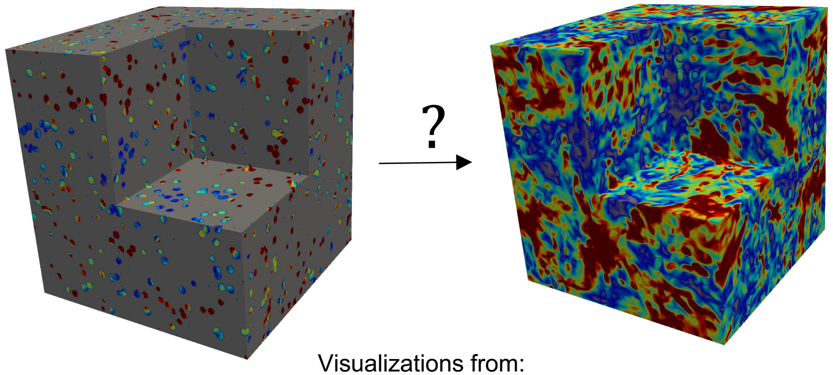
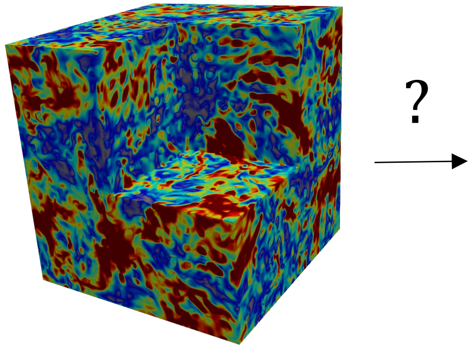
Classifying Turbulent Environments via Machine Learning

APS DFD 2022
75th Annual Meeting
November 20 – 22, 2022
Indianapolis



Visualizations from:

Di Leoni, P. C., Mazzino, A., & Biferale, L. (2020). Physical Review X, 10(1), 011023.



$$\frac{d\,\boldsymbol{u}}{dt}$$

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CREDITS: L. Biferale (Uni. Tor Vergata, IT), **F. Bonaccorso** (Uni. Tor Vergata, IT), **P. Clark di Leoni** (Uni. of Buenos Aires, ARG)

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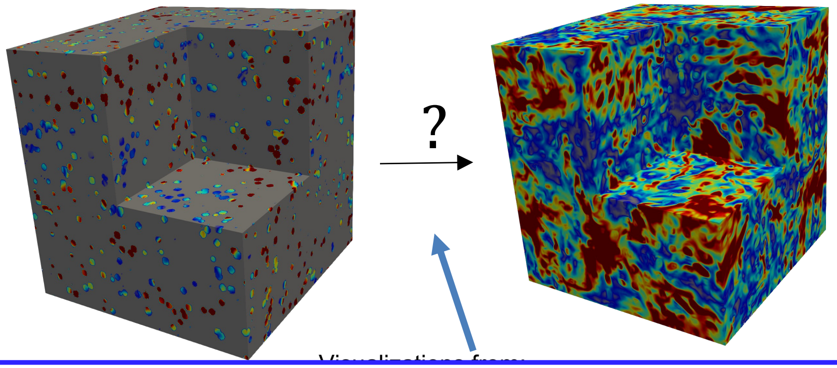

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Tor Vergata, IT),
ata, IT), **P. Clark di**
Aires, ARG)

Data reconstruction of turbulent flows with Gappy POD and Generative Adversarial Networks T. Li, M. Buzzicotti, F. Bonaccorso, L. Biferale, M. Wan and S. Chen *arXiv preprint arXiv:2210.11921* (Submitted to JOT)

Reconstructing Rayleigh–Bénard flows out of temperature-only measurements using nudging L Agasthya, P Clark Di Leoni, L Biferale Physics of Fluids 34 (1), 015128

Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database M Buzzicotti, F Bonaccorso, PC Di Leoni, L Biferale Physical Review Fluids 6 (5), 050503

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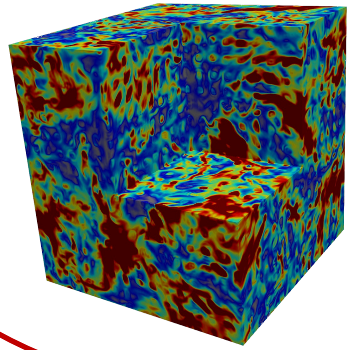

$$\xrightarrow{?} \frac{d\,\boldsymbol{u}}{dt}$$

Can we improve our data-analysis capability to refine our physical knowledge of complex systems?

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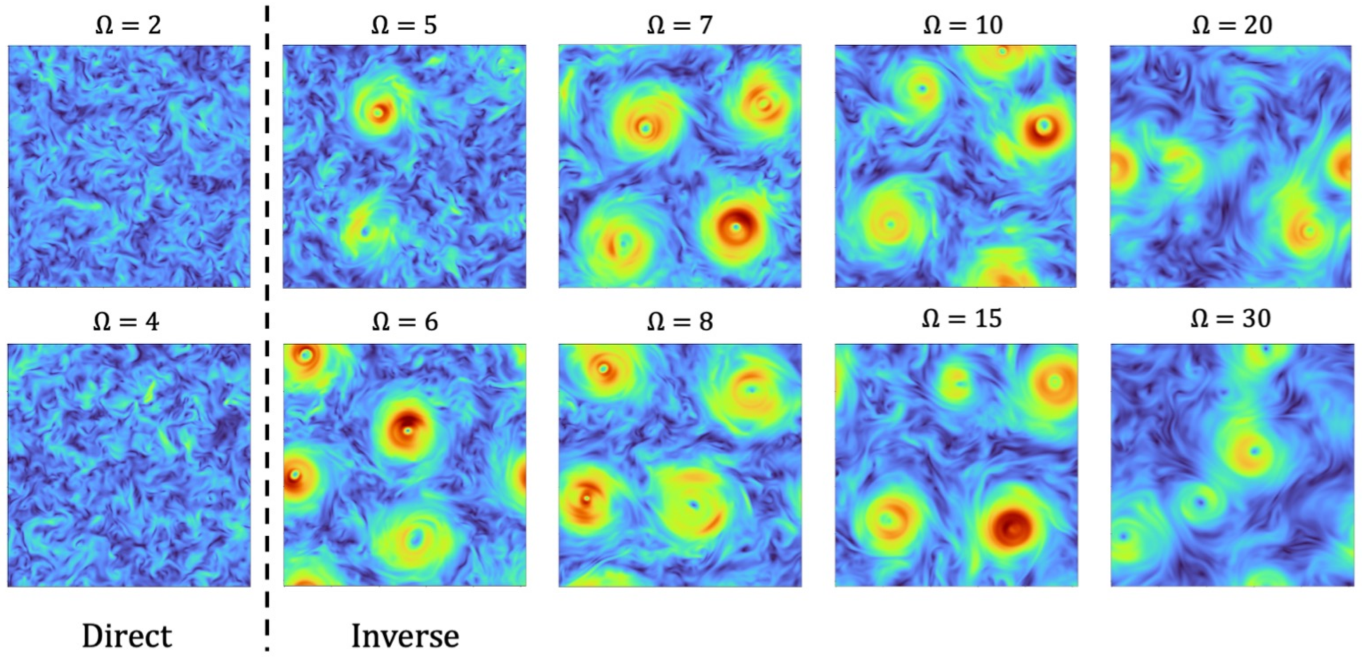
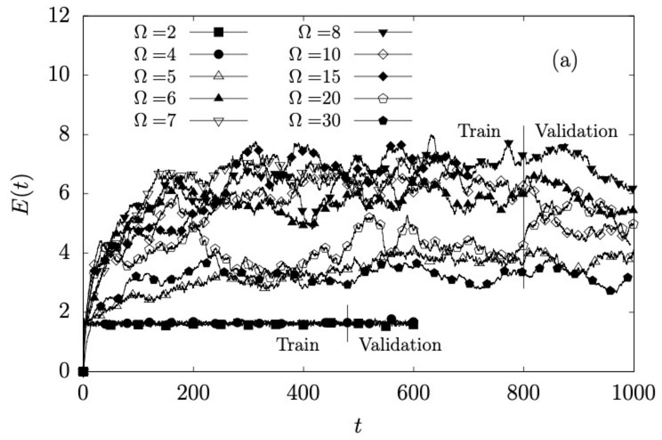
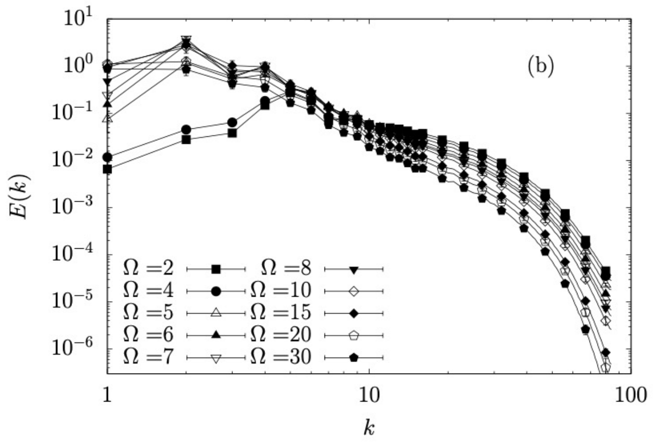
Problem: Inferring the rotation rate

