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TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA

Generative Adversarial Networks to infer velocity component in rotating turbulent flows

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FIRST EDITION!

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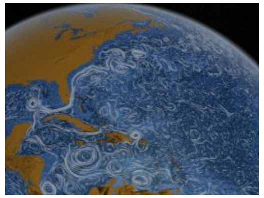
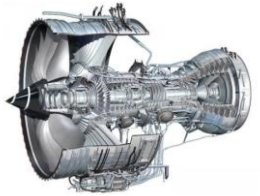
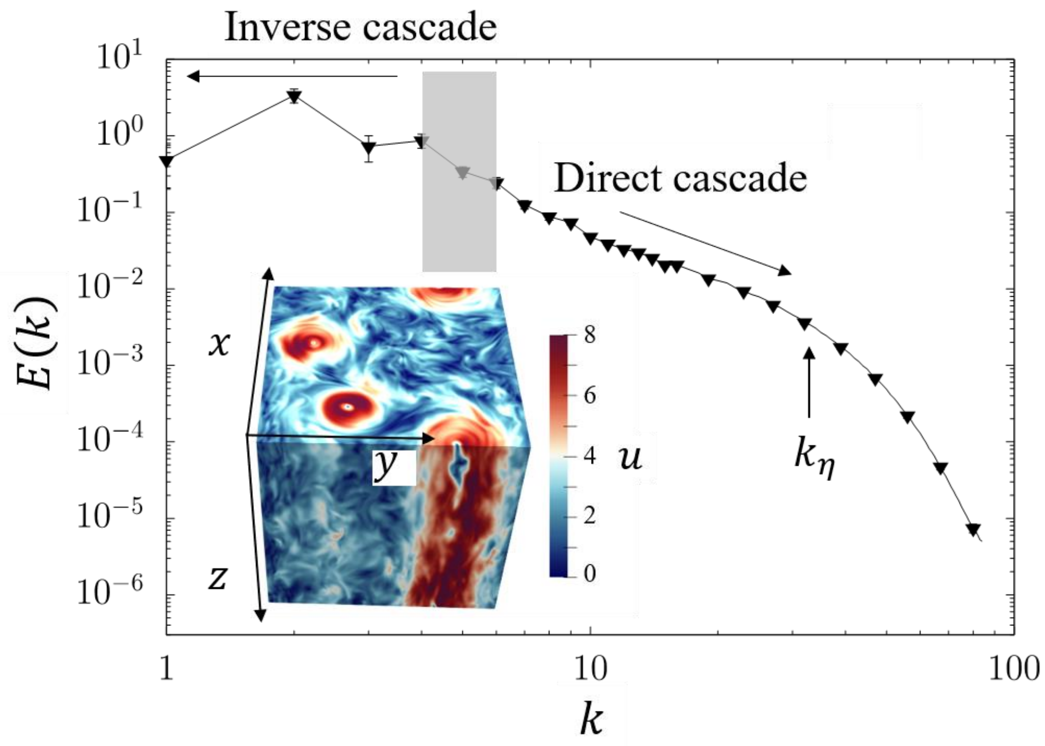
T. Li *et al.*, arXiv:2210.11921 (2022).
T. Li *et al.*, Eur. Phys. J. E 46, 31 (2023).

