

AI and physical models

F. Gamboa-S. Gratton

September 28-29 2020







MEMBERS

Definition/scientific perimeter of the theme

Thread 1 Accelerating physical models

Thread 2 Improving learning with physics

On-going work

Highlight & main results

Scientific animation of the theme

Publications

MEMBERS I

Chairs



- Fabrice Gamboa: Al for physical models with geometric tools
- Serge Gratton: Data Assimilation and Machine Learning
- Thomas Schiex: Design using intuition¹ and logic²
- Jérôme Bolte: Large scale optimization for AI
- Nicolas Dobigeon: Fusion-based inference from heterogeneous data

Co chairs

- Al for physical models with geometric tools: Reda Chhaibi (IMT) and Thomas Pellegrini (IRIT)
- Data Assimilation and Machine Learning: Pierre Boudier (Nvidia), Alfredo Buttari (IRIT), Selime Gurol (Cerfacs), Corentin Lapeyre (Cerfacs)
- Design using intuition and logic: S. Barbe (INSA/INRAE), D. Simoncini (IRIT/UT1), G. Katsirelos & S. de Givry (INRAE)
- Large scale optimization for AI: J. Bolte (UT1) and external collaborators A. Blanchet (UT1), L. Miclo (CNRS), M. Fathi (P7), S. Villeneuve (UT1).
- Fusion-based inference from heterogeneous data: M. Fauvel (INRAe)
- 3 ANITI DAYS 2020



ANITI Resources

- AI for physical models with geometric tools: Virgile Foy Ph.D (ANITI SAFRAN)
- Data Assimilation and Machine Learning: Anthony Fillion PD (ANITI), 4 interns → 3 CIFRE PhD, Philippe Toint (Visitor)
- Design using intuition and logic: D. Allouche & N. Rousse (INRAe),
- Large scale optimization for AI: J. Bolte



Other Resources

- Al for physical models with geometric tools: Louis Berry and Faouzi Hakimi CEA Cadarache Bayesian data assimilation, Clément Benesse (IMT-ENS Lyon scholarship) Fairness and sensitivity
- Data Assimilation and Machine Learning: Ehouarn Simon (IRIT), Elisa Riccietti (IRIT TOTAL)
- Design using intuition and logic: M. Defresne (PhD, SEVAB)
- Large scale optimization for AI: none yet

Can ML techniques be extended to solve problems, involving Physics represented by raw data or by partial differential equations?

Thread 1 Improve (accuracy, time, explainability,stability,...) physical models simulation and optimization via ML, statistical and geometric, approaches How physical information can be used to train machine learning algorithms? Replace (totally, partially) numerical simulations with ML ? Energy based models

Thread 2 Improving learning models with physical constraints Propagate sensor information in training method, provide reduced models Enhance Data Assimilation with ML Develop ML models ensuring biophysical constraints

Thread 1 Accelerating physical models I



ML techniques = complex classification or regression tasks (images, text, audio signals, 3D objects..)

Wish to hybrid these methods with physical reality

Tranversality physical modelling and applied maths

- data assimilation
- optimisation
- geometry
- complex simulation
- statistical learning
- uncertainty quantification and sensitivity analysis
- high performance computing in large scale systems, aggressive reduction of computing accuracy

Thread 1 Accelerating physical models II



Can ML improve standard modelling techniques?

- Numerically solve PDE's with data centric approaches using ML techniques
- Approximate PDE solutions by deep learning functions
- Learn from data suitable approximations of physical quantities (fluxes in finite volumes, energy..)

How physical information can train machine learning algorithms?

- Penalizing by physical equation
- Introduce smart parametrization related to physics
- Performance achieved compared to standard methods?
 - HPC and non convex programming
 - Online learning of physical processes



Dynamical systems from physics are inspirational for optimization: steepest descent and heat equations, Newton's law with friction and heavy ball descent, simulated annealing and thermodynamics

Goal: pursue this research line with new physical models & solve ML problems

Optimization through measure spaces

- Embed and regularize problems in measure spaces
- Apply classical dynamics/algorithms (e.g. steepest descent) in the embedding space
- Model the problem through discrete systems (e.g. Markov chains, Metropolis algorithms)
- Quantify convergence: rates, role of hyperparameters
- Analyze the impact for ML problems



Data assimilation = putting heterogeneous observed data in physical models

Wish to systematise and implement smartly

Tranversality physical modelling and applied maths

- optimisation
- geometry
- complex simulation
- statistical learning
- uncertainty quantification



- How can data assimilation reinforce physical approaches?
 - Filtering and ensemble techniques
 - Variational algorithms
- How can ML provide better data assimilation then existing DA approaches?
 - Use of recurrent Elman networks to (out)perform DA
 - Go beyond Gaussianity and nonlinearity
 - Fresh look on the analysis-propagation DA paradigm
- Are extensions to non highly linear dynamic achievable?
 - HPC and neural networks modelling
- How designing ML models satisfying physical constraints?
 - To reduce dependence of the algorithms on the learning sets
 - To provide explainable and interpretable models

On-going work I





On-going work II





13 ANITI DAYS 2020

On-going work III





On-going work IV



15 ANITI DAYS 2020



Scientific event organisation or participation

- Co-organisation Indo-French Workshop on Statistics and Artificial Intelligence for Data Science (Calcutta January 2020)
- Organisation Workshop mathematical statistics and artificial intelligence. ANITI Toulouse-ISM Tokyo (July 2020 Canceled)
- ICTS conference on Statistical Physics of Machine Learning (Bangalore Janary 2020)



Description of the theme agenda (weekly seminar,...)