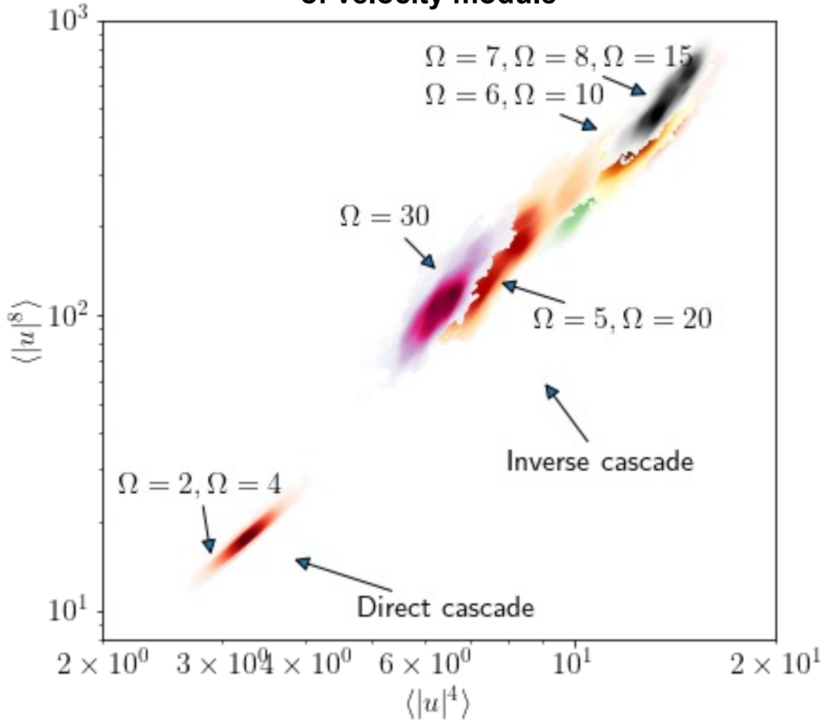
$$\partial_t \boldsymbol{v} + \boldsymbol{v}\cdot\partial_x \boldsymbol{v} + \partial_x P - \nu\Delta \boldsymbol{v} = 2\,\boldsymbol{v}\times\boldsymbol{\Omega} + \mathbf{f}$$







Scatterplot of **8th vs 4th order moments of velocity module**

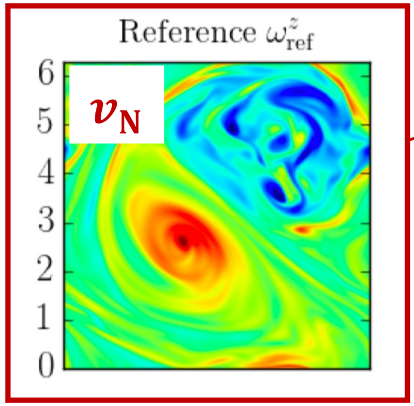


How can we extract useful information from one single velocity plane?

-] Alexakis, A., & Biferale, L. (2018). Cascades and transitions in turbulent flows. *Physics Reports*, *767*, 1-101.
-] Di Leoni, P. Clark, Alexandros Alexakis, L. Biferale, and MB. "Phase transitions and flux-loop metastable states in rotating turbulence." *Physical Review Fluids* 5, no. 10 (2020): 104603.

NUDGING: AN **EQUATION-INFORMED** TOOL TO INFER THE PHYSICS

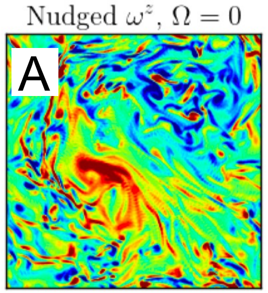
Reference DNS:

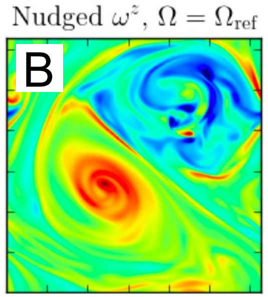


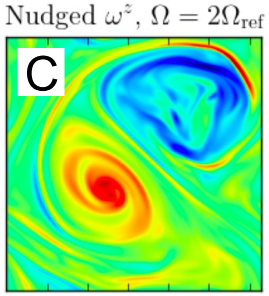
Nudging Simulation:

DNS with the addition of a drag term against partial field measurements

$$\partial_t \boldsymbol{v} + \boldsymbol{v}\cdot\partial_x \boldsymbol{v} + \partial_x P - \nu\Delta\boldsymbol{v} = 2\,\boldsymbol{v}\times\boldsymbol{\Omega} + \mathbf{f} \;-N(\boldsymbol{v}_{\rm N} - \boldsymbol{v})$$

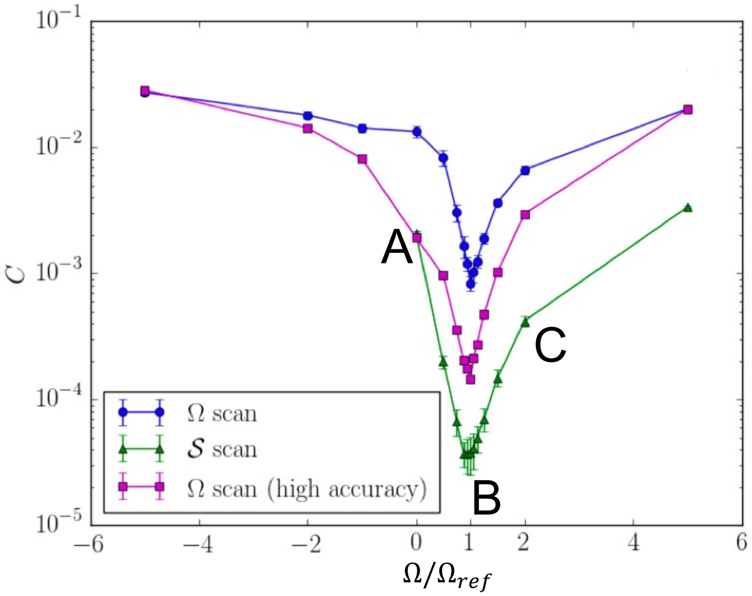






$$E_\Delta(k) = \int_{|\boldsymbol{k}|=k} |\hat{u}(\boldsymbol{k}) - \hat{u}_N(\boldsymbol{k})|^2\, d\boldsymbol{k}$$

$$\boxed{C = \int_0^{k_c} E_\Delta(k)dk}$$



Shows strong sensitivity to the physical parameter used in the nudged simulation

Di Leoni, P. C., Mazzino, A., & Biferale, L. (2018). Inferring flow parameters and turbulent configuration with physics-informed data assimilation and spectral nudging. *Physical Review Fluids*, *3*(10), 104604.

NUDGING: TO OPTIMIZE SUBGRID SCALE MODELS

Nudging the Large Eddy Simulation:

Filtered solution from fully resolved DNS:

$$\partial_t \tilde{\boldsymbol{v}} + \tilde{\boldsymbol{v}} \cdot \nabla \tilde{\boldsymbol{v}} = -\boldsymbol{\nabla} \tilde{p} + \nu \Delta \tilde{\boldsymbol{v}} - \nabla \cdot \boldsymbol{\tau} + \mathbf{f} - N(\tilde{\boldsymbol{v}}_N - \tilde{\boldsymbol{v}})$$

$$\tilde{v}_i = \mathcal{F}(v_i) \qquad \tilde{p} = \mathcal{F}(p) \qquad \tau_{ij} = \mathcal{F}(v_i v_j) - \mathcal{F}(v_i)\,\mathcal{F}(v_j)$$

Filtered fields

Smagorinsky closure

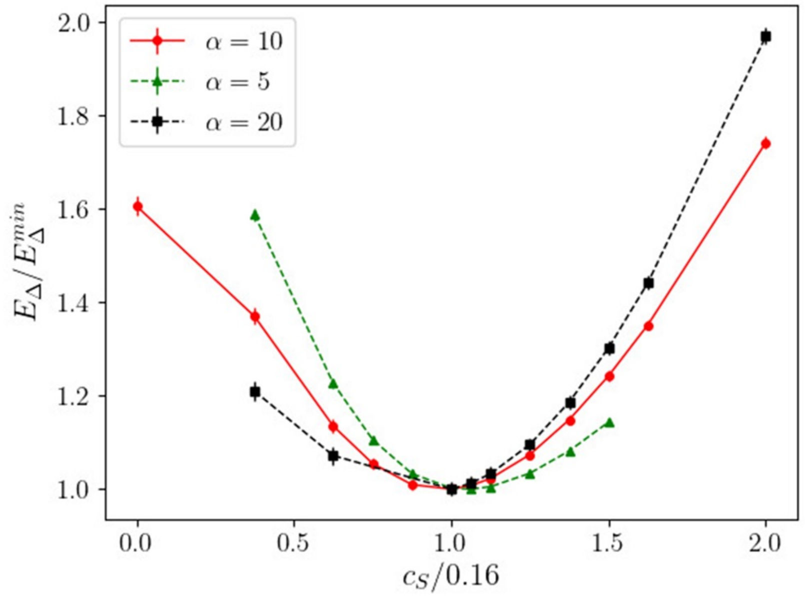
$-2\nu_S\, S_{ij}$, with:

$$S_{ij} = \frac{1}{2}\left(\partial_j \tilde{v}_i + \partial_i \tilde{v}_j\right) \qquad \nu_S = (c_s \Delta)^2 \sqrt{2\, S_{kl} S_{kl}}$$

Is there an optimal value of c_s ?

