Machine Learning for WSI

- Some Literature overview on Deep Learning for Turbulence
- Test case 1): GNN as Poisson solver
- Test case 2): Raynold test case
- Test case 3): StyleGAN as deconvolution operator for LES in BOUT++

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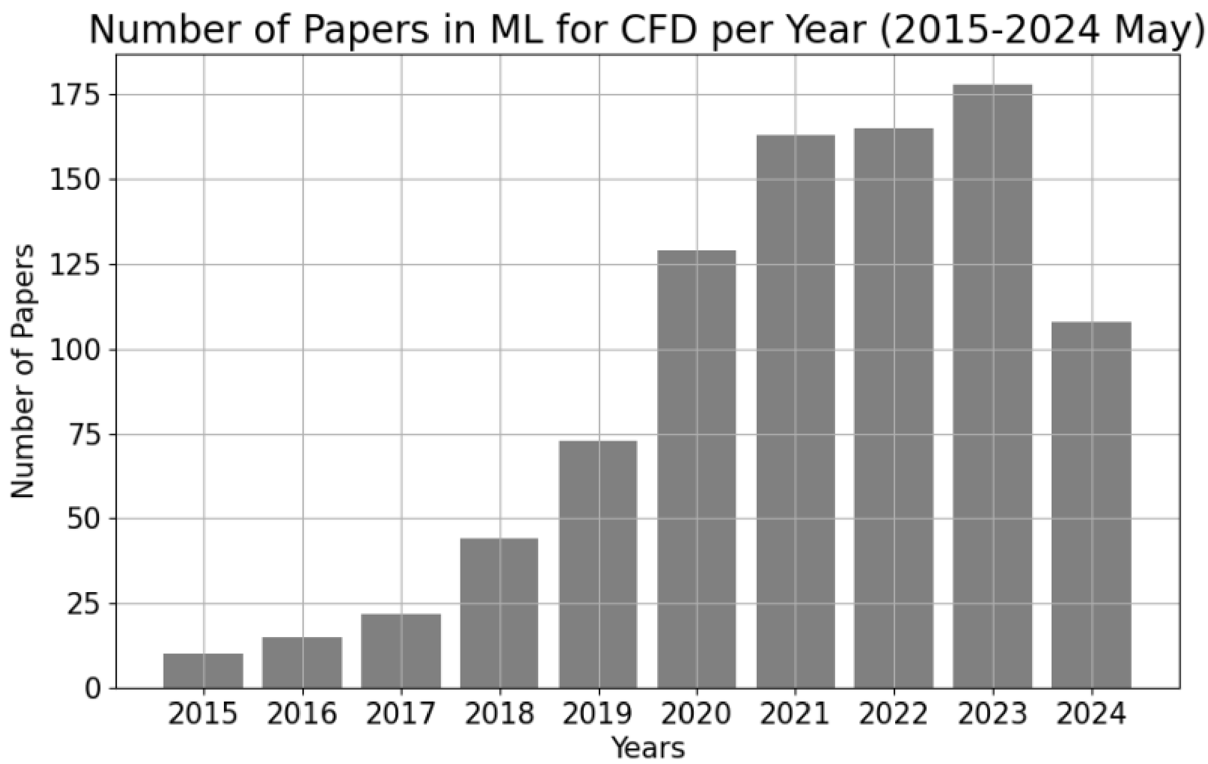
ML for CFD



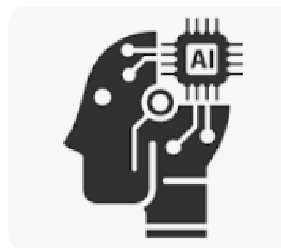
Recent Advances on Machine Learning for Computational Fluid Dynamics: A Survey
https://arxiv.org/pdf/2408.12171

Current CFD methodologies

Pure physics-driven

CPU

Mixed physics-data driven



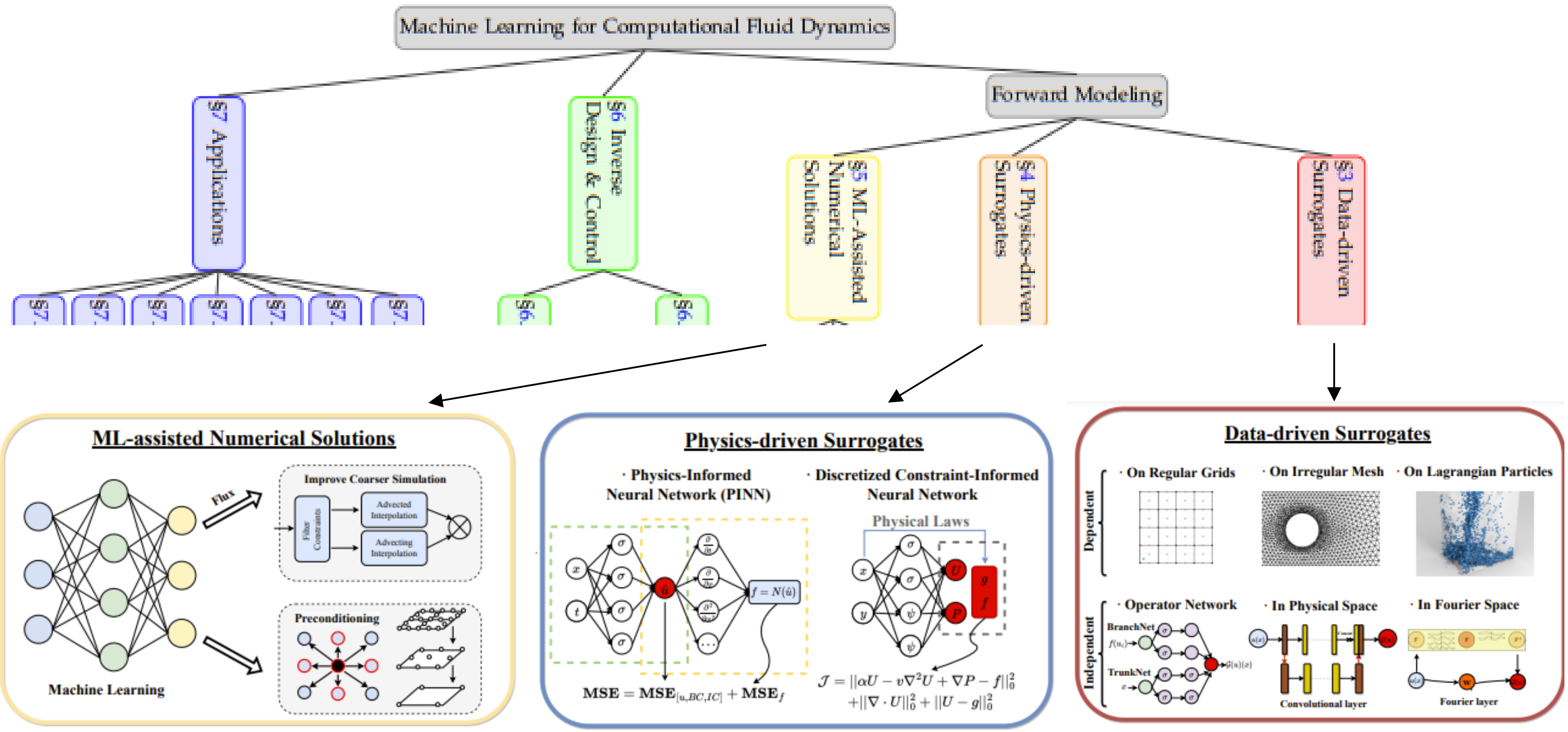
CPU-GPU

Pure data-driven

GPU

from a hardware perspective

ML method for CFD



Physics, mixed, data

mixed

data

Recent Advances on Machine Learning for Computational Fluid Dynamics: A Survey
https://arxiv.org/pdf/2408.12171

GNN for Poisson solver

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Raynold ML

StyleGAN as deconvolution operator for LES in BOUT++

Jony Castagna – Hartree Centre
Francesca Schiavello- Hartree Centre
Josh Williams – Hartree Centre
Lorenzo Zanisi – UKAEA