Background



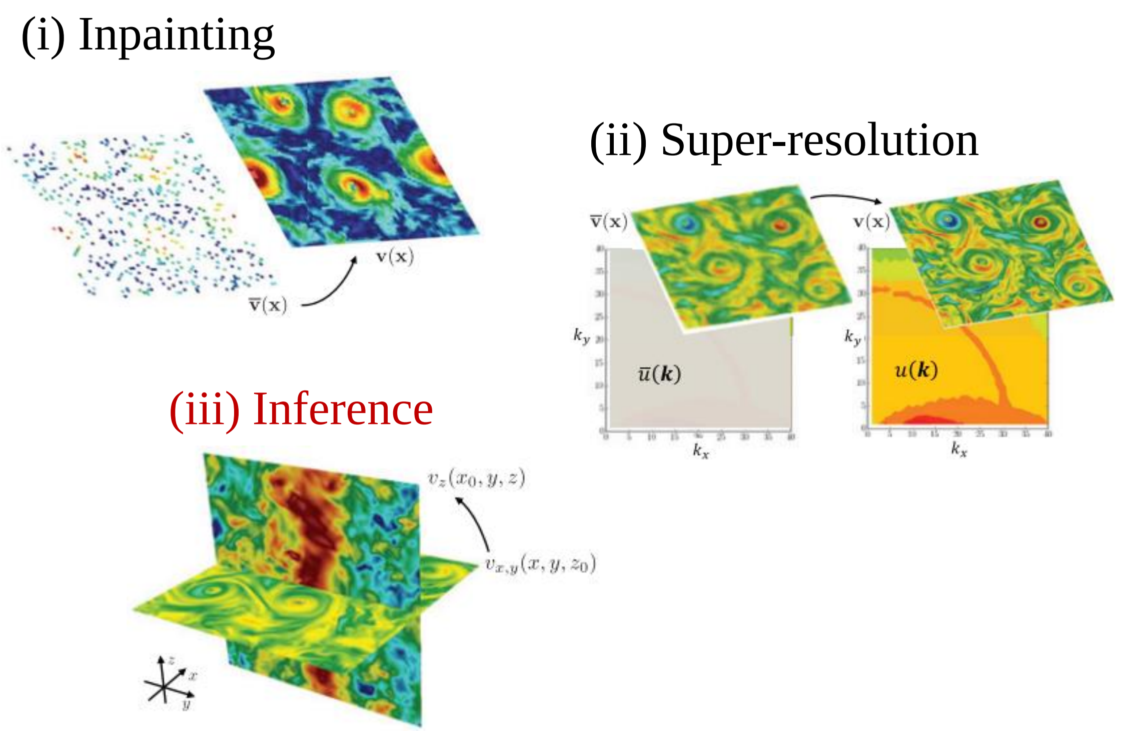


Rotating turbulence



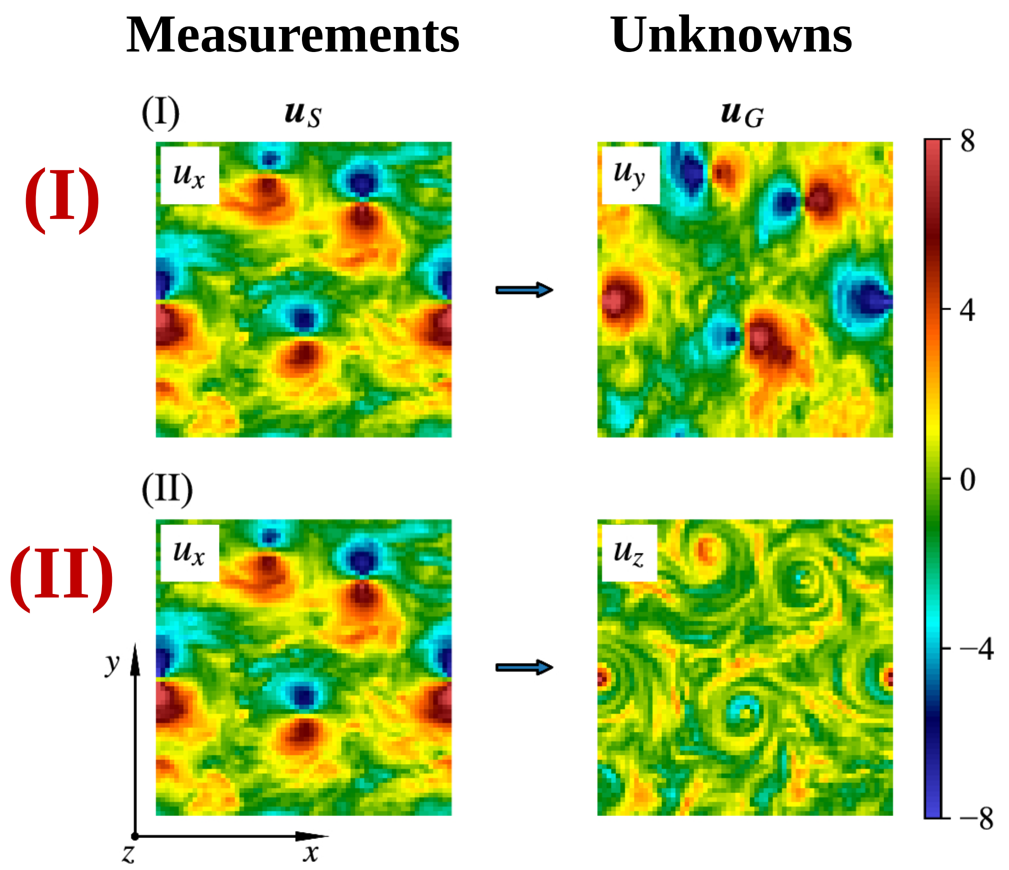
Large-scale vortical structures
Small-scale non-Gaussian fluctuations

