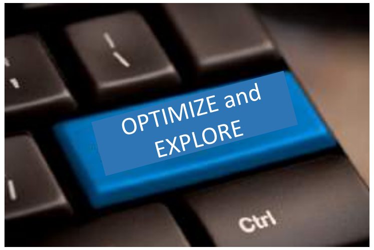
1970-1990

1990-2010



2010-2020

2020+

INSTITUT CLÉMENT ADER

isae Institut Supérieur de l'Aéronautique et de l'Espace SUPAERO

ONERA THE FRENCH AEROSPACE LAB

Recent progress in engineering design with MDO/AI4E

Prof. Joseph Morlier

AGENCE NATIONALE DE LA RECHERCHE ANR

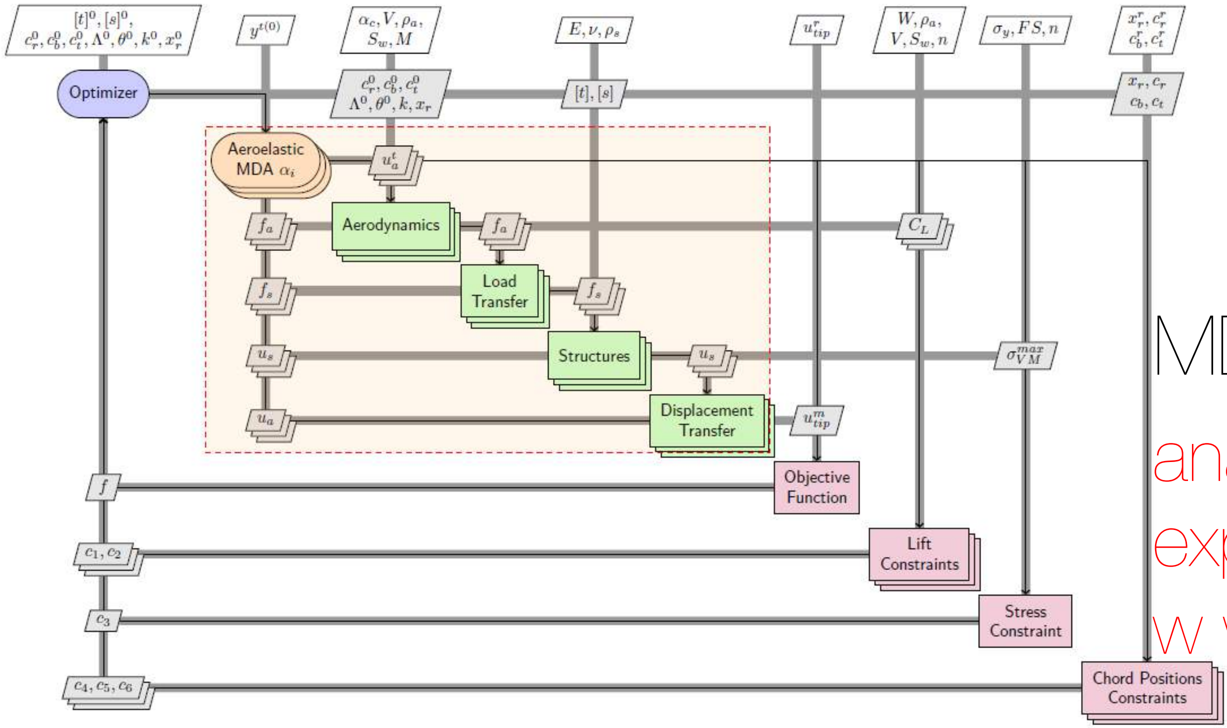
Fondation ISAE-SUPAERO Reconnue d'utilité publique

Pseven 12/10/22

Multidisciplinary Design Optimization

No MDO without MDA

- Multidisciplinary Design Optimization (MDO) focuses on solving optimization problems spanning across multiple interacting disciplines



MDO/AI4E

analytics/PDE/ODE

experimental results

w w/o gradients

A way to fully automate the design process

Wing span
Airfoil shapes
Structural sizing

Fuel burn

Structural stresses

Design changes

Design optimization problem:

minimize	$f(x)$	objective
with respect to	x	design variables
subject to	$c(x) \leq 0$	constraints

Nowadays' Engineering Design Optimization is MDO {M:Multidisciplinary}

Wing span
Airfoil shapes
Structural sizing

Fuel burn
Structural stresses

Design changes

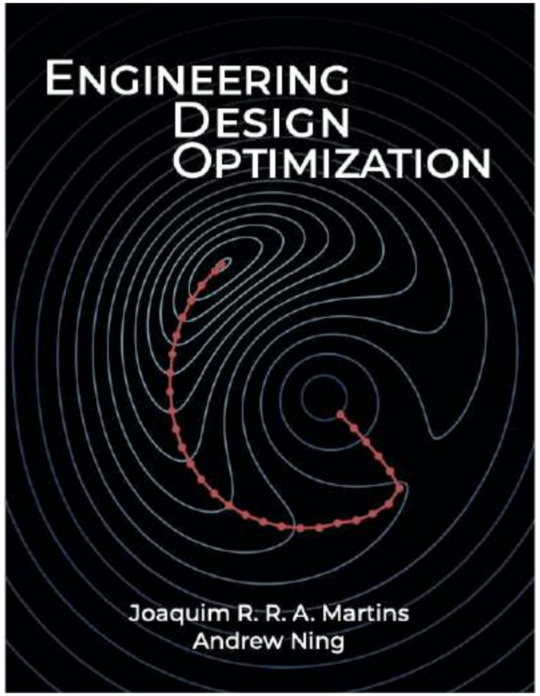
Reformulate optimization problem

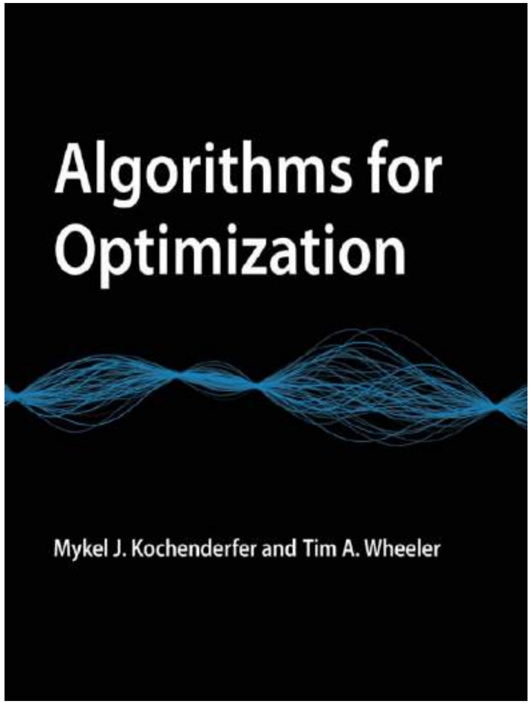
May include large numbers of disciplines, design variables, constraints,

scalability due to <u>gradient</u> based approach

<u>Post-optimality studies</u>

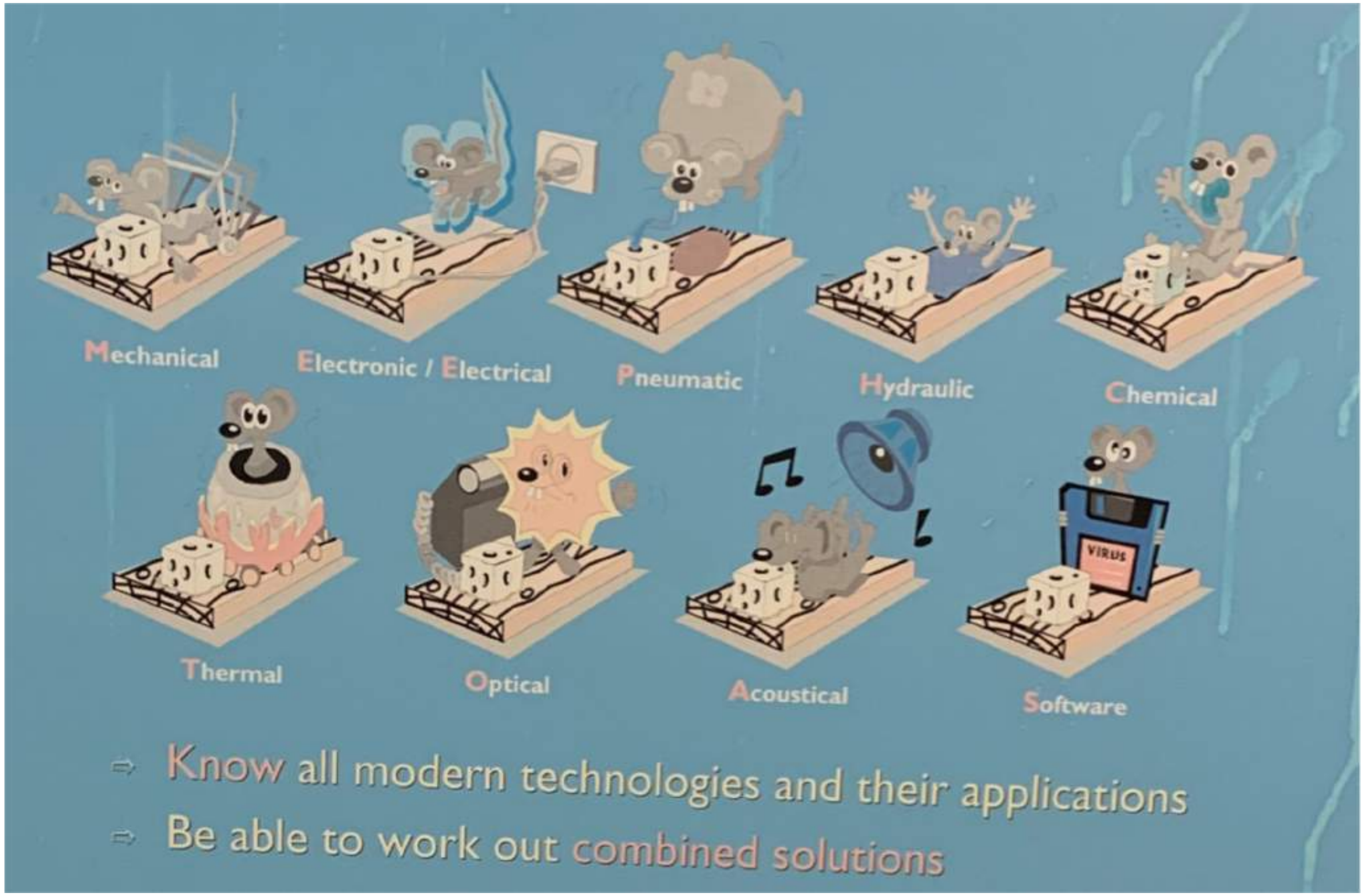
Good Starting Point (x0)





https://github.com/mdobook/resources https://github.com/sisl/algforopt-notebooks

@Philips : Combining disciplines provides better solutions



Au programme

Duration	Description	Agenda
3’	MDO/AI	New trends
7’	Surrogate	SMT
7’	Ecodesign	Lighter, Stronger, Greener
3’	Conclusions	And future works?

Tools/Results » oriented presentation

The initial Question was: ***« Joseph I have a costly multiphysics simulation chain. Can you give me the optimal design at fixed budget ? Let’s say after the week end (48h of HPC) ? »***

For theoretical background, have a look to

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, 135, 102662.

N. Bartoli, T. Lefebvre, S. Dubreuil, R. Olivanti, N. Bons, J.R.R.A. Martins, M.-A. Bouhlel, J. Morlier, " Adaptive modeling strategy for constrained global optimization with application to aerodynamic wing design ", Aerospace Science and Technology, 90, 85-102., 2019

Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Approximate Inference in Related Multi-output Gaussian Process Regression. Lecture Notes in Computer Science. 10163, 88-103. 2017

Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Adding Flight Mechanics to Flight Loads Surrogate Model using Multi-Output Gaussian Processes. AIAA AVIATION 2016

Saves, P., Bartoli, N., Diouane, Y., Lefebvre, T., Morlier, J., David, C., ... & Defoort, S. (2022). Multidisciplinary design optimization with mixed categorical variables for aircraft design. In AIAA SCITECH 2022 Forum (p. 0082). has been awarded the 2022 AIAA Multidisciplinary Design Optimization Best Paper Award

Bellier P., , Urbano A., Morlier J. Bil C., and Pudsey A., Impact of Life Cycle Assessment Considerations on Launch Vehicle Design, 73rd International Astronautical Congress (IAC) 2022 – Paris, France

Au programme

Duration	Description	Agenda
3’	MDO/AI	New trends
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3’	Conclusions	

MDO/AI What’s new?

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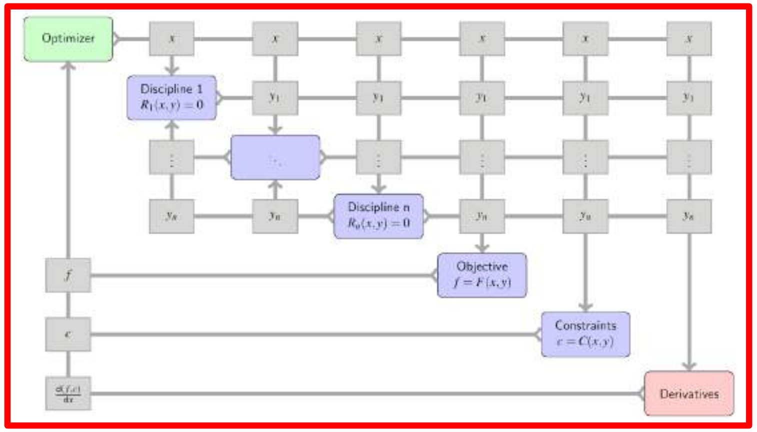
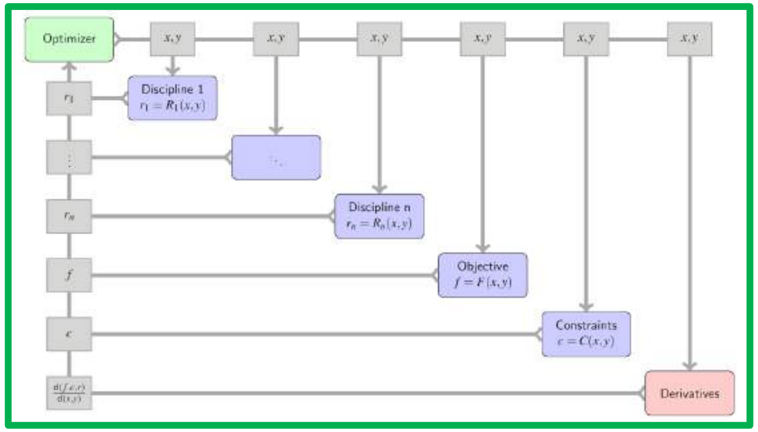
UNIVERSITY of MICHIGAN

Large-scale MDO?