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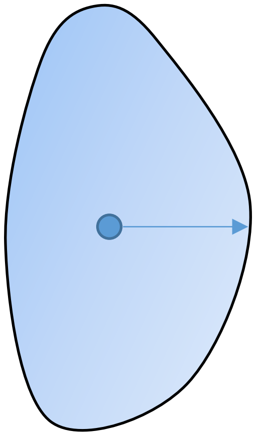
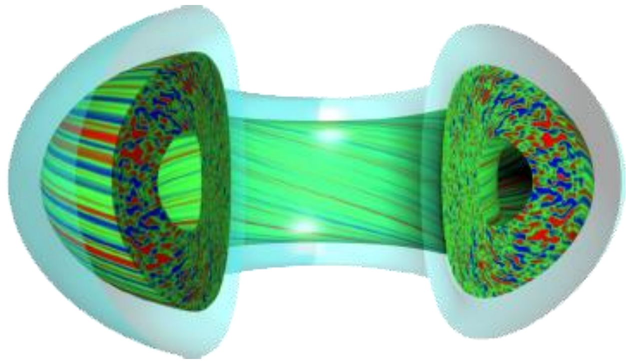
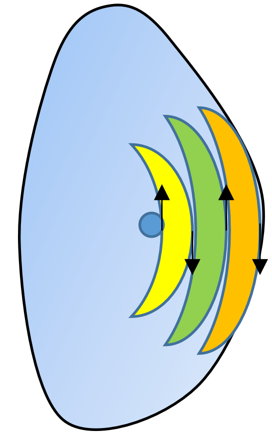
Turbulence in plasma fusion (I)



Classic transport τ_0
(pure diffusion)

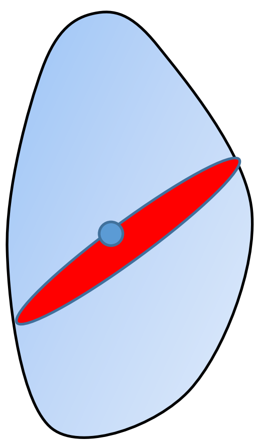


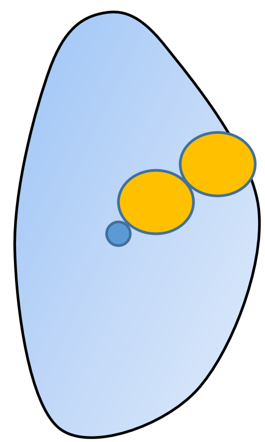
https://w3.pppl.gov/~hammett/viz/viz.html



Neoclassic transport $\tau < \tau_0$

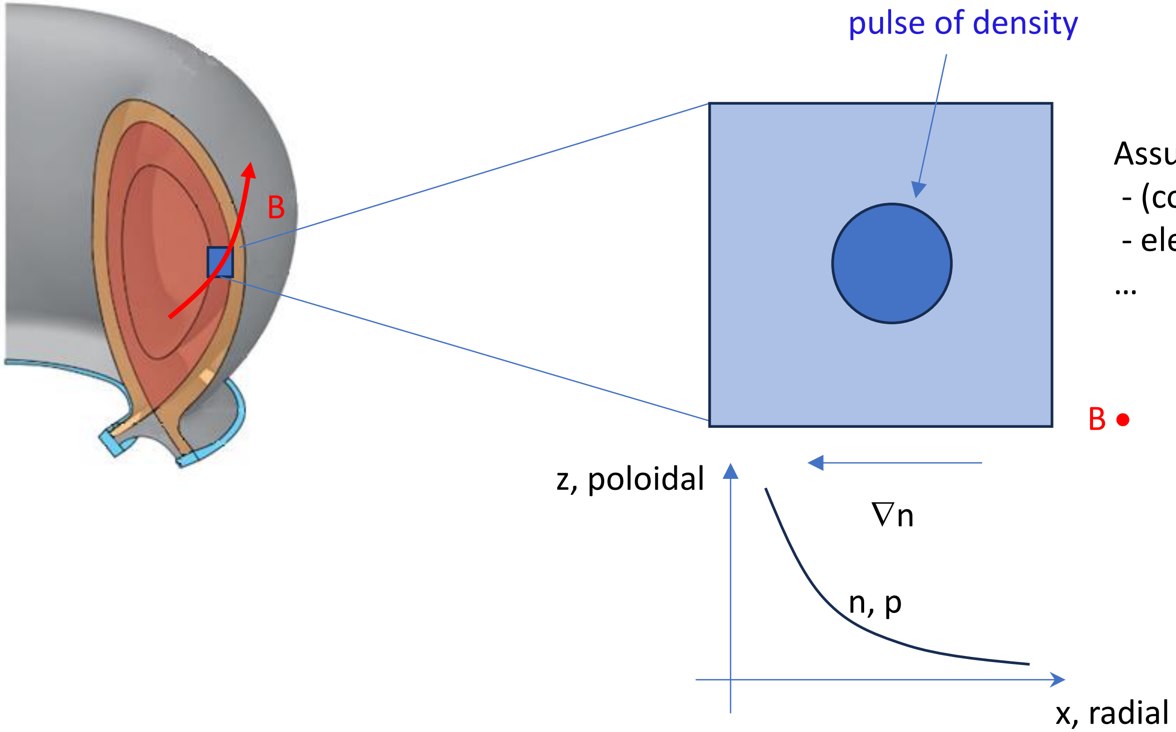
Turbulent transport
(L-mode) $\tau << \tau_0$





Turbulent transport
(H-mode) $\tau << \tau_0$

Turbulence in plasma fusion (II)



Assumptions:
- (cold) ions, move only 2D (poloidal plane)
- electrons can move 3D!

...

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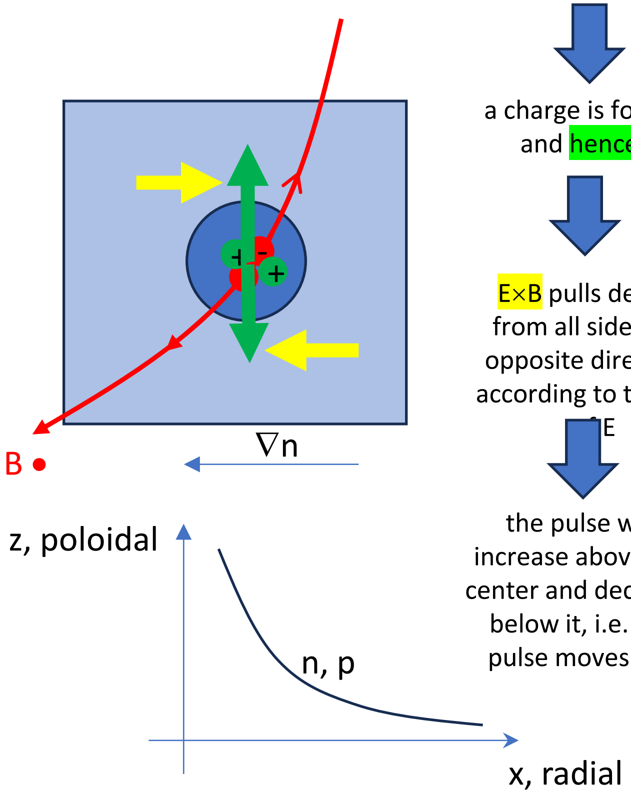
Turbulence in plasma fusion (III)



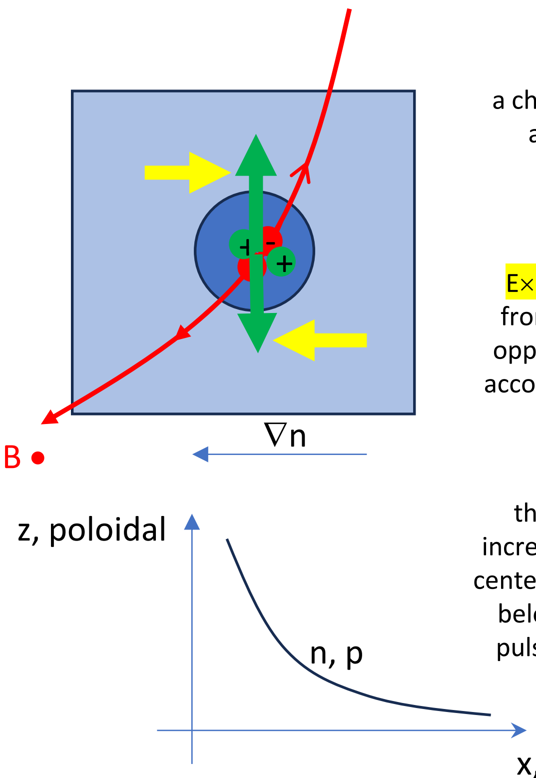
electrons move along B

a charge is formed and hence E

E×B pulls density from all sides, but opposite directions according to the sign of E

the pulse will increase above the center and decrease below it, i.e. the pulse moves up!

