Introduction To Data Driven Modeling and Machine Learning (for Fluids)

Steve Brunton
University of Washington

Introduction To Data Driven Modeling and Machine Learning (For Fluids)

Nathan Kutz

Bing Brunton

Josh Proctor

Brian Polagye

Sam Taira

Bernd Noack

JC Loiseau

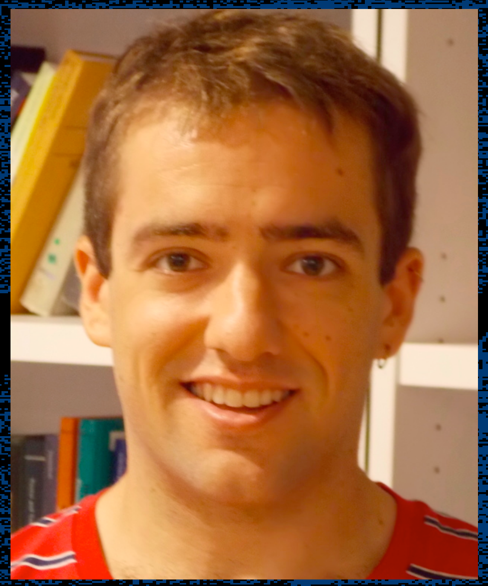
Eurika Kaiser

Bethany Lusch

Krithika Manohar

Isabel Scherl

Sam Rudy



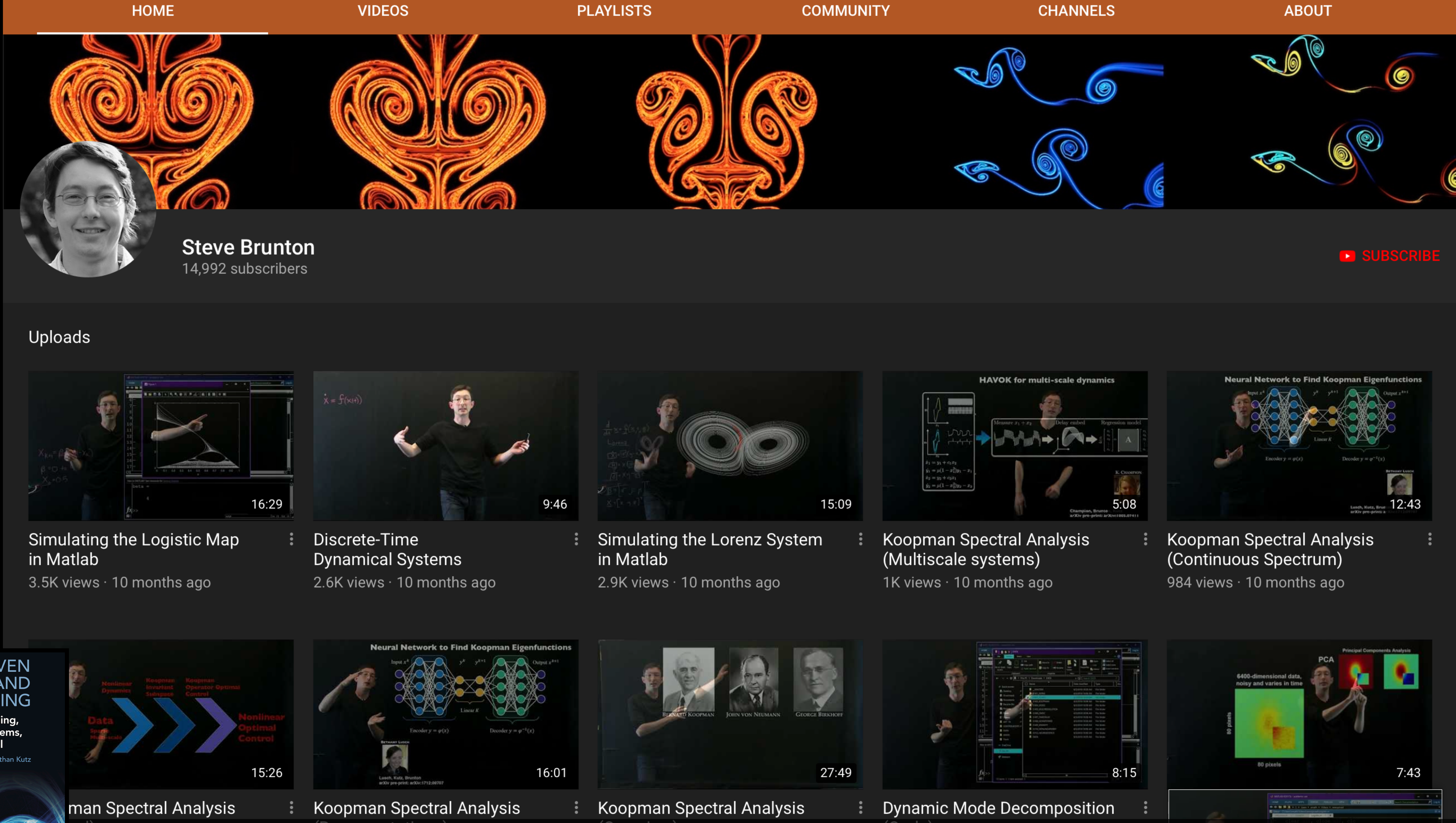
Jared Callaham

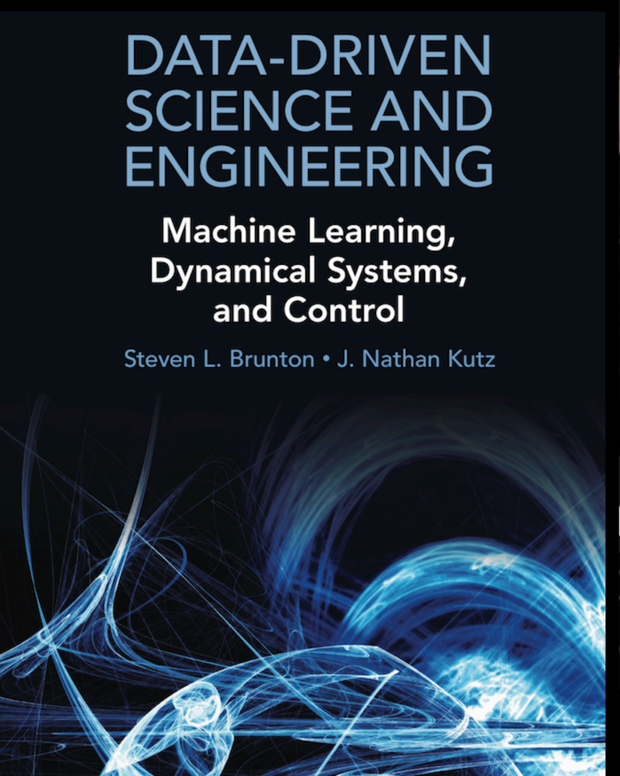
Ben Erichson

Kathleen Champion

SCIENCE TO SHAPE THE FUTURE OF THE ARMY
ARMY RESEARCH OFFICE
1951
AIR FORCE RESEARCH LABORATORY
AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
UNITED STATES AIR FORCE
DARPA
BOEING

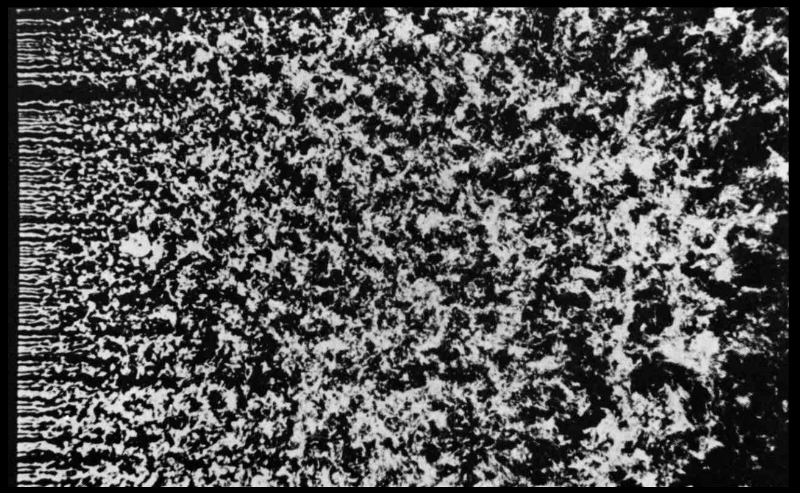
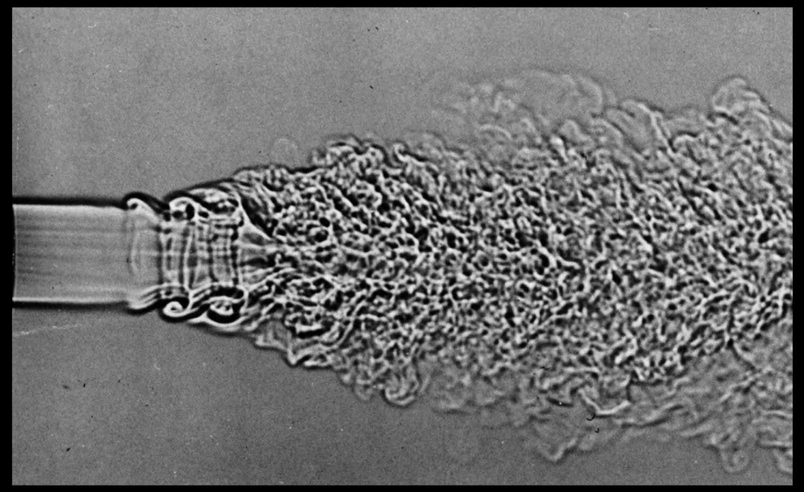
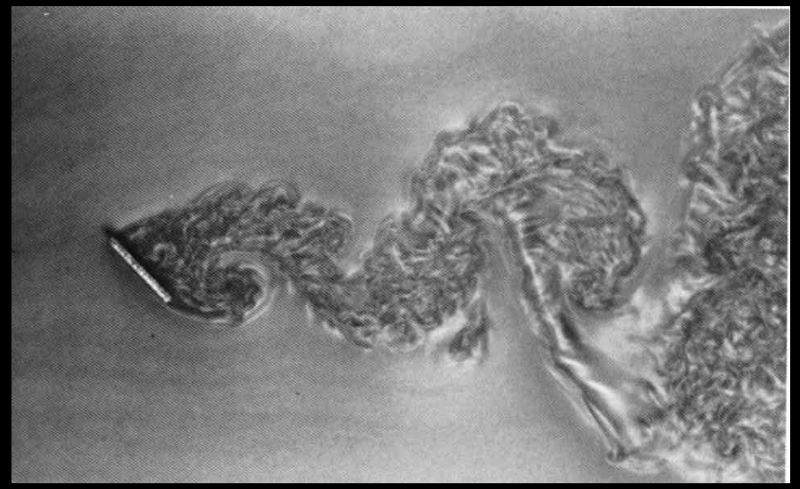
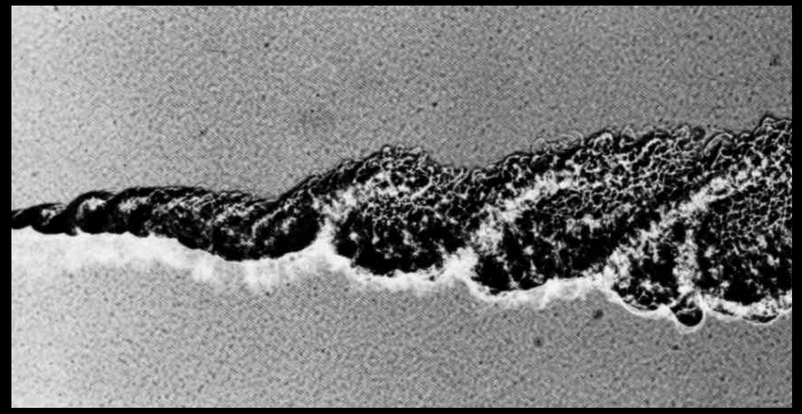
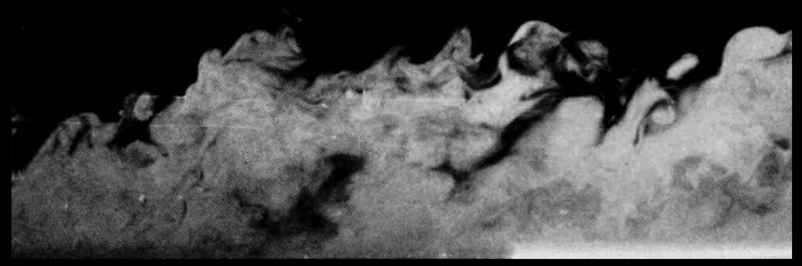
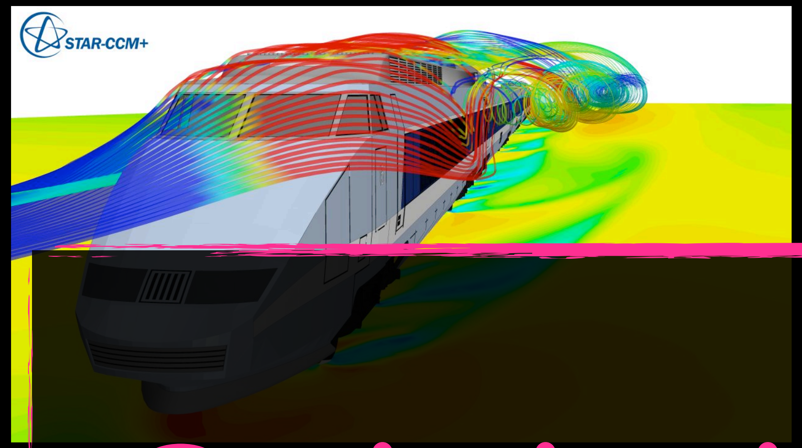
VIDEOS