We can optimize the Smagorinsky free-parameter, by minimizing the error between the reference DNS and the nudged LES:

$$E_\Delta = \int_0^{k_c} \int_{|\boldsymbol{k}|=k} |\hat{\mathrm{u}}(\boldsymbol{k}) - \hat{u}_N(\boldsymbol{k})|^2 \, d\boldsymbol{k}$$



$c_s = 0.16$ Is found to minimize the average relative error.

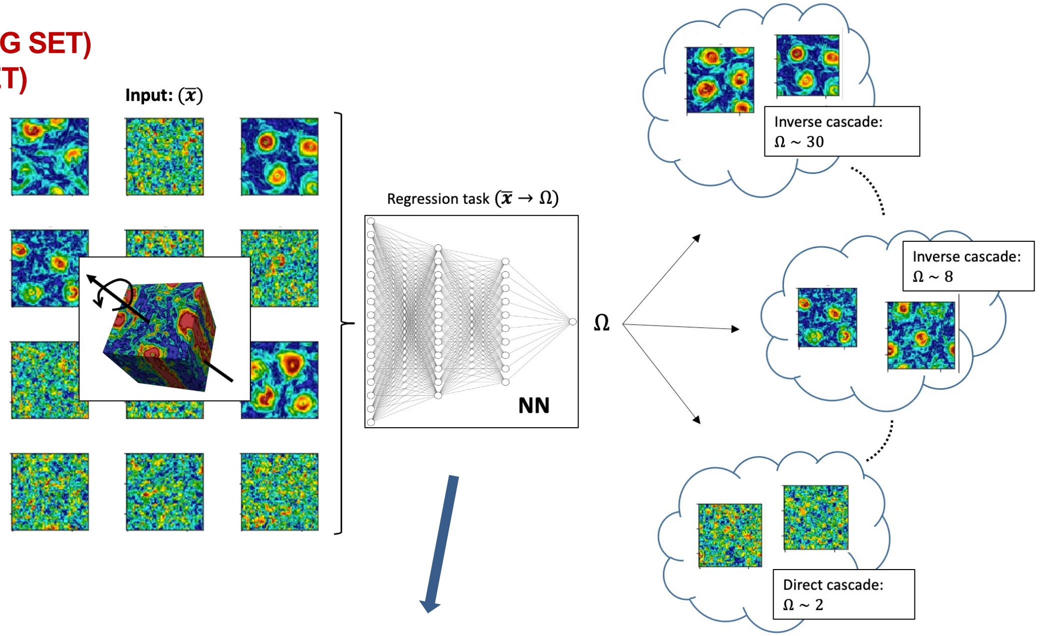
Important result to optimize new model and/or modeling in different setups (i.e. non-homogenous flows)

MB, & Clark Di Leoni, P. (2020). Synchronizing subgrid scale models of turbulence to data. Physics of Fluids, 32(12), 125116.

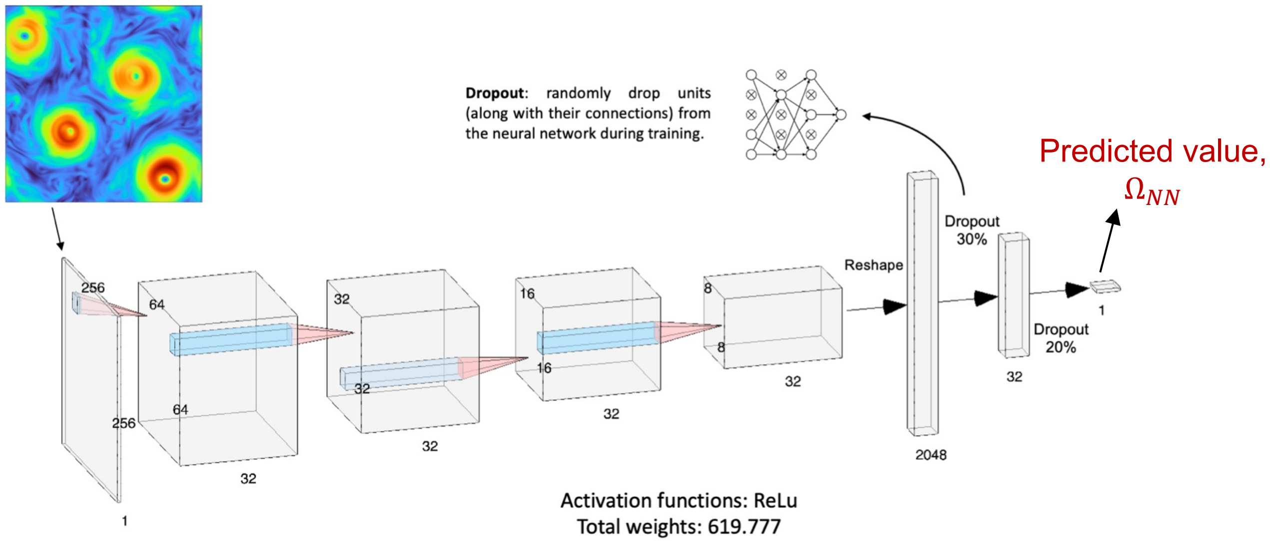
MACHINE LEARNING: A **DATA-DRIVEN** TOOL TO INFER THE PHYSICS

PROBLEM SETUP & DATASET

- 400k 2D planes (TRAINING SET)
- 100k 2D planes (TEST SET)
- 10 Ω values
- Velocity module
- No time information



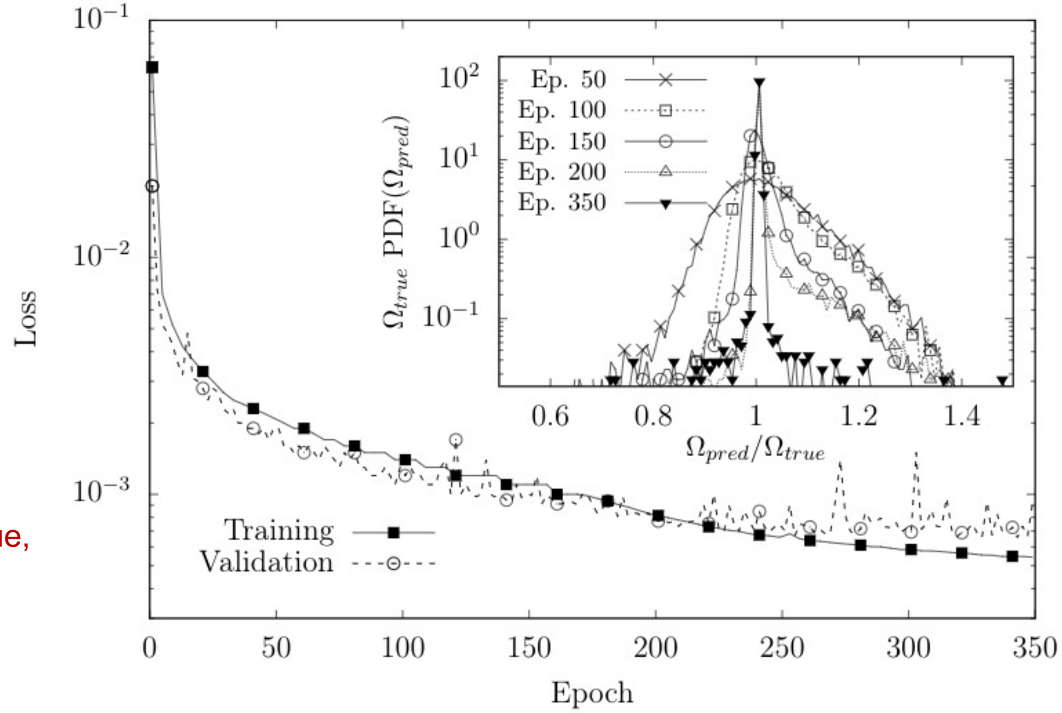
Neural Network (DCNN) used for regression



Activation functions: ReLu
Total weights: 619.777

Loss Function for the Ω regression task:

$$\mathcal{L} = \mathbb{E}\{ (\Omega_{true} - \Omega_{NN})^2 \}$$



Training details: Minibatch 256 planes, Adam optimizer with Nesterov momentum, learning rate 10^{-5}, ReLu activation function

MB and Fabio Bonaccorso. "Classifying Turbulent Environments via Machine Learning" *arXiv preprint arXiv:2201.00732* (2022) (Submitted to EPJE).

