
- Gives better interaction between model fuselage and wing
- Alpha = [1 : 0.1 : 3] = **21 alphas**
- Mach = [0.84 : 0.005: 0.86] = **5 machs**
- yLocationCuts = [6.03, 11.99, 17.76, 27.85]
- Wanted to be close to (as used in the drag prediction workshop)
  - y/b = [0,105, 0,37, 0,5024, 0,8456]
  - Building a model between alpha, mach and x

▪Chiplunkar, Ankit and Bosco, Elisa and Morlier, Joseph Gaussian Process for Aerodynamic Pressures Prediction in Fast Fluid Structure Interaction Simulations. (2017) In: 12th World Congress on Structural and Multidisciplinary Optimization, 5 June 2017 - 7 June 2017 (Braunschweig, Germany).

Different models





Pressure dataset $P_i(d_j)$

Decompose into mode shapes ϕ and amplitude α

Keep Mode shapes constant while Interpolating α between parameters

Linear summation to predict pressures at new points

POD

Build a GP model between

Use Neural network Covariance for defining family of functions

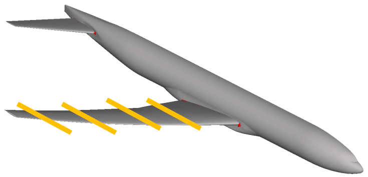
Use distributed GP to accomodate for the huge number of datapoints