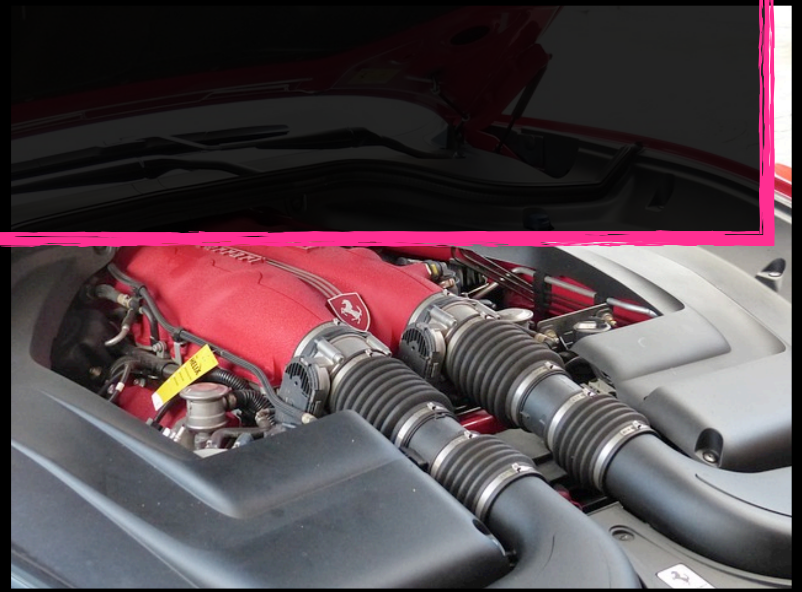
NEW BOOK: DATABOOKUW.COM/DATABOOK.PDF

Machine Learning: Models from Data via Optimization

Optimization problems:

- High-dimensional
- Nonlinear
- Non-convex
- Multiscale

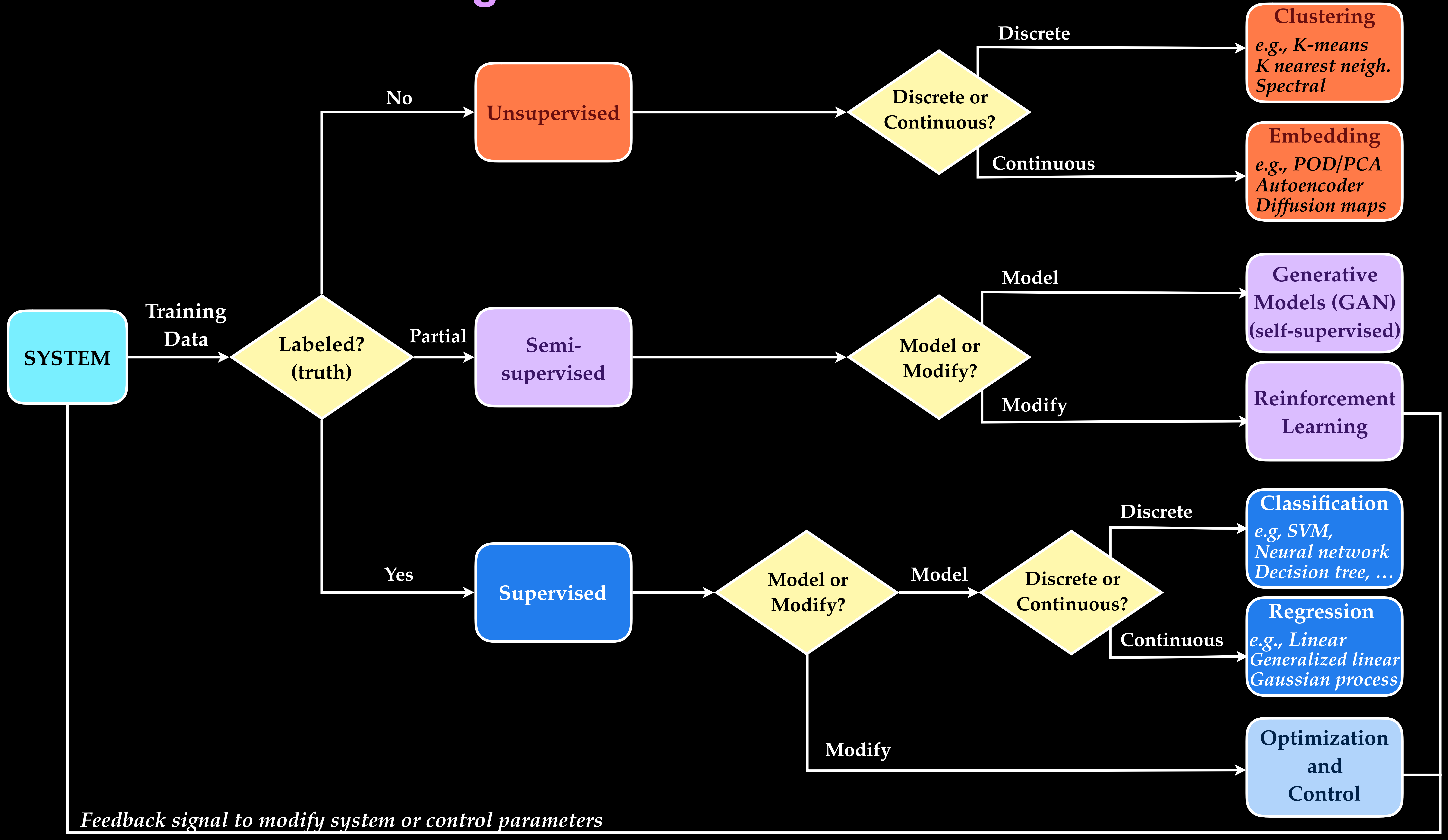
Fluid dynamics tasks:

- Reduction
- Modeling
- Control
- Sensing
- Closure

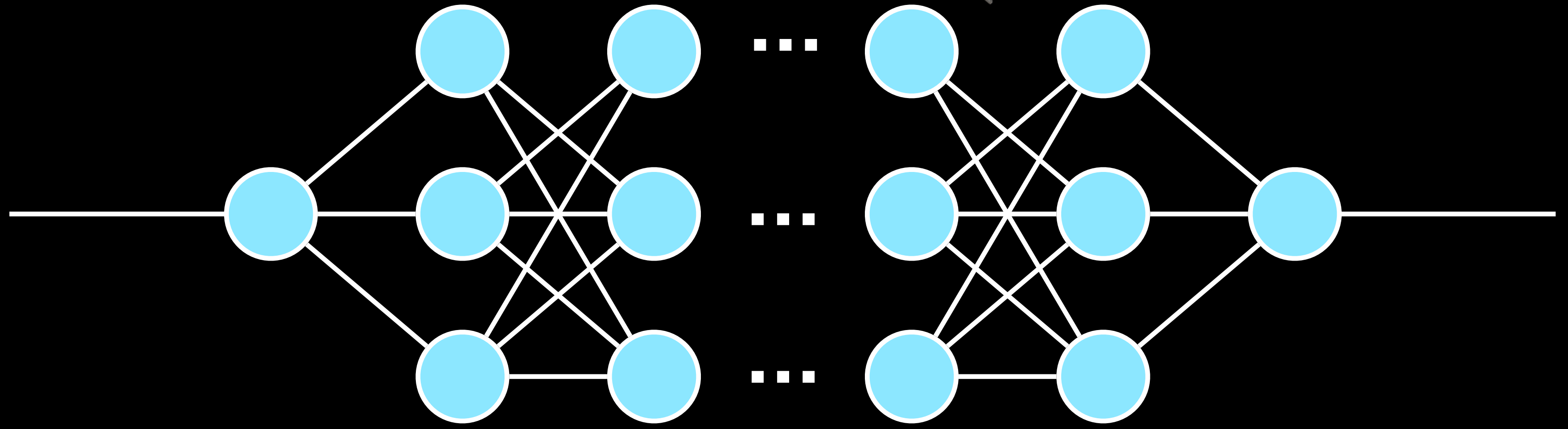
ANY SUFFICIENTLY ADVANCED TECHNOLOGY
IS INDISTINGUISHABLE FROM MAGIC.