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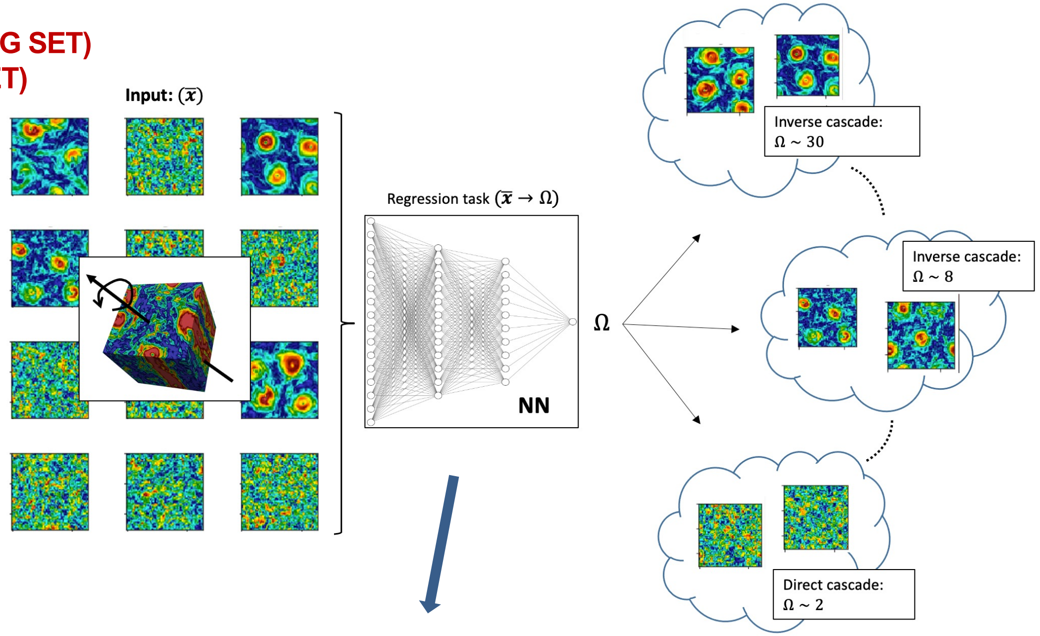
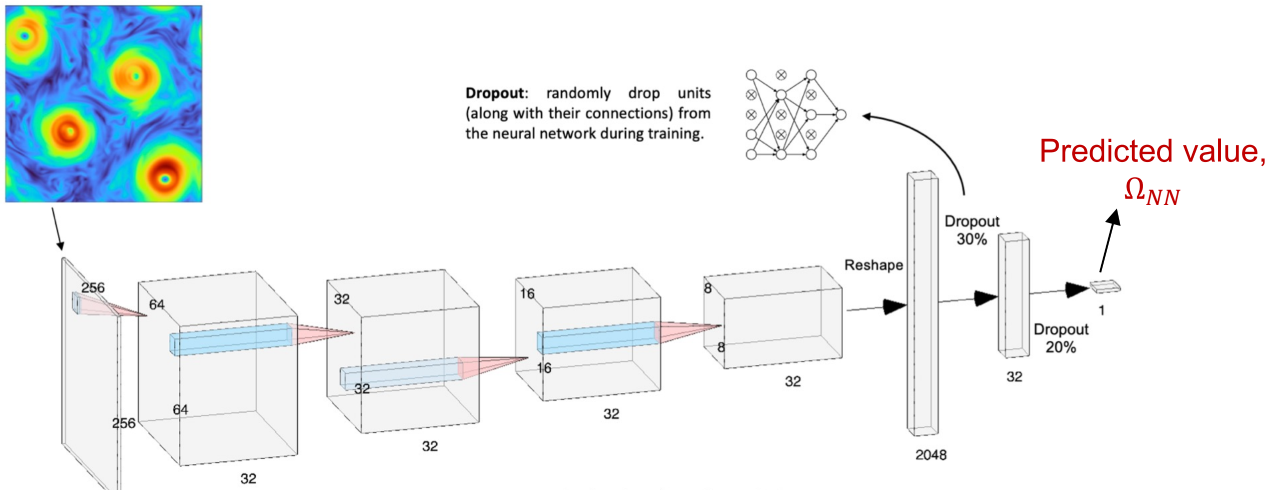


Input Image

Neural Network (DCNN) used for regression



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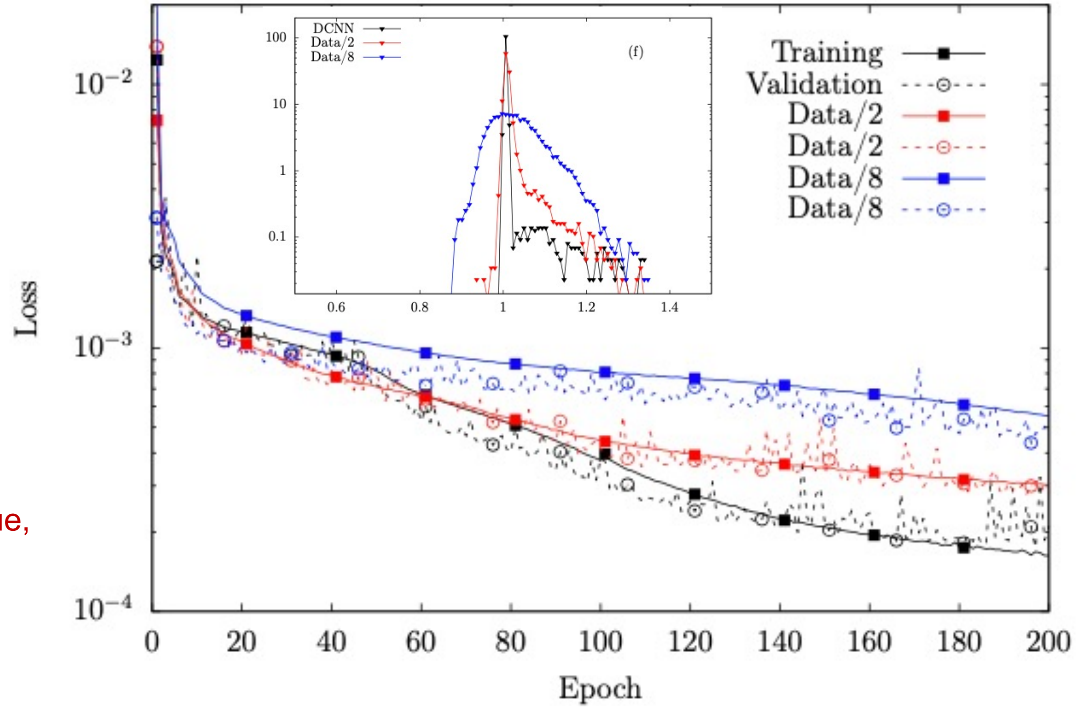

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DATA-DRIVEN BAYESIAN INFERENCE

$$\Omega_{Bay}(\mathcal{O}) = \max_{\Omega_i} P(\Omega_i|\mathcal{O})$$

We measure **mean squared velocity** and **mean squared velocity gradients** :