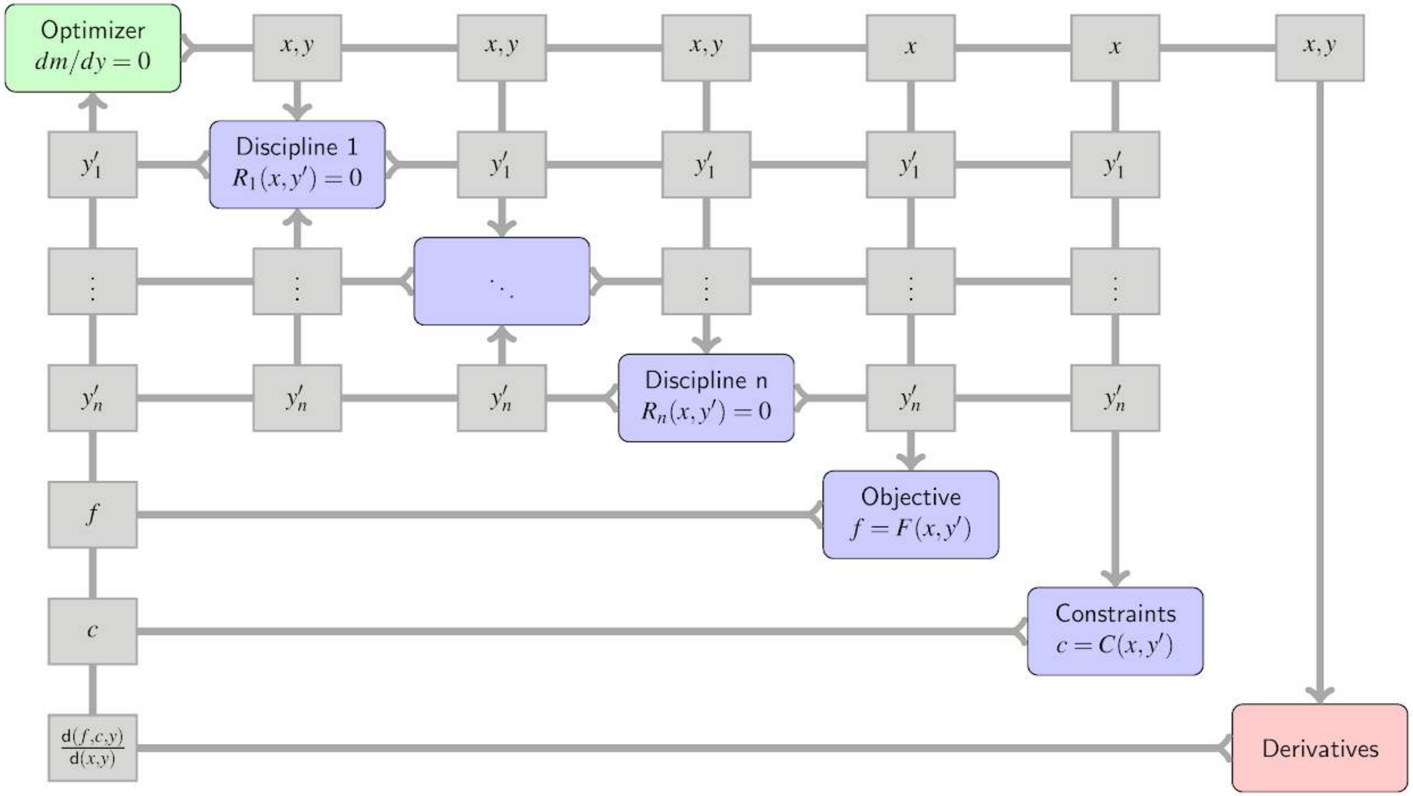
- https://lsdo.eng.ucsd.edu/research
- Proff. John Hwang

In the reduced-space method, the variables are computed by solvers that are part of the model. In the full-space method, the optimizer is responsible for computing the state variables. **The reduced-space method results in a smaller, easier-to-solve optimization problem**, while the full-space method has more inexpensive model evaluations.



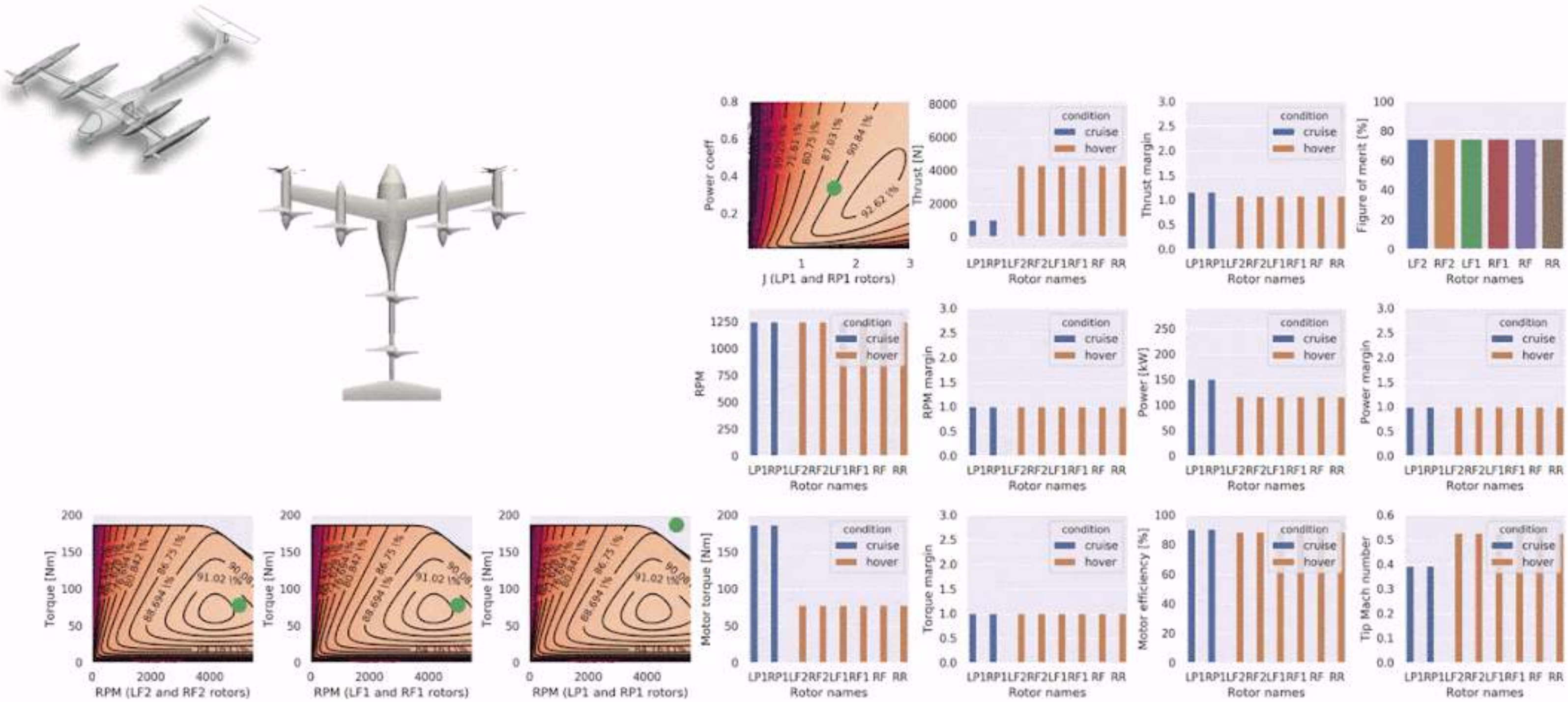


Best of both worlds:



the efficiency of the full-space method **and** the robustness of the reduced-space method.

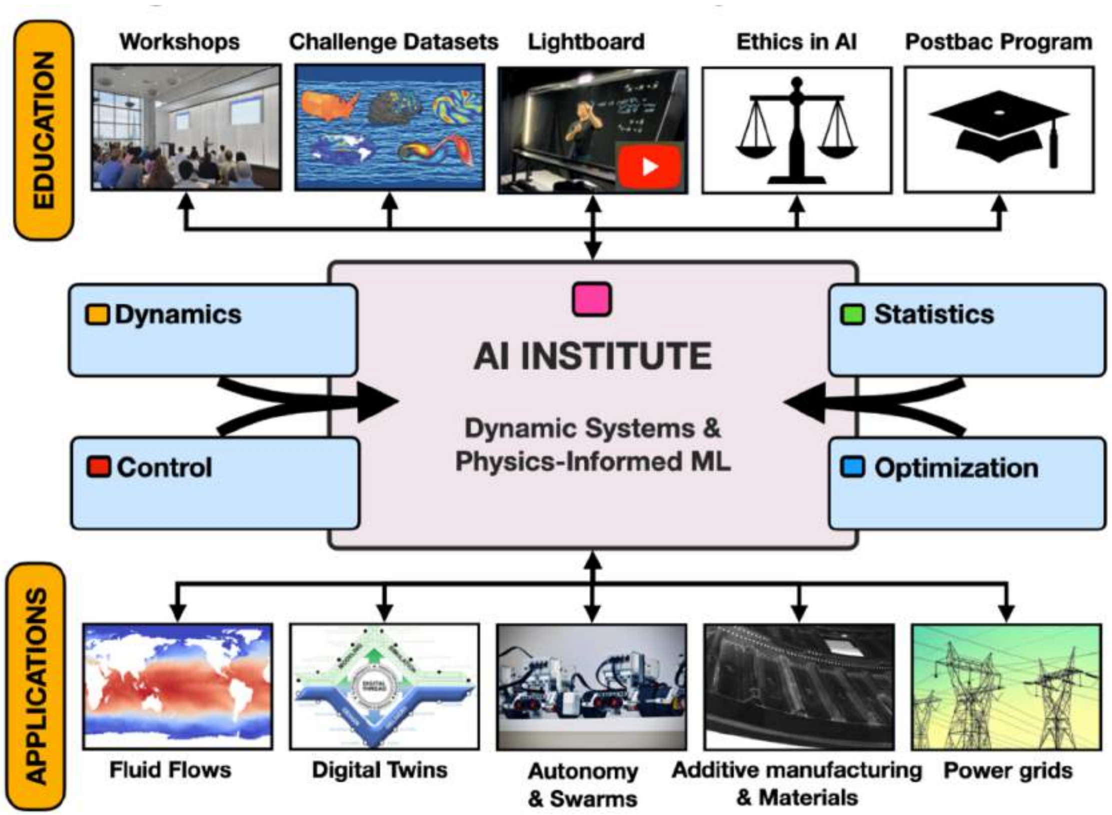
Large-scale design optimization is an invaluable tool in the eVTOL



AI4E

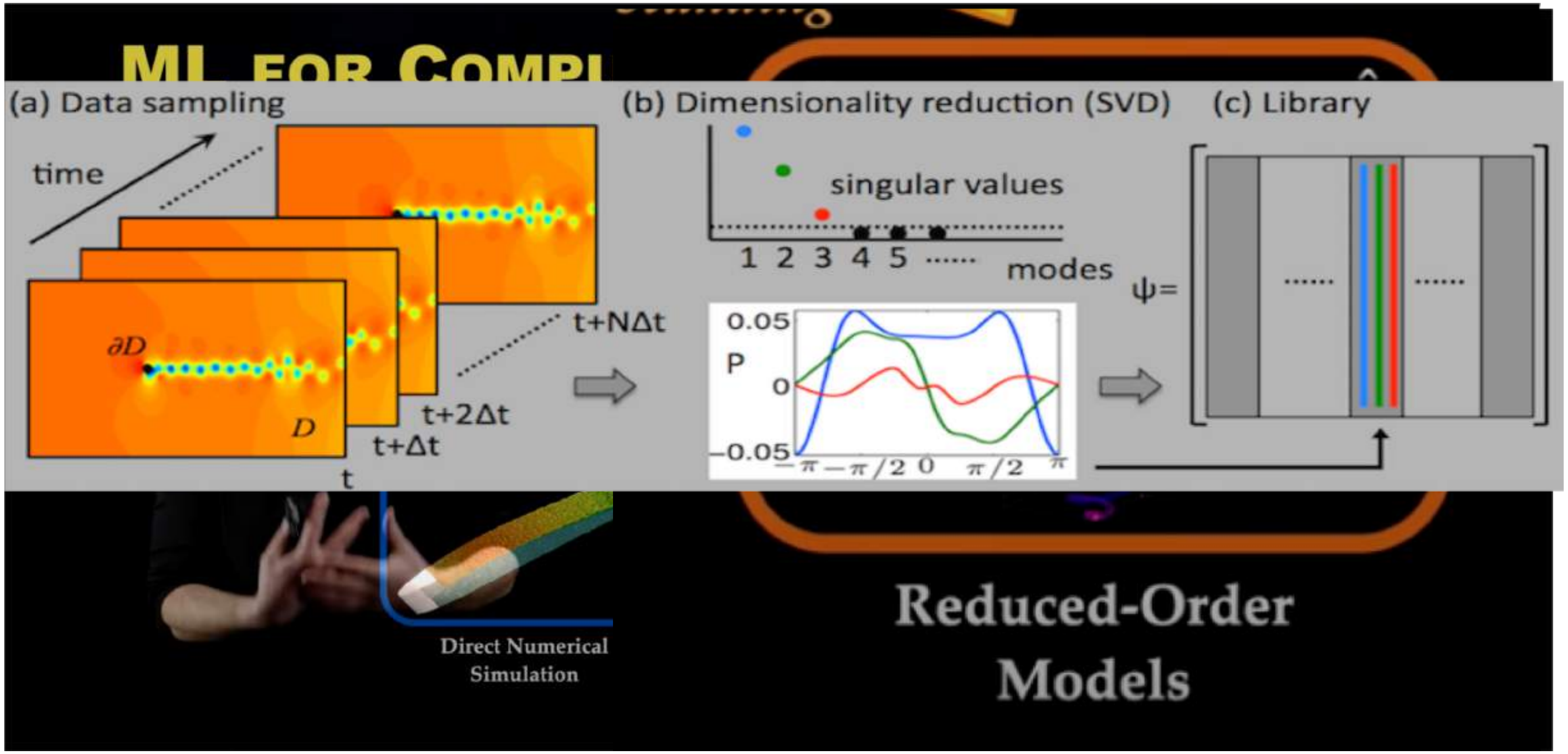
- http://dynamicsai.org

- Prof. J. Nathan Kutz,
- Prof. S. Brunton



"The goal is that anyone anywhere interested in AI for engineering can self-educate. There's no barrier to entry for those who want to learn."
J. Nathan Kutz,

AI can Accelerate CFD

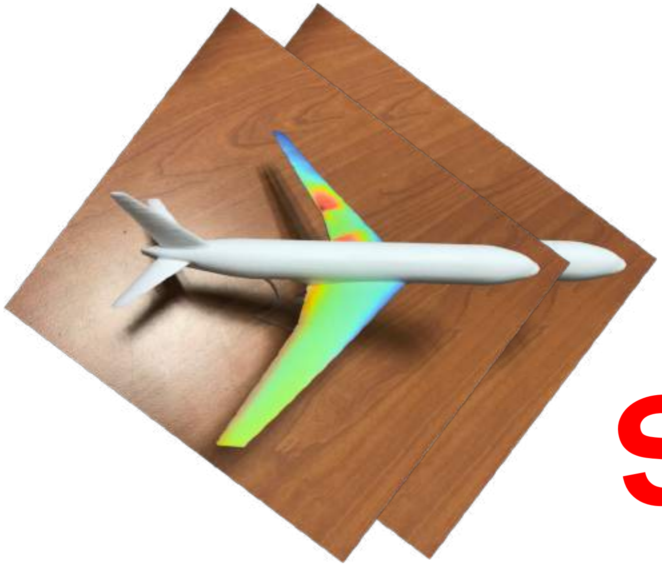


Reduced Order Model
ROM for digital twin

K. Willcox UTEXAS
C. Fahrat STANFORD
etc…

Au programme

Duration	Description	Agenda
3’	MDO	New trends
7’	Surrogate	SMT
7’	Ecodesign	Lighter, Greener, stronger
3’	Conclusions	