Arthur C. Clarke

Types of Machine Learning



Why Now?

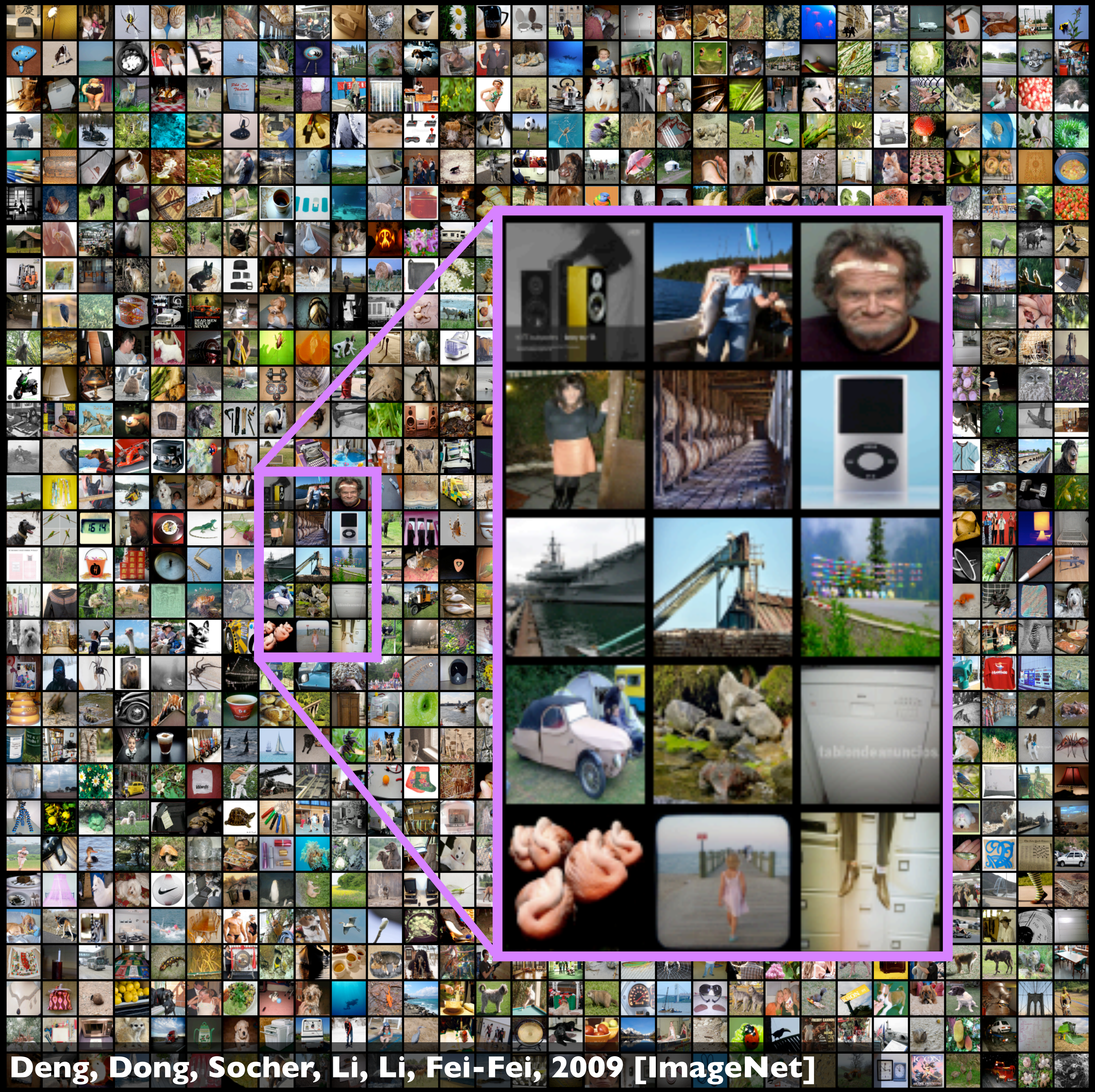


TensorFlow

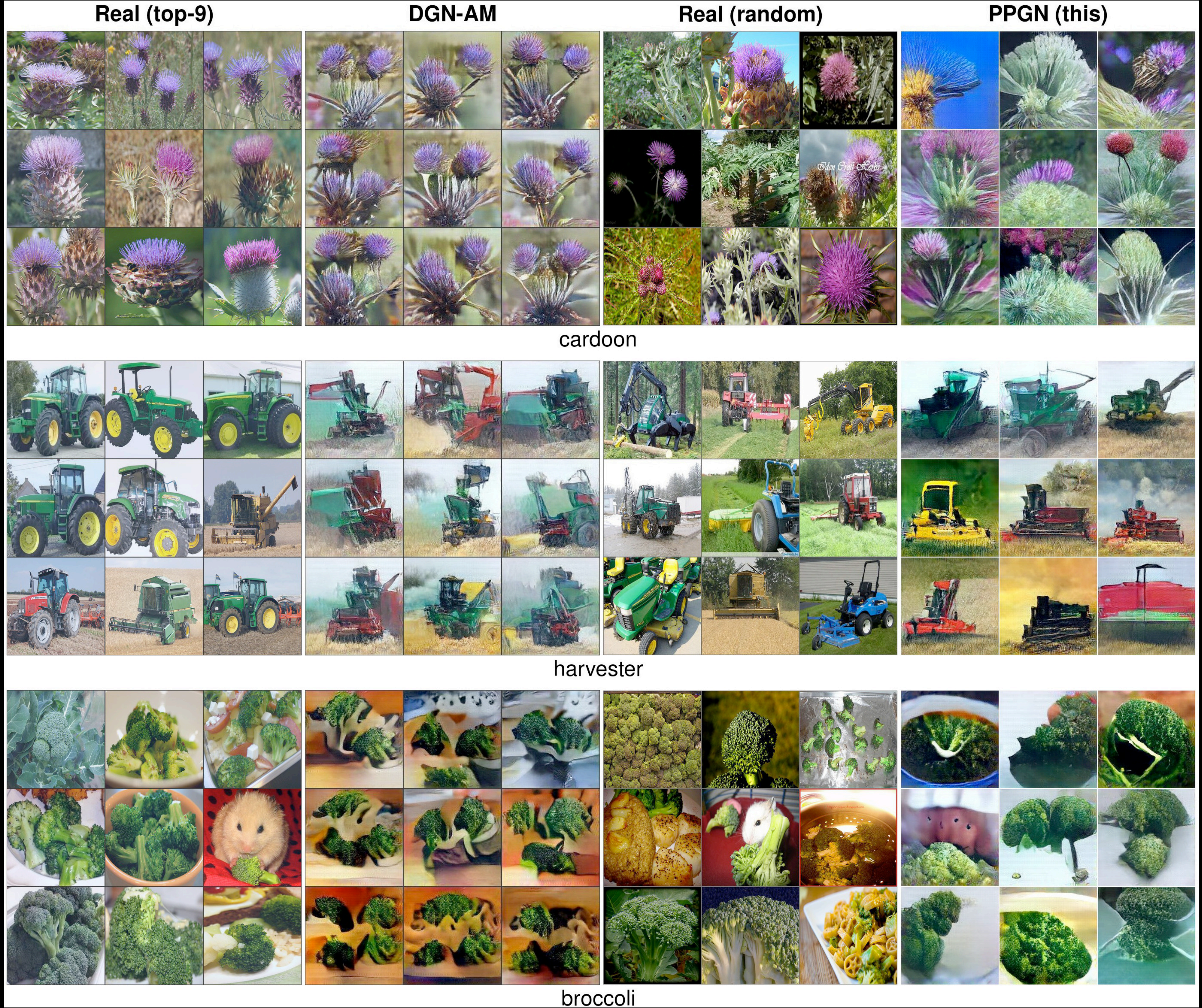
PyTorch

K Keras

Image Classification



Deng, Dong, Socher, Li, Li, Fei-Fei, 2009 [ImageNet]


Real (top-9)
DGN-AM
Real (random)
PPGN (this)
cardoon
harvester
broccoli

https://www.freecodecamp.org/news/chihuahua-or-muffin-my-search-for-the-best-computer-vision-api-cbda4d6b425d/