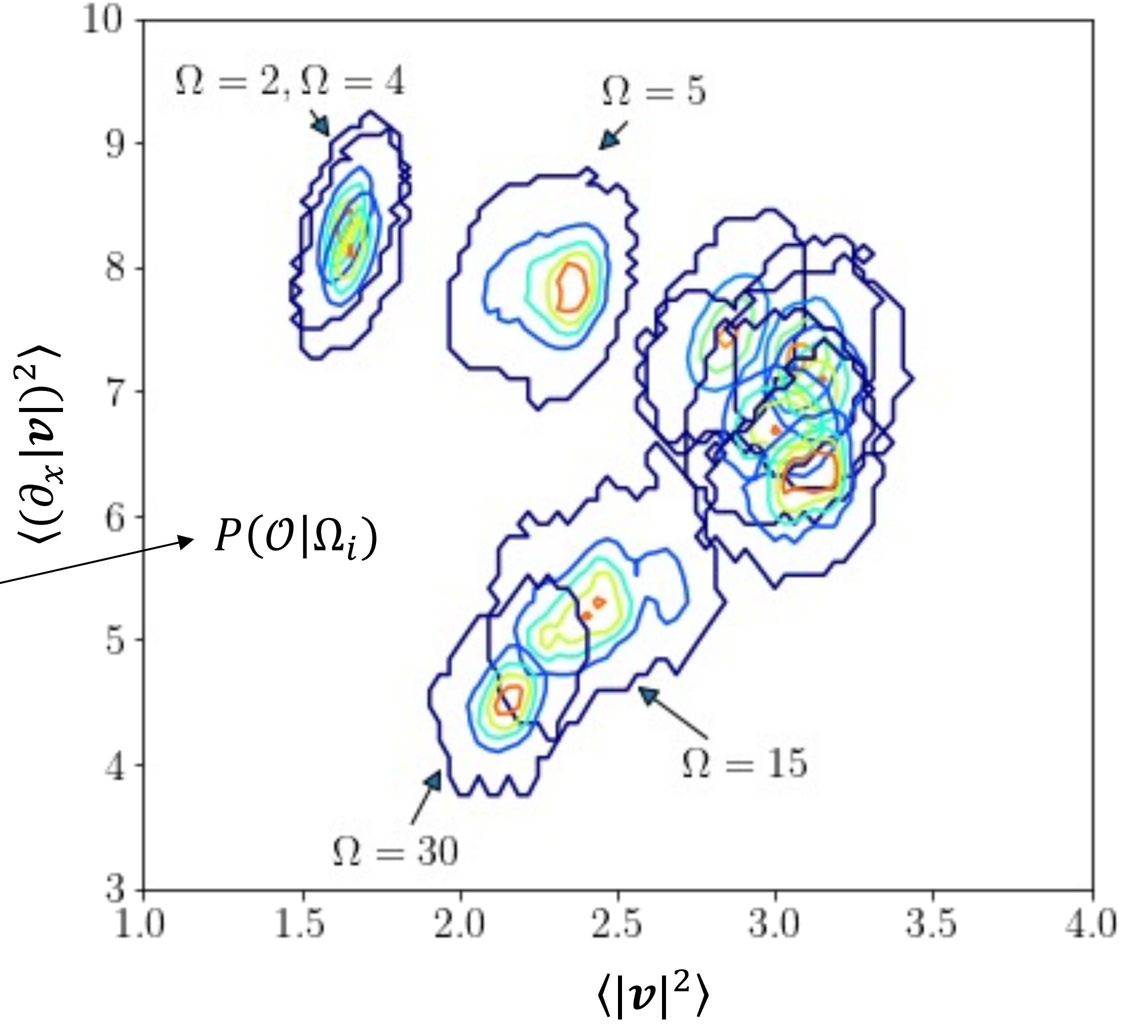
$$\mathcal{O} = (\langle|\boldsymbol{v}|^2\rangle, \langle(\partial_x|\boldsymbol{v}|)^2\rangle)$$

$\langle..\rangle$ mean on space, over the 2D plane

We can obtain the joint probability using Bayes Theorem:

$$P(\Omega_i|\mathcal{O}) = \frac{P(\mathcal{O}|\Omega_i)P(\Omega_i)}{P(\mathcal{O})} = \frac{P(\mathcal{O}|\Omega_i)P(\Omega_i)}{\sum_i P(\mathcal{O}|\Omega_i)P(\Omega_i)}$$

Joint-PDF of **mean squared velocity** and **mean squared velocity gradients**
(estimated over the 400k planes of the training set)



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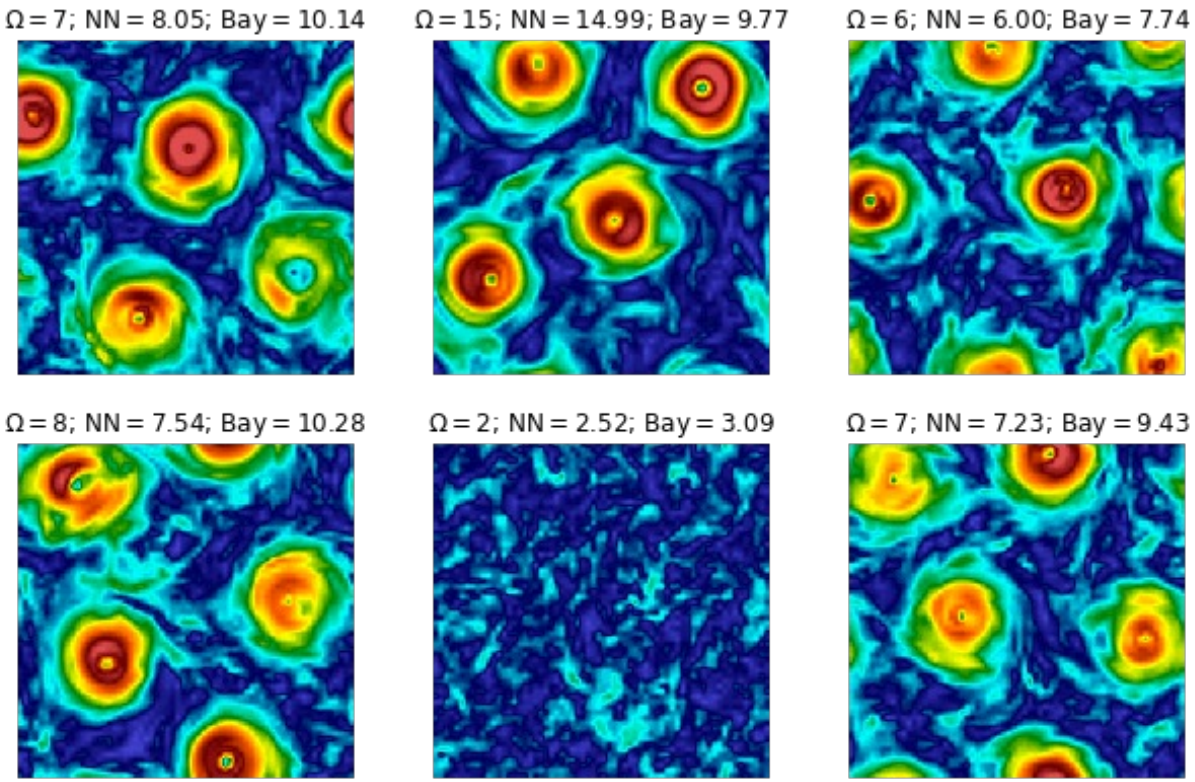
comparison: BAYESIAN INFERENCE vs ML



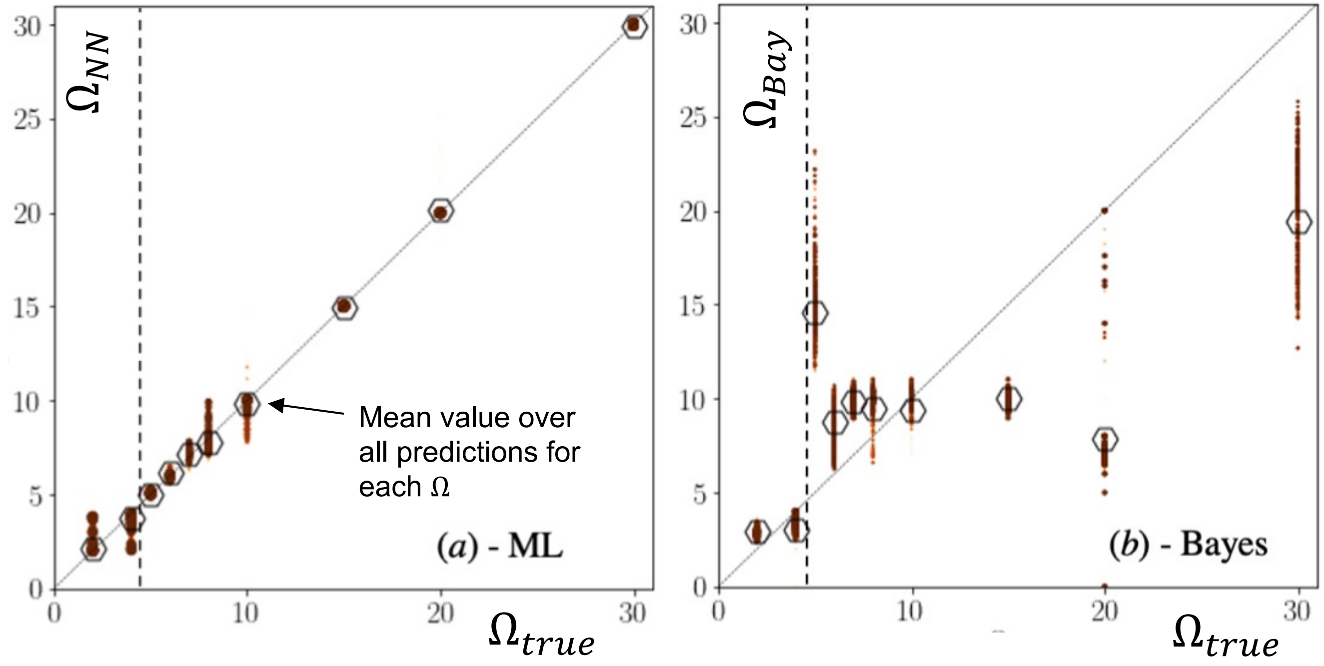
Examples of Ω inferring by Neural Network
and Bayesian Inference

Scatterplot of Prediction vs True Ω values

Results obtained on the TEST SET (100k planes)