Surrogate: AI4E

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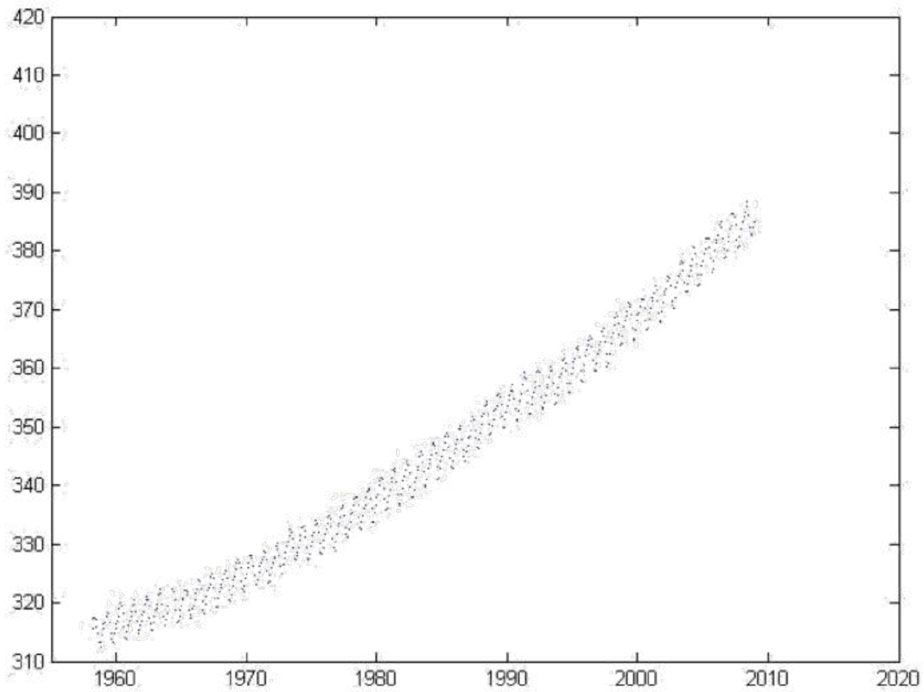
ML vs Engineering

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
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

Qualitative claims such as "ML works OK for interpolation but doesn't work for extrapolation" are wrong.
https://arxiv.org/abs/2110.09485

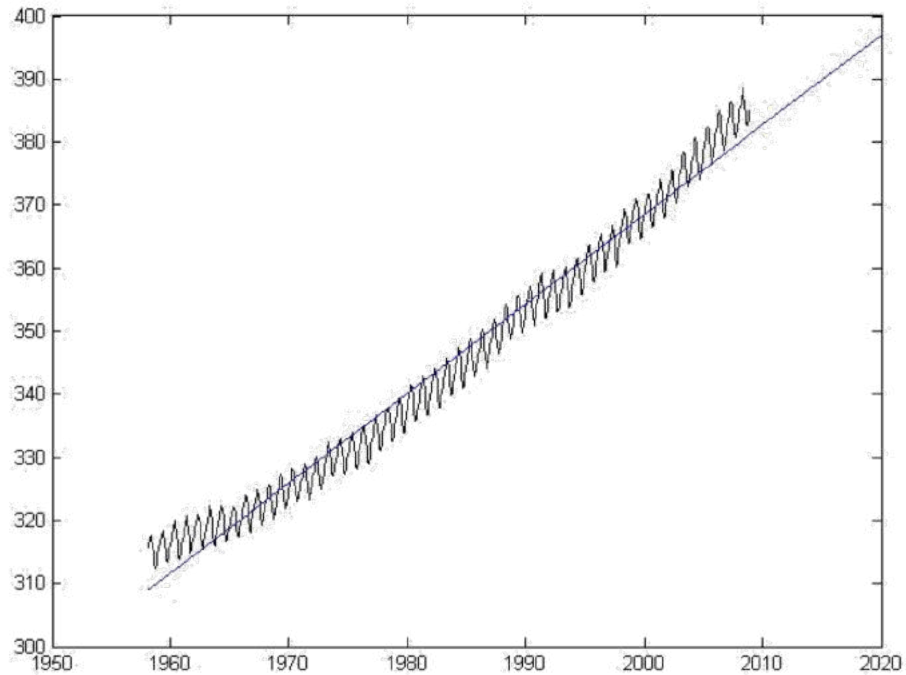
Limit of linear models for prediction



Month-wise data of Co2 concentration in atmosphere at Hawaii

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

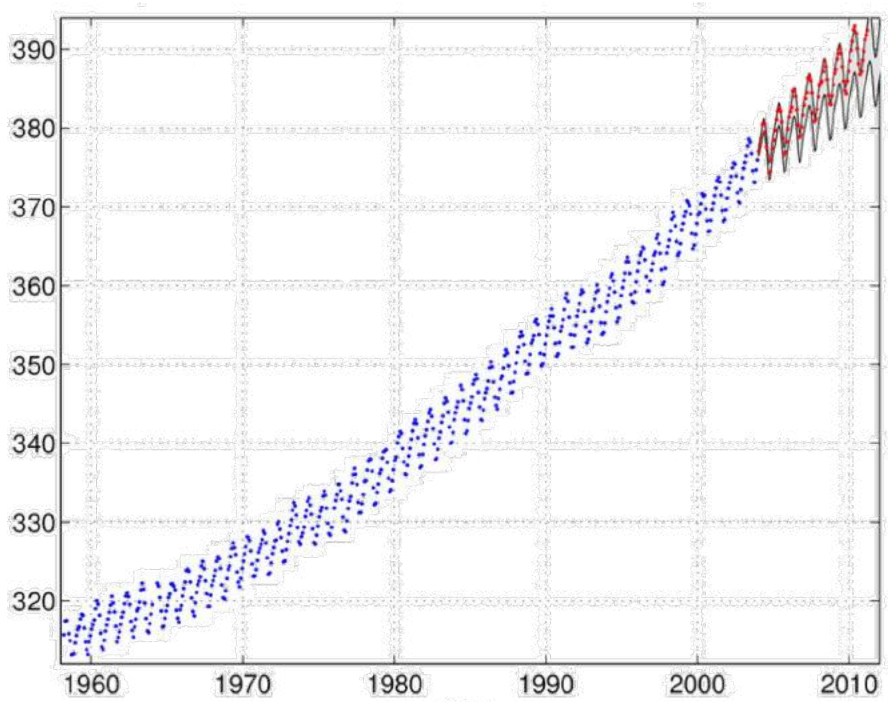
Example – Linear Regression



Should we choose a polynomial?
What degree of polynomial should we choose? (overfitting)
For a given degree, what parameters of polynomial should we choose

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

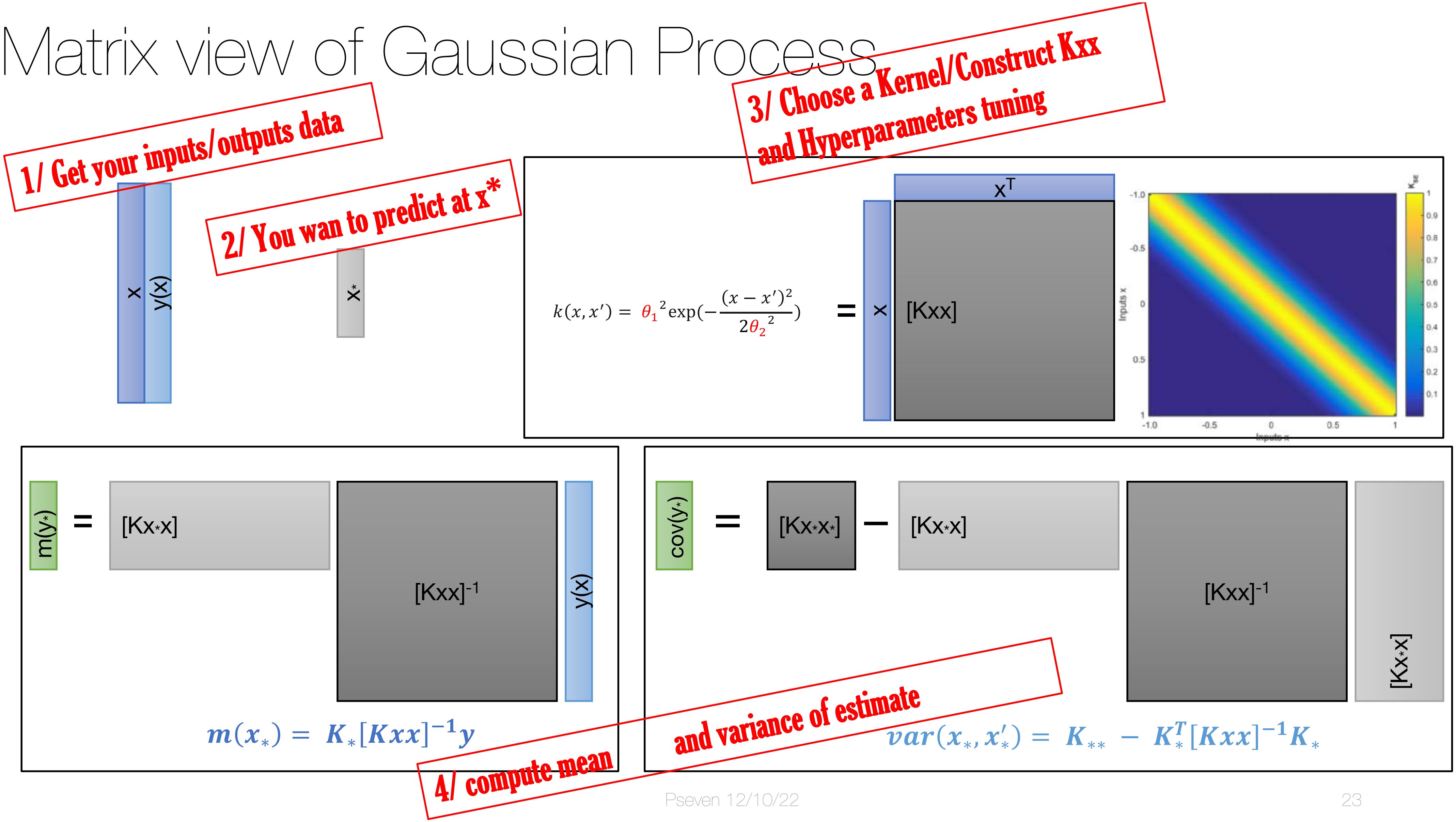
Example – Gaussian Process



Predicted variance after year 2005 in grey, real data-points in red

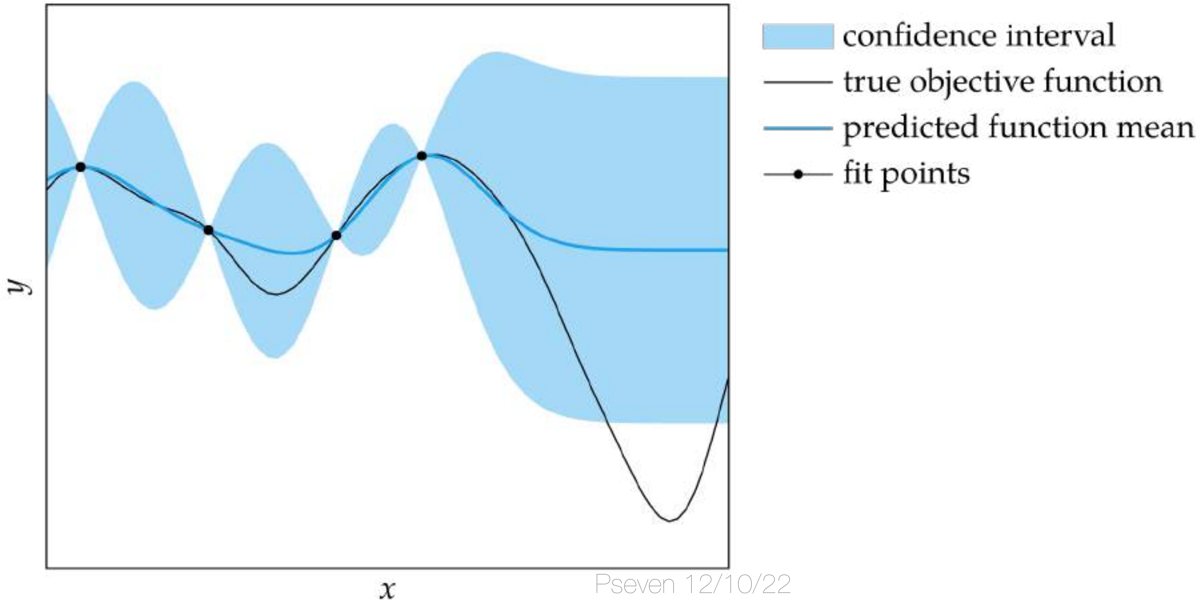
Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

Matrix view of Gaussian Process



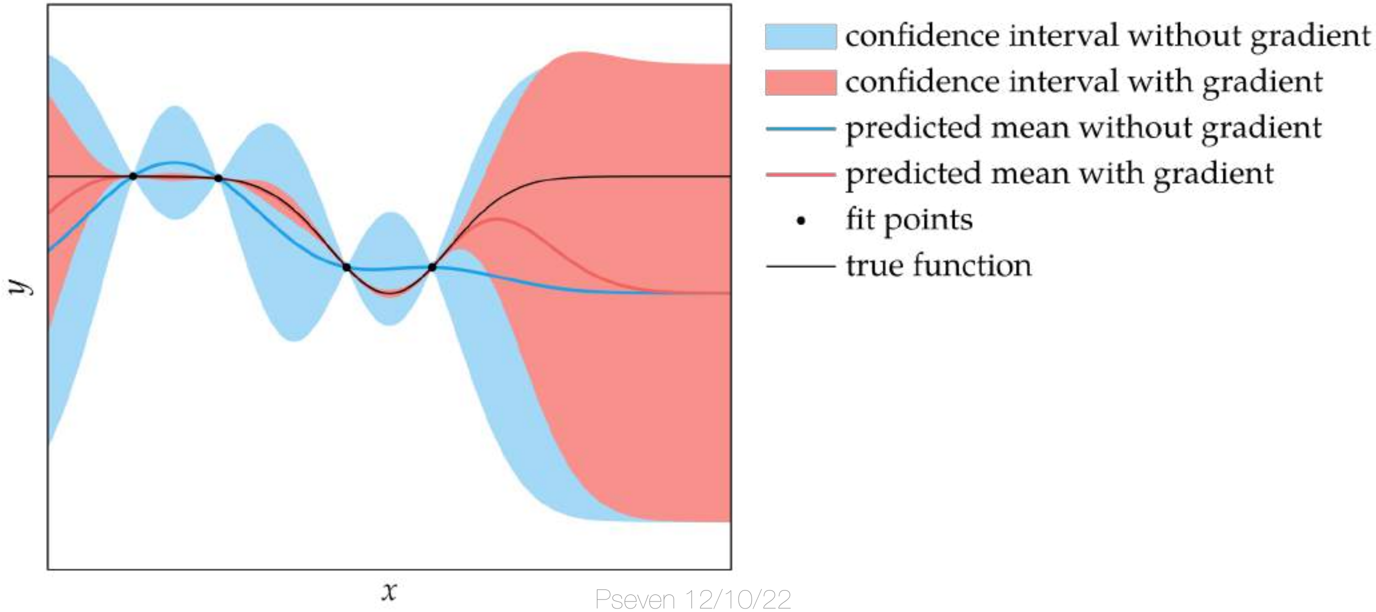
Prediction

- Using variance to compute standard deviation, the predicted mean and standard deviation can be computed at any point
- This enables calculation of the 95% confidence region



