A platform for decoding and recoding turbulence

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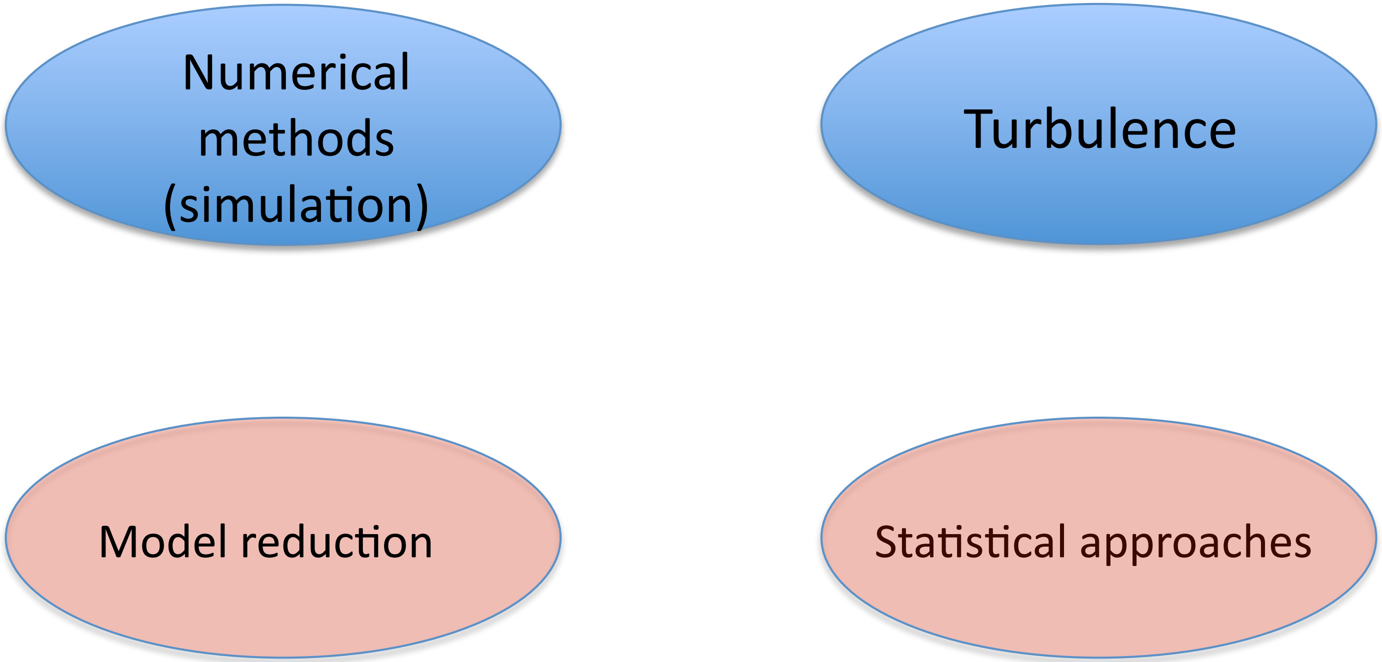
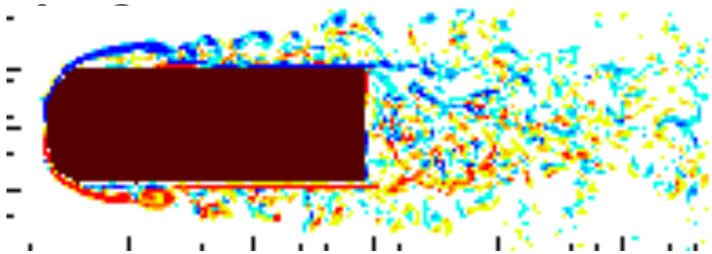
The team

- AERO Team at LIMSI: Aérodynamique instationnaire

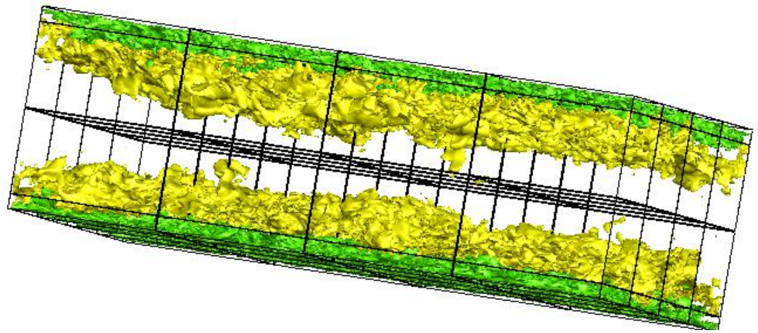


Some turbulent flows

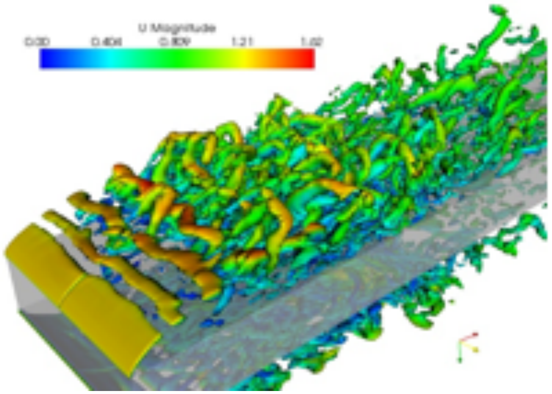
Ahmed body (S. Pellerin)