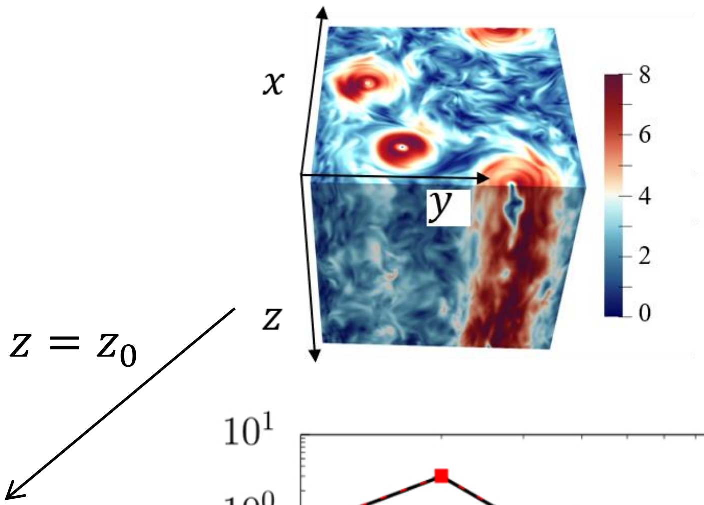
Data reconstruction

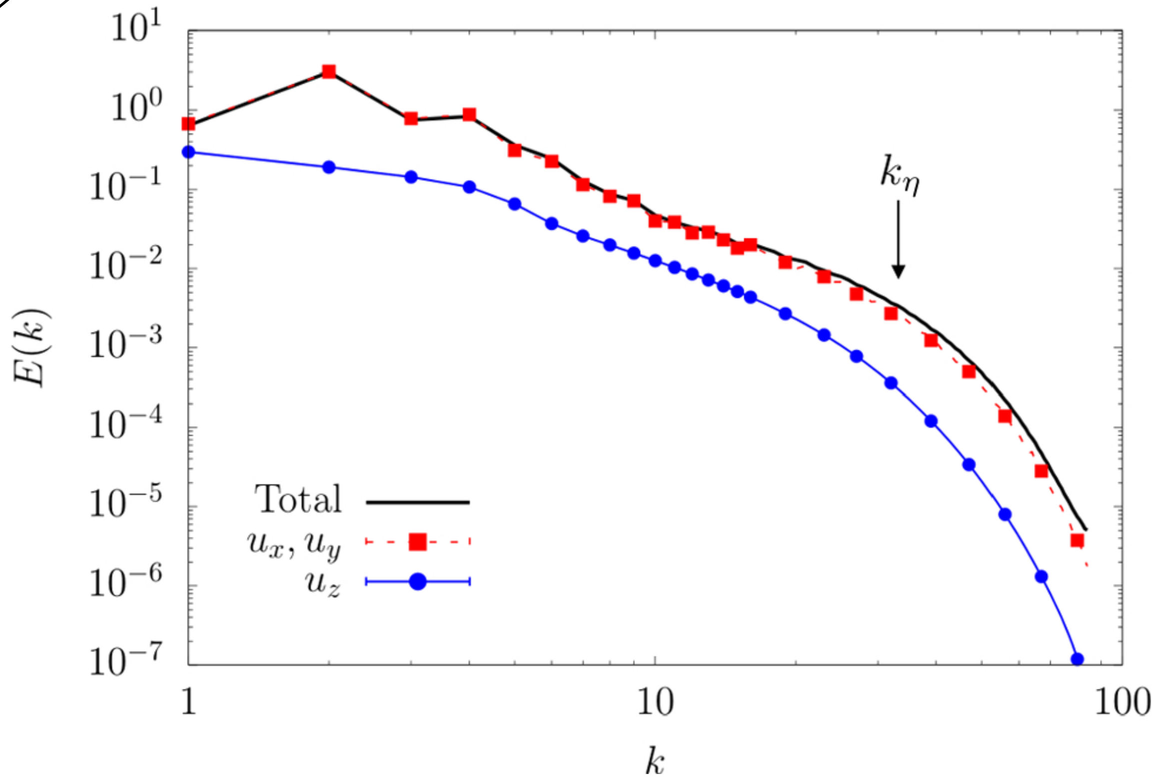


M. Buzzicotti, *Data reconstruction for complex flows using AI: recent progress, obstacles, and perspectives*. Europhysics Letters (2023).

Problem set-up







L. Biferale, F. Bonaccorso, M. Buzzicotti, P. Clark Di Leoni, *TURB-Rot. A large database of 3D and 2D snapshots from turbulent rotating flows*. arXiv preprint arXiv:2006.07469 (2020).

EPOD inference *(Extended Proper Orthogonal Decomposition)*

$$\mathcal{R}_S(\boldsymbol{x},\boldsymbol{y}) = \langle \boldsymbol{u}_S(\boldsymbol{x})\boldsymbol{u}_S(\boldsymbol{y})^T \rangle$$

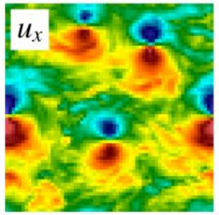
$$\int_\Omega \mathcal{R}_S(\boldsymbol{x},\boldsymbol{y}) \cdot \boldsymbol{\phi}_S^{(n)}(\boldsymbol{y})\mathrm{d}\boldsymbol{y} = \sigma_n \boldsymbol{\phi}_S^{(n)}(\boldsymbol{x})$$

$$\boldsymbol{u}_S(\boldsymbol{x}) = \sum_{n=1}^{N_\Omega} b_S^{(n)} \boldsymbol{\phi}_S^{(n)}(\boldsymbol{x})$$

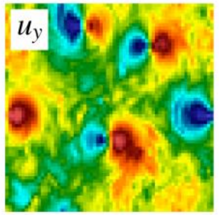
$$\boldsymbol{\phi}_S^{(n)}(\boldsymbol{x}) = \langle b_S^{(n)} \boldsymbol{u}_S(\boldsymbol{x}) \rangle / \sigma_n$$

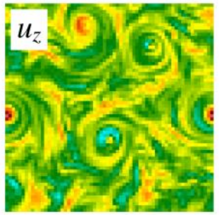
$\boldsymbol{\phi}_E^{(n)}(\boldsymbol{x}) = \langle b_S^{(n)} \boldsymbol{u}_G(\boldsymbol{x}) \rangle / \sigma_n$ **(TRAINING)**

Measured quantities: $\boldsymbol{u}_S$



Quantities to be inferred: $\boldsymbol{u}_G$





Ω

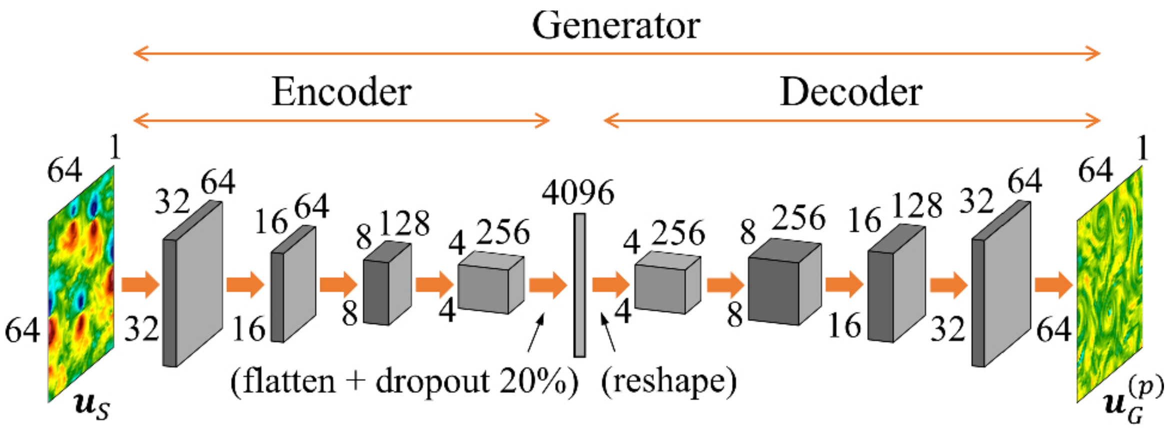
$\boldsymbol{u}_G^{(p)}(\boldsymbol{x}) = \sum_{n=1}^{N_\Omega} b_S^{(n)} \boldsymbol{\phi}_E^{(n)}(\boldsymbol{x})$ **(PEDICTION)**

J. Borée, *Extended proper orthogonal decomposition: a tool to analyse correlated events in turbulent flows*. Experiments in fluids (2003) 35.2: 188–192.