Source: @teenybiscuit/Twitter


FAIRPLEX
FAIRPLEX
FAIRPLEX
6:16:34 05/06/2015

There is a need for INTERPRETABLE and GENERALIZABLE Machine Learning

$F = ma$

There is a need for

INTERPRETABLE and GENERALIZABLE

Machine Learning

EVERYTHING SHOULD BE MADE

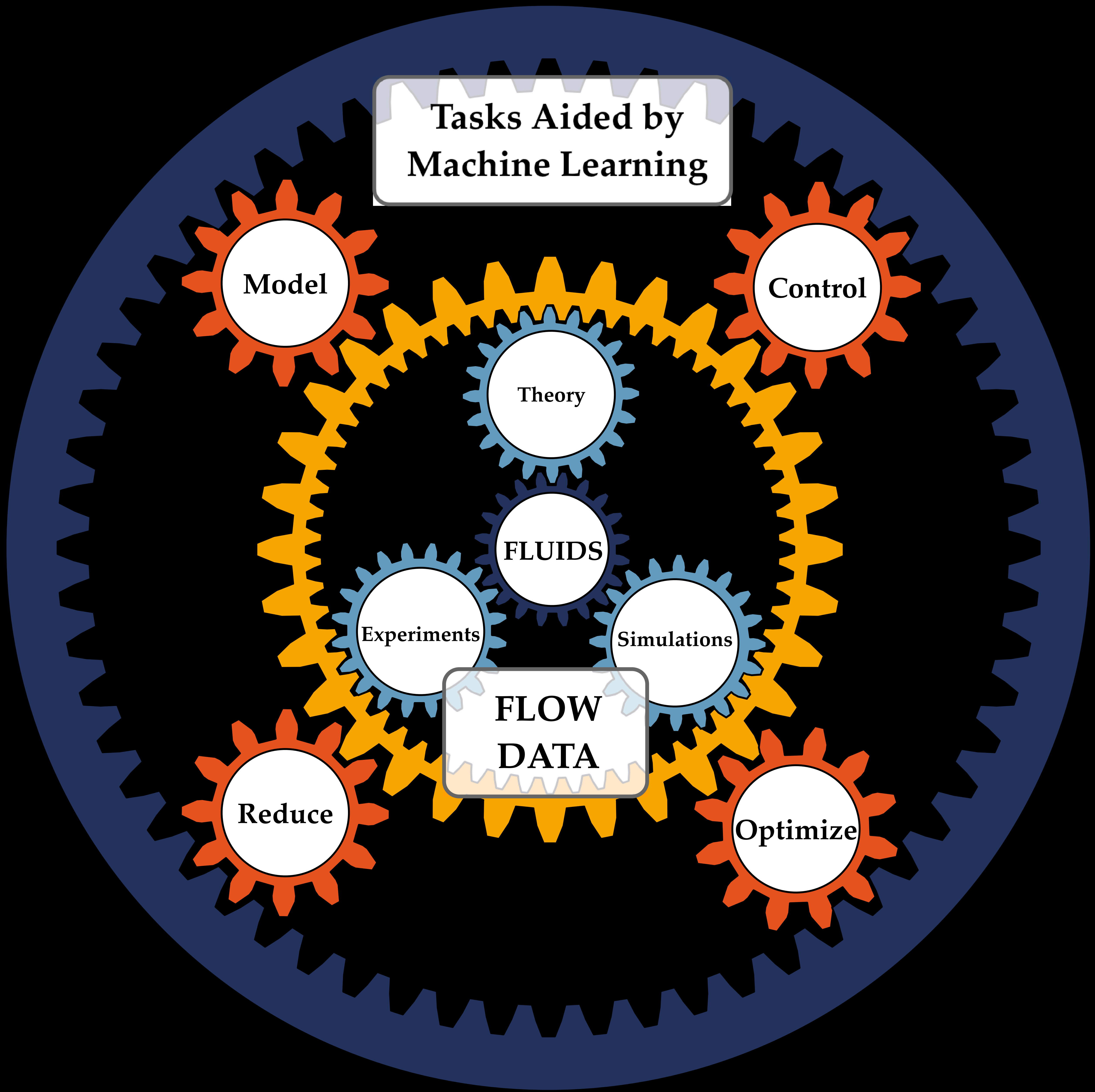
AS SIMPLE AS POSSIBLE,

BUT NOT SIMPLER.

Albert Einstein

There is a need for INTERPRETABLE and GENERALIZABLE Machine Learning

- SPARSE
- LOW-DIMENSIONAL
- ROBUST



Machine Learning for Fluid Mechanics

Steven L. Brunton,[1] Bernd R. Noack,[2] and Petros Koumoutsakos[3,4]

Keywords

machine learning, data-driven modeling, optimization, control

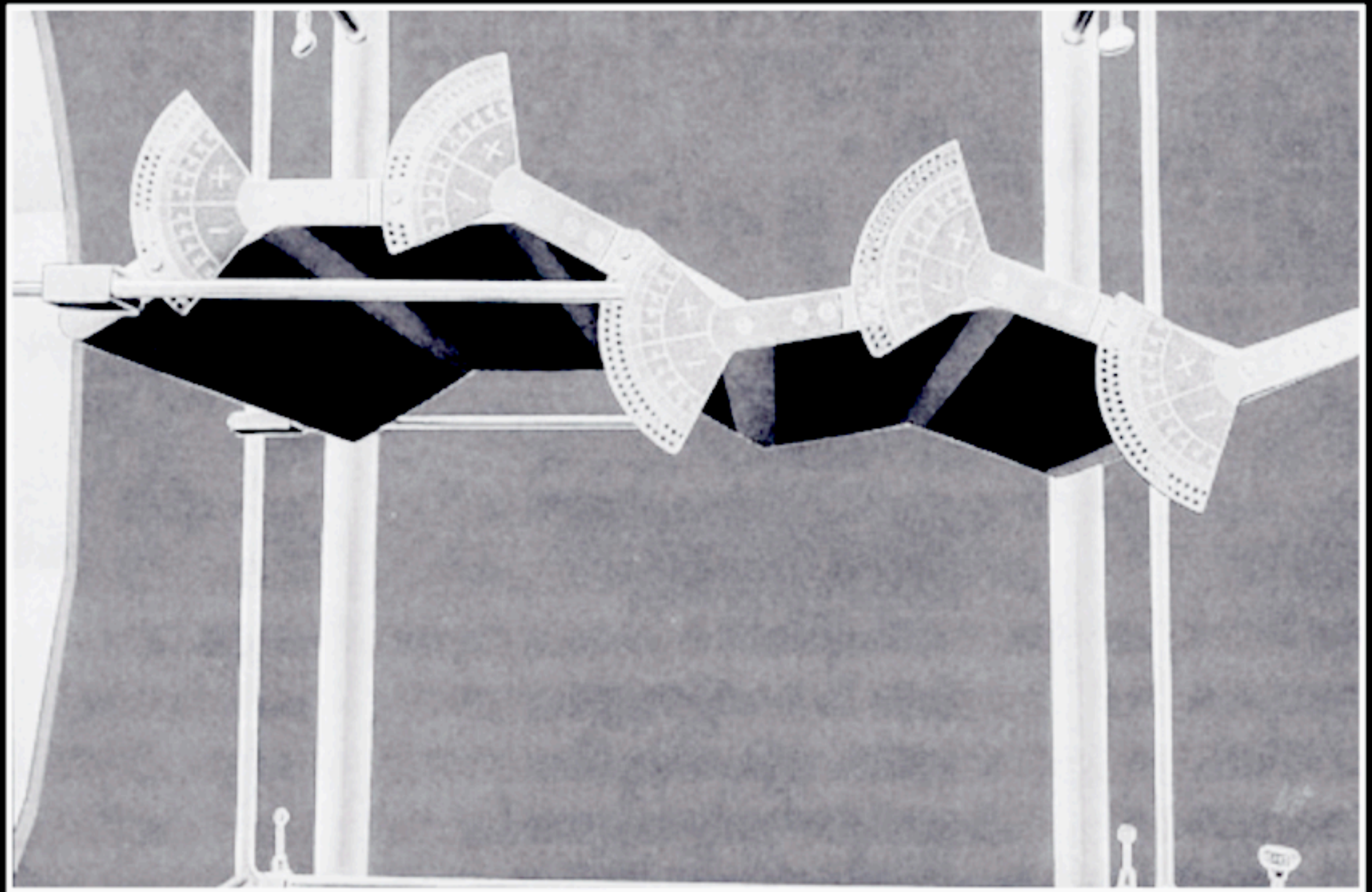
Abstract

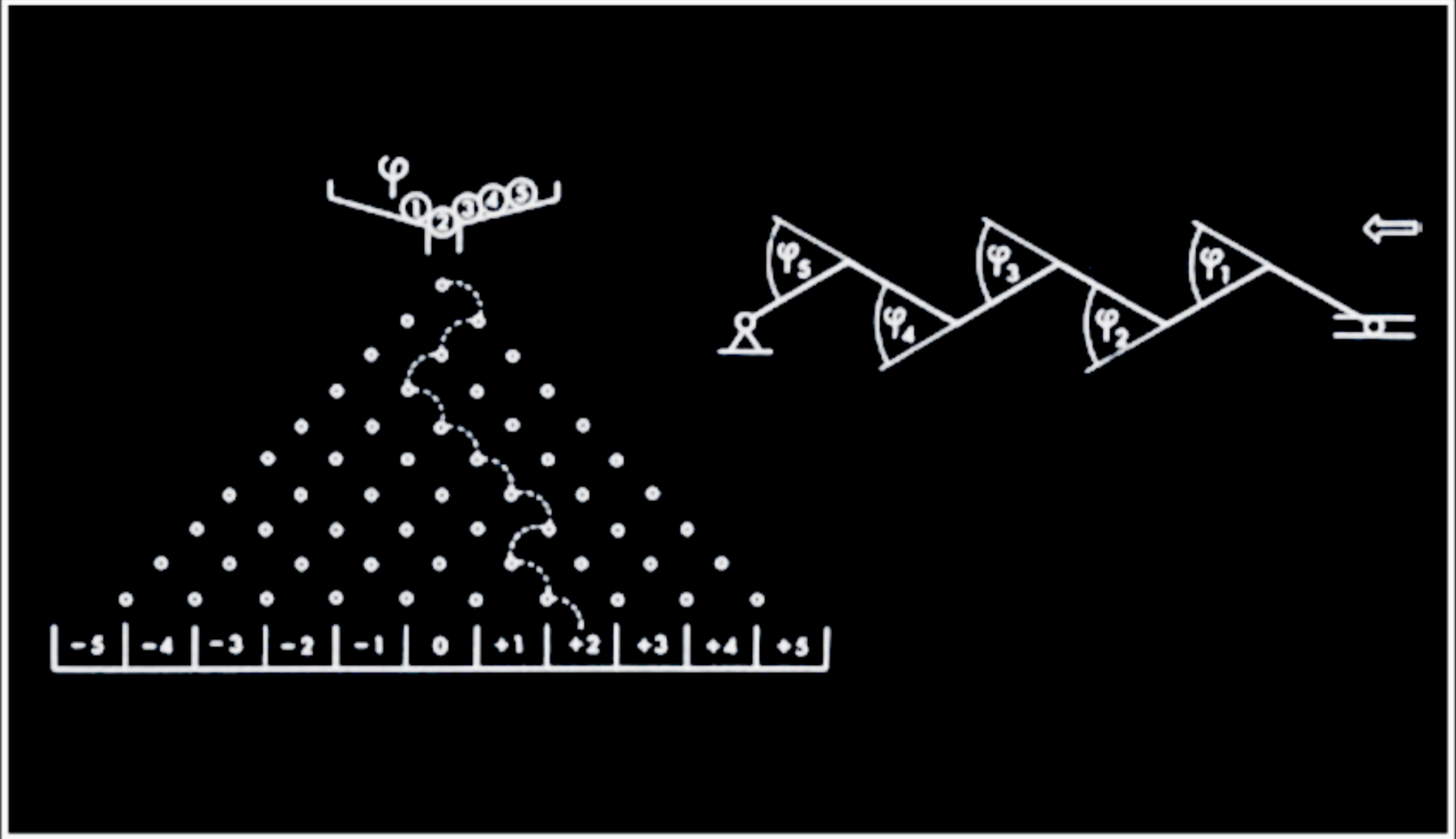
The field of fluid mechanics is rapidly advancing, driven by unprecedented volumes of data from experiments, field measurements, and large-scale simulations at multiple spatiotemporal scales. Machine learning presents us with a wealth of techniques to extract information from data that can be translated into knowledge about the underlying fluid mechanics. Moreover, machine learning algorithms can augment domain knowledge and automate tasks related to flow control and optimization. This article presents an overview of past history, current developments, and emerging opportunities of machine learning for fluid mechanics. We outline fundamental machine learning methodologies and discuss their uses for understanding, modeling, optimizing, and controlling fluid flows. The strengths and limitations of these methods are addressed from the perspective of scientific inquiry that links data with modeling, experiments, and simulations. Machine learning provides a powerful information processing framework that can augment, and possibly even transform, current lines of fluid mechanics research and industrial applications.