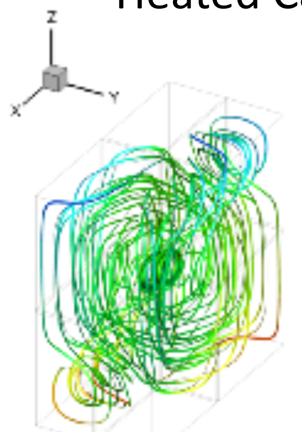
Channel (Y. Fraigneau)



Flat plate (Y. Fraigneau)



Heated Cavity (W. Daussin)



Some Data Science challenges in Fluid Mechanics

- Simulations of canonical turbulent flows generate large volumes of spatio-temporal data.

➡ **need for efficient post-treatment techniques beyond standard statistics (*decoding*)**

- Direct simulations of real-life, multi-physics, turbulent configurations are typically inaccessible

➡ **need for simplified representations (*recoding*)**

- Experiments only give access to partial (gappy) data

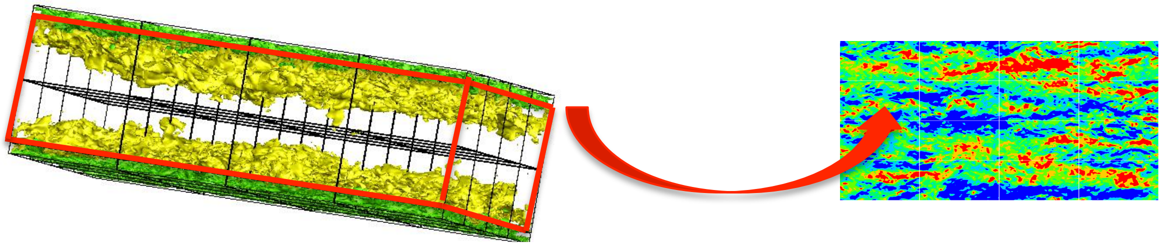
➡ **need to infer missing information and to cross-check results of heterogeneous sources (comparison between simulations or between simulation and experiment)**

Objectives of the project

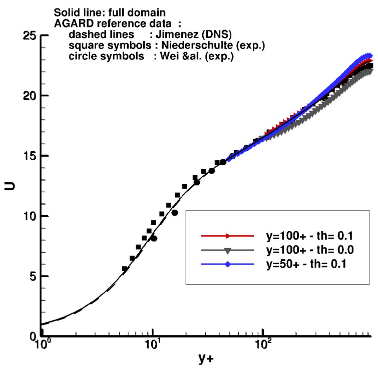
- Develop tools for flow analysis and extraction of coherent structures which are adapted to **large data size** and/or **missing data**
- Develop reconstruction methods able to generate turbulent data inexpensively and efficiently with a view to **coupling** data with simulations and experiments

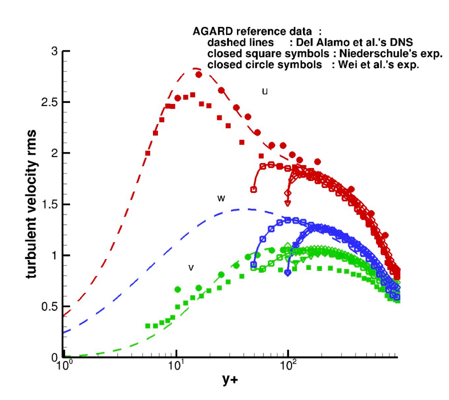
Example 1 : Synthetic boundary conditions for efficient simulation of wall turbulence

- <u>Objective</u>: simulate channel flow in reduced domain with synthetic boundary condition which mimics the turbulent flow in wall region