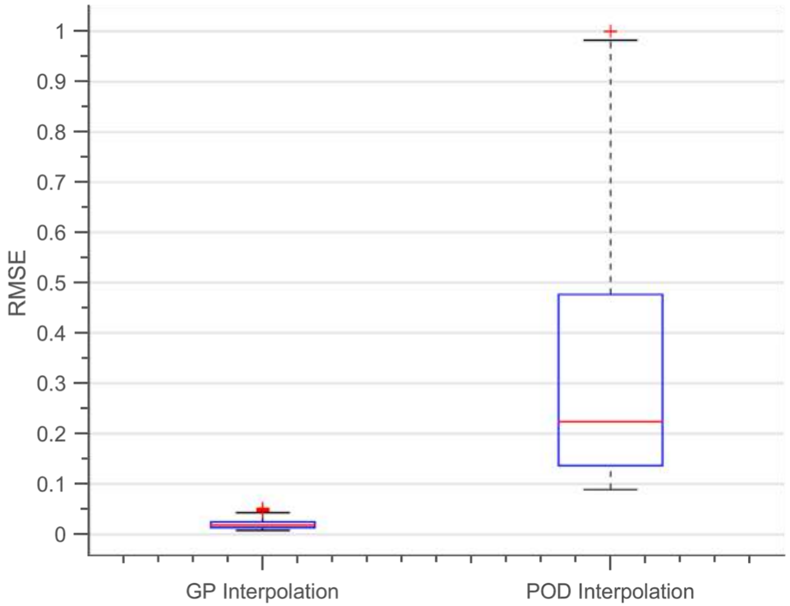
Calculate the posterior at new points

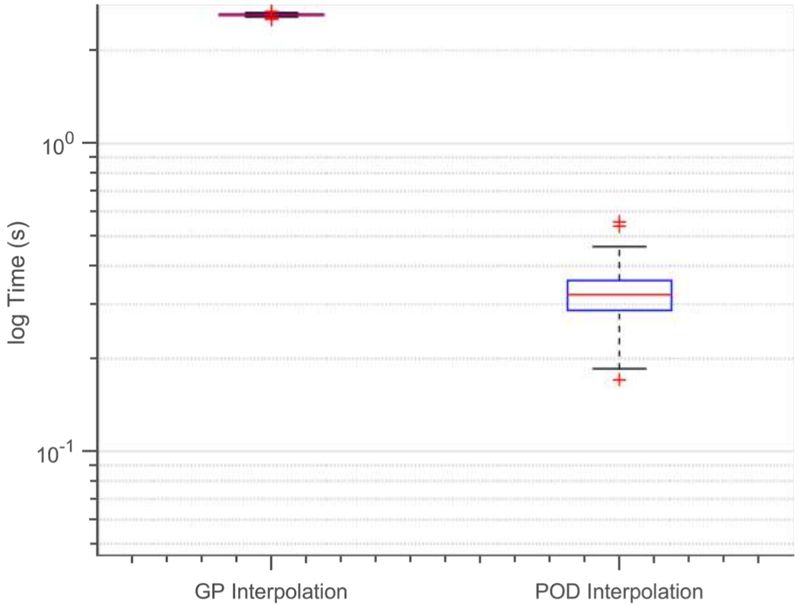
dGP

References:
Proper orthogonal decomposition extensions and their applications in steady aerodynamics. Master of Engineering in High Performance Computation for Engineered Systems (HPCES), 2003.
Radford M Neal. Bayesian learning for neural networks, volume 118. Springer Science & Business Media, 2012

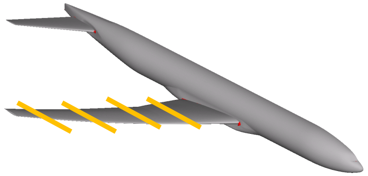
Comparison of results: Cut1 (y/B = 0,105)