Gradient Measurements

- If function gradient evaluations can be made as well, the process can be extended to include gradient predictions for higher prediction fidelity

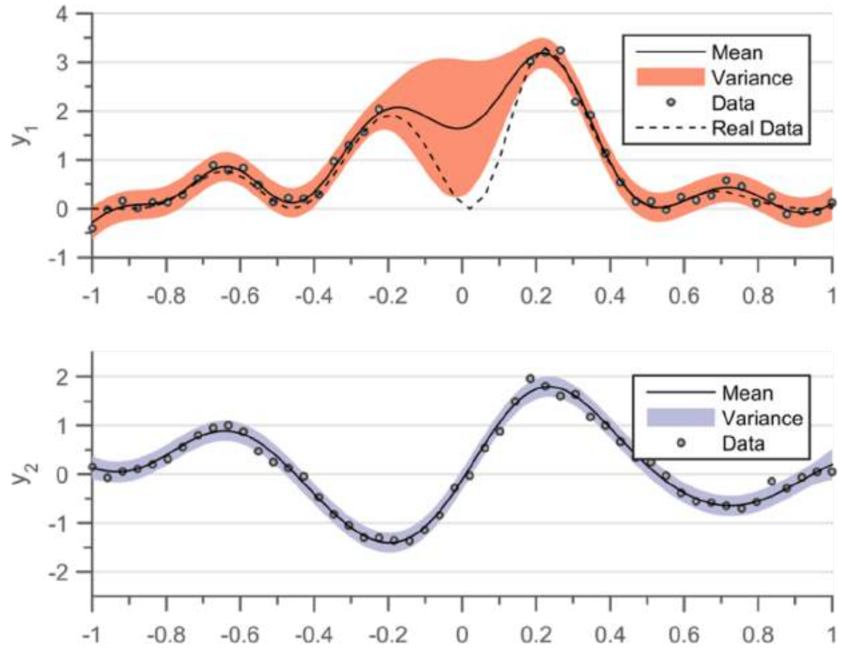


What we did few years ago before PINN and SciML…

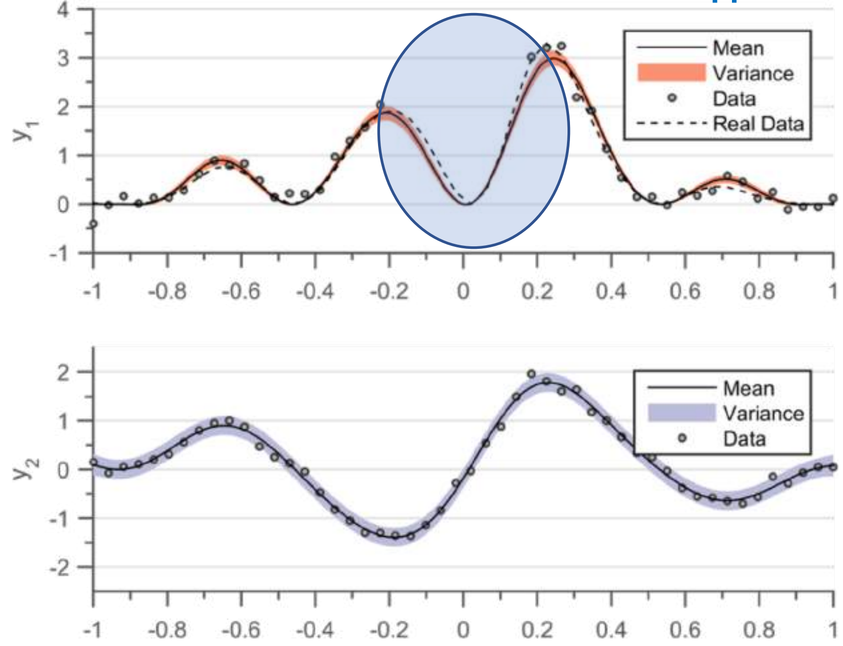
https://github.com/ankitchiplunkar/thesis_isae

$$y_1 = (y_2)^2$$

Variance reduction + better approximation



Independent GPs



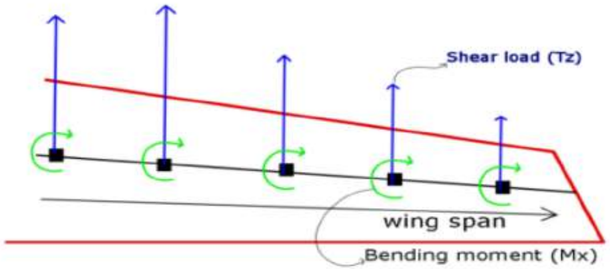
Related GPs

Related GPs

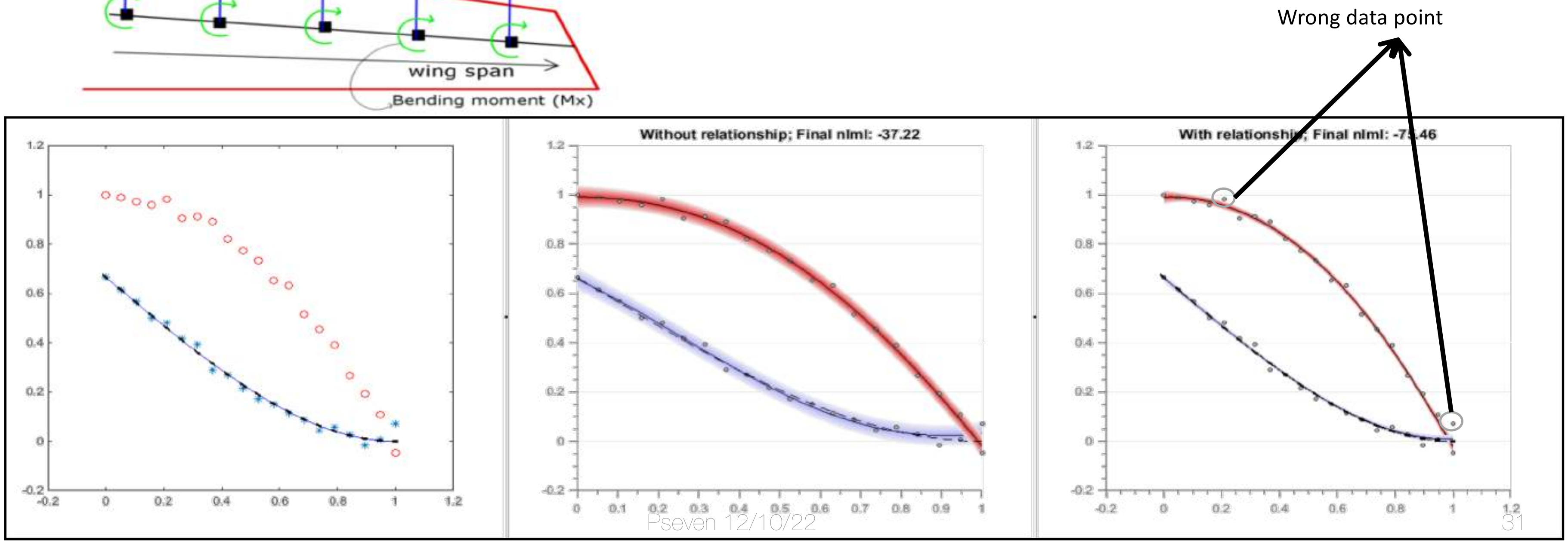
What we did few years ago before PINN and SciML…

https://github.com/ankitchiplunkar/thesis_isae

Flight test - Relationship between Tz and Mx



$$Mx = \int_{\eta}^{\eta_{edge}} (x - \eta)\, Tz\, dx$$

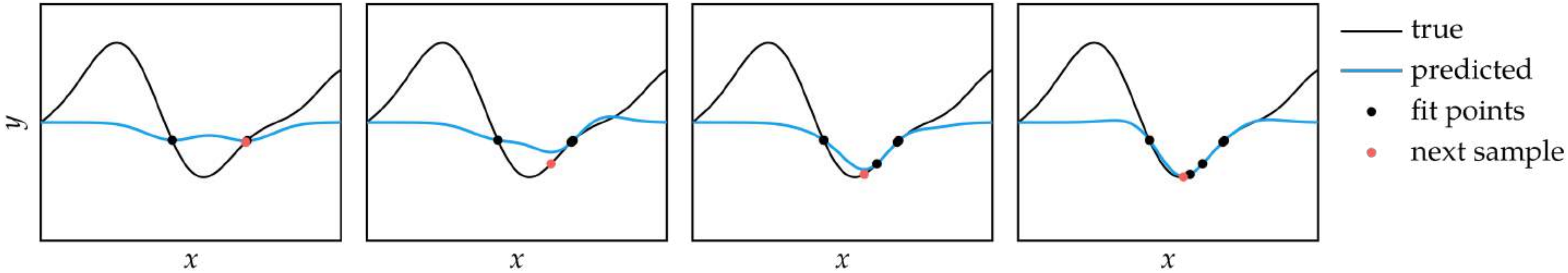


Surrogate Optimization

- Given a surrogate model with both prediction and confidence parameters, an optimization procedure must balance the search for the expected optimal point and decreasing uncertainty
- In other words, the optimization algorithm must balance exploitation with exploration

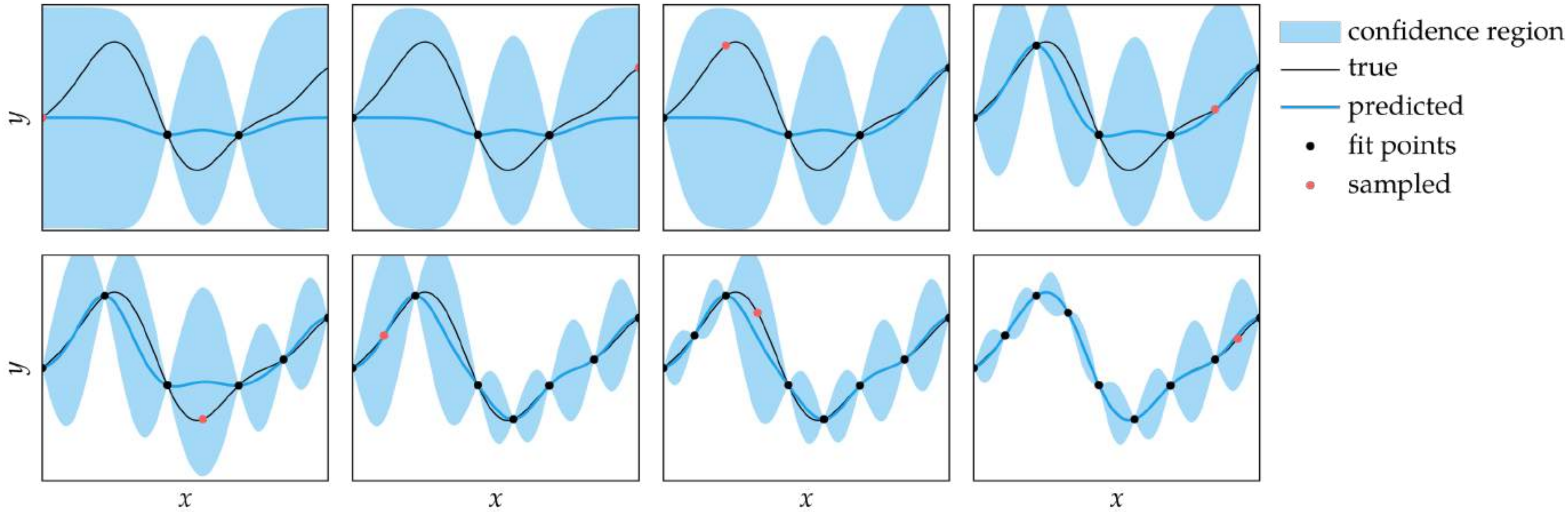
Prediction-Based Exploration

- Focuses exclusively on exploitation, also called greedy approach
- When using a Gaussian process surrogate model, prediction-based exploration simply optimizes over the mean function and ignores uncertainty



Error-Based Exploration

- Focuses exclusively on exploration
- For Gaussian processes, error-based exploration simply minimizes the maximum standard deviation within a specified domain

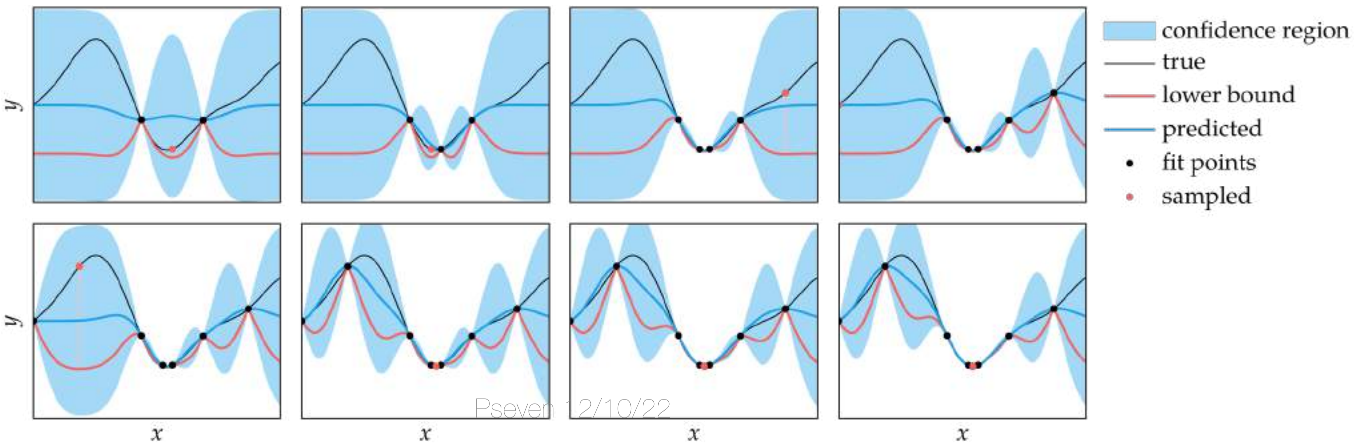


Lower Confidence Bound Exploration

- Tradeoff between exploration and exploitation
- The next sample minimizes the lower confidence bound of the objective function