$\mathrm{JSD}(P\|Q) = \frac{1}{2}\mathrm{KL}(P\|M) + \frac{1}{2}\mathrm{KL}(Q\|M),\ M = \frac{1}{2}(P+Q)$

$\mathrm{KL}(P\|Q) = \int_{-\infty}^{\infty} P(x)\log(P(x)/Q(x))\mathrm{d}x$

CNN-based inference *with context encoders*



Expression of nonlinearity 😄

Often gives 'blurry' predictions!!! 😅

Loss functions

$$\mathcal{L}_{GEN} = (1-\lambda_{adv})\mathcal{L}_{\mathrm{MSE}} + \lambda_{adv}\mathcal{L}_{adv}$$

$$\mathcal{L}_{\mathrm{MSE}} = \langle \frac{1}{A_\Omega}\int_\Omega \|\boldsymbol{u}_G^{(p)}(\boldsymbol{x}) - \boldsymbol{u}_G^{(t)}(\boldsymbol{x})\|^2 \mathrm{d}\boldsymbol{x}\rangle$$

$$\mathcal{L}_{adv} = \langle \log(1 - D(\boldsymbol{u}_G^{(p)}))\rangle$$

Minimize $\mathrm{JSD}(p_t(\boldsymbol{u}_G)\|p_p(\boldsymbol{u}_G))$

$$\mathcal{L}_{DIS} = \langle \log(D(\boldsymbol{u}_G^{(t)}))\rangle + \langle \log(1 - D(\boldsymbol{u}_G^{(p)}))\rangle$$

M. Buzzicotti, F. Bonaccorso, P. C. Di Leoni, L. Biferale, *Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database.* Physical Review Fluids (2021) 6.5: 050503.

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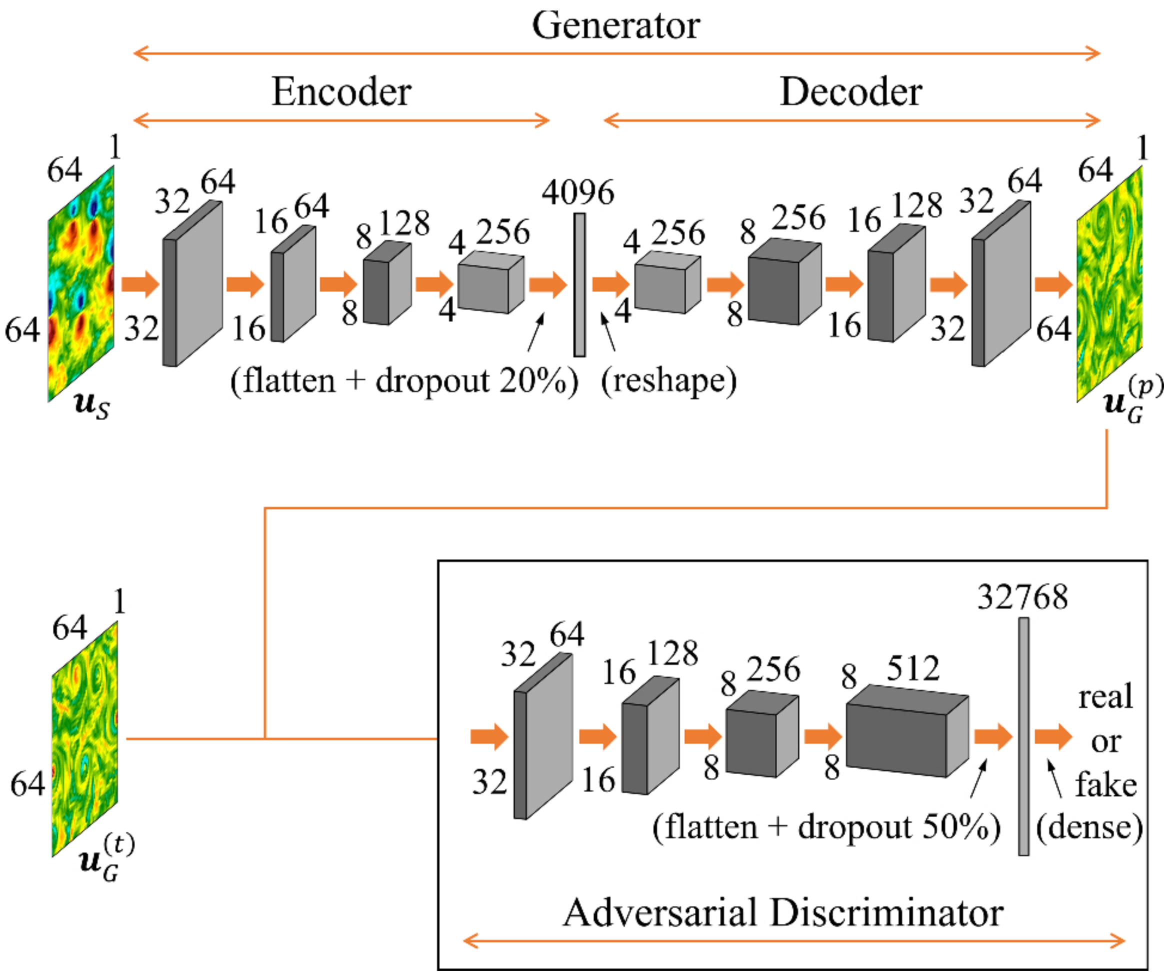
GAN-based inference *with context encoders*