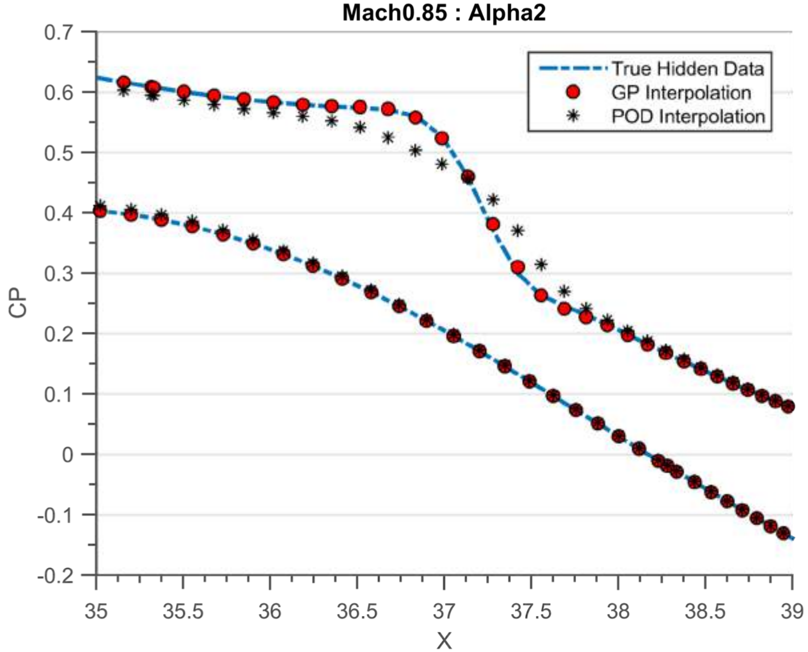


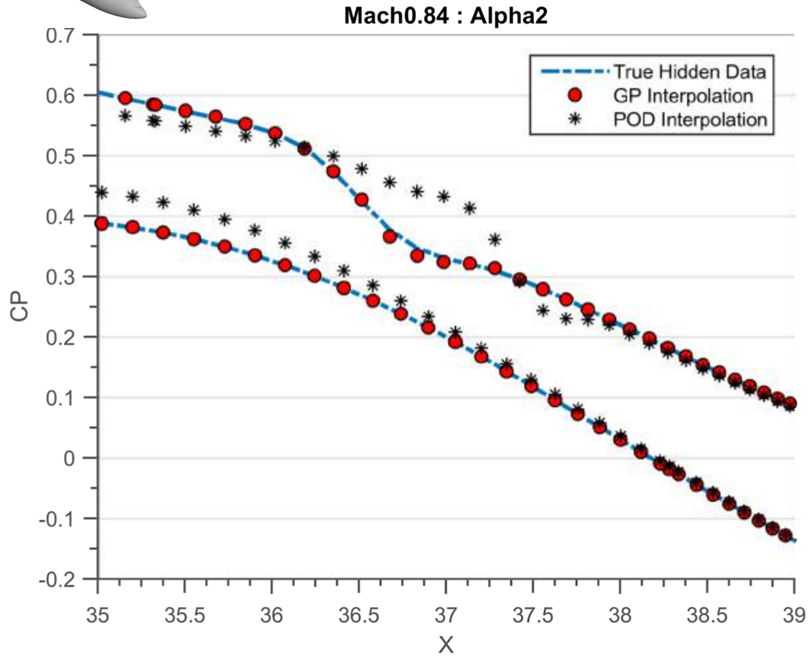




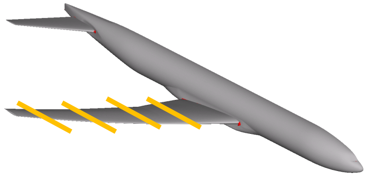
Comparison of results: Cut1 (y/B = 0,105)