Turbulence in plasma fusion (IV)



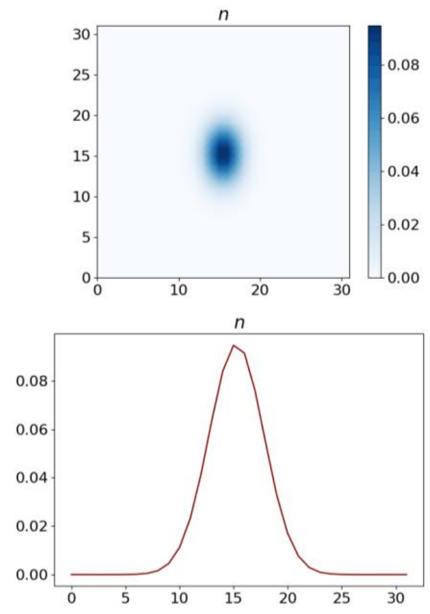
electrons move along B

a charge is formed and hence E

E×B pulls density from all sides, but opposite directions according to the sign of E

the pulse will increase above the center and decrease below it, i.e. the pulse moves up!

Is it true? Tested with BOUT++:



α=100

where α is the inverse of the resistive, i.e. the larger value the lower the resistivity along B for the electrons (adiabatic response)!

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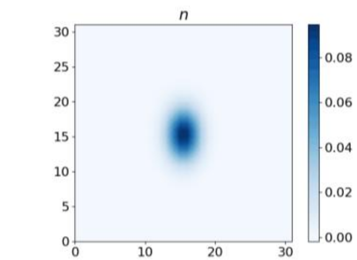
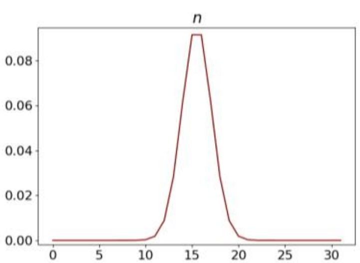
Turbulence in plasma fusion (V)

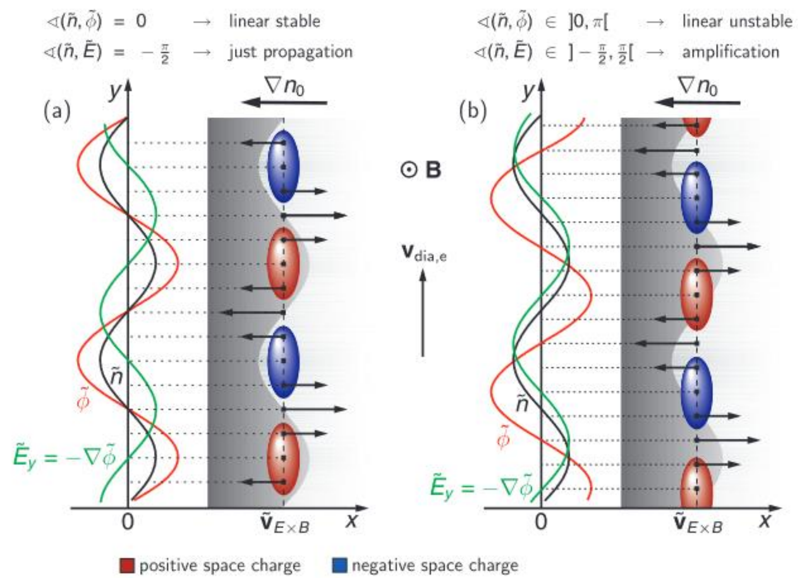




α=0.001

if the resistivity is very high (friction of ions, Landau dumpi and Alfven waves), α is small ar the hydrodyanimc behaviour (Navier-Stokes equations) are recovered.

However, intermedium values o α (~1) trigger the instabilities growth…



Active Control of Drift Wave Turbulence
https://epub.ub.uni-greifswald.de/frontdoor/deliver/index/docId/477/file/diss_brandt_christian.pdf

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The Hasegawa-Wakatani equations

$$\frac{\partial \tilde{\zeta}}{\partial t} + \widetilde{\{\phi, \zeta\}} = \alpha(\tilde{\bar{\phi}} - \tilde{\bar{n}}) - \mu \nabla^4 \tilde{\zeta}$$

$$\frac{\partial \tilde{n}}{\partial t} + \widetilde{\{\phi, n\}} = \alpha(\tilde{\bar{\phi}} - \tilde{\bar{n}}) - k \frac{\partial \tilde{\phi}}{\partial y} - \mu \nabla^4 \tilde{n}$$

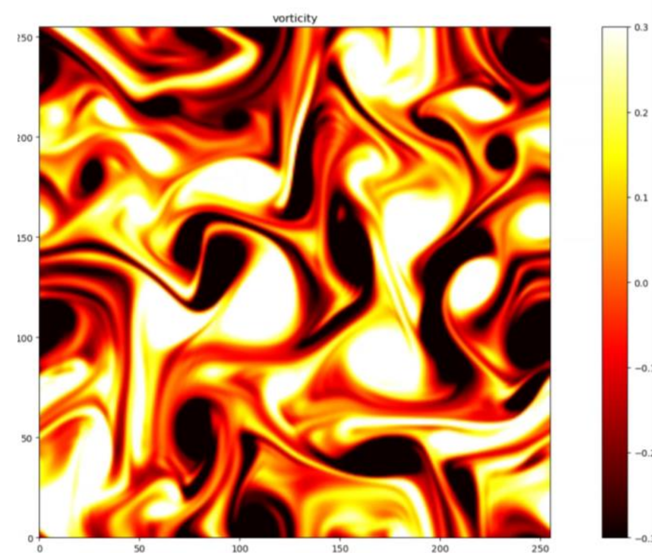
for $\alpha \to 0$

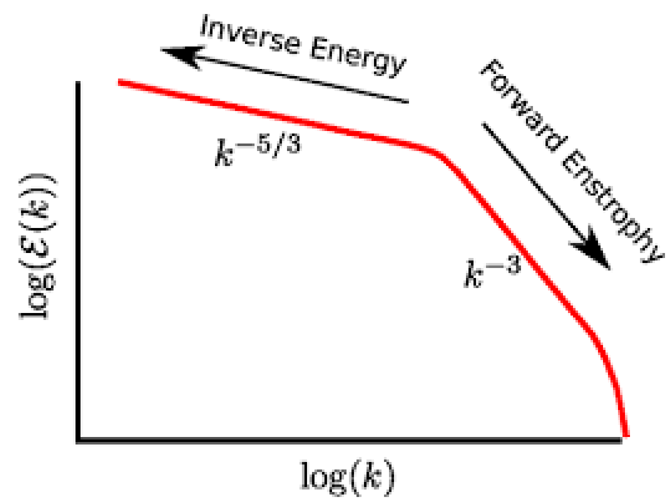
Similar fluid dynamic behaviours of 2D Navier-Stokes!