Bayes infers on: velocity square module

$$P(\Omega_i|\langle|\boldsymbol{v}|^2\rangle)$$



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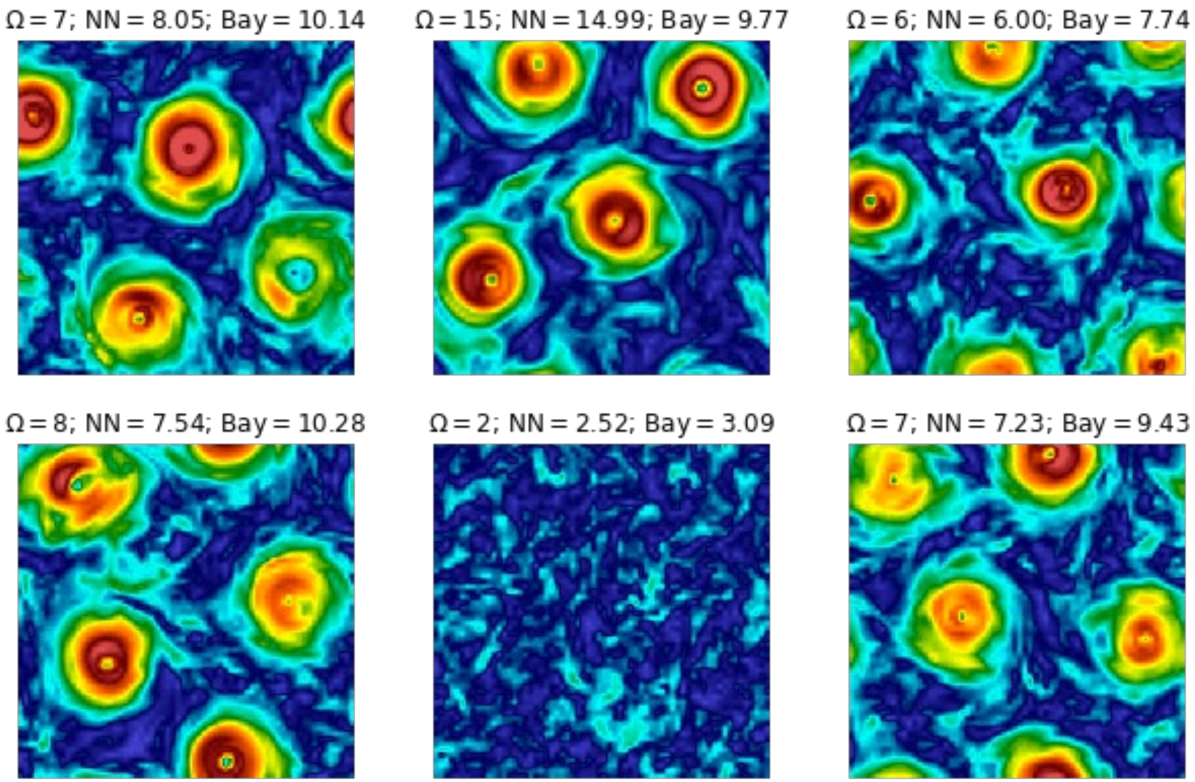

Examples of Ω inferring by Neural Network and Bayesian Inference

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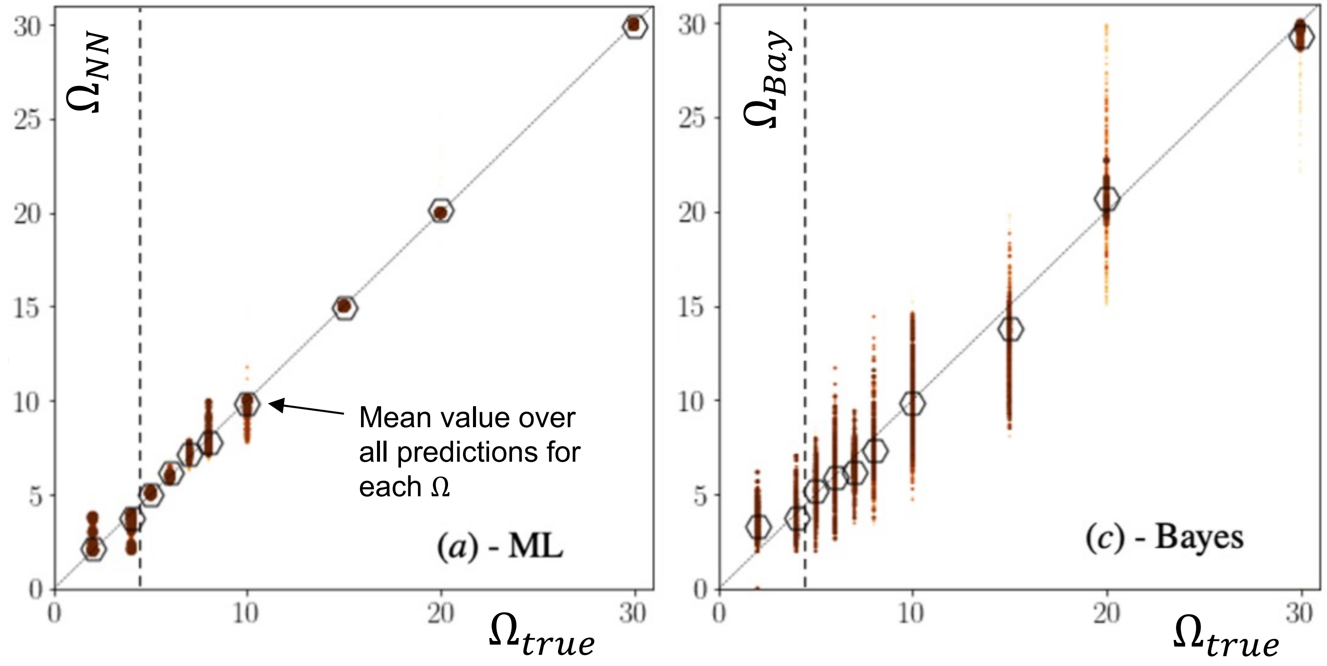

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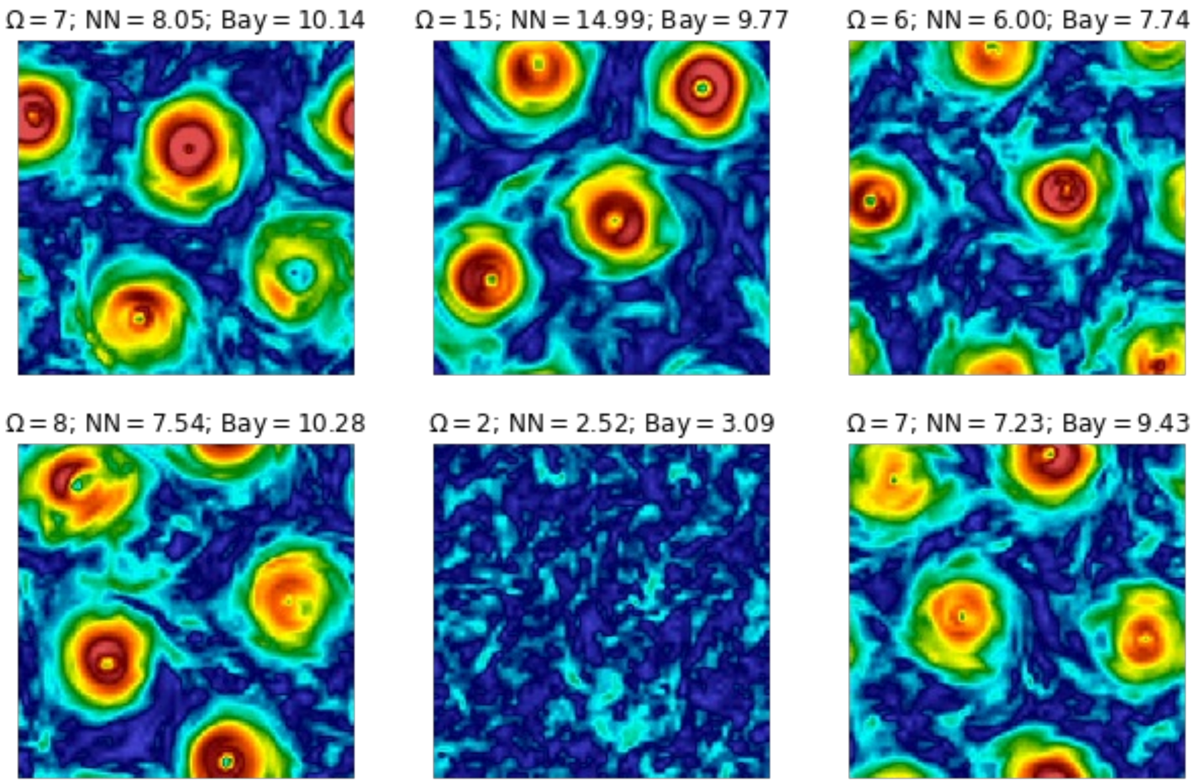