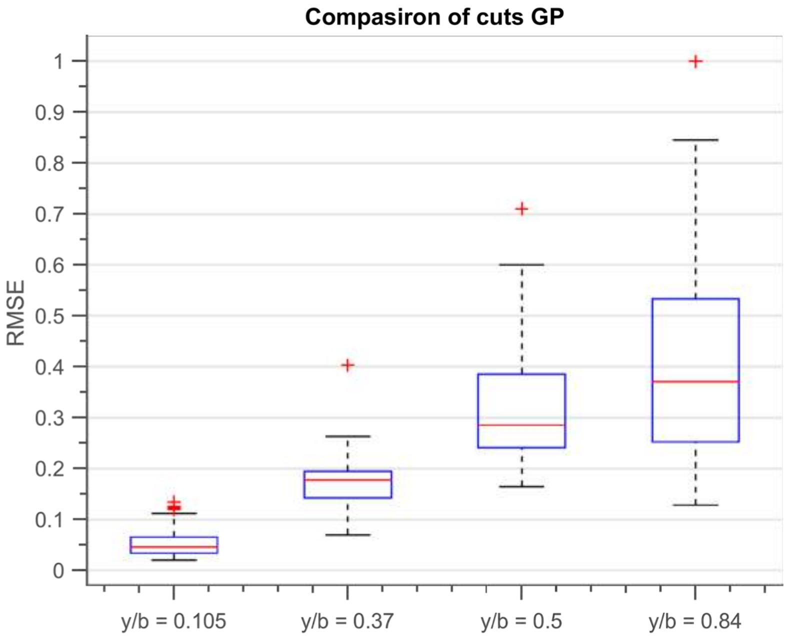


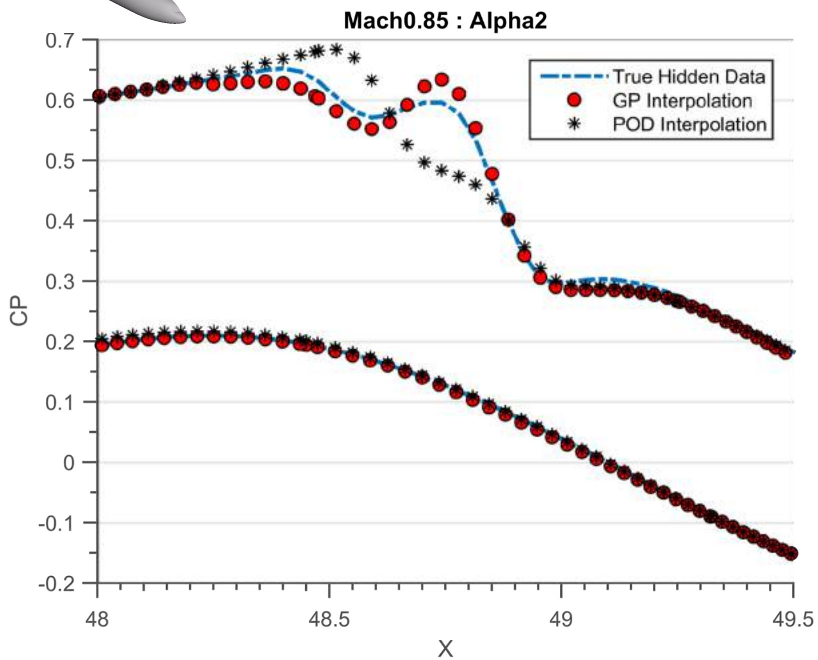




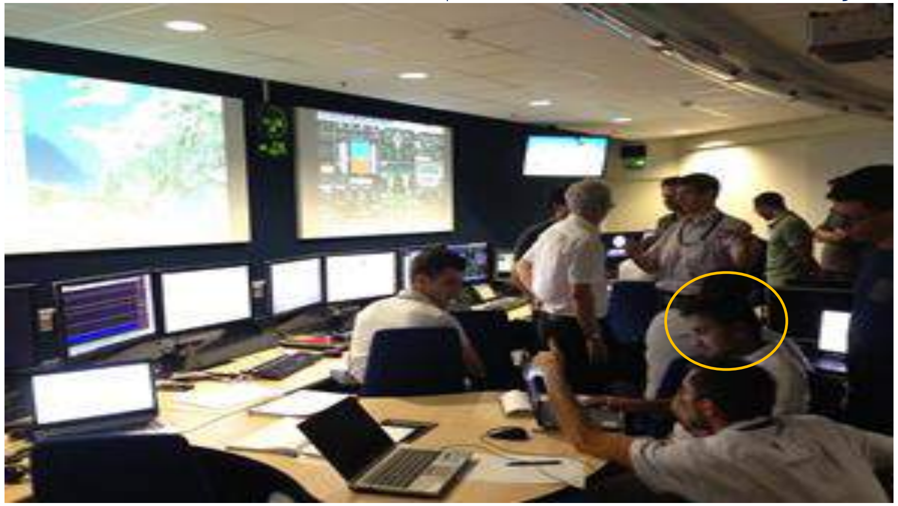
Comparison across Cuts

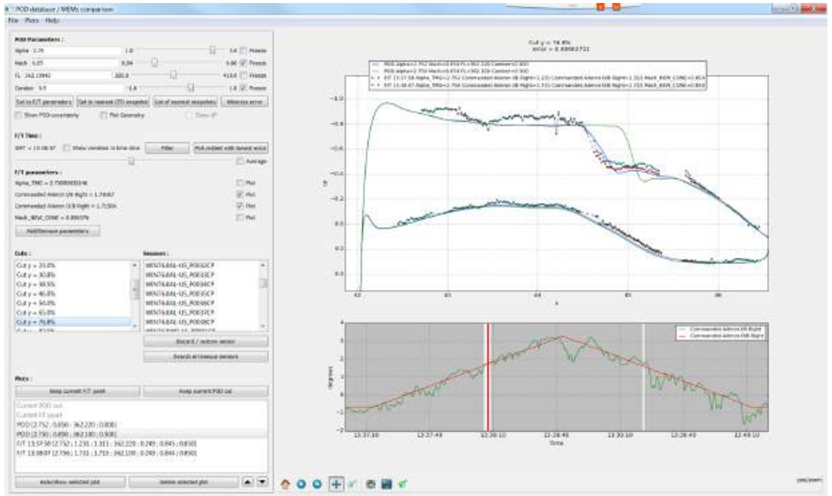






A350-1000 : CP interpolation in telemetry room





1. Once validated the fast CFD/CSM model can be used in the telemetry room
2. Generally this task used to take 3 weeks now it is done in 3 seconds in the telemetry room
3. Opened many other use cases in the telemetry room, assisting performance optimization, verifying values of flight parameters etc
4. PODCraft selected for EG Innovation Recognition Event 2017