$$LB(\mathbf{x}) = \hat{\mu}(\mathbf{x}) - \alpha\hat{\sigma}(\mathbf{x})$$

where $\alpha \geq 0$ is the tradeoff parameter



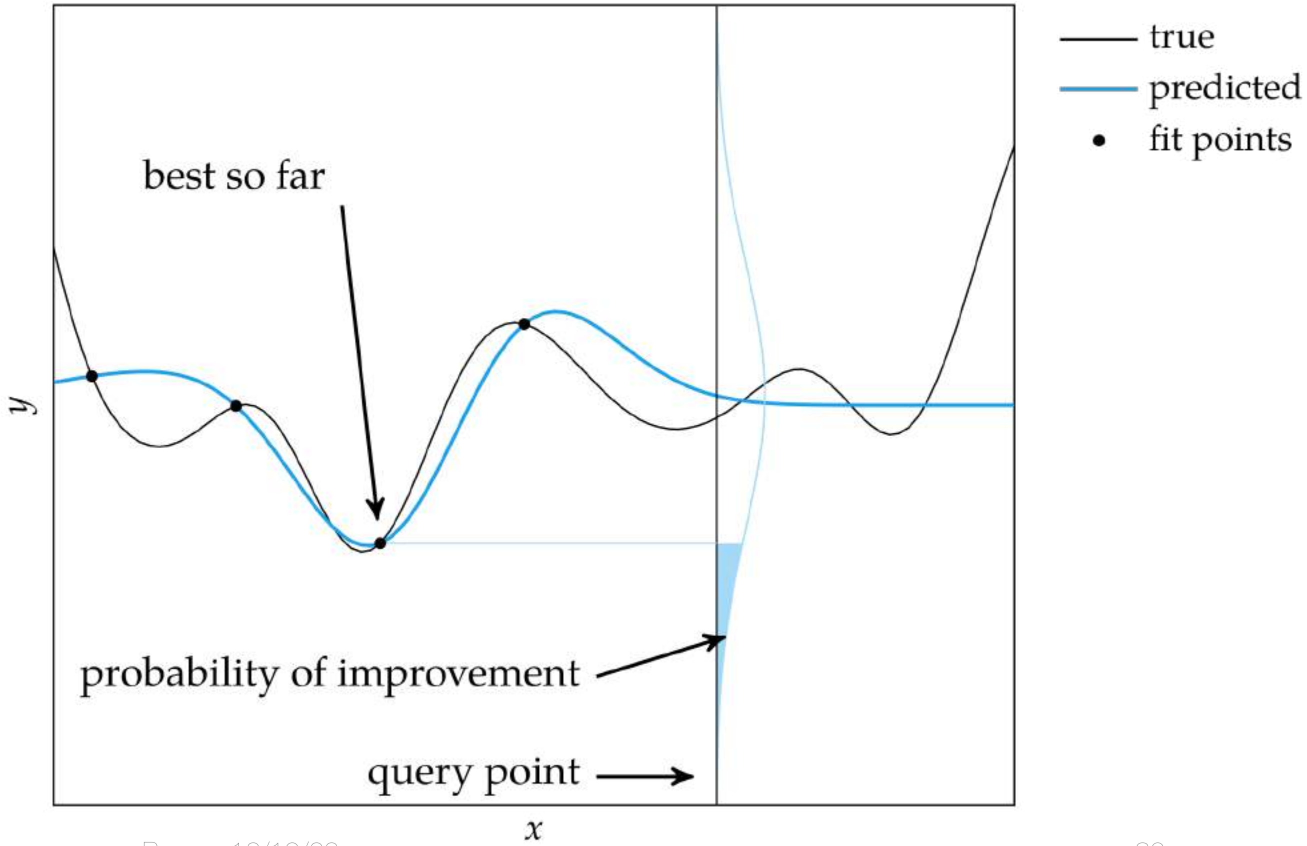
Probability of Improvement Exploration

- Searches at the location with the highest probability of improvement
- Improvement is defined as

$$I(y) = \begin{cases} y_{\min} - y & \text{if } y < y_{\min} \\ 0 & \text{otherwise} \end{cases}$$

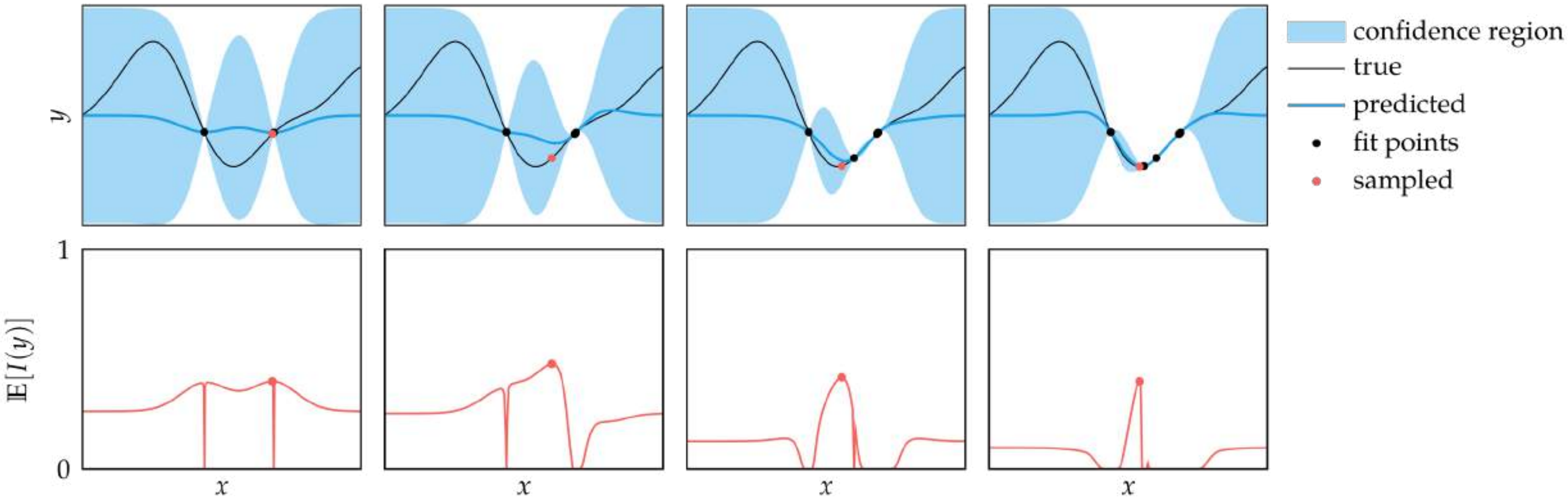
- The probability of improvement is defined as

$$P(y < y_{\min}) = \int_{-\infty}^{y_{\min}} \mathcal{N}(y \mid \hat{\mu}, \hat{\sigma})\,dy$$
$$= \Phi\left(\frac{y_{\min} - \hat{\mu}}{\hat{\sigma}}\right)$$



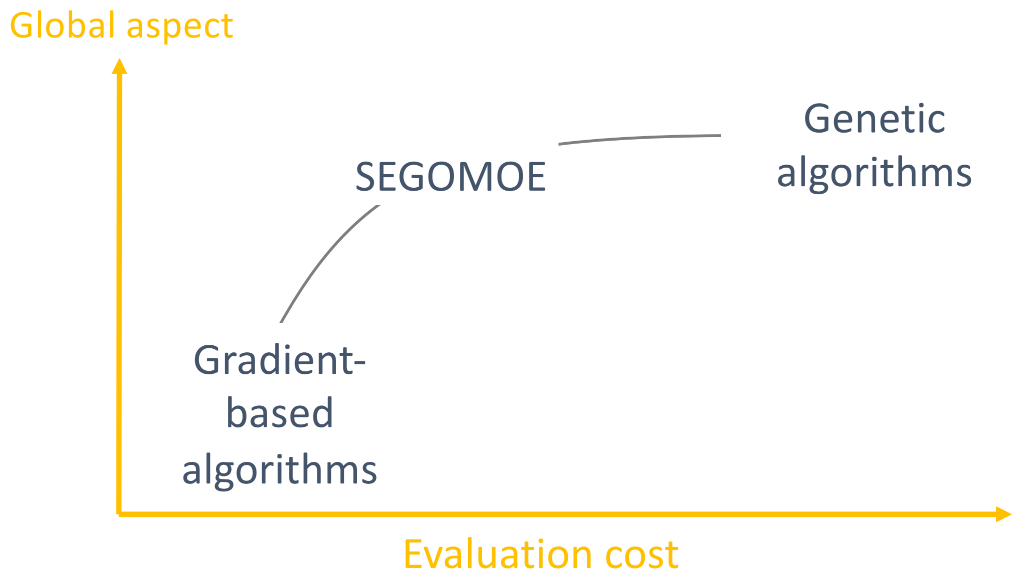
Expected Improvement Exploration

EI Expected Improvement exploration seeks to maximize expected improvement at each step



How to build an efficient iterative process?

- Find the global minimum with a limited budget of function evaluations
- Use Bayesian information to detect interesting and promising areas
  (exploitation/exploration trade-off)
- ➔ SEGOMOE optimizer

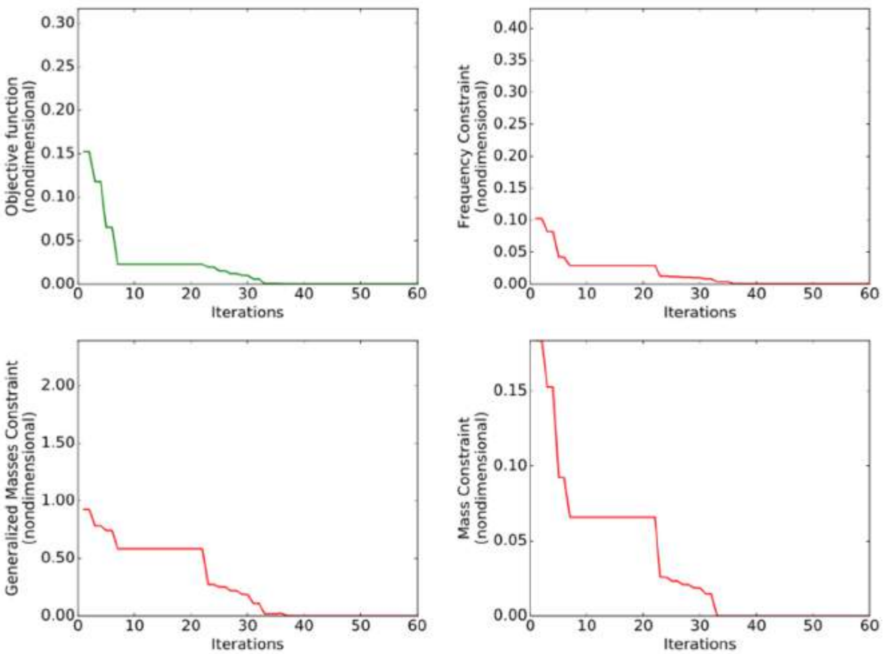


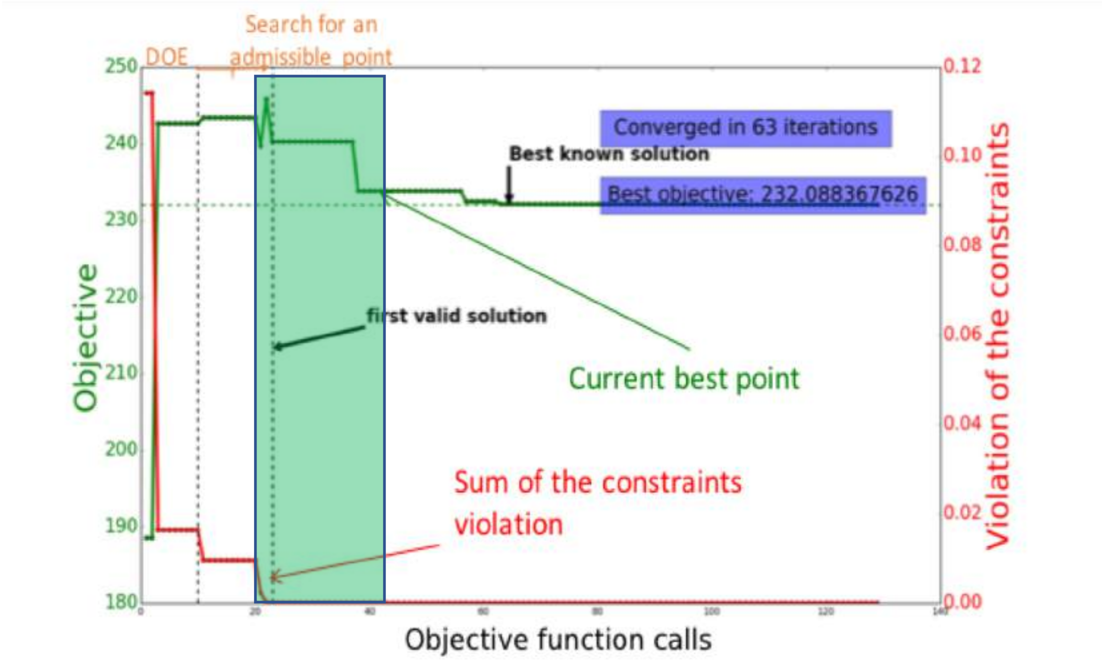
N. Bartoli, T. Lefebvre, S. Dubreuil, R. Olivanti, N. Bons, J.R.R.A. Martins, M.-A. Bouhlel, J. Morlier, " Adaptive modeling strategy for constrained global optimization with application to aerodynamic wing design ", Aerospace Science and Technology, 90, 85-102., 2019

Convergency graphs

Gradient based Optimality, Feasibility

SBO Exploration, Exploitation





Stopping criteria: tolfun, tolx, maxiter

Stopping criteria: Max Budget (Function calls)