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = 0$$

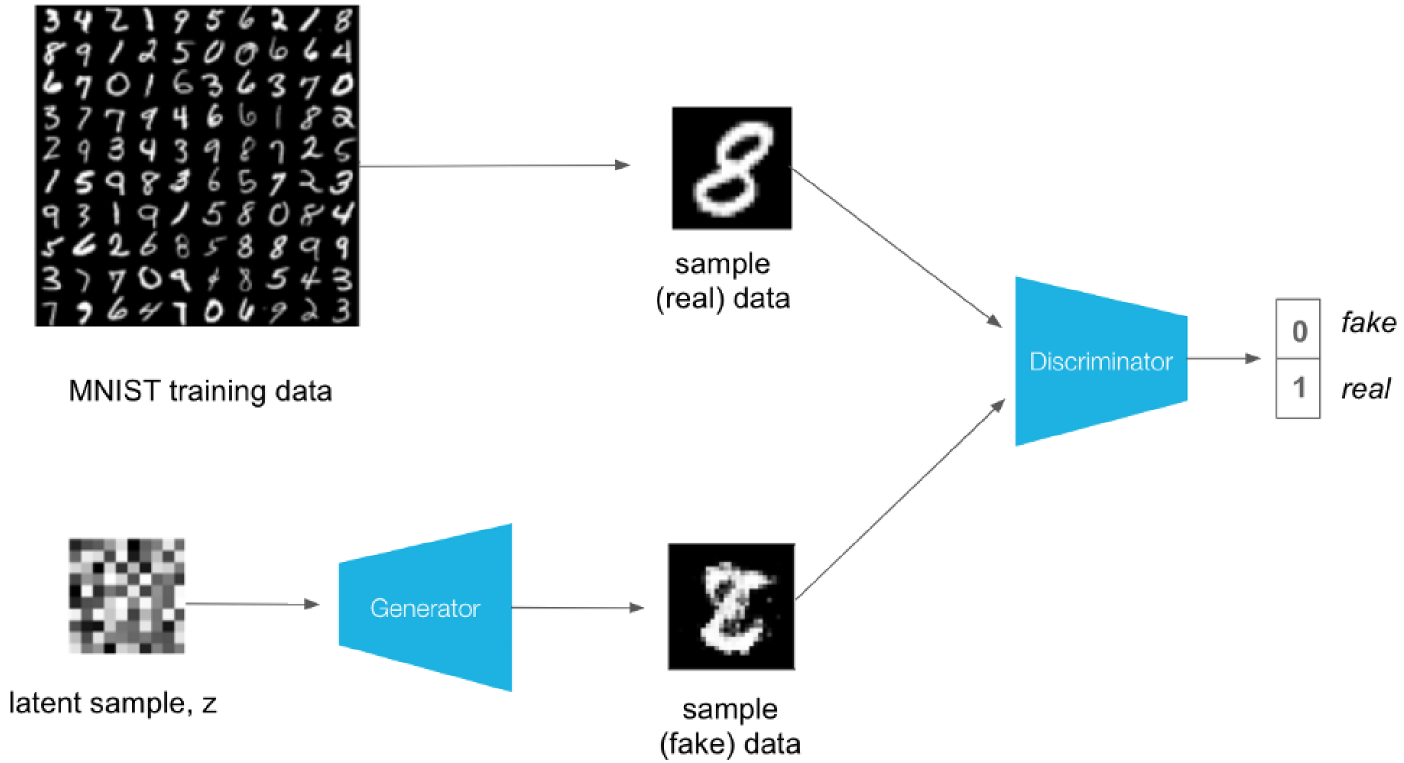
$$\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} = -\frac{1}{\rho}\frac{\partial p}{\partial x} + \nu\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right)$$

$$\frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} = -\frac{1}{\rho}\frac{\partial p}{\partial y} + \nu\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}\right)$$





Generative Adversarial Networks (GANs)



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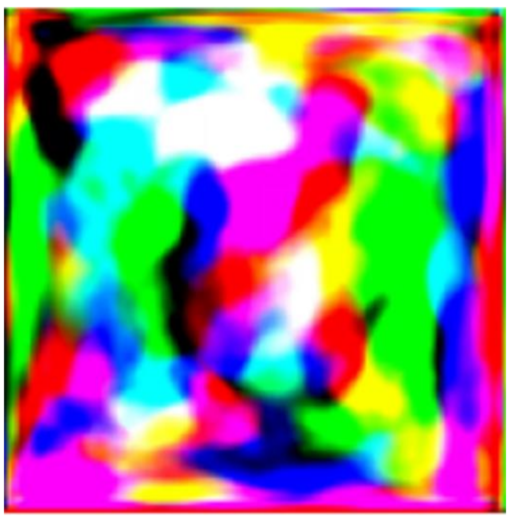
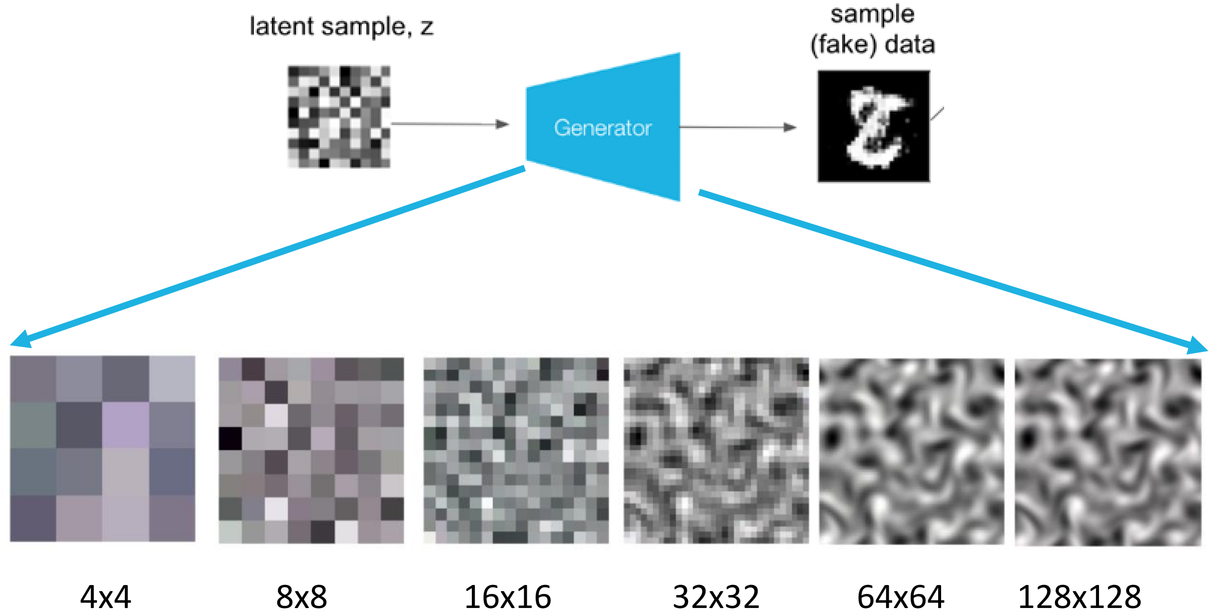
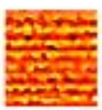
A trained GAN

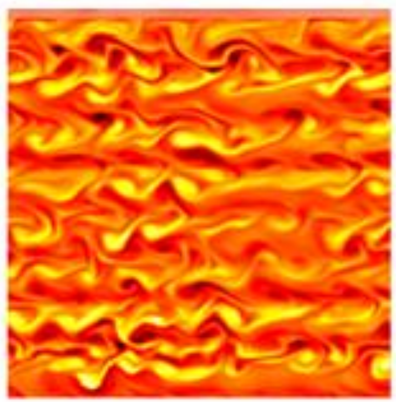




Can I train a GAN to reconstruct the DNS fields from the internal fields seen as LES fields?

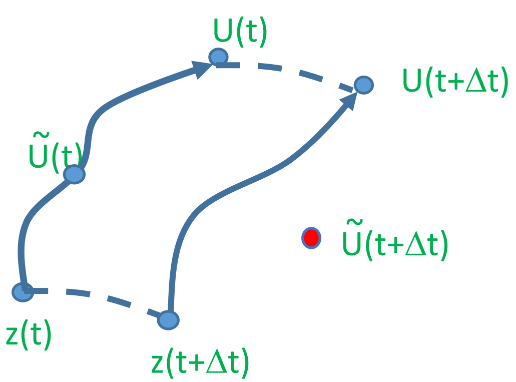


LES field (32x32)



DNS field (256x256)

Potentially, two instantaneous of the same Navier-Stoke problem can be obtained, **U(t)** and **U(t+Δt)** but there is no guarantee that the internal layers are representation of the same filtered Navier-Stoke problem, **Ũ(t)** and **Ũ(t+Δt)** !



A RNN can be used to move in time the latent space z -> very hard!
(Kim and Lee, Journal Computational Physics - 2019)

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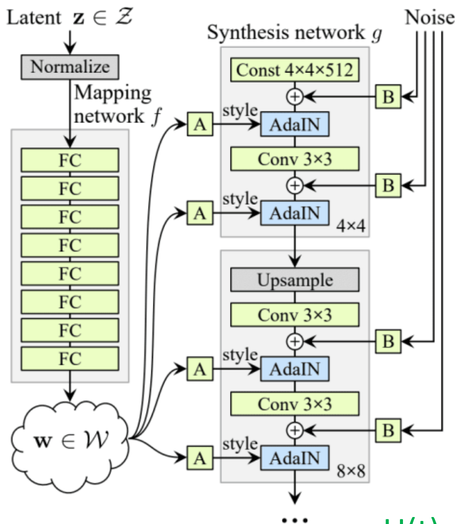
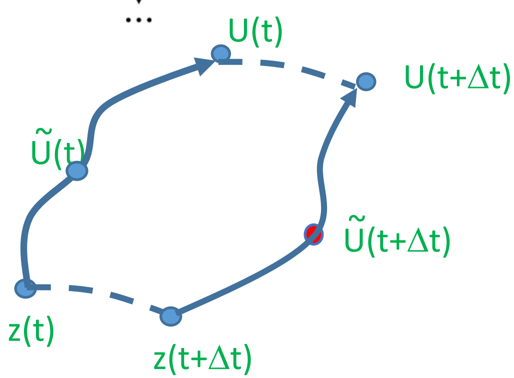
…I need a more “flexible GAN”, StyleGAN!