CONFIDENTIAL

Conclusion

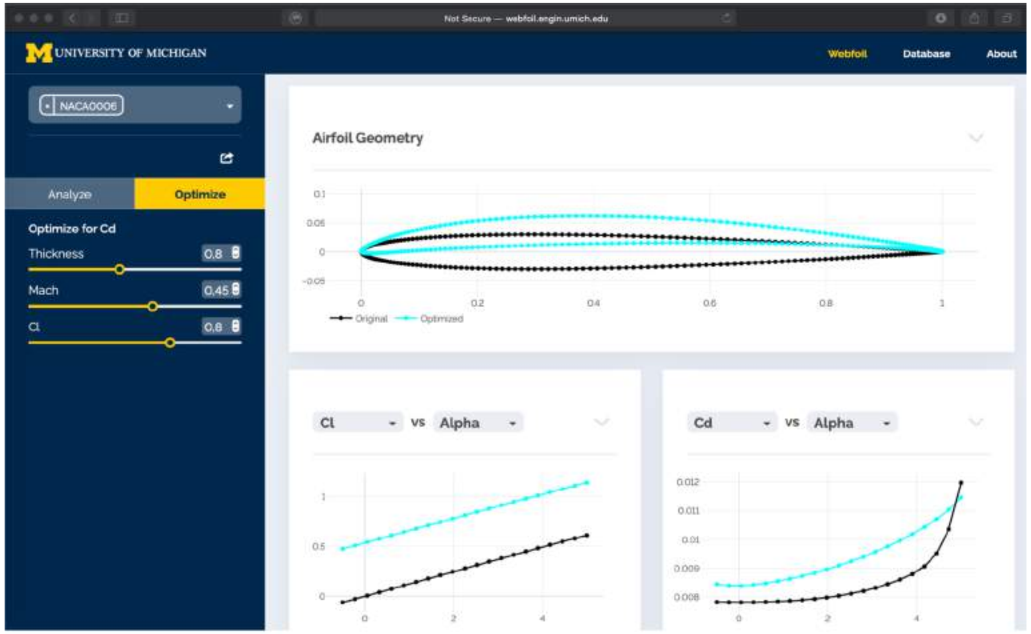
- Machine Learning technics are widely used in MDO to speed up the process *(Offline/Online)*

- A nice example is the XFOIL « regression » with SMT

http://webfoil.engin.umich.edu

- Go deeper with BO before the Python Practice (23/10)

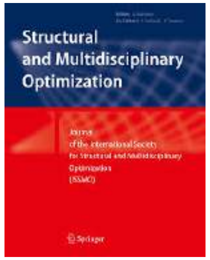
http://krasserm.github.io/2018/03/21/bayesian-optimization/

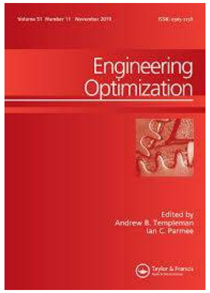


Webfoil is a free, web-based airfoil design tool

Recent Papers on this topic

EGO on SMT





Bouhlel, M. A., Bartoli, N., Otsmane, A., & Morlier, J. (2016). Improving kriging surrogates of high-dimensional design models by Partial Least Squares dimension reduction. Structural and Multidisciplinary Optimization, 53(5), 935-952.

Bouhlel, M. A., Bartoli, N., Otsmane, A., & Morlier, J. (2016). An improved approach for estimating the hyperparameters of the kriging model for high-dimensional problems through the partial least squares method. Mathematical Problems in Engineering, 2016.

Bouhlel, M., Bartoli, N., Regis, R. G., Otsmane, A., & Morlier, J. (2018). Efficient global optimization for high-dimensional constrained problems by using the Kriging models combined with the partial least squares method. Engineering Optimization, 1-16.

Bouhlel, M. A., Hwang, J. T., Bartoli, N., Lafage, R., Morlier, J., & Martins, J. R. (2019). A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 102662.

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.

Chiplunkar A., Rachelson E., Colombo M., Morlier J. (2017) Approximate Inference in Related Multi-output Gaussian Process Regression. In: Fred A., De Marsico M., Sanniti di Baja G. (eds) Pattern Recognition Applications and Methods. ICPRAM 2016. Lecture Notes in Computer Science, vol 10163. Springer, Cham