...in 2017 the first SMT version was released

Table of Contents

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}}
```

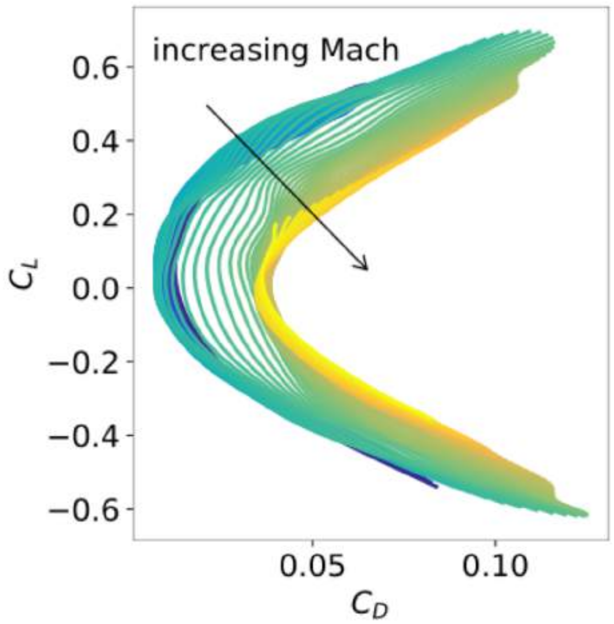
Focus on derivatives

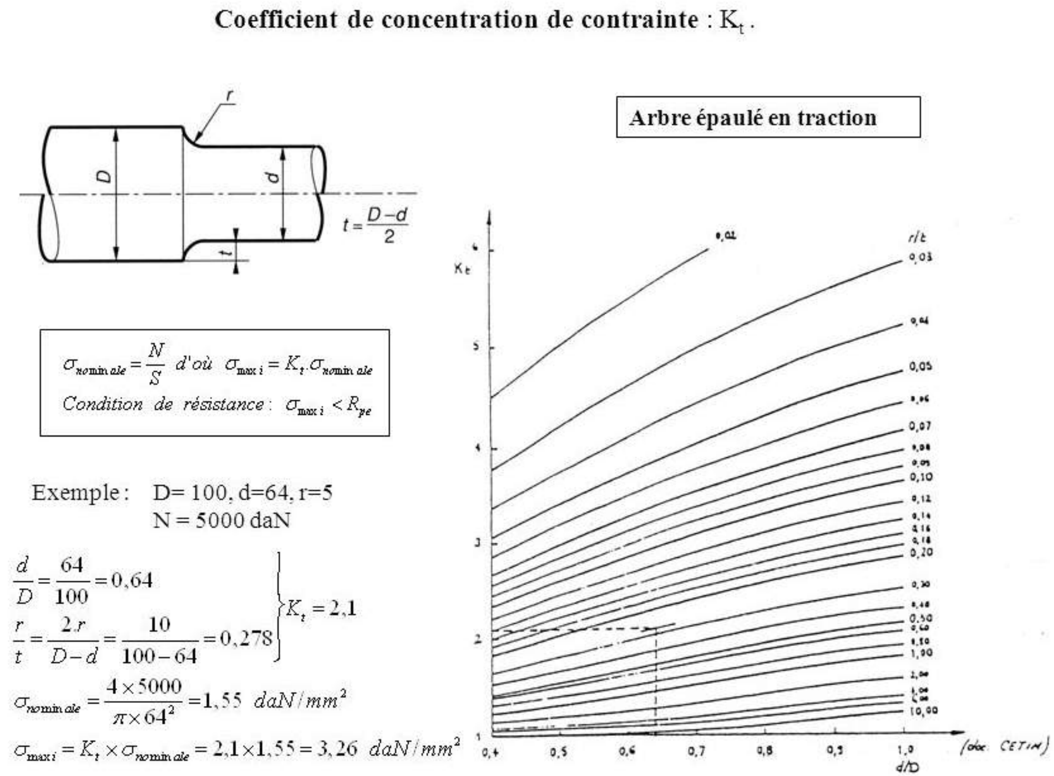
SMT is meant to be a general library for surrogate modeling (also known as metamodeling, interpolation, and regression), but its distinguishing characteristic is its focus on derivatives, e.g., to be used for gradient-based optimization.

The paper had to wait until 2019...

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*, *135*, 102662.

Surrogate is the new abacus





SMT structure – Surrogate

1.1.0 Latest

Compare

relf released this 1 hour ago · v1.1.0 · 651df91

- Mixed integer surrogate enhancements (thanks **@Paul-Saves**)
  - Add number of components estimation in KPLS surrogate models (#325)
  - Add `propagate_uncertainty` option in MFK method (#320) : when True the variance of lower fidelity levels are taken into account.
  - Add ordered variables management in mixed integer surrogates (#326, #327). Deprecation warning: INT type is deprecated and superseded by ORD type.
  - Update version for the GOWER distance model. (#330)
  - Implement generalization of the homoscedastic hypersphere kernel from Pelamatti et al. (#330)

Svante Wold (1978) Cross-Validatory Estimation of the Number of Components in Factor and Principal Components Models, Technometrics, 20:4, 397-405, DOI: 10.1080/00401706.1978.10489693

- Radial basis functions
- Inverse-distance weighting
- Regularized minimal-energy tensor-product splines
- Least-squares approximation
- Second order polynomial approximation
- Kriging
- Kriging with partial least square (KPLS)
- KPLSK
- Gradient-enhanced KPLS
- Gradient-enhanced neural networks
- Marginal Gaussian process

Useful for low dimensional problem

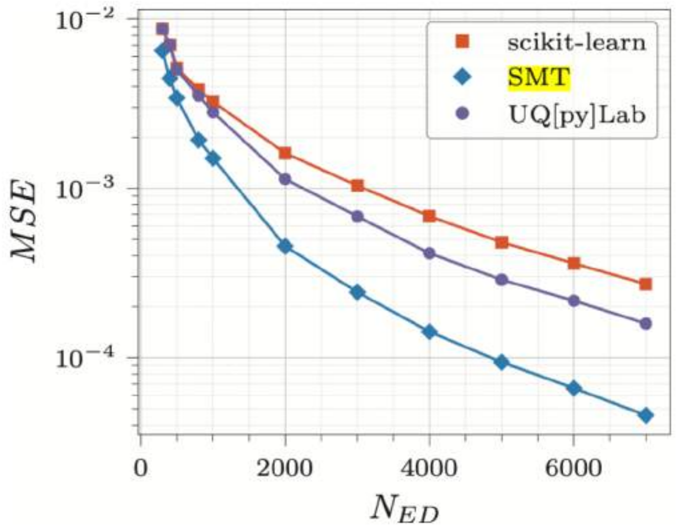
useful for kriging in high dimension

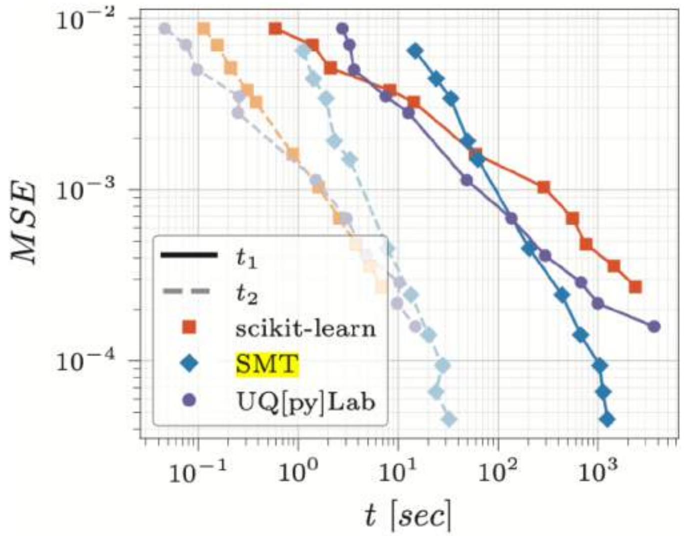
Focus on derivatives

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, 135, 102662.

Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)

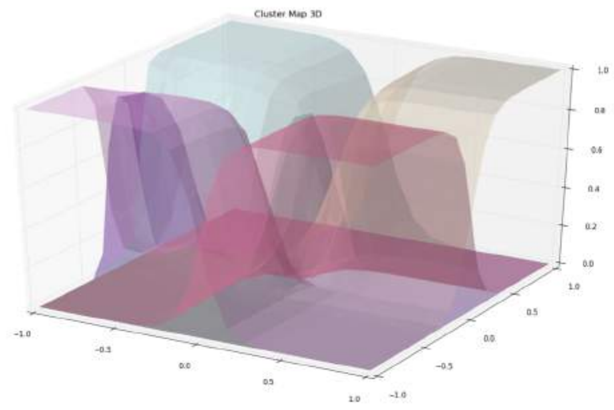
- As evidence, the SMT package reaches a better accuracy (up to almost an order of magnitude) than the other toolboxes.
- SMT tends to perform quickly than the other packages for higher ***NED*** in calibrating the Kriging model, but not in its evaluation.





AI4E

- Mixture of experts (MOE) - if 1 expert , comparison of all experts
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance



How to approximate highly non linear function?

•Handle heterogeneity and non linearity (all phases in the flight mission, buckling factor for composite fuselage)

•Combine multiple surrogate models divide-and- conquer strategy

AI4E

- Mixture of experts (MOE)
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
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- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance

How to handle multi-information sources?

- Access to different information sources that approximate $y(x)$ with varying accuracy and cost

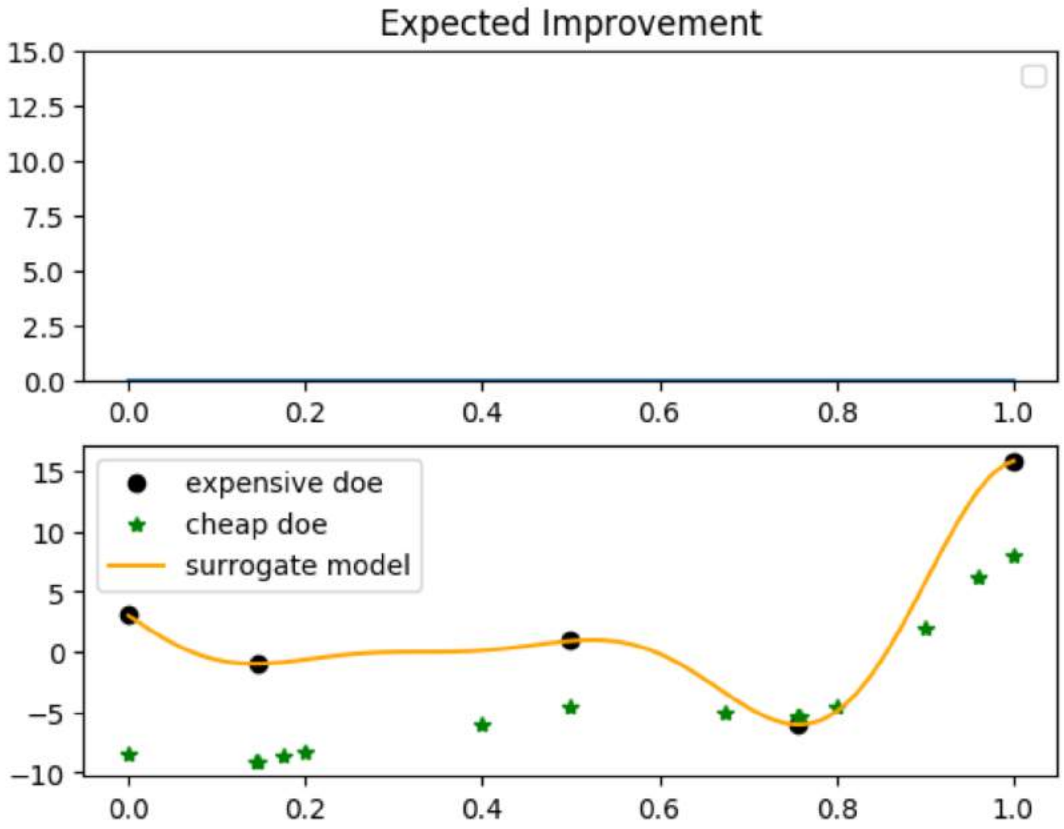
Hierarchical relationships among information sources: low-fidelity / high-fidelity

Why multifidelity?

Artificial Intelligence for Engineers, means learning for optimizing a computational design.

Given a surrogate model with both prediction and confidence parameters, an optimization procedure must balance the search for the expected optimal point and decreasing uncertainty (Bayesian Optimization)

What if Several levels of fidelity of the same simulation are available?