- Turbulent statistics recovered with 50% less grid points with POD + LSE



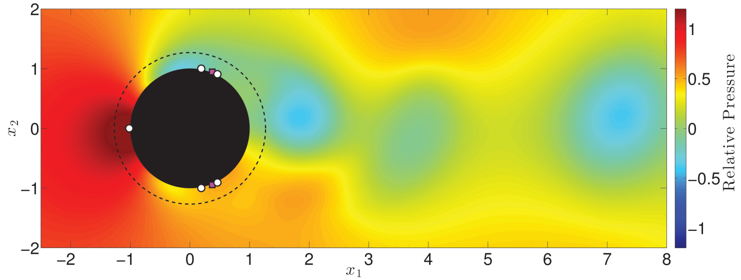


Podvin et Fraigneau. JoT 2014

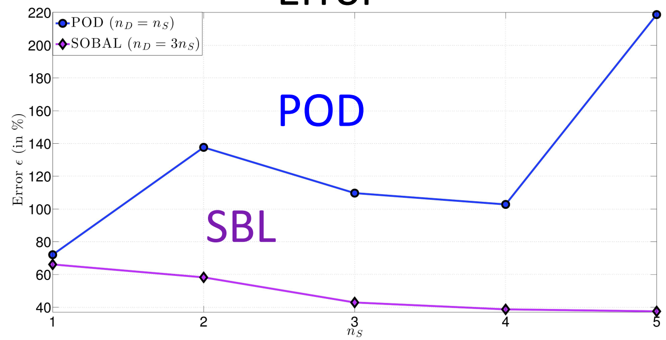
Example 2: Pressure field reconstruction using Bayesian dictionary learning

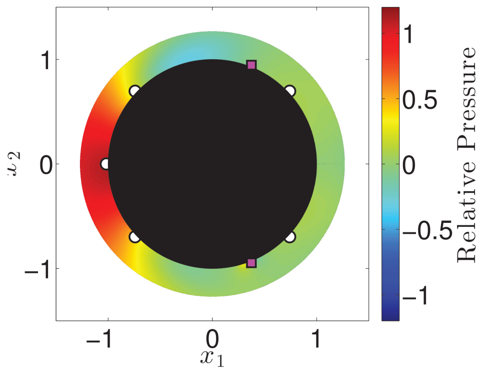
Objective: Estimate pressure from realistic sensor data for real-time feedback control

Controlled field

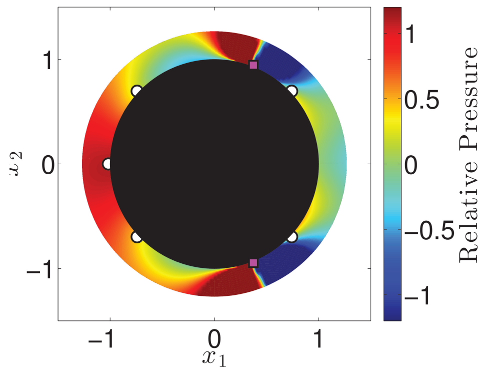


Error

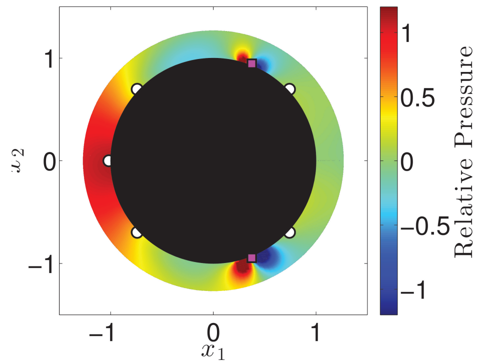




Real solution



Reconstruction (PCA/POD)



Reconstruction (dictionary)

Example 2: Pressure field reconstruction using dictionary learning

- Basis learning **[offline]**
  - Form a snapshot matrix Y of expected realizations of the field and corresponding sensor matrix S,
  - Given the sensors, learn representation dictionaries D (and D_{feat}) using Sparse Bayesian Dictionary Learning
- Field reconstruction **[online]**
  - Use SBDL with the measure $\boldsymbol{s}$ to estimate

  $\boldsymbol{x} \sim N(\boldsymbol{x} \mid \mu, \Sigma)$.
  - Reconstruct the maximum a posteriori total field from $\boldsymbol{y} = D\,\mu$ or use Markov chain Monte Carlo.

Analysis and reconstruction tools

- Modal bases
  (Fourier, wavelets)
- Data-dependent bases (POD, dictionary-learning)

- Stochastic estimation (linear, quadratic)
- (Ensemble / unscented) Kalman filter
- Compressed sensing

- Supervised learning (pattern recognition, model reduction)
- Unsupervised learning (clustering)

Plan

- Support for project:

  <u>Objective</u>: Test unsupervised and supervised learning techniques for analysis and reconstruction of wall turbulence

- Support for MFN school on statistical approaches

MFN School

- Ecole de Mécanique des Fluides Numérique: **Approches statistiques pour la Mécanique des Fluides**
- Organized by labs from Université Paris-Saclay with national audience
- 30-hour, 5-day program in April 2017
- 40% curriculum on state of the art numerical methods for flow simulation
- 60% curriculum on specific theme: statistical methods for Fluid Mechanics + seminars