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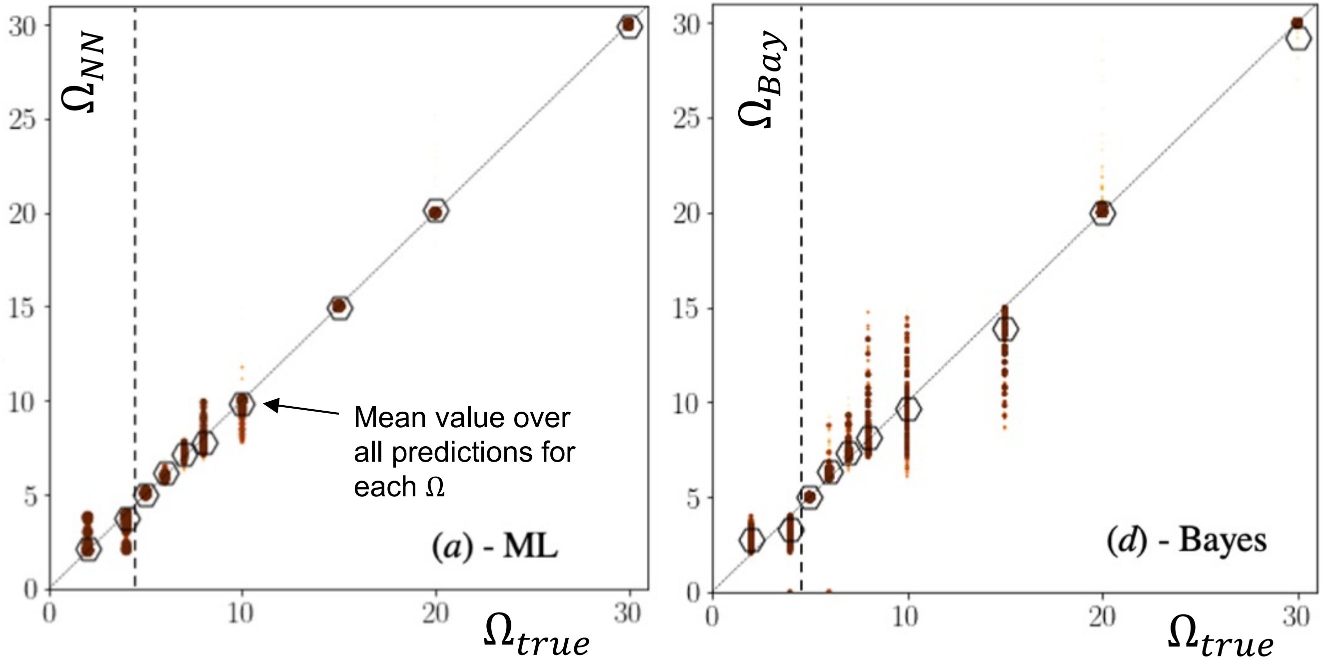

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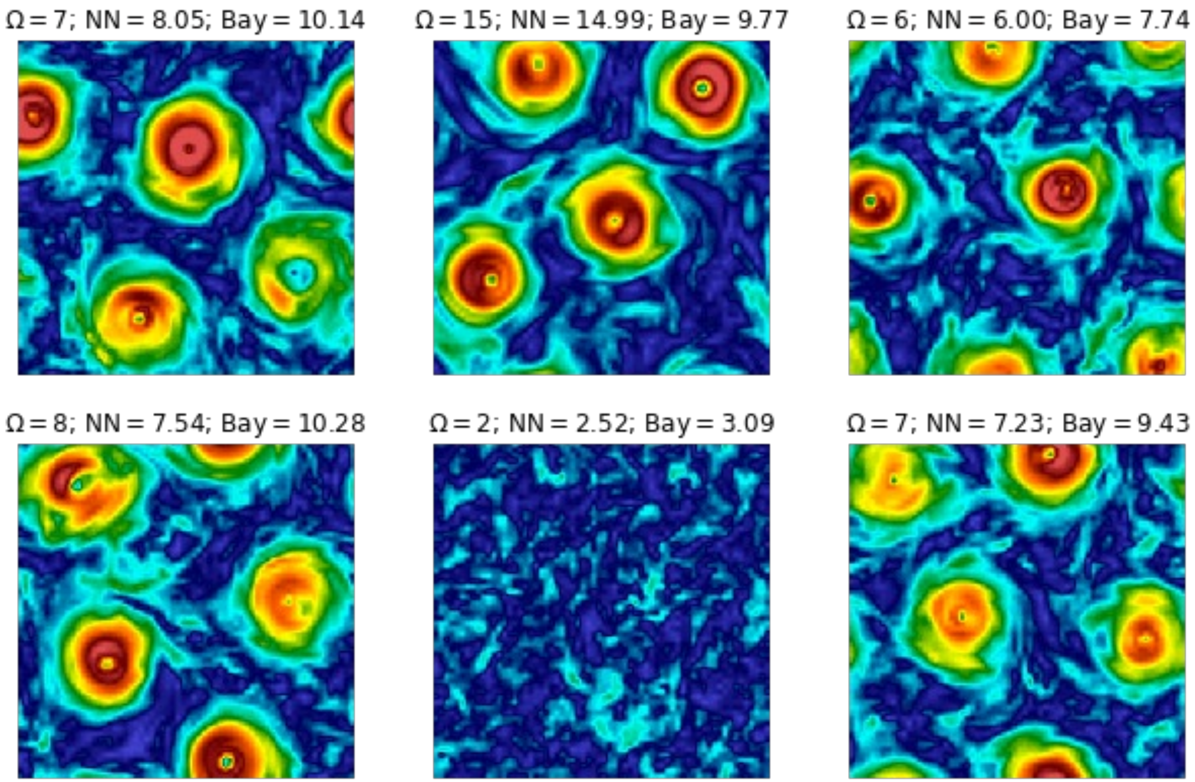
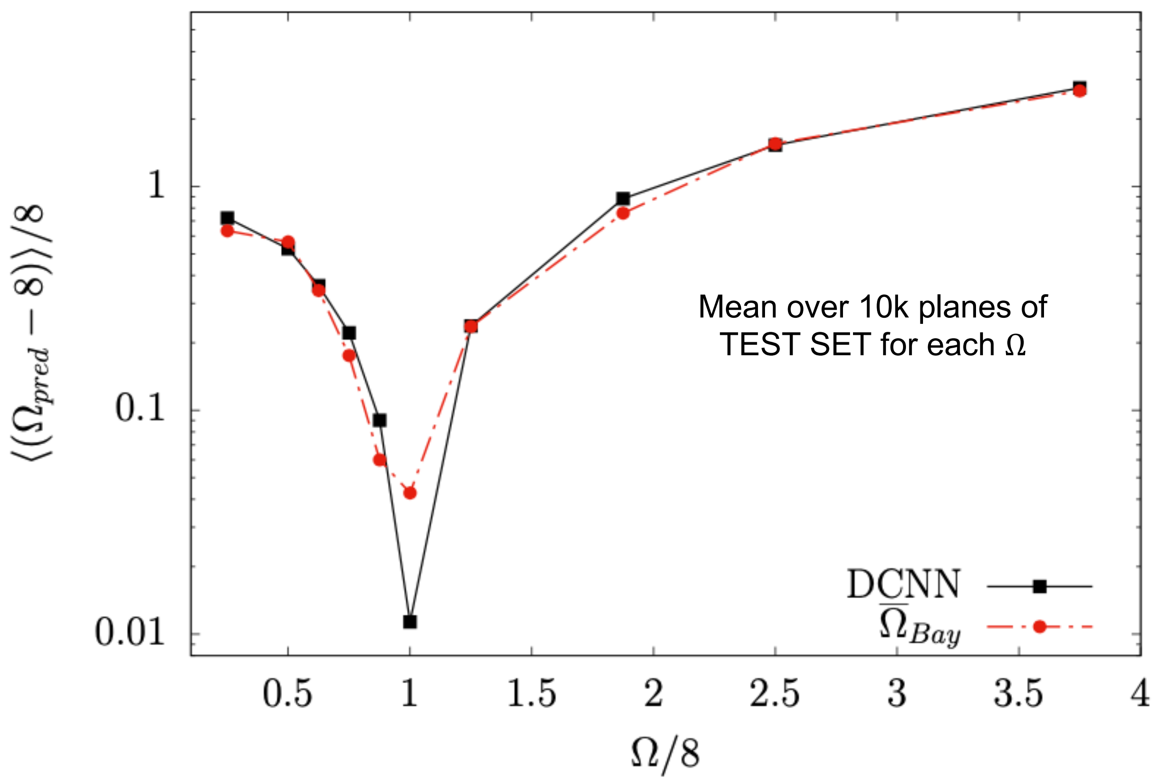
comparison: BAYESIAN INFERENCE vs ML