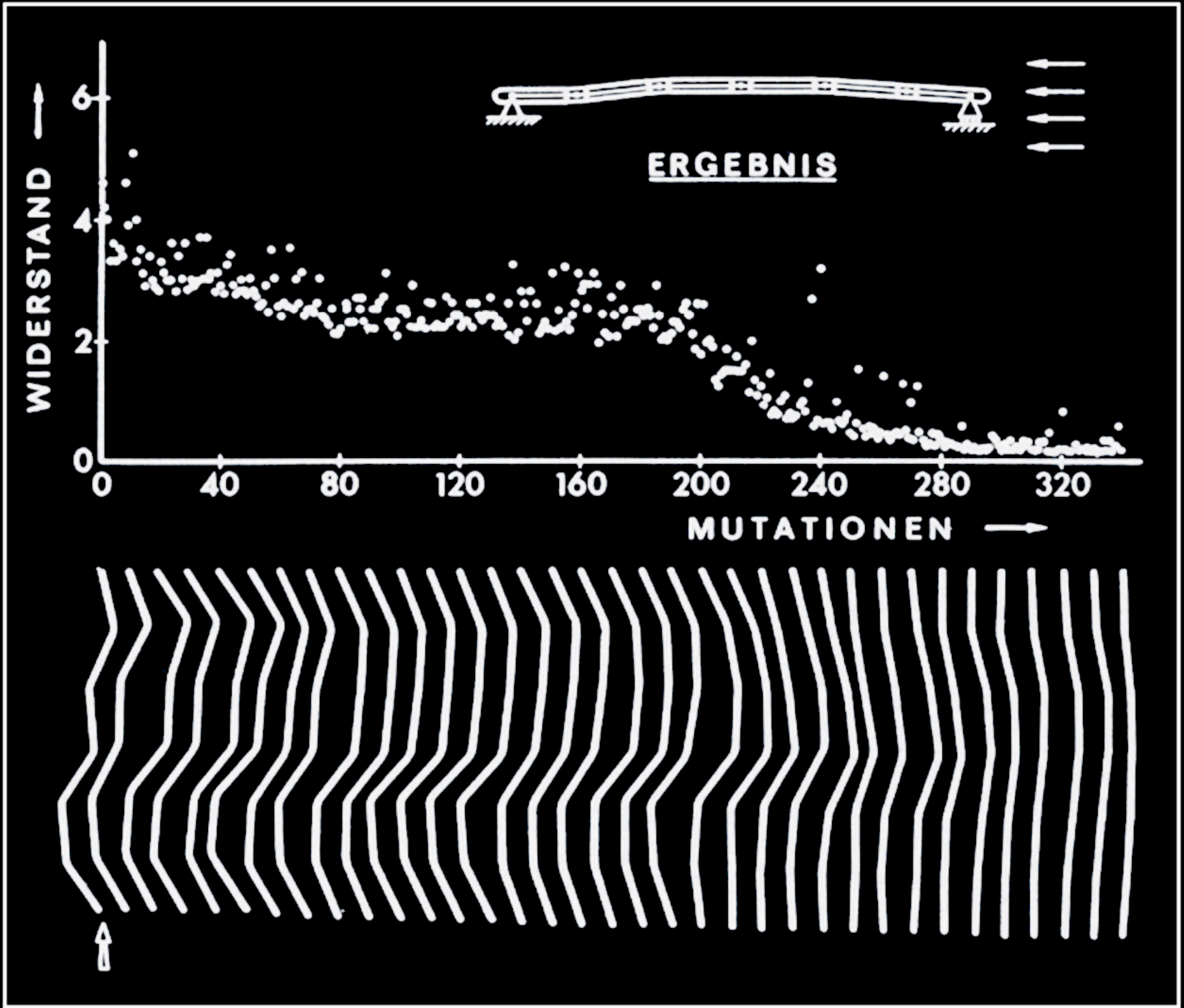
HISTORY

Reichenberg, 1960s-1970s
Schweifel, 1970s

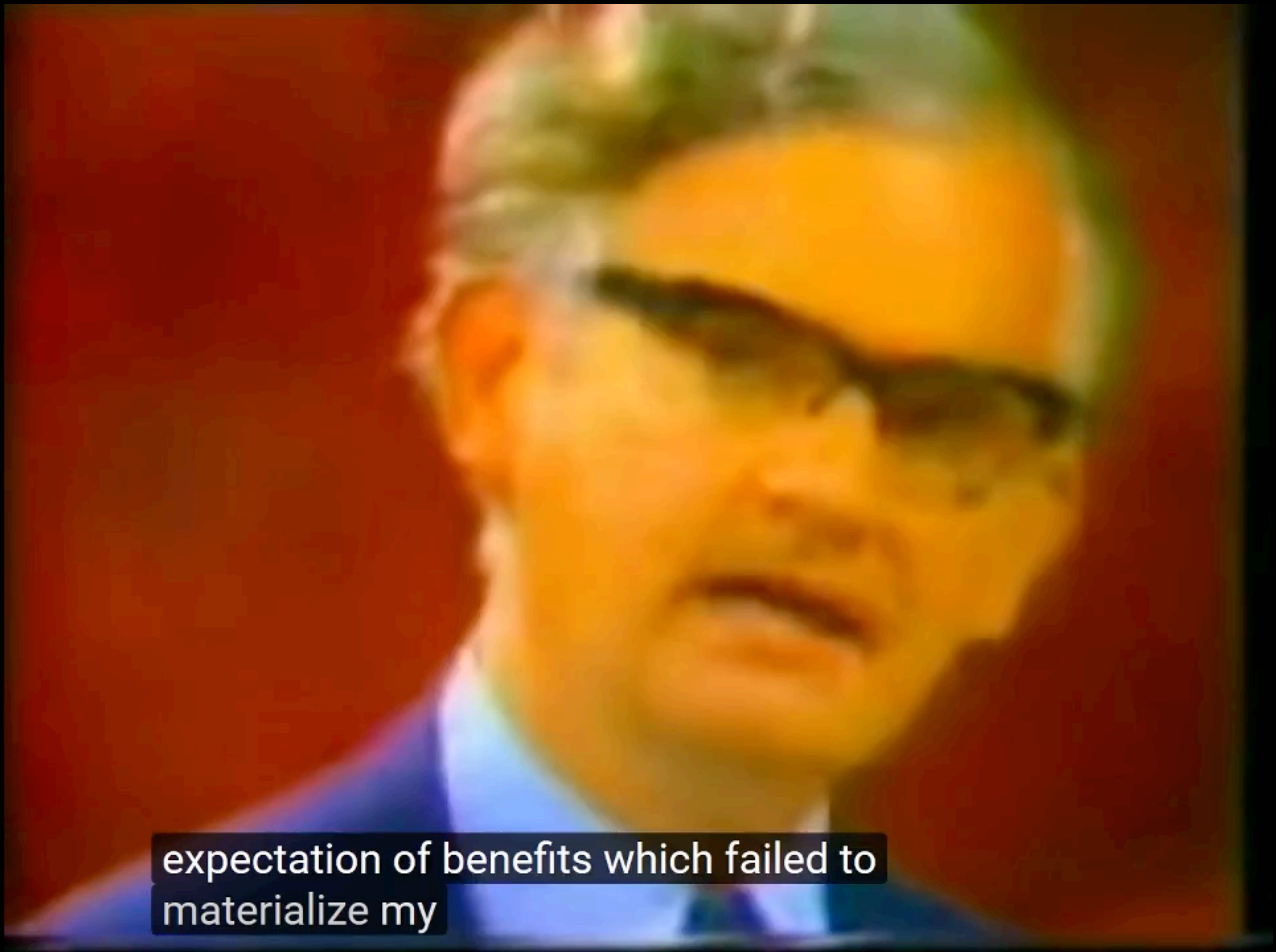
SLB, Noack, Koumoutsakos,
Ann. Rev. Fluid Mech. 2019







Sir Lighthill and the AI Winter (1974)