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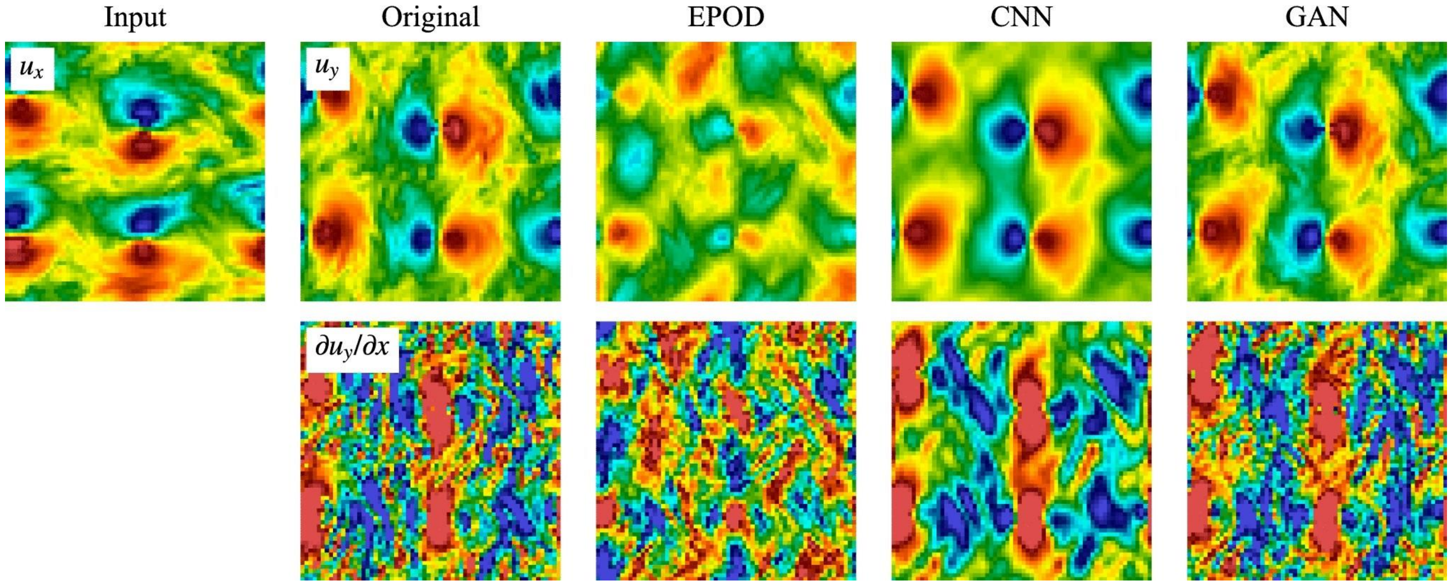
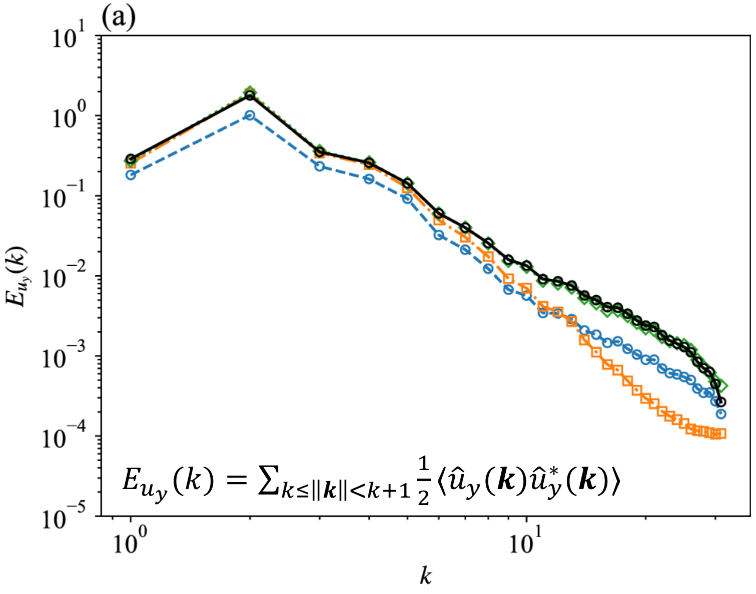
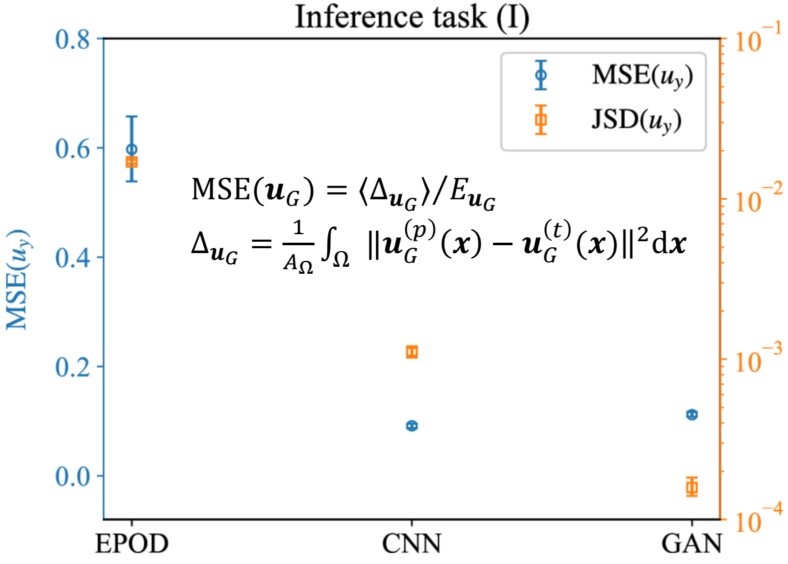
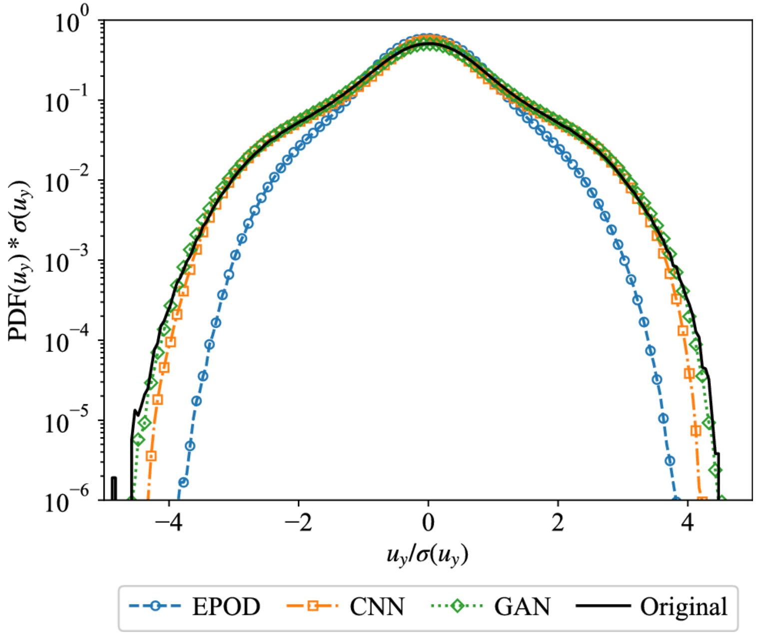
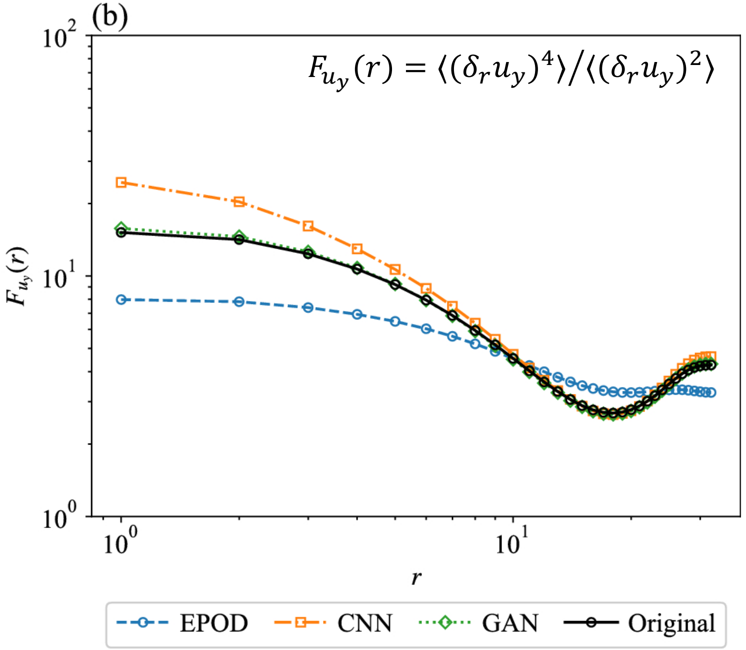
Results: Inference task (I)