Examples of Ω inferring by Neural Network and Bayesian Inference

Sensitivity of Data-Driven Tools

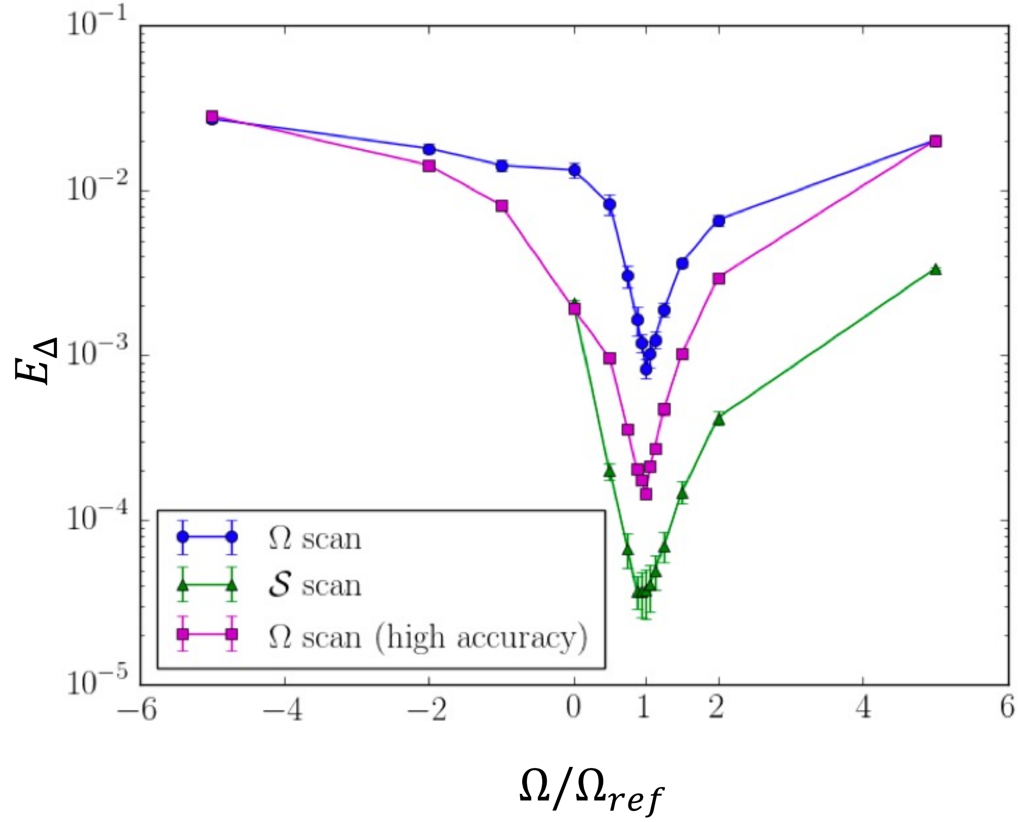


$$\partial_t \boldsymbol{v} + \boldsymbol{v} \cdot \partial_{\boldsymbol{x}} \boldsymbol{v} + \partial_{\boldsymbol{x}} P - \nu \Delta \boldsymbol{v} = 2\, \boldsymbol{v} \times \Omega\, \hat{\mathrm{z}} + \mathbf{f}$$

MB and Fabio Bonaccorso. "Classifying Turbulent Environments via Machine Learning" *arXiv preprint arXiv:2201.00732* (2022) (Submitted to EPJE).

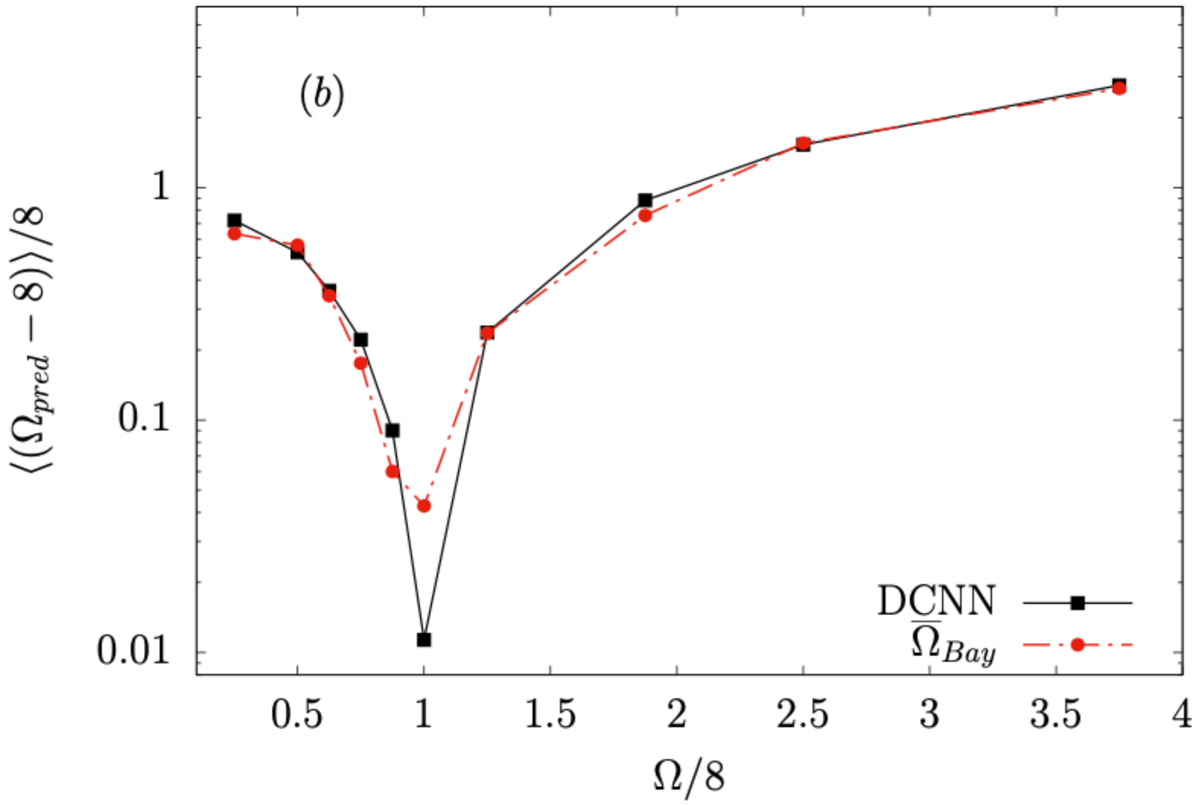
Contributions

NUDGING: EQUATION-INFORMED



- + Strong Sensitivity to the physical parameter
- + No need of Ensemble/Training Dataset
- - It requires complete knowledge of the Equations
- - Heavy in computation – it requires DNS

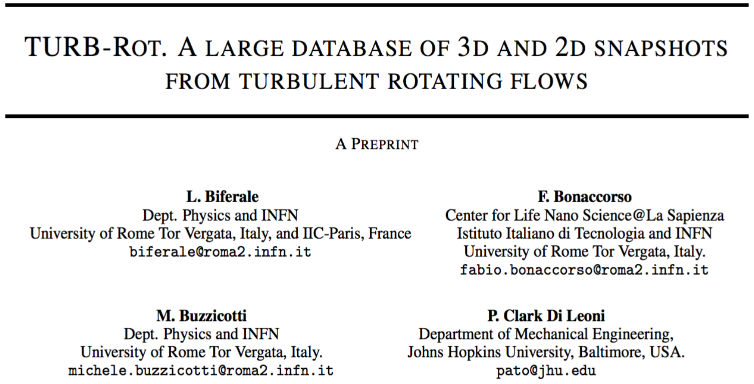
DATA-DRIVEN TOOLS



- + Strong Sensitivity to the physical parameter
- + No need of Eq. of Motion
- + Fast in computation after the training
- - Need of large Training Dataset

References

- MB and Fabio Bonaccorso. “Classifying Turbulent Environments via Machine Learning" ***arXiv preprint arXiv:2201.00732*** **(2022)**.
- MB, Bonaccorso, Clark Di Leoni & Biferale. **Phys. Rev. Fluids 6, 050503 (2021).** Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database.
- Biferale, Bonaccorso, MB & Clark di Leoni. **arXiv:2006.07469 (2020).** TURB-Rot. A large database of 3d and 2d snapshots from turbulent rotating flows.
- Biferale, Bonaccorso, MB, Clark Di Leoni & Gustavsson. **Chaos: An Interdisciplinary Journal of Nonlinear Science. 2019 Oct 24;29(10):103138.** Zermelo’s problem: Optimal point-to-point navigation in 2D turbulent flows using reinforcement learning.
- MB, Biferale, Bonaccorso, Clark Di Leoni & Gustavsson. **Springer, Cham, (2021)**. Optimal Control of Point-to-Point Navigation in Turbulent Time Dependent Flows Using Reinforcement Learning.
- Clark Di Leoni, Mazzino, Biferale. **Phys. Rev. Fluids 3, 104604, (2018)**. Inferring flow parameters and turbulent configuration with physics-informed data-assimilation and spectral nudging.
- Clark Di Leoni, Mazzino, Biferale. **Phys. Rev. X 10.1, 011023, (2020)**. Synchronization to big-data: nudging the Navier-Stokes equations for data assimilation of turbulent flows.
- Colabrese, Gustavsson, Celani, Biferale. **Phys. Rev. Fluids 3**, **084301, (2018)**. Smart Inertial Particles.
- Colabrese, Gustavsson, Celani, Biferale. **Phys. Rev. Letters 118 (15), 158004, (2017)**. Flow navigation by smart microswimmers via reinforcement learning.


TURB-ROT. A LARGE DATABASE OF 3D AND 2D SNAPSHOTS FROM TURBULENT ROTATING FLOWS

A PREPRINT

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