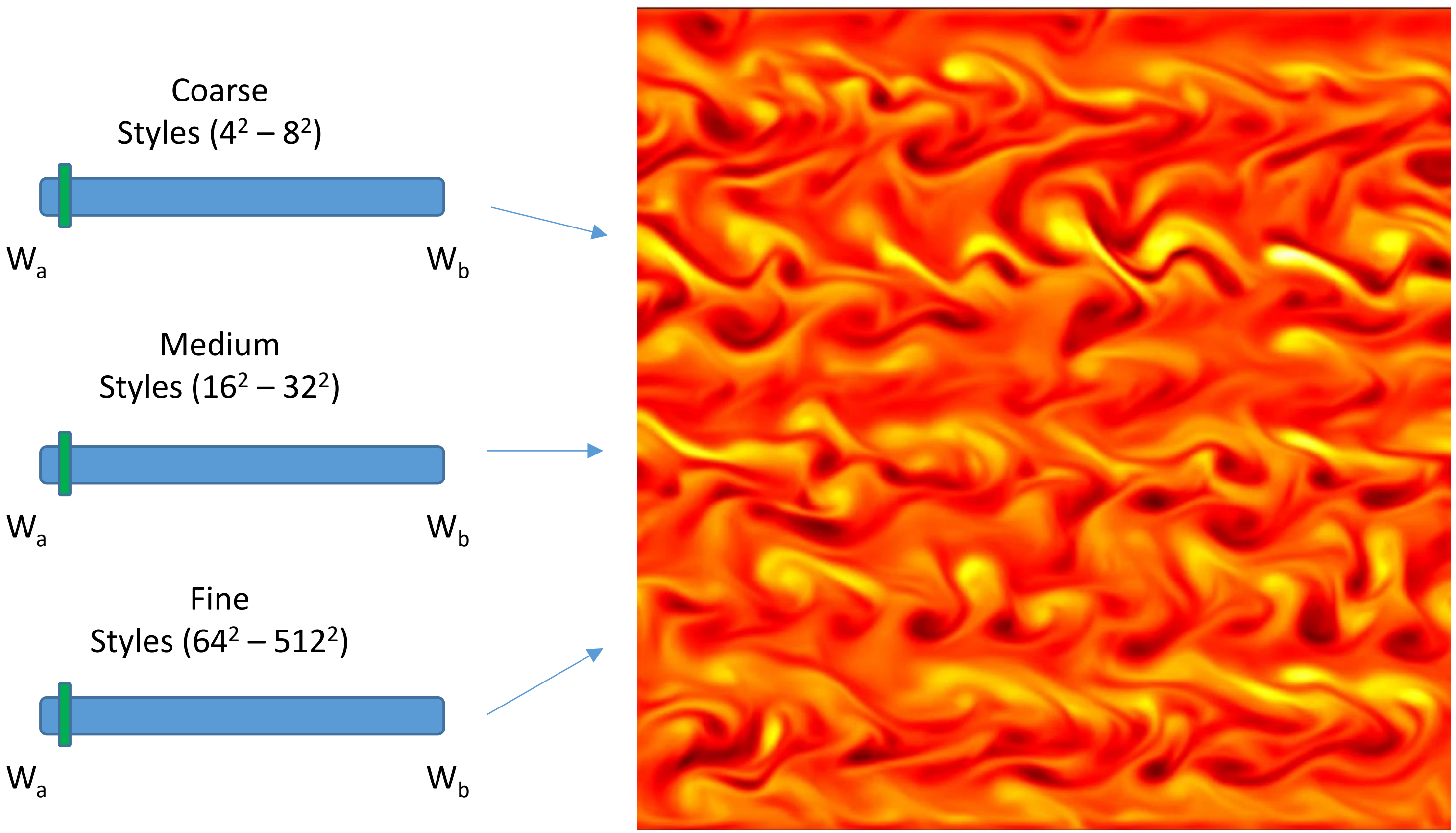


Our generator thinks of an image as a collection of “styles”, where each style controls the effects at a particular scale

- Coarse styles → pose, hair, face shape
- Middle styles → facial features, eyes
- Fine styles → color scheme

Each layer (style) can be adjusted without interfering with the other levels!

Latent space interpolation applied to a voracity field



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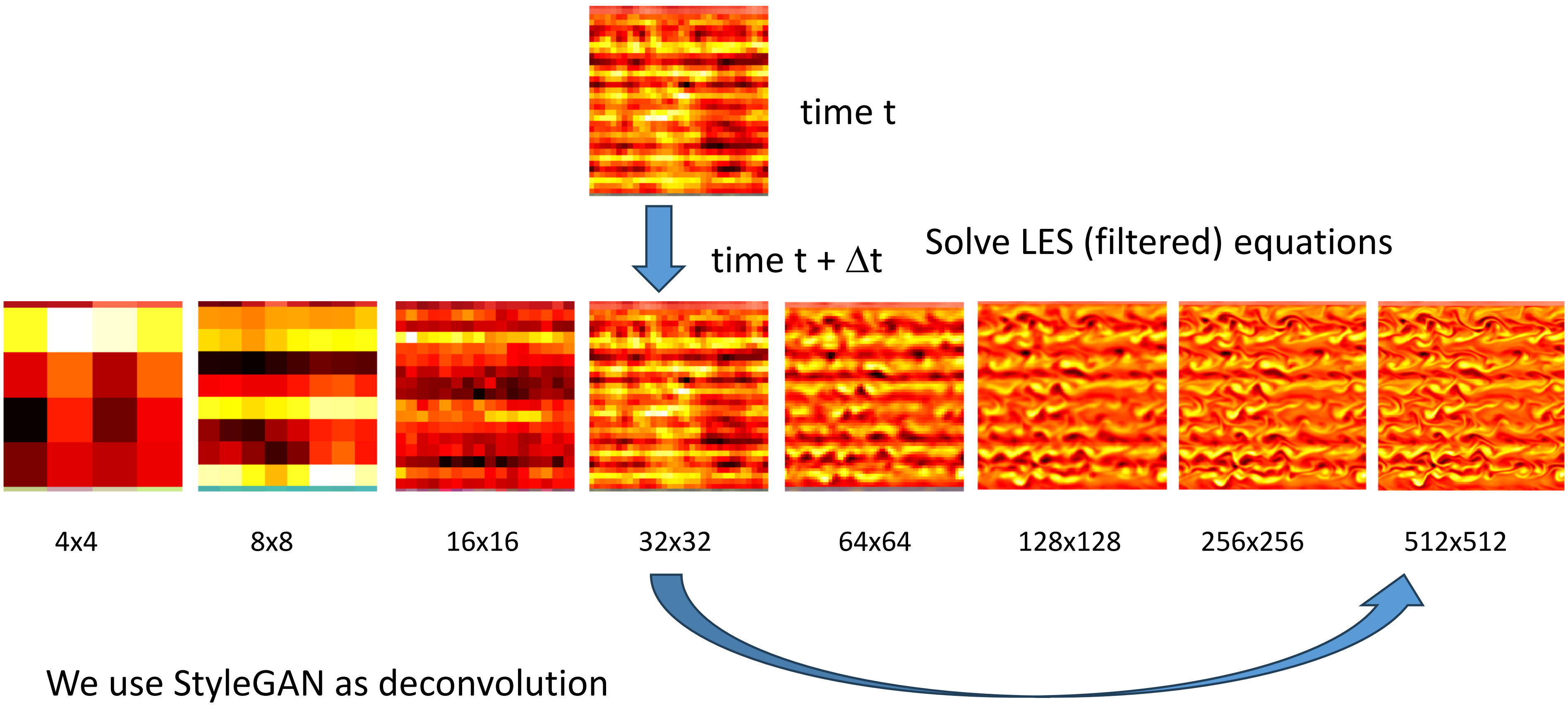
How StyleGAN is linked to the LES?