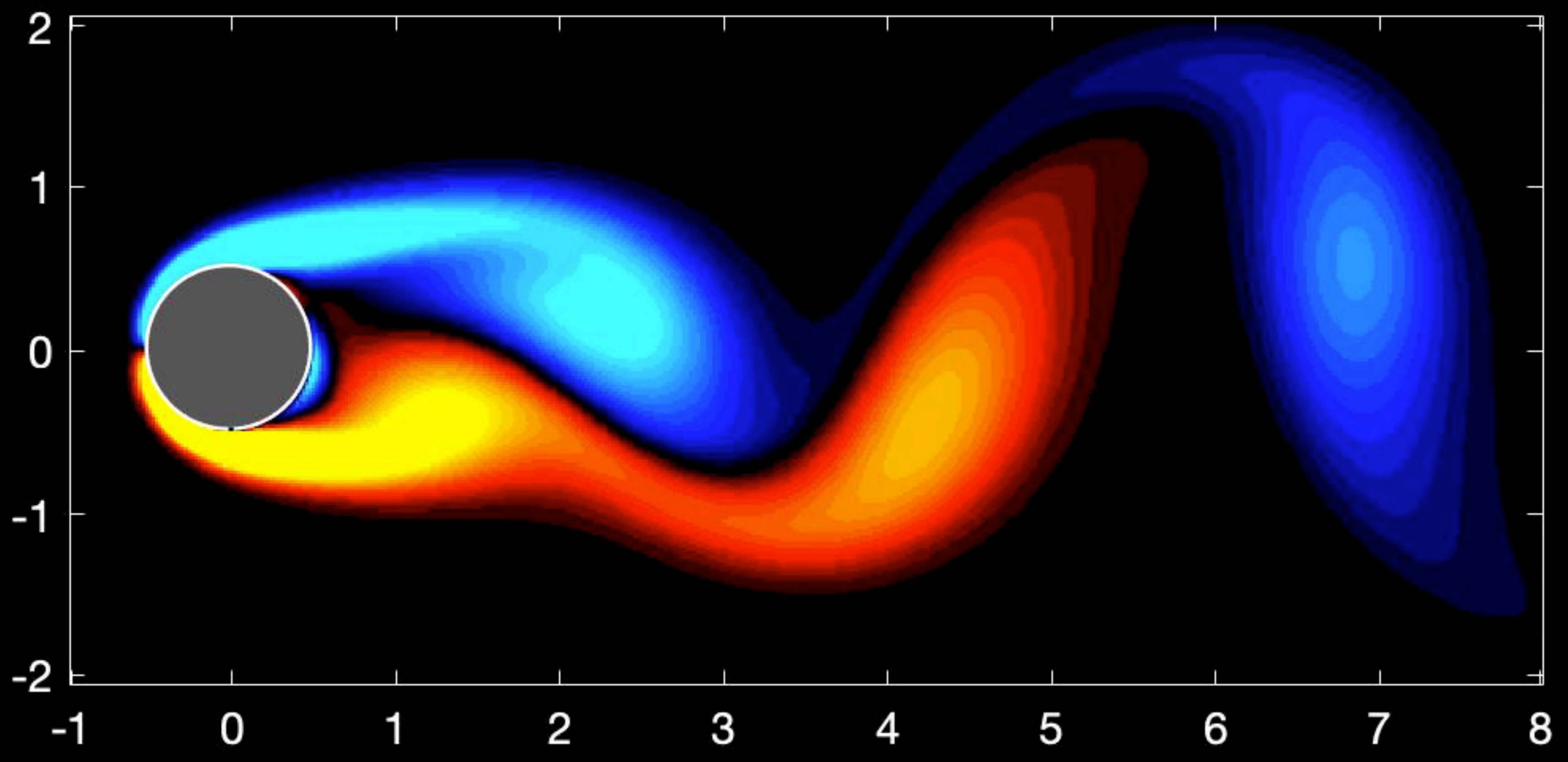


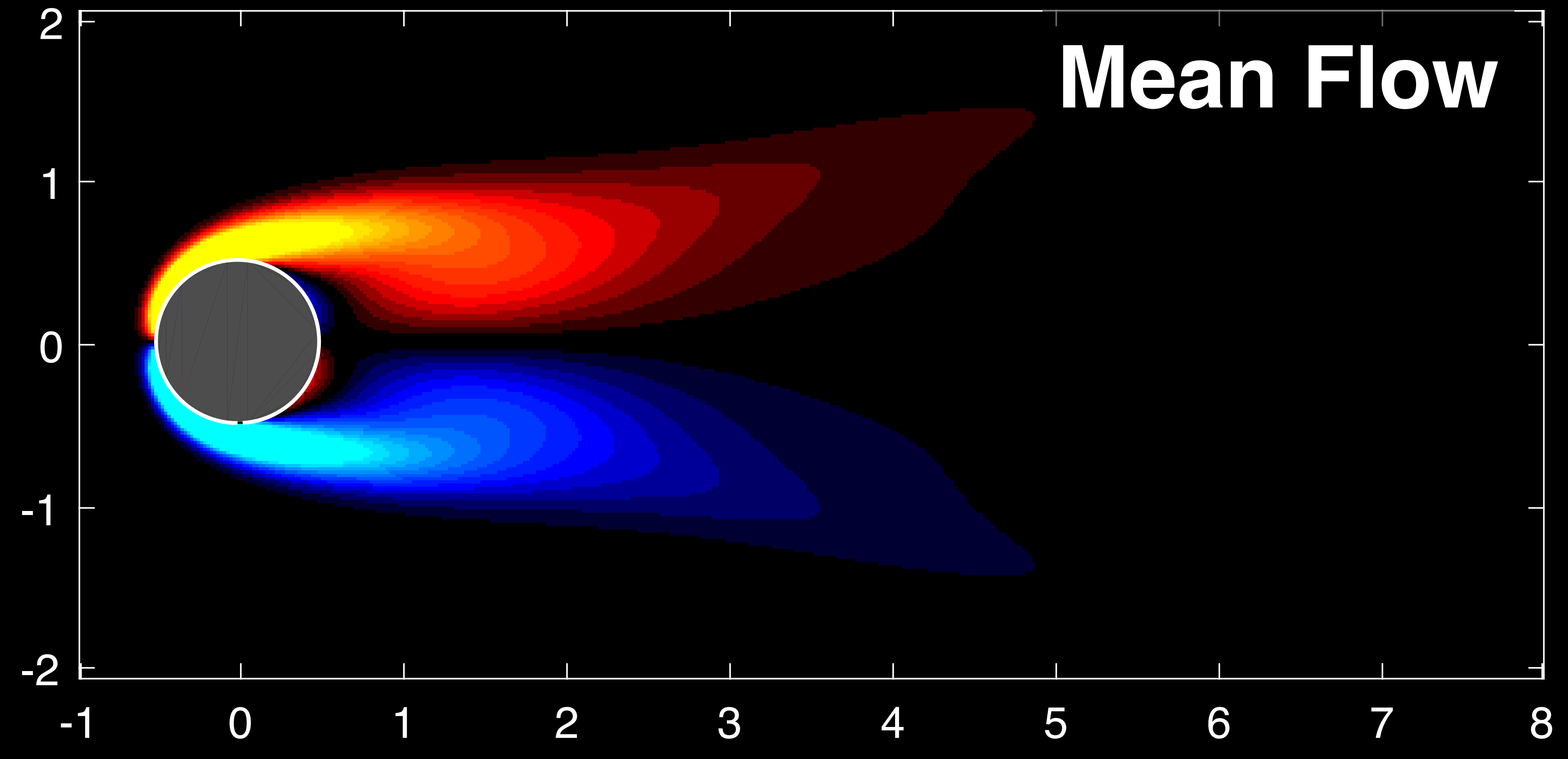
https://www.youtube.com/watch?v=ug0oZAwjC6g