(in aerodynamics **multifidelity** means: Liflting line theory, Vortex lattice method, and RANS CFD simulation tools available)



Raw approach luse ow fidelity for exploration and high fidelity for exploitation

Our approach combine Bayesian optimization with multifidelity

AI4E

- Mixture of experts (MOE
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance

Bayesian optimization (EGO without constraint) for continuous and mixed variables

Included some dedicated Jupyter Notebooks

..

SMT_EGO_application.ipynb

SMT_MixedInteger_application.ipynb

SMT_Noise.ipynb

SMT_Tutorial.ipynb

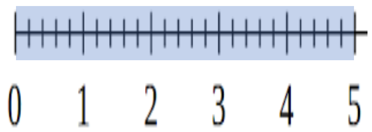
AI4E

- Mixture of experts (MOE
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance

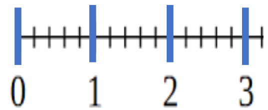
Focus on mixed integer

Variables types :

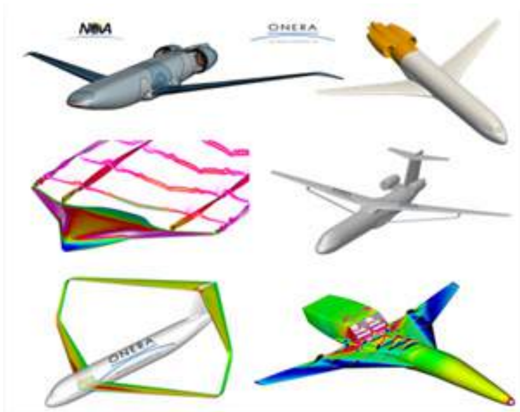
Continuous (x) Ex: wing length



Integer (z) Ex: winglet number



Categorical (u) Ex: Plane shape



Categorical variables: n variables,
n=2
u1= shape
u2= color

Levels: L_i levels for I in 1,..,n,
L_1=3, L_2=2.
Levels(u1)= square, circle, rhombus
Levels(u2)= blue, green

Categories: $\prod_{i=1}^{n} L_i$, 2*3=6
- Blue square
- Blue circle
- Blue rhombus
- Green square
- Green circle
- Green rhombus

Focus on mixed integer

Continuous relaxation

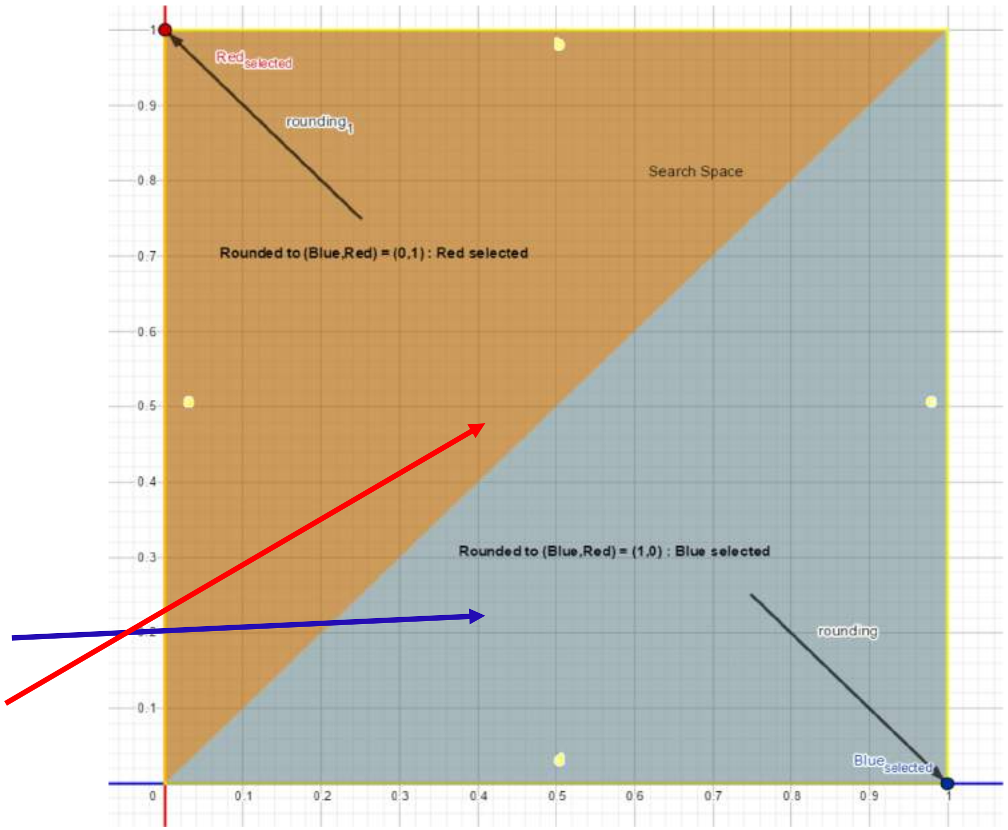
E. C. Garrido-Merchán, and D. Hernández-Lobato. "Dealing with categorical and integer-valued variables in Bayesian Optimization with Gaussian processes". Neurocomputing, vol. 380 (2020), pages 20-35

Example with 1 categorical variable and two levels

- Red color
- Blue color

➔Categorical variable replaced by two continuous variables denoted by X_1 and X_2

- If $X_1 > X_2$ => (1., 0.) => Blue color
- If $X_1 < X_2$ => (0., 1.) => Red color

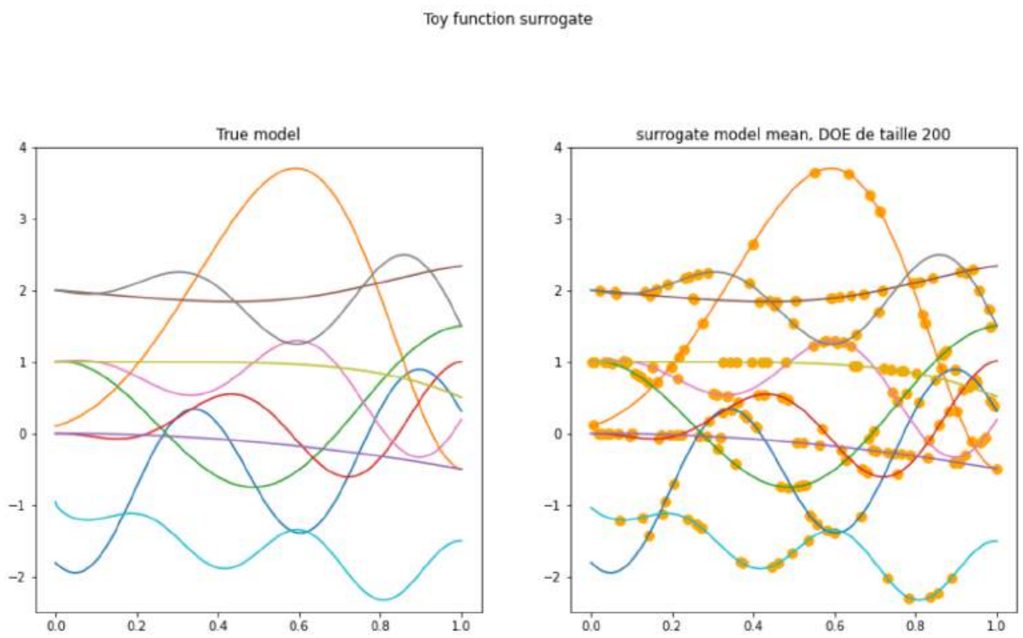


Focus on mixed integer

Continuous relaxation

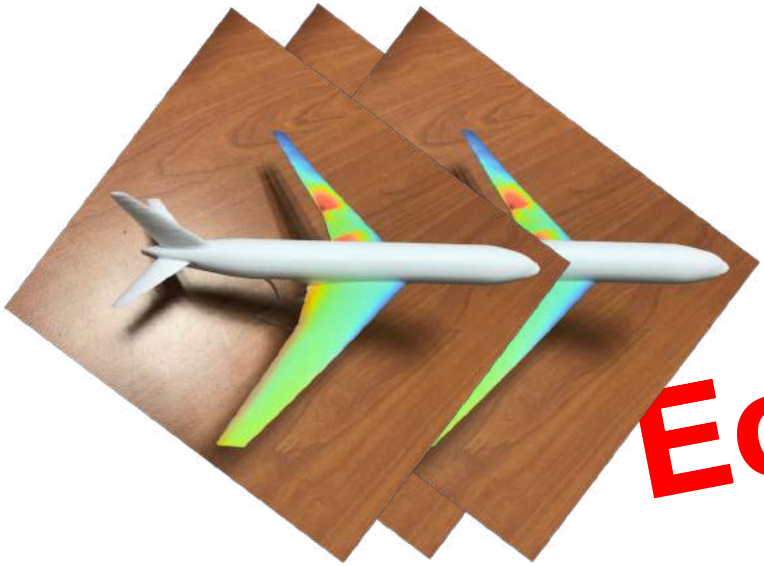
Validation problem $n_{var} = 2$
Variable types: continuous and categorical with 10 levels. $n_{var,relaxed} = 11$

$$f(x,z) = \begin{cases} \cos(3.6\pi(x-2)) + x - 1 & \text{if} \quad z = 1, \\ 2\cos(1.1\pi\exp(x)) - \frac{x}{2} + 2 & \text{if} \quad z = 2, \\ \cos(2\pi x) + \frac{1}{2}x & \text{if} \quad z = 3, \\ x\left(\cos(3.4\pi(x-1)) - \frac{x-1}{2}\right) & \text{if} \quad z = 4, \\ -\frac{x^2}{2} & \text{if} \quad z = 5, \\ 2\cos(\frac{\pi}{4}\exp(-x^4))^2 - \frac{x}{2} + 1 & \text{if} \quad z = 6, \\ x\cos(3.4\pi x) - \frac{x}{2} + 1 & \text{if} \quad z = 7, \\ x(-\cos\left(7\frac{\pi}{2}x\right) - \frac{x}{2}) + 2 & \text{if} \quad z = 8, \\ -\frac{x^5}{2} + 1 & \text{if} \quad z = 9, \\ -\cos(5\frac{\pi}{2}x)^2\sqrt{x} - \frac{\ln(x+0.5)}{2} - 1.3 & \text{if} \quad z = 10. \end{cases}$$



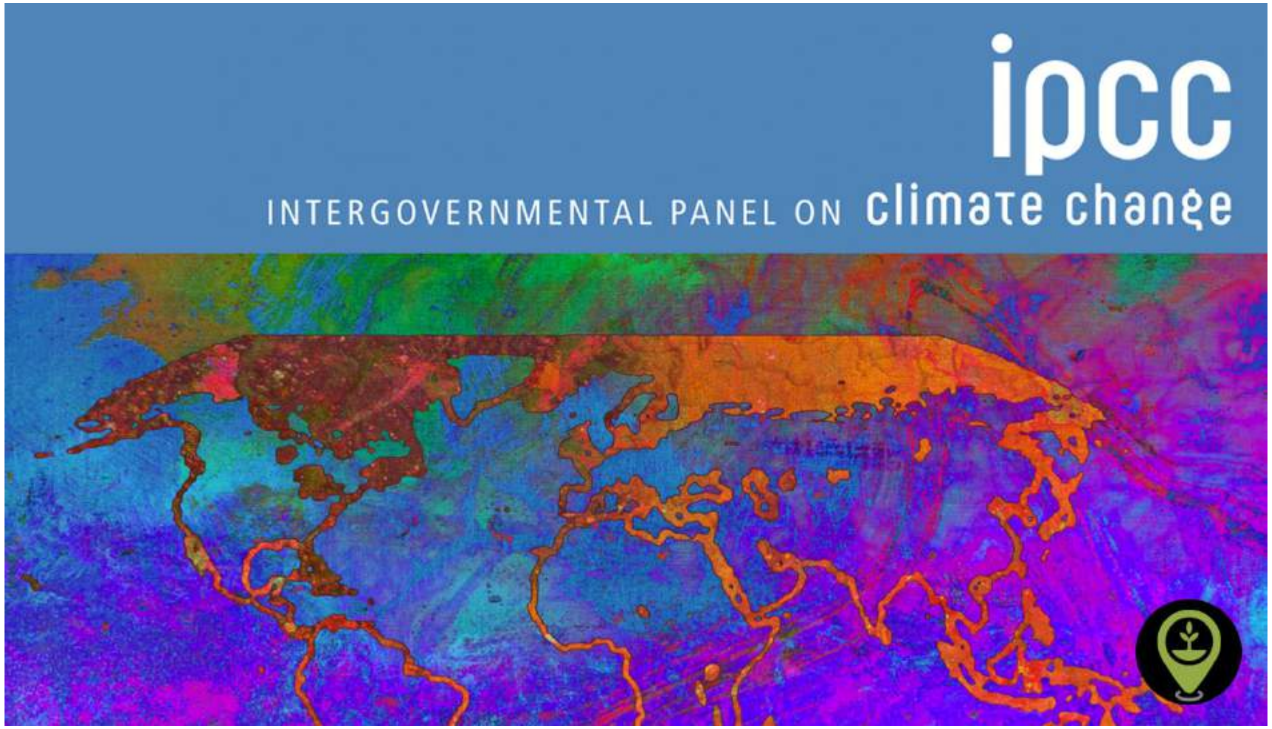
Au programme

Duration	Description	Agenda
3’	MDO	New trends
7’	Surrogate	SMT
7’	Ecodesign	Lighter, Stronger, Greener
3’	Conclusions	



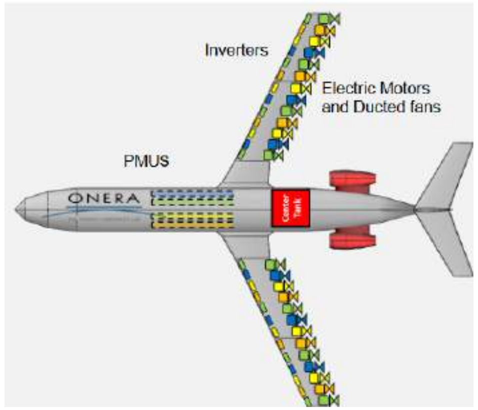
Ecodesign

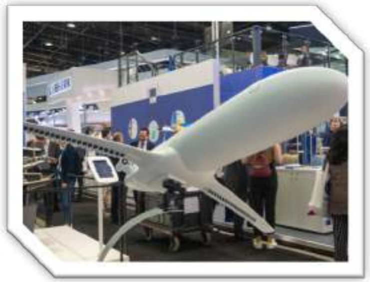
Aerospace sustainability: combining the growth of (new) Aerospace activities with the urgent need to reduce global environmental impact



MDO for greener aircraft

- ✓ 30% reduction of CO_2 emissions by 2035
- ✓ Distributed electric propulsion aircraft: propulsive efficiency
- ✓ 150 passengers over 2750nm
- ✓ Transonic cruise speed (M0.78)





P. Schmollgruber, C. Doll, J. Hermetz, R. Liaboeuf, M. Ridel, I. Cafarelli, O. Atin-ault, C. Francois, and B. Paluch. “Multidisciplinary Exploration of DRAGON: an ONERA Hybrid Electric Distributed Propulsion Concept”. In: AIAA Scitech 2019, 2019