We use StyleGAN as deconvolution operator of a LES field to find the corresponding DNS field: we named Style Eddy Simulation (StylES)

Reconstruct DNS fields after matching the LES fields via linear interpolation!

<u>We do not need a RNN!</u>

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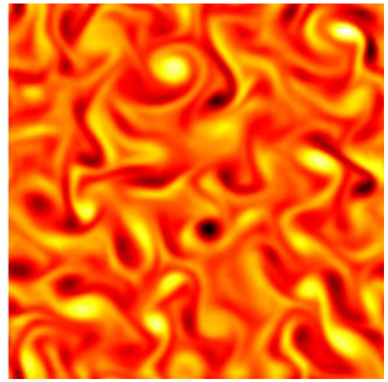
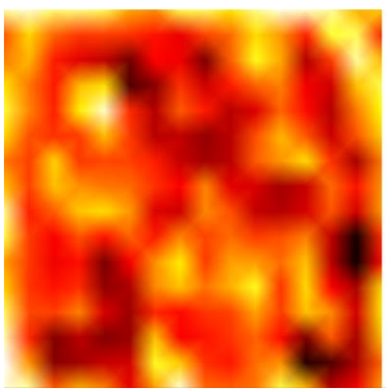
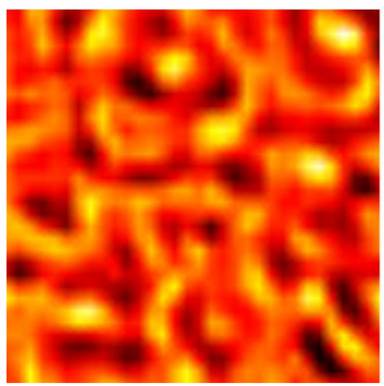
HW reconstructed vorticity fields



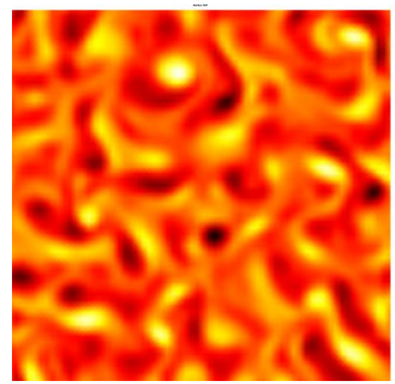
DNS
(256x256)



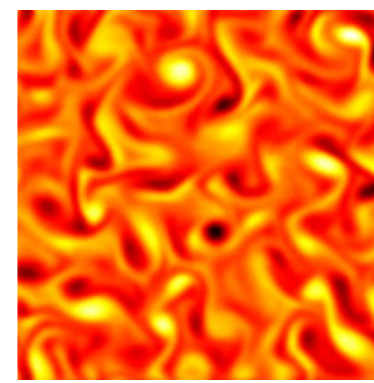
16x16



32x32



64x64



128x128

At low resolution, features can be “non-physical”!

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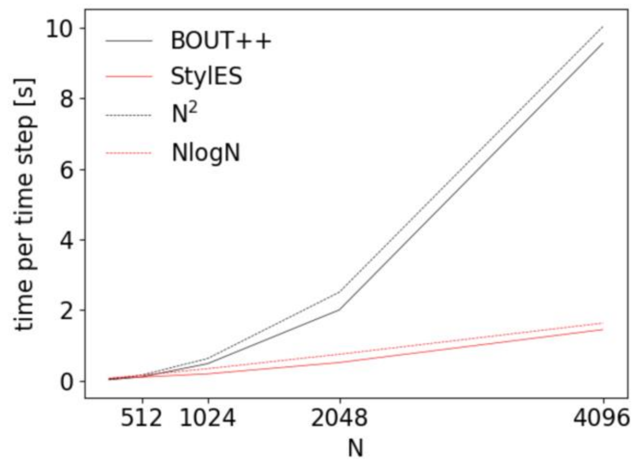
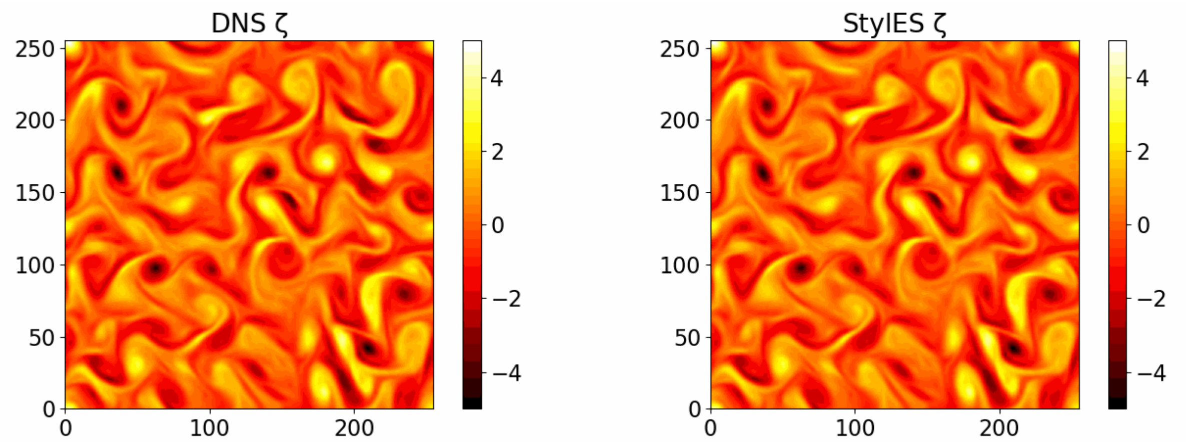
Integration with BOUT++

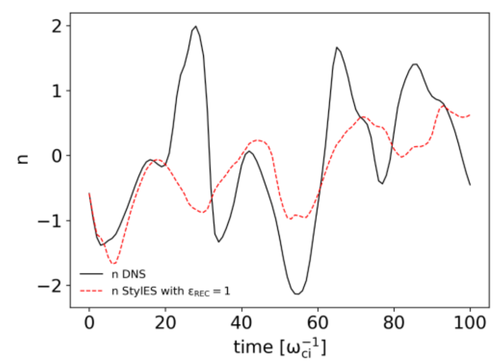
The integration occurs via an embedded Python call (TensorFlow) from C++



We are looking at 3 possible usages of StyleGAN:

- StylES
- to create valid initial conditions for DNS
- to accelerate DNS via better initial guess for PVODE





Fully integrated BOUT++ with StylES: reconstruction $32^2 \rightarrow 256^2$

100 time units ~20k time steps!

Castagna et al. Physics of Plasma (2024)

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Improvements on StyleGAN

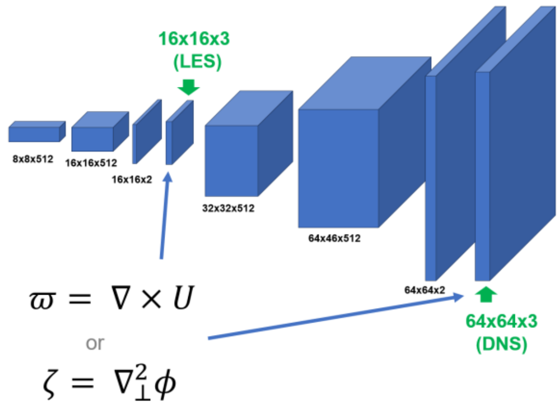
1) Added hard physics constrains into the generator

- conservation of mass and electric charge
- vorticity derived from potential $\zeta = \nabla_{\perp}^{2}\phi$