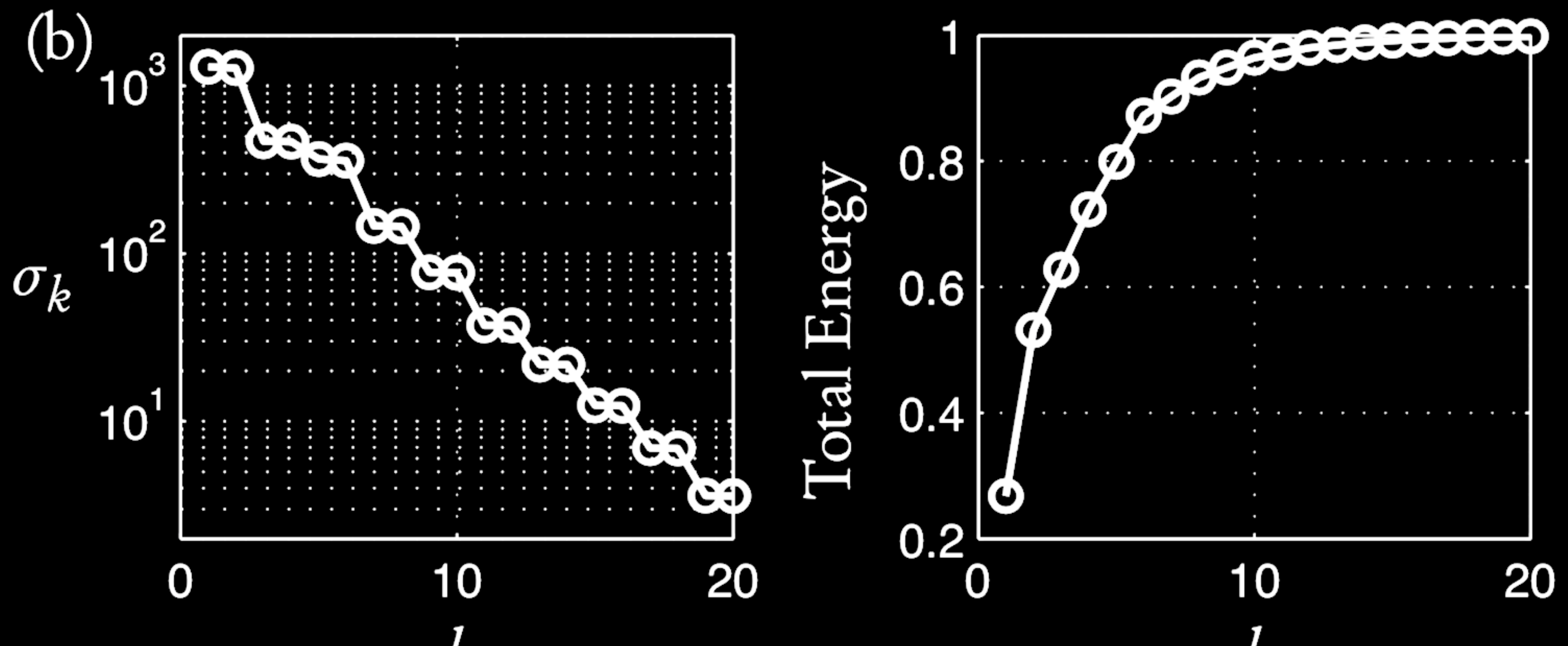
ROBUST PROPER ORTHOGONAL DECOMPOSITION

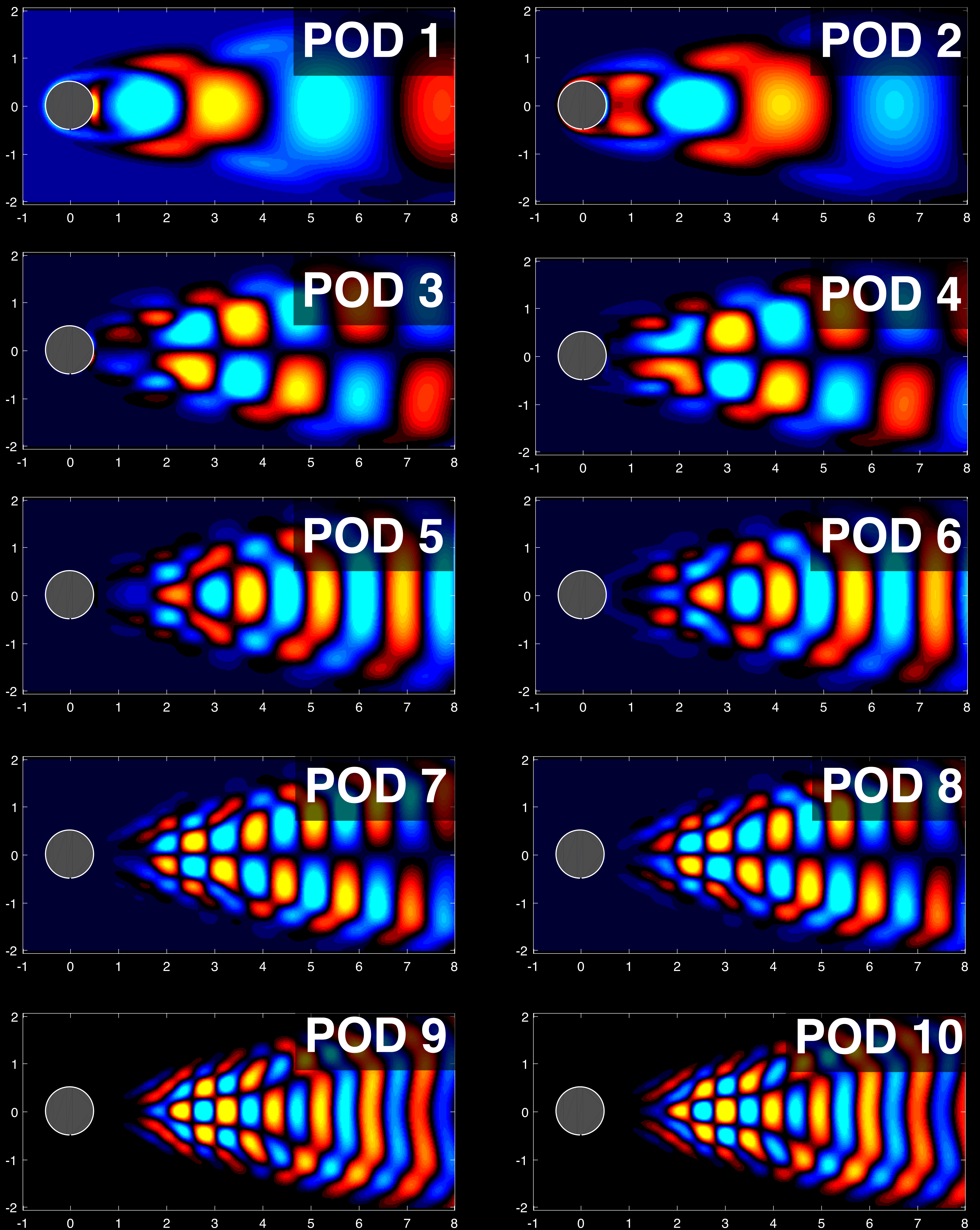
POD/PCA

$$\mathbf{u}(\mathbf{x},t) \approx \bar{\mathbf{u}} + \sum_{k=1}^{r} \boldsymbol{\varphi}_k(\mathbf{x})\mathbf{a}_k(t)$$

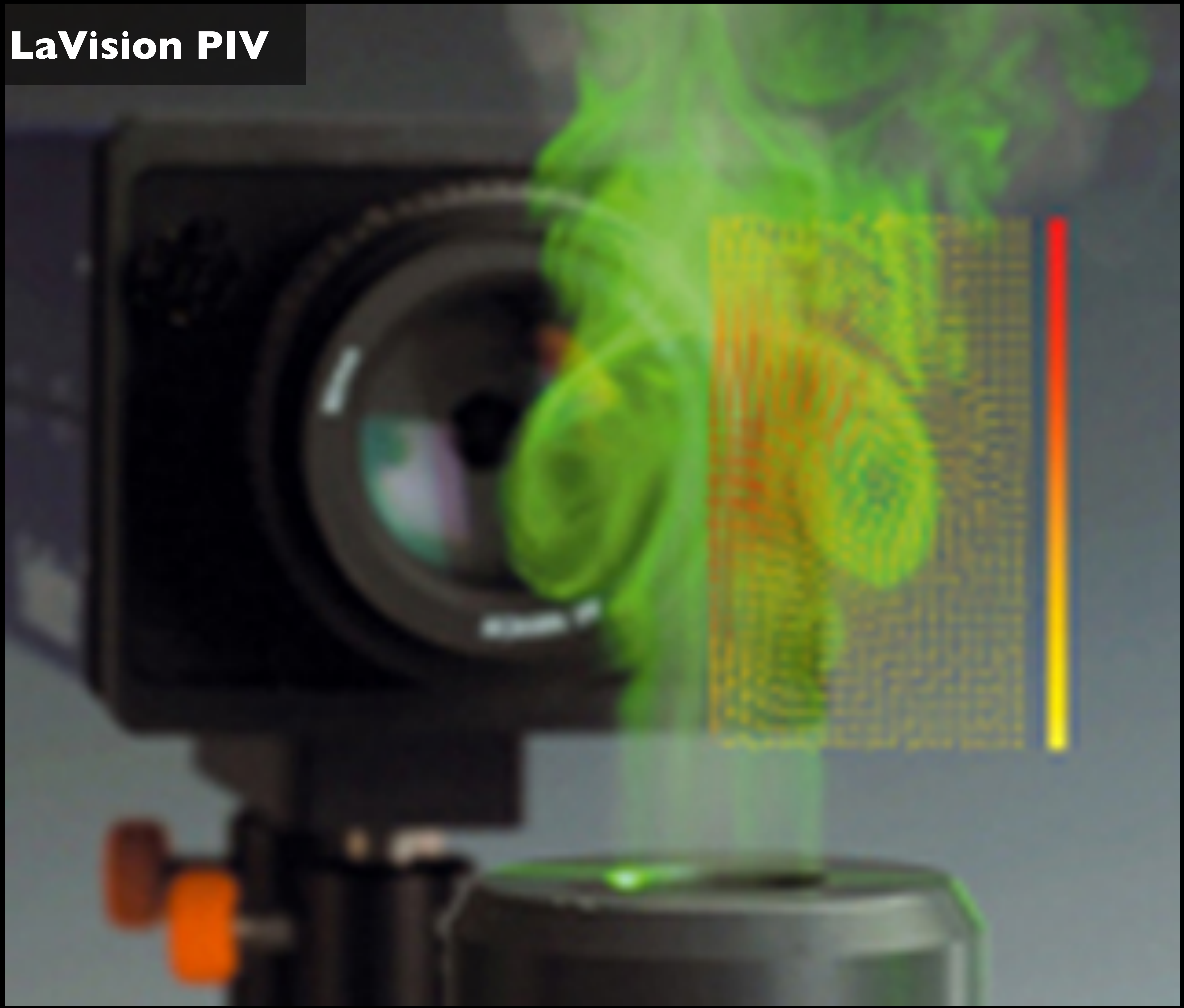




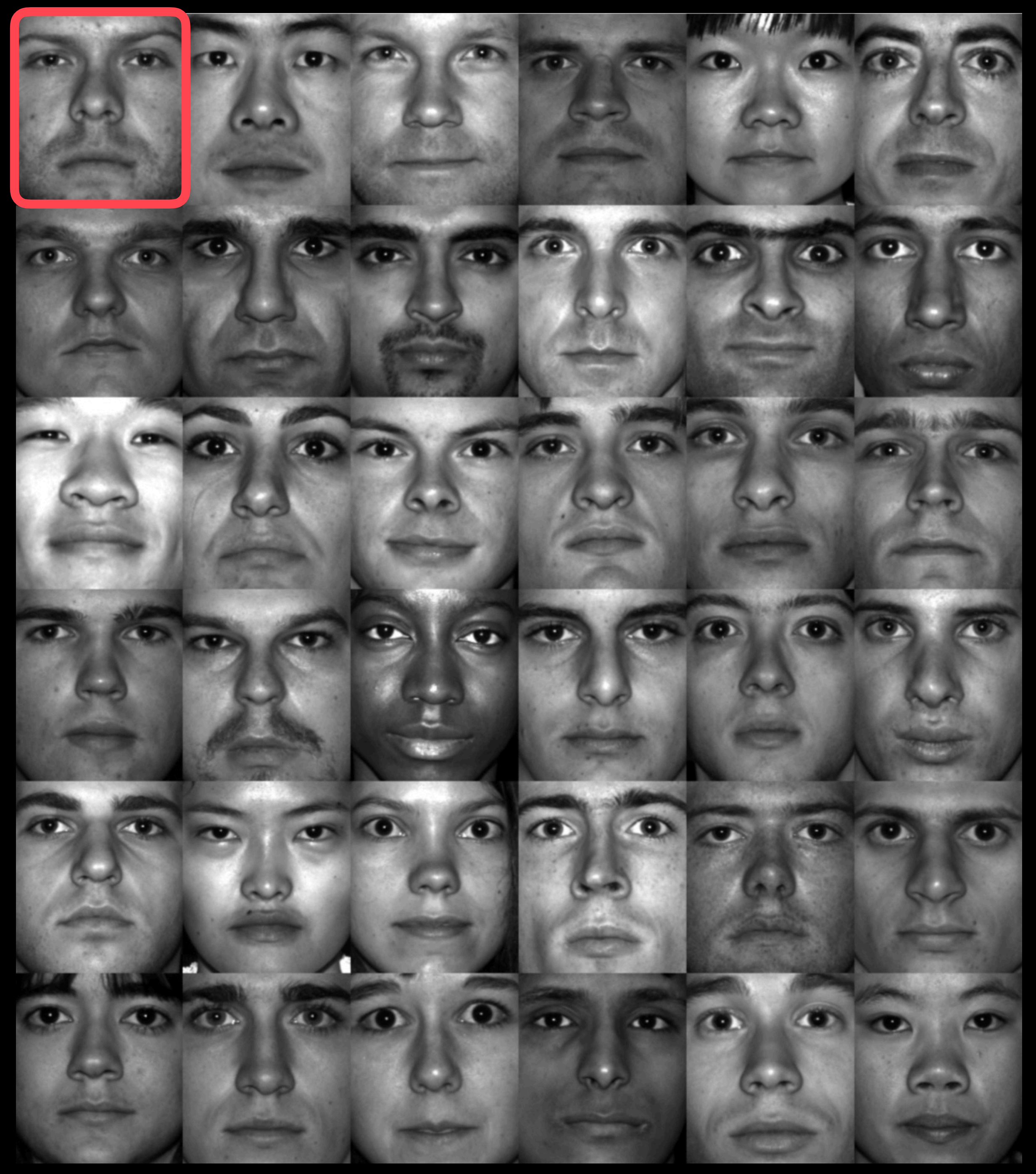




Particle Image Velocimetry (PIV)



ROBUST STATISTICS (RPCA)