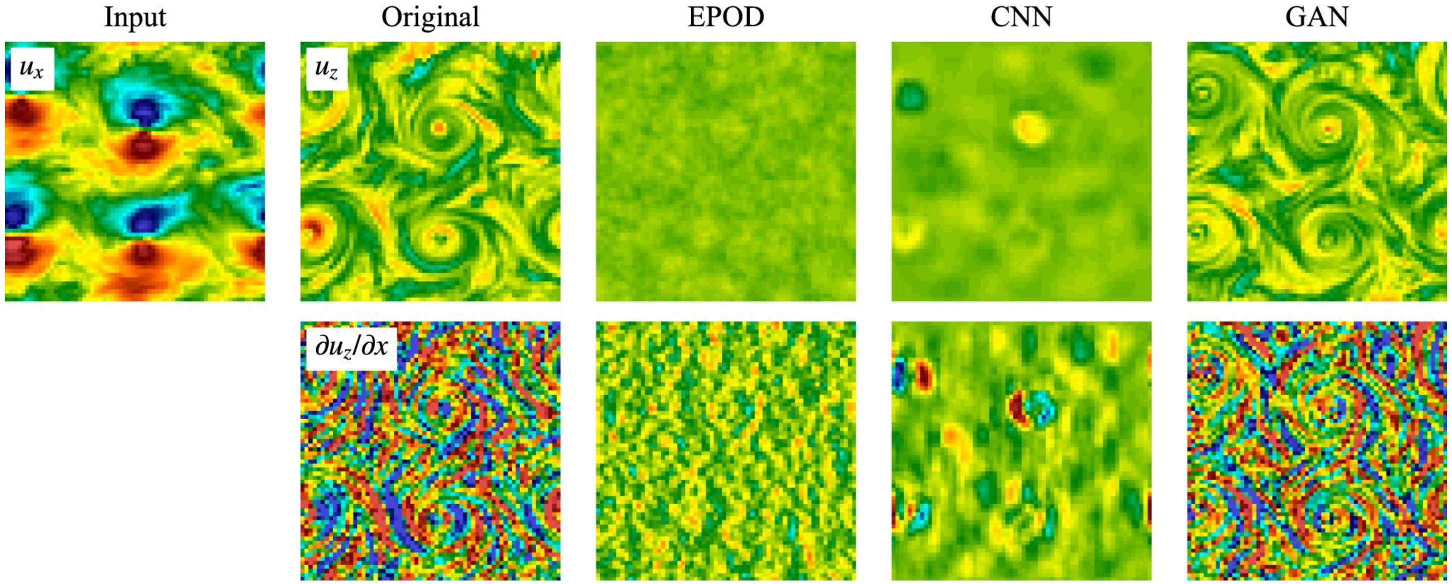


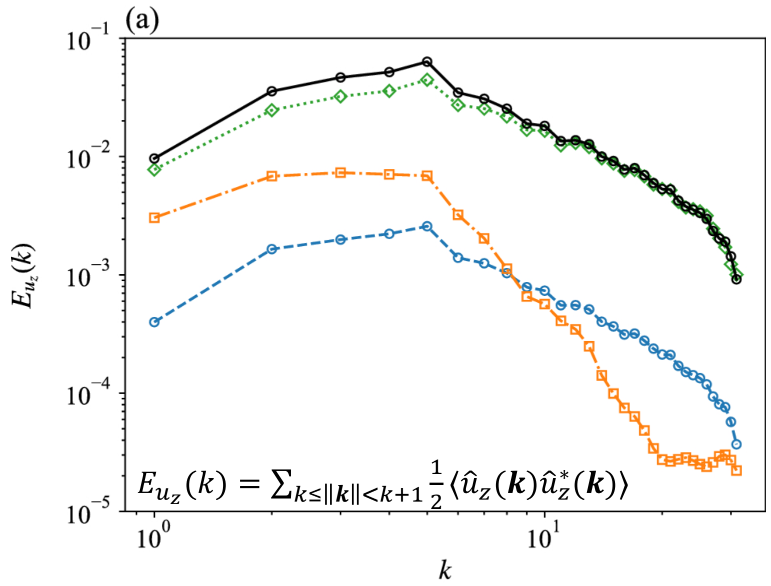


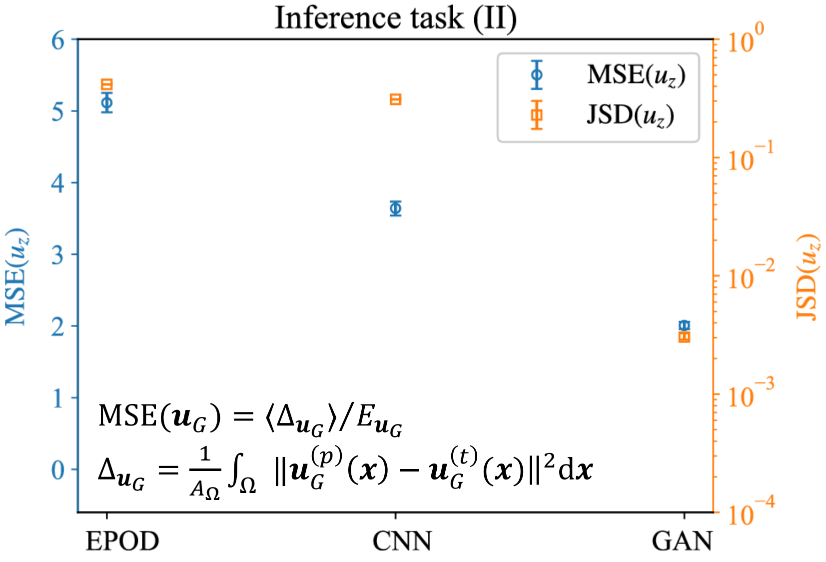


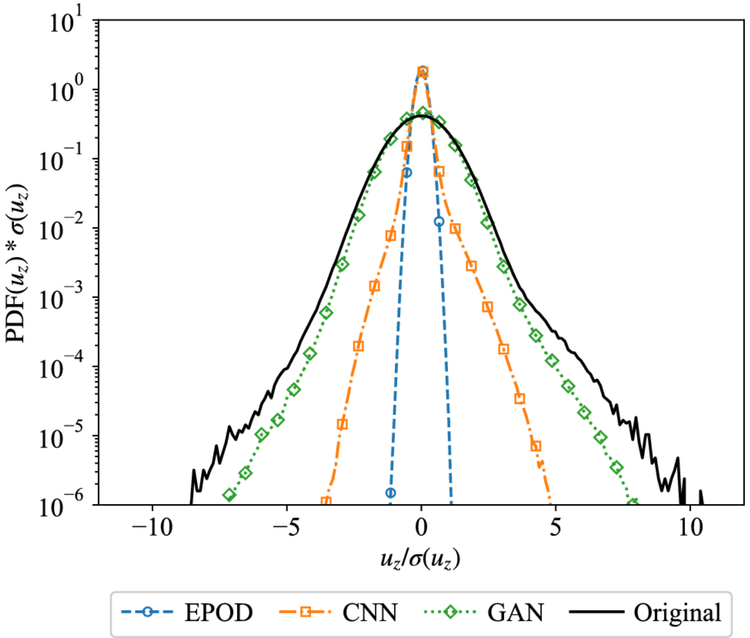


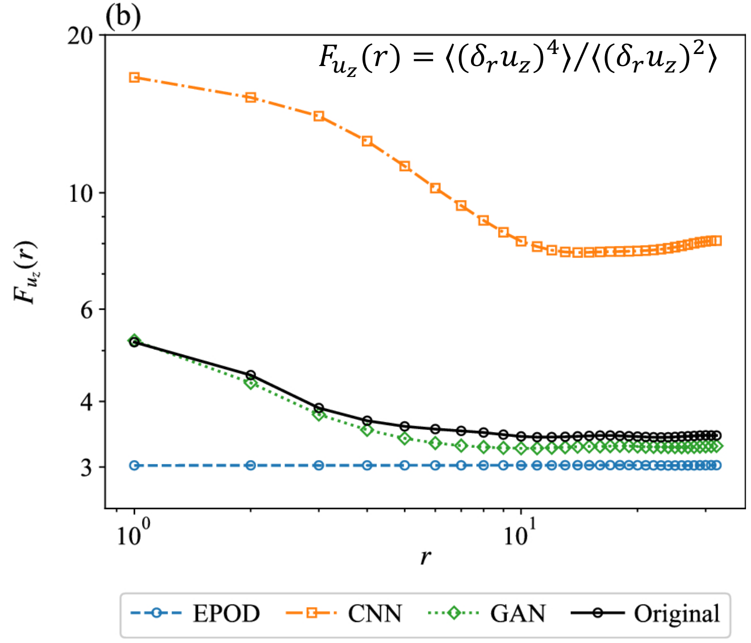
Results: Inference task (II)











Summary

1.Purpose: Explored practical geophysical/engineering problem of inferring one velocity component from another in 2D rotating turbulent flows.