→

- Faster and better training
- Avoid initial "jump" in potential

2) Moved from MSG-StyleGAN to LES-StyleGAN

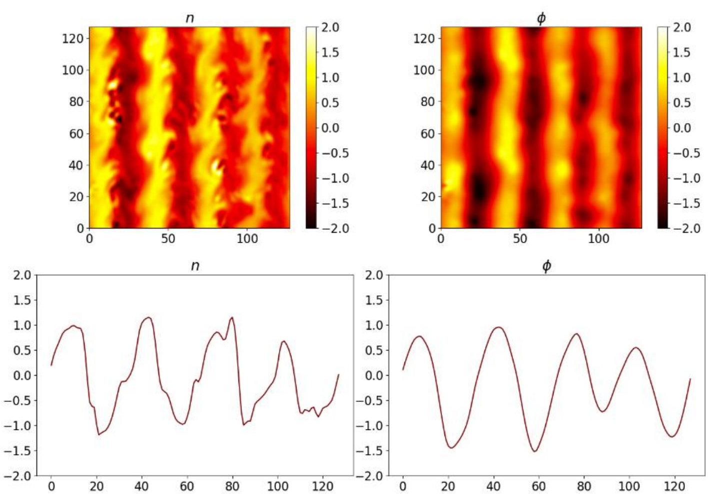


→

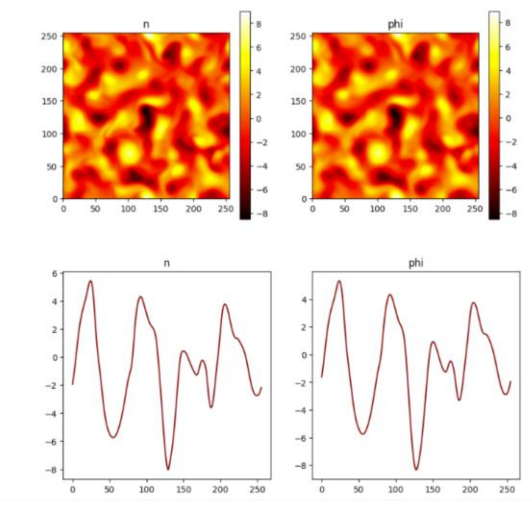
- Satisfy uniqueness
- Faster inference
- Avoids search into latent space during time integration!

Improvements on StyleGAN

3) Moving to single channel (valid for $\alpha \geq 1$)



α=0.1

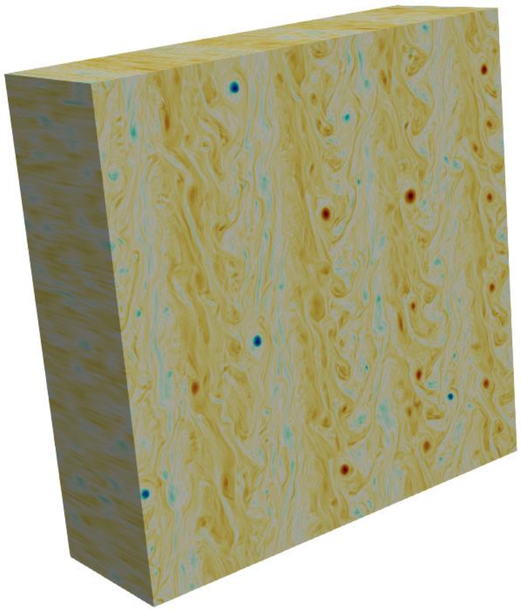


α=2

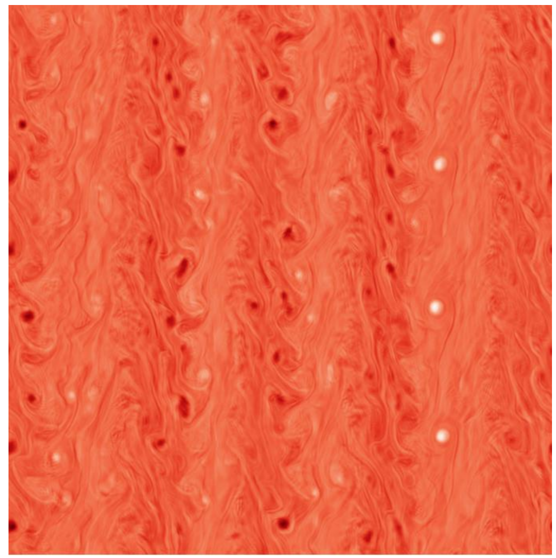
- Faster training and inference
- Lower memory requirements

Lower channels -> ready for the HERMES model!

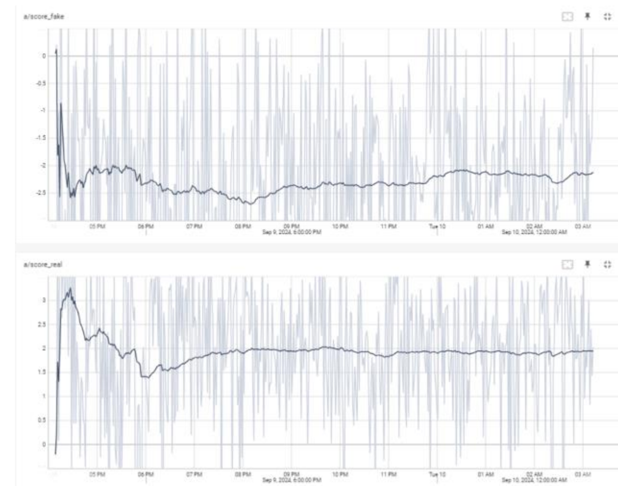
Results from improvements on StyleGAN



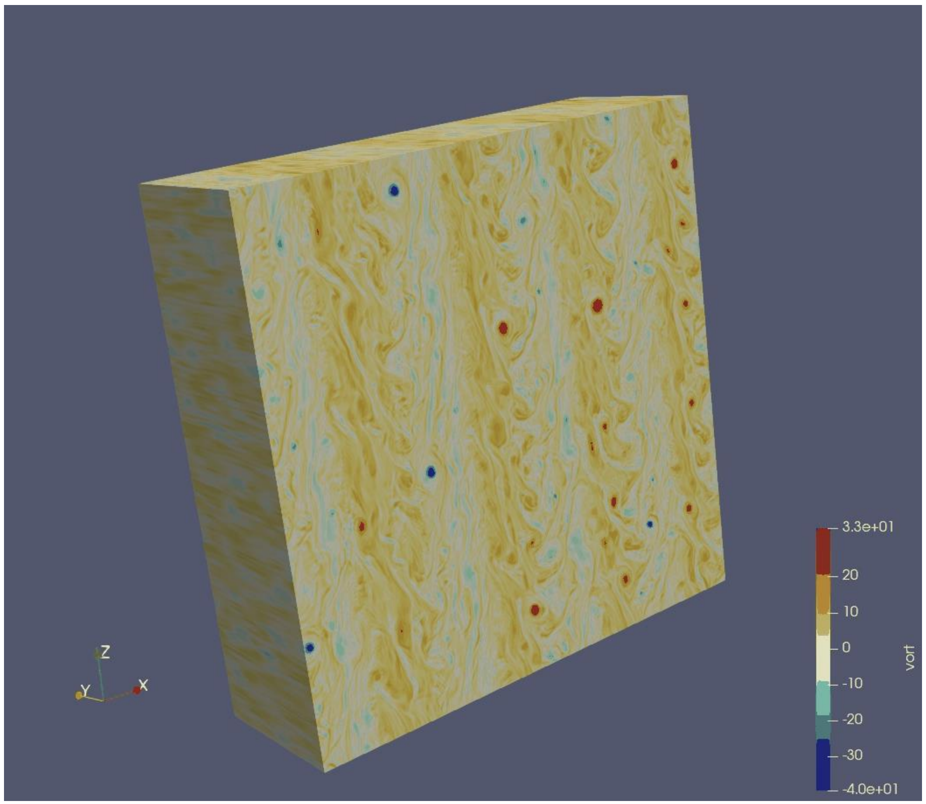
3D HW
initial DNS field from
StyleGAN on single
channel



Training on 1024^2 went down
from 2 weeks to 11h!