Optimization problem: DRAGON

Table 4 Definition of the "DRAGON" optimization problem.

	Function/variable	Nature	Quantity	Range
Minimize	Fuel mass	cont	1	
with respect to	Fan operating pressure ratio	cont	1	[1.05, 1.3]
	Wing aspect ratio	cont	1	[8, 12]
	Angle for swept wing	cont	1	[15, 40] (°)
	Wing taper ratio	cont	1	[0.2, 0.5]
	HT aspect ratio	cont	1	[3, 6]
	Angle for swept HT	cont	1	[20, 40] (°)
	HT taper ratio	cont	1	[0.3, 0.5]
	TOFL for sizing	cont	1	[1800., 2500.] (m)
	Top of climb vertical speed for sizing	cont	1	[300., 800.](ft/min)
	Start of climb slope angle	cont	1	[0.075., 0.15.](rad)
	Total continuous variables		10	
	Architecture	cat	17 levels	{1,2,3, . . . ,15,16,17}
	Turboshaft layout	cat	2 levels	{1,2}
	Total categorical variables		2	
	Total relaxed variables		**29**	
subject to	Wing span < 36 (m)	cont	1	
	TOFL < 2200 (m)	cont	1	
	Wing trailing edge occupied by fans < 14.4 (m)	cont	1	
	Climb duration < 1740 (s)	cont	1	
	Top of climb slope > 0.0108 (rad)	cont	1	
	Total constraints		**5**	

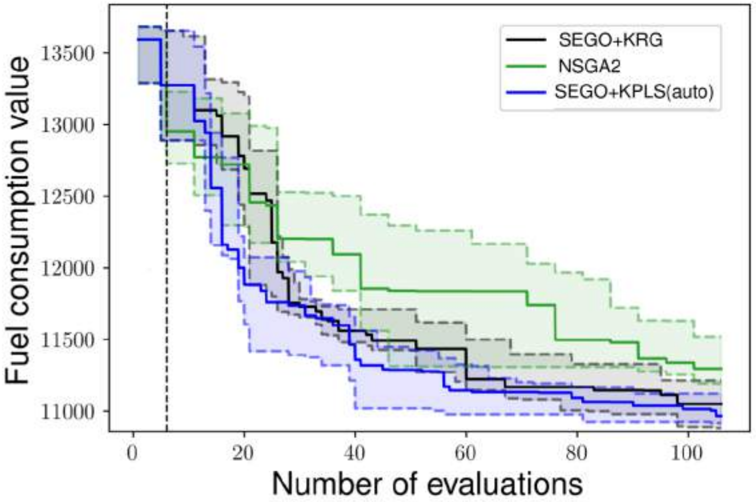
n = 12
Variable types: continuous (10), categorical (2)
n' = 29

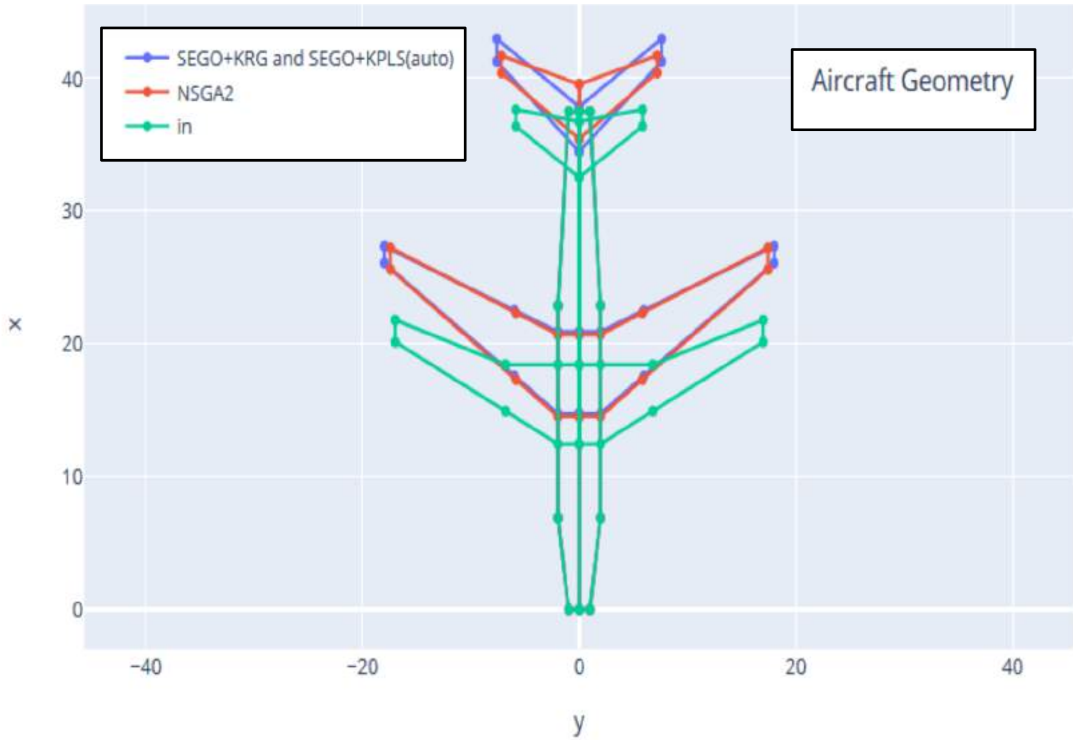
- 5 inequality constraints (MC)
- Fuel mass to minimize

Optimization results: DRAGON

Options for SEGO-KPLS
From *n' = 29* to *d(auto)*
d ~ 1.6

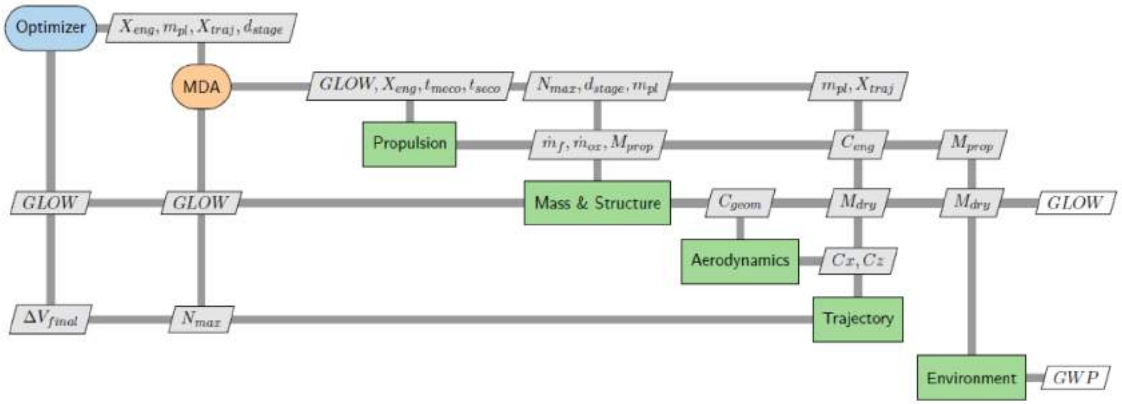
Convergence plots for DRAGON

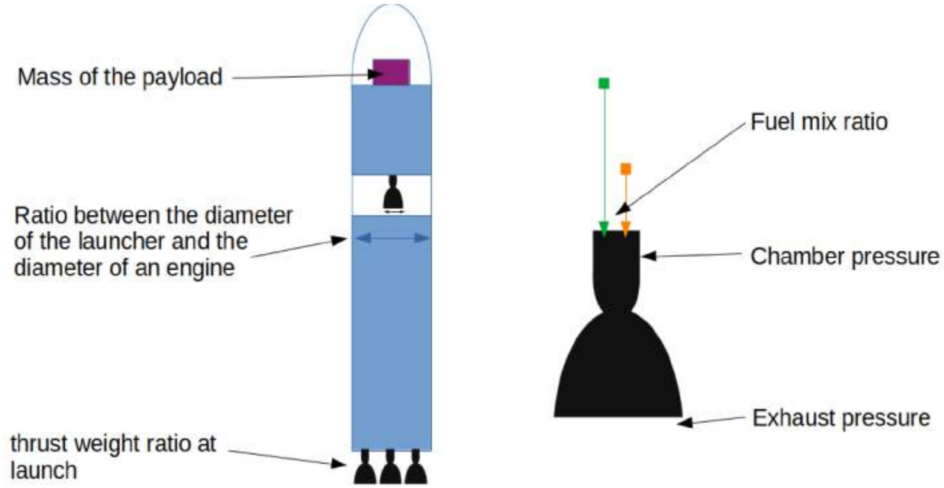




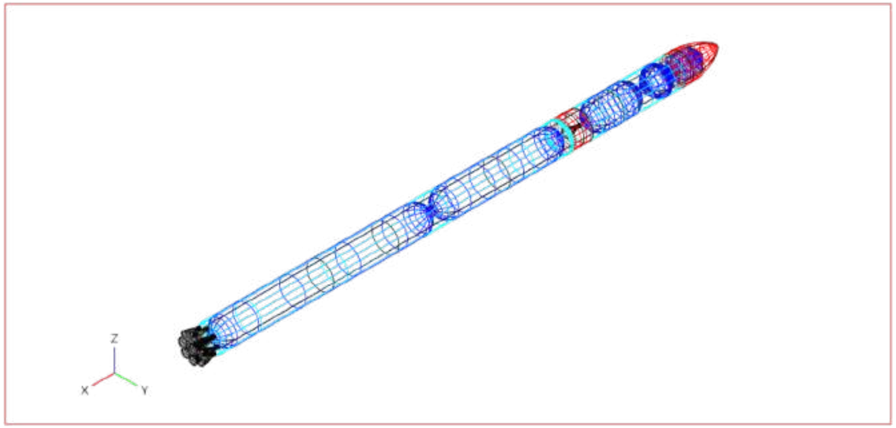
MDO for ECOlauncher design

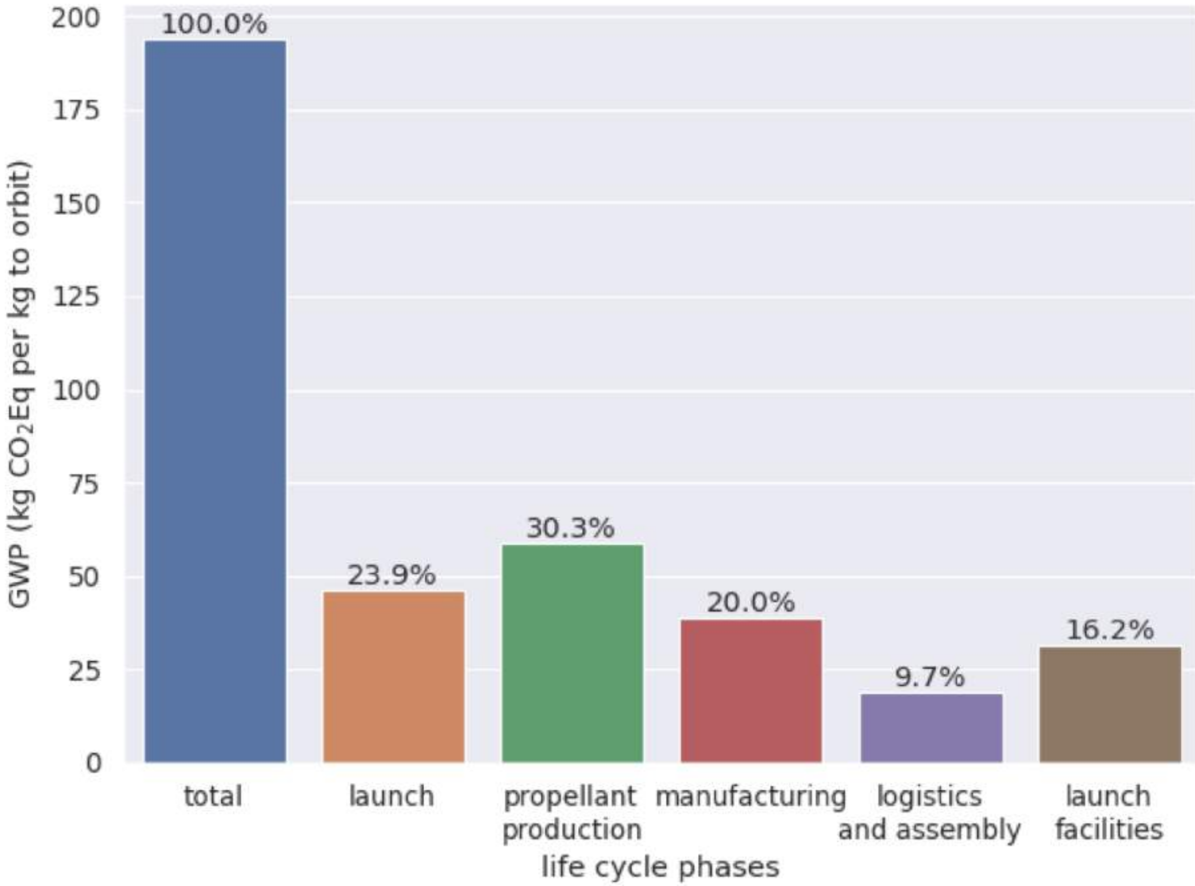
Objective function : GLOW
Design variables : $X_{eng}, m_{pl}, X_{traj}, d_{stage}$
Constraints : $\Delta V_{final} \geq 0$





X* and LCA (X*)

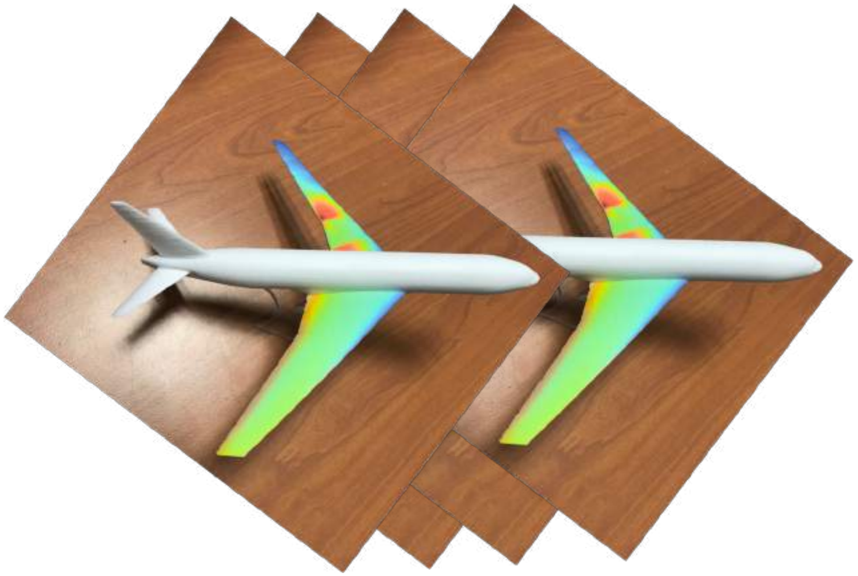




Early LCA results demonstrate that manufacturing take into account 20% of GWP (wrt 1% in Aircraft)

Time to conclude

Duration	Description	Agenda
10’	MDO	Examples
10’	Surrogate	SMT
10’	Ecodesign	Lighter and Greener
4’	Conclusions	And future works?



Conclusions

« Learning » an industrial (&costly) simulation code is interesting to easilly exchange data only (without having access to the code in a collaborative project)

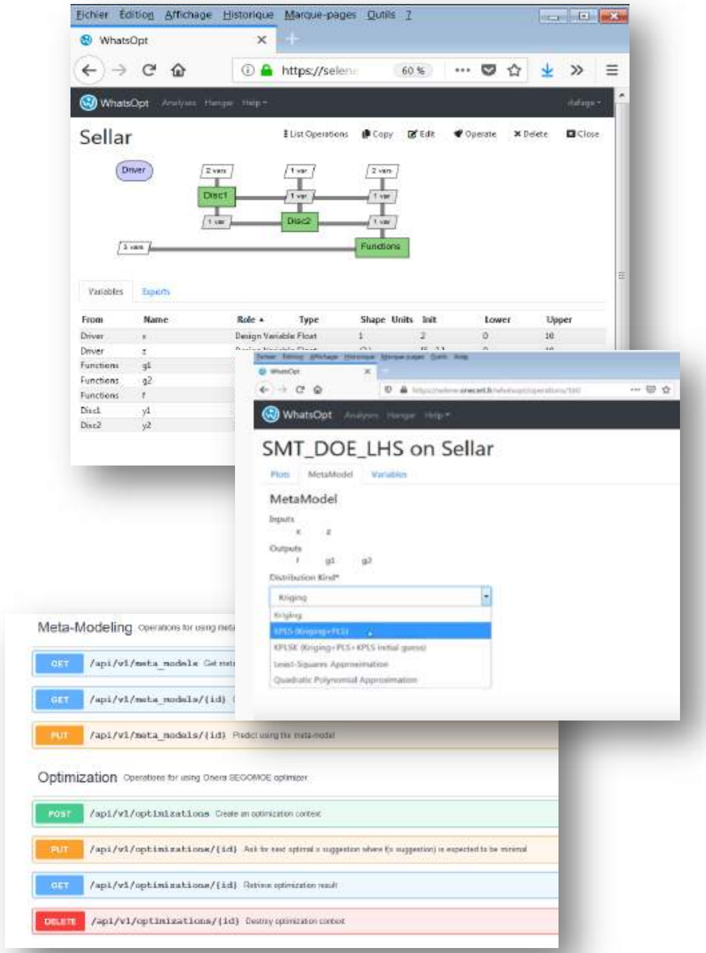
1. **SMT is a natural framework for Bayesian Optimization (DV>+100 thanks KPLS)**
2. **SMT core capabilities has been adapted for efficient mixed variables / multifidelity / multiObjectives but is not a Global {Constrained} Optimizer (SEGO-MOE is…)**
3. **Combining MDO/AI can solve Engineering problem up to +100 DV, and lots of constraints (thanks to KS function) (SEGO-MOE can do this!)**
4. **By including Ecodesign constraints we can accelerate the path toward greener aerospace vehicules.**

Focus on WhatsOpt

- **Web application for MDO**
  - MDA management
  - Code generation
    - MDO Frameworks (OpenMDAO, GEMSEO)
    - DOE run
    - Surrogate models (SMT)
    - Sensitivity analysis (SAlib)
    - Uncertainty quantification (OpenTURNS)
    - Distant code execution (Thrift)
    - Parallel execution (DOE with Linux MPI)
  - Import / Export of Data
  - Results visualisation

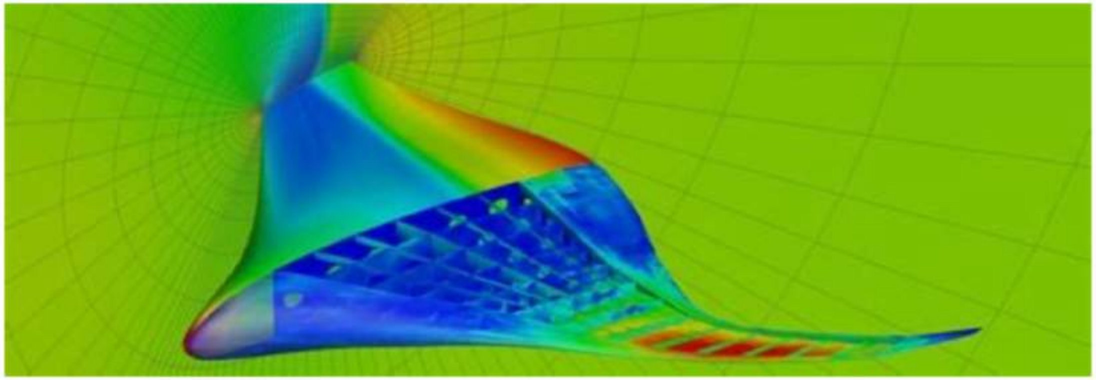
- **Surrogate Models**
  - Creation of metamodels from database
  - Creation of metamodels from MDA or discipline

- **External access**
  - External server (**https://ether.onera.fr/whatsopt**) allows acces to :
  - **Metamodels capabilities**
  - **SEGOMOE optimizer**



Popularization 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

Thanks to all my Students and Colleagues at **SUPAERO, ONERA, AIRBUS, ICA**

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Paul Saves, Thomas Bellier