2.Methods: Compared linear (EPOD) and nonlinear (CNN & GAN) methods using two tasks with different complexities.

3.Findings:

1. For simpler tasks, EPOD produced meaningful but unsatisfactory results. Improvements observed using CNN and further refined with GAN.
2. For complex tasks, EPOD failed due to low correlation between components. CNN and GAN recognized coherent structures but had limitations.

4.Conclusion: GANs optimize both instantaneous and statistical reconstruction, outperforming EPOD, which only minimizes field variance. GANs deliver more realistic results, albeit at a higher computational cost.

Smart-Turb ∞ Datasets Organizations Help About U

Guide for users

What is Smart-TURB? It is a brand new software infrastructure (born June 2020) for the research community working on turbulence and complex flows with particular emphasis to collect/standardize and preserve huge datase ... ig-data and Machine Learning approaches to fluid mechanics in genera ... ce, in particular. It is an easily accessible web platform for high qua ... is to host, standardize and manage a large collecti ... rimental and numerical data sets from high-end fluid dyn ... ties and High Performance Computational centers. Smart- ... ble performances when accessing/uploading/searching data. The ... munity is asked to contribute, by deploying freely downloadable, accurate an ... mented dataset for the sake of "reproducibility": The process of documenting ... edures and archiving data so that others can fully reproduce scientific results. ... se contact the administrator for infos about how to upload your dataset. We ... by deploying a first dataset made of 2d and 3d turbulent configurations under ... on TURB-Rot. More will come.

https://smart-turb.roma2.infn.it/

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

A PREPRINT

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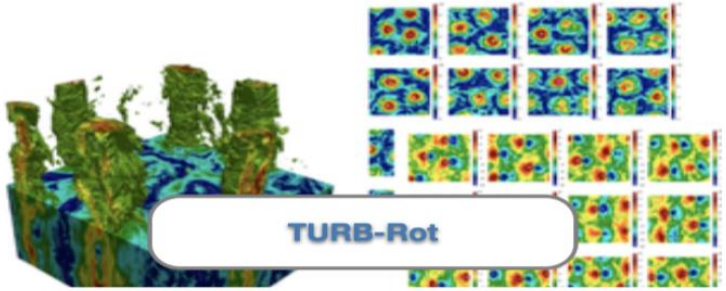
Search for datasets

1 Datasets

TURB-Rot
A large database of 3d and 2d snapshots from turbulent rotating



2 Organizations

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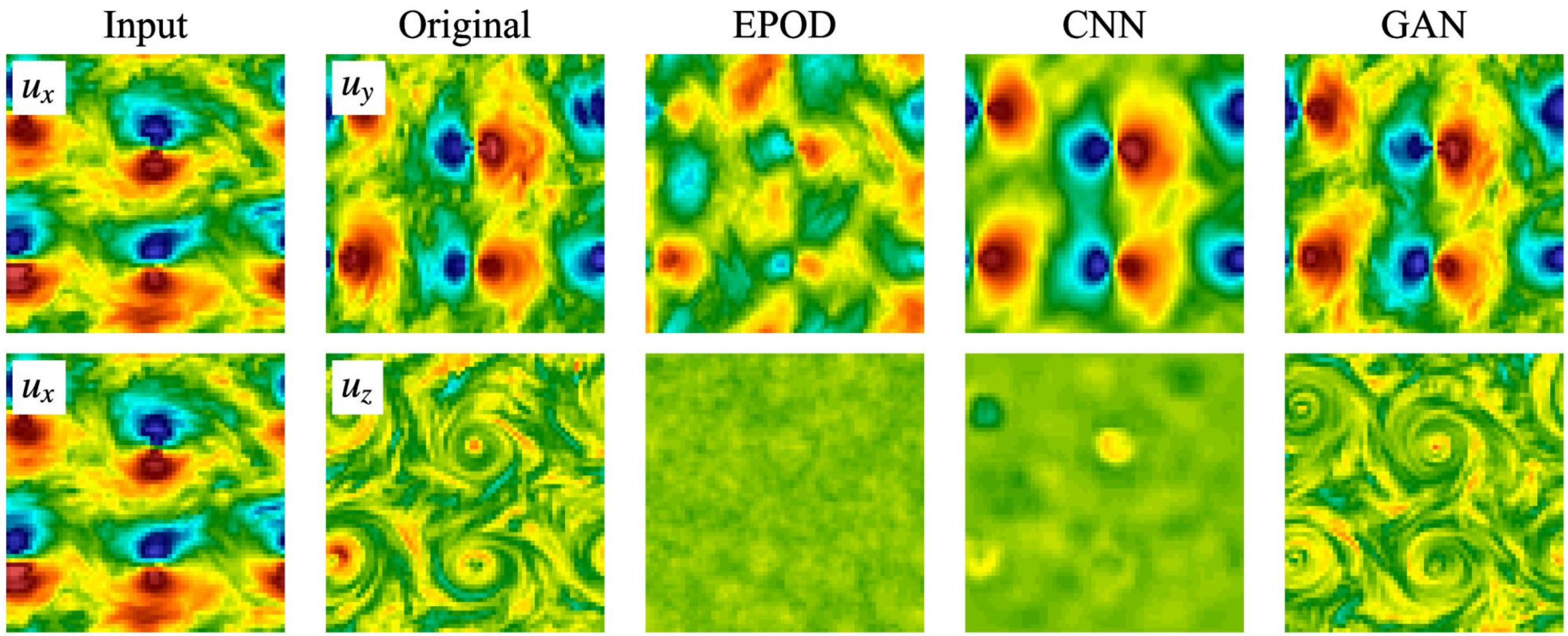
1 member

Thank you! Questions?



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