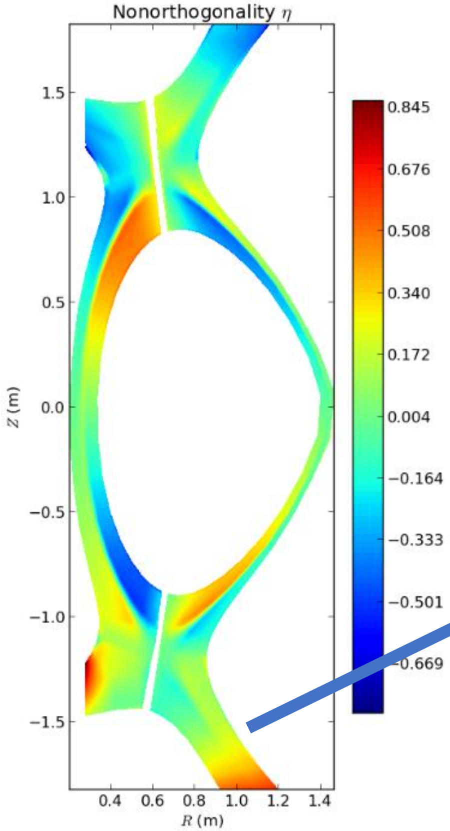


The 3D HW on a slab geometry

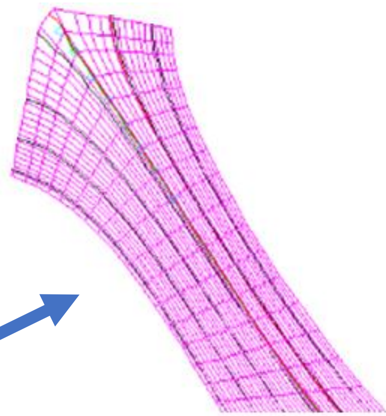


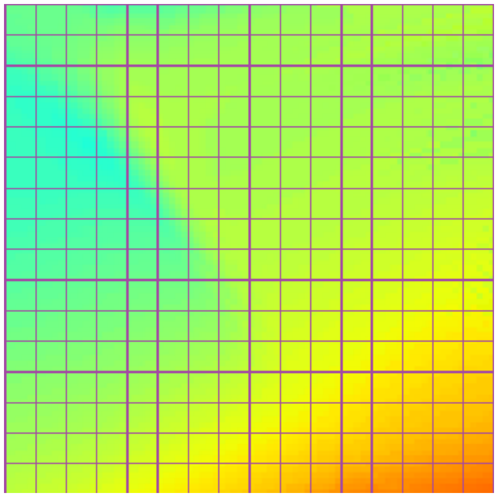
- 1024 x 8 x 1024, 64 bit (max on 1 GPU!)
- Trained on 2D mHW single channel
- $\alpha=1$, $k=1$, $\mu_n=\mu_\zeta = 10^{-6}$!
- inference on 8 planes using y direction as batch size (8 x 1024 x 1024)
- on Farscape Github and weights on Zenodo
- writing paper
- pip install styles

Mapping BOUT++ divertor to StyleGAN



Simple element by element mapping

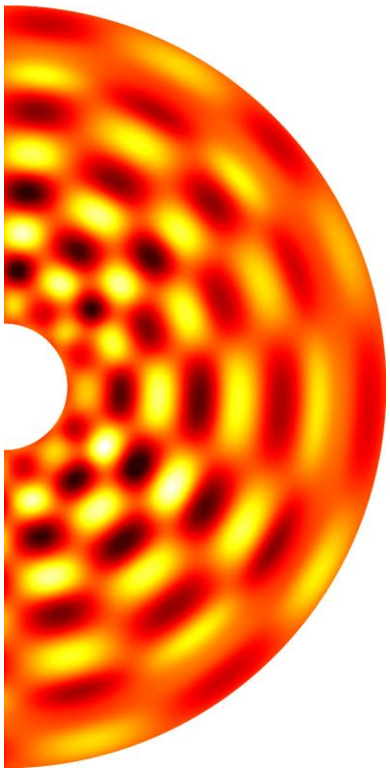




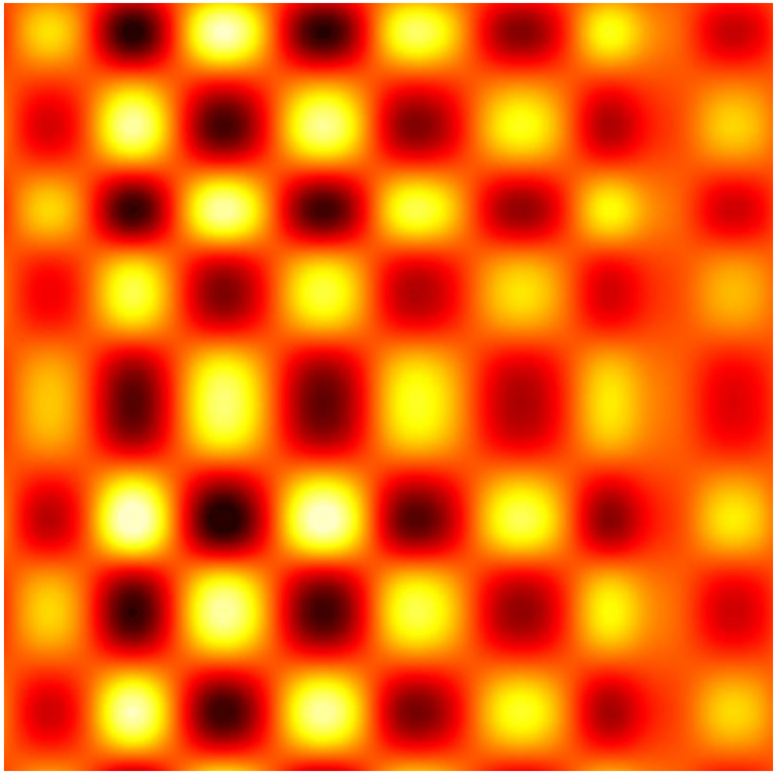
The GAN does NOT care about the physical shape!

Leddy's thesis "Integrated modelling of tokamak core and edge plasma turbulence" (2016)

Mapping curved geometries



DNS on highly curved surfaces used for training StyleGAN



data

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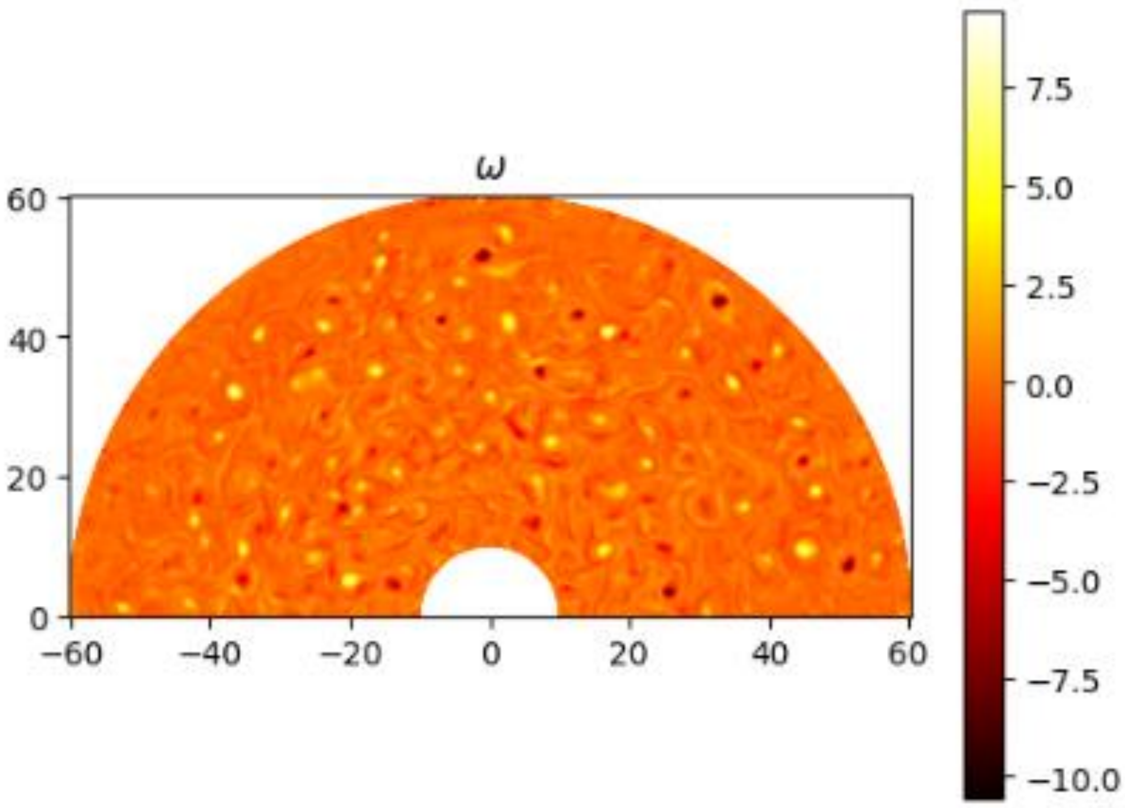
Inference from StyleGAN after training on curved geometry



Questions?

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