Half day bimonthly meeting with all the members of Al for physical models with geometric tools and Data Assimilation and Machine Learning chairs.

Emerging collaboration between chairs & industrial partner

 Al for physical models with geometric tools with NXP (mean field model) and Laplace/Vitesco on hydrogen fuel cell

Publications- AI for physical models with geometric tools



- Daouda, T., Chhaibi, R., Tossou, P., & Villani, A. C. (2020). Geodesics in fibered latent spaces: A geometric approach to learning correspondences between conditions. arXiv preprint arXiv:2005.07852.
- Gamboa, F., Klein, T., Lagnoux, A., & Moreno, L. (2020). Sensitivity analysis in general metric spaces. arXiv preprint arXiv:2002.04465.
- Fraiman, R., Gamboa, F., & Moreno, L. (2020). Sensitivity indices for output on a Riemannian manifold. International Journal for Uncertainty Quantification, 10(4).
- Gamboa, F., Gremaud, P., Klein, T., & Lagnoux, A. (2020). Global Sensitivity Analysis: a new generation of mighty estimators based on rank statistics. arXiv preprint arXiv:2003.01772.
- Gamboa, F., Gueneau, C., Klein, T., & Lawrence, E. (2020). Maximum entropy on the mean approach to solve generalized inverse problems with an application in computational thermodynamics.
- Idier, D., et al. (2020). Toward a user-based, robust and fast running method for coastal flooding forecast, early warning, and risk prevention. Journal of Coastal Research, 95 (sp1), 1111-1116.
- Roustant, O., Gamboa, F., & looss, B. (2020). Parseval inequalities and lower bounds for variance-based sensitivity indices. Electronic Journal of Statistics, 14(1), 386-412.
- Stenger, J., Gamboa, F., Keller, M., & looss, B. (2020). Optimal Uncertainty Quantification of a risk measurement from a thermal-hydraulic code using Canonical Moments. International Journal for Uncertainty Quantification, 10(1).
- Stenger, J., Gamboa, F., & Keller, M. (2019). Optimization Of Quasi-convex Function Over Product Measure Sets. arXiv preprint arXiv:1907.07934.
- Stenger, J., Gamboa, F., Keller, M., & looss, B. (2019, August). Canonical Moments for Optimal Uncertainty Quantification on a Variety. In International Conference on Geometric Science of Information (pp. 571-578). Springer, Cham.

Publications- Data Assimilation and Machine Learning



- Serge Gratton, Ehouarn Simon, Philippe Toint An algorithm for the minimization of nonsmooth and nonconvex functions using inexact evaluations and its worst-case complexity in Mathematical Programming, Series A, Springer, 2020
- Serge Gratton, Philippe L. Toint: A note on solving nonlinear optimization problems in variable precision. Comput. Optim. Appl. 76(3): 917-933 (2020)
- Serge Gratton, Ehouarn Simon, David Titley-Péloquin, Philippe L. Toint: Exploiting variable precision in GMRES, (https://arxiv.org/abs/1907.10550), 2019
- 4. Henry Calandra, Serge Gratton, Elisa Riccietti and Xavier Vasseur, On iterative solution of the extended normal equations, SIAM Journal on Matrix Analysis and Applications, acepted 2020
- Henry Calandra, Serge Gratton, Elisa Riccietti and Xavier Vasseur, On a multilevel Levenberg-Marquardt method for the training of artificial neural networks and its application to the solution of partial differential equations, Optimization Methods and Software, accepted 2020
- Anthony Fillion, Marc Bocquet, Serge Gratton, Selime Gurol, Pavel Sakov, An iterative ensemble Kalman smoother in presence of additive model error, accepted in SIAM JUQ
- 7. Serge Gratton, Ehouarn Simon, David Titley-Peloquin, Ph. Toint. Minimizing convex quadratics with variable precision conjugate gradients, Numer. Linear Algebra Appl., in press
- Henry Calandra, Serge Gratton, Elisa Riccietti and Xavier Vasseur, On high-order multilevel optimization strategies, in review for SIAM Journal on Optimization, 2019.
- Antoine Bernigaud, Serge Gratton, Flavia Lenti, Ehouarn Simon, Oumeima Sohab. p-norm regularization in variational data assimilation, submitted, 2020
- 10. Serge Gratton, Ehouarn Simon, David Titley-Peloquin. Computing optimal empirical covariance matrices

from multi-ensembles with application to ensemble-based Kalman filters, submitted, 2019

19 ANITI DAYS 2020



Brouard, Céline, Simon de Givry, and Thomas Schiex. "Pushing data into CP models using Graphical Model Learning and Solving." (2020). Proc. CP'2020. Pages 811-826, LNCS 12333, Springer.