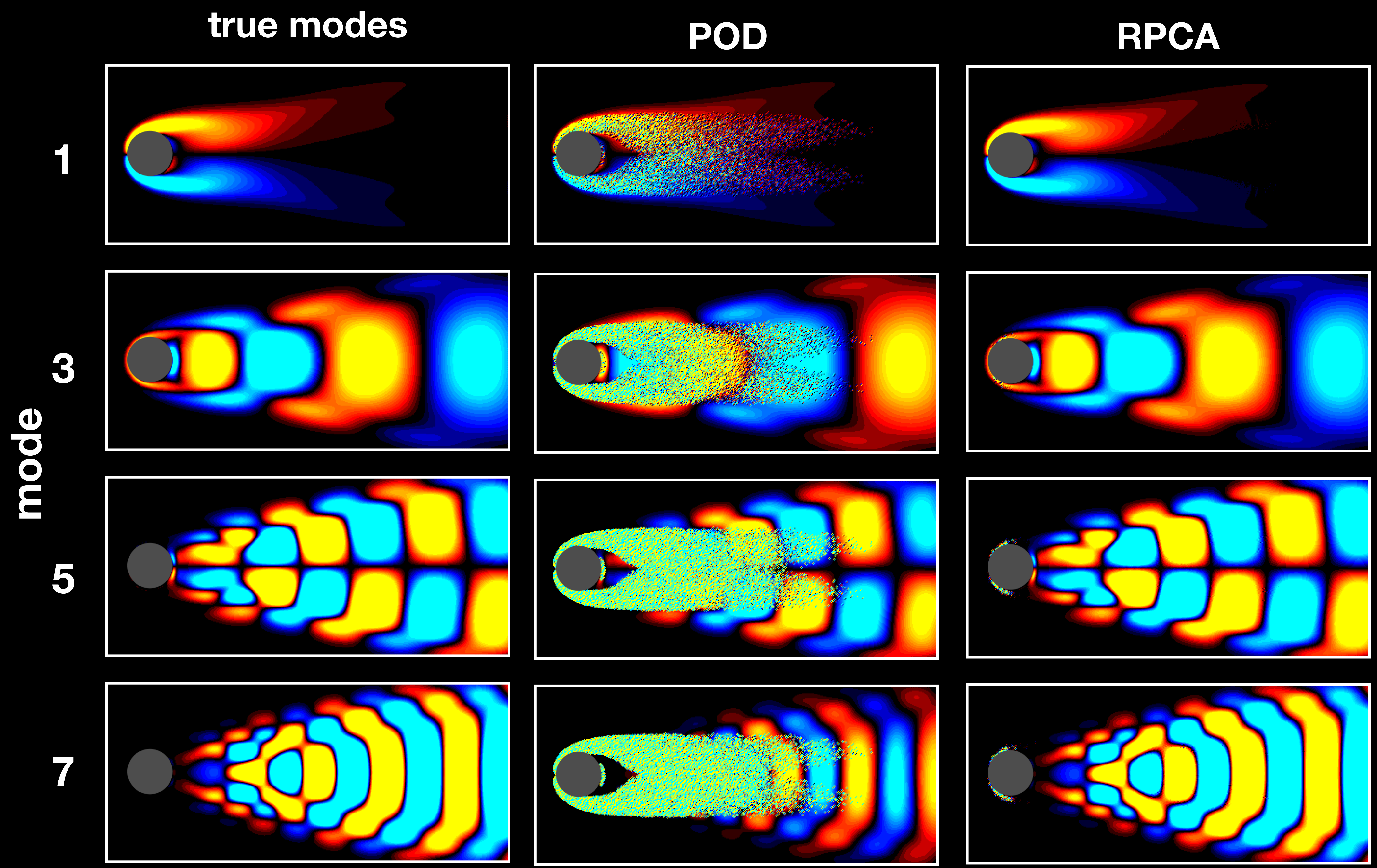
Candes *et al.*, *J. ACM*, 2011

$$\min_{\mathbf{L},\mathbf{S}} \textbf{rank}(\mathbf{L}) + \|\mathbf{S}\|_0 \quad \textbf{subject to} \quad \mathbf{L} + \mathbf{S} = \mathbf{X}$$

Convex Relaxation

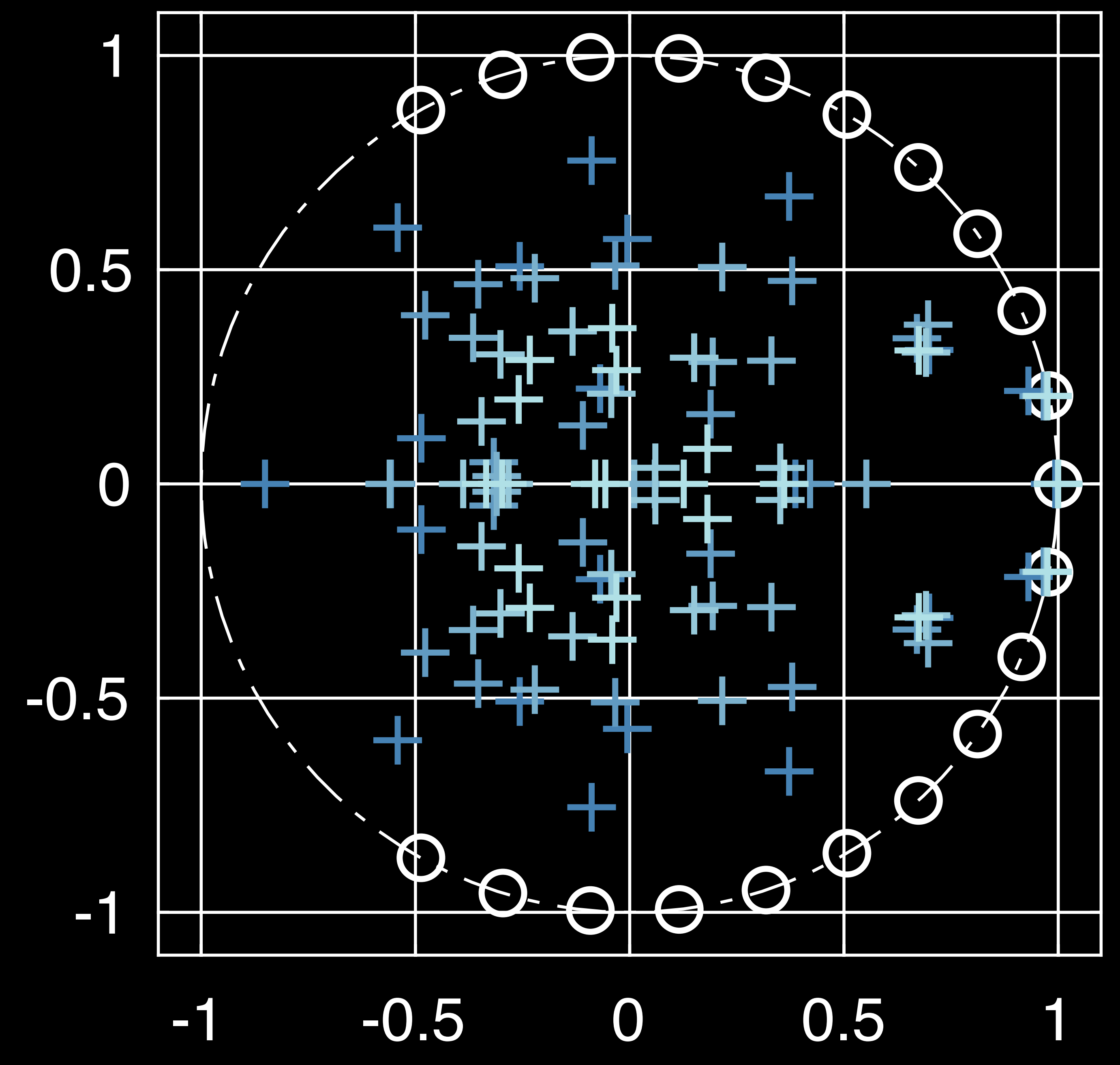
$$\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda_0\|\mathbf{S}\|_1 \quad \textbf{subject to} \quad \mathbf{L} + \mathbf{S} = \mathbf{X}$$

Candes *et al.*, *J. ACM*, 2011
Scherl *et al.*, arXiv:1905.07062, 2019

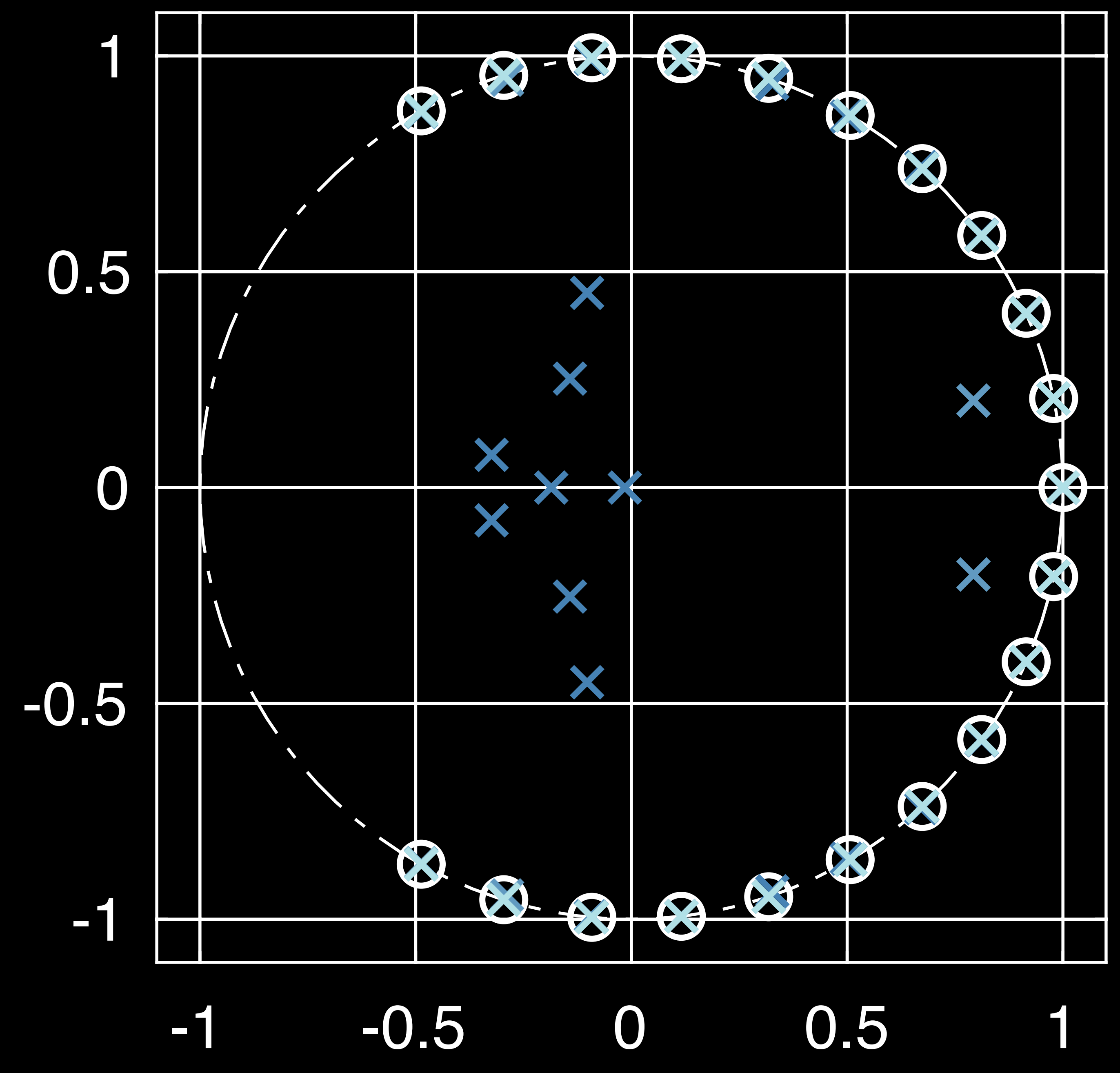


Candes *et al.*, *J. ACM*, 2011
Scherl *et al.*, arXiv:1905.07062, 2019

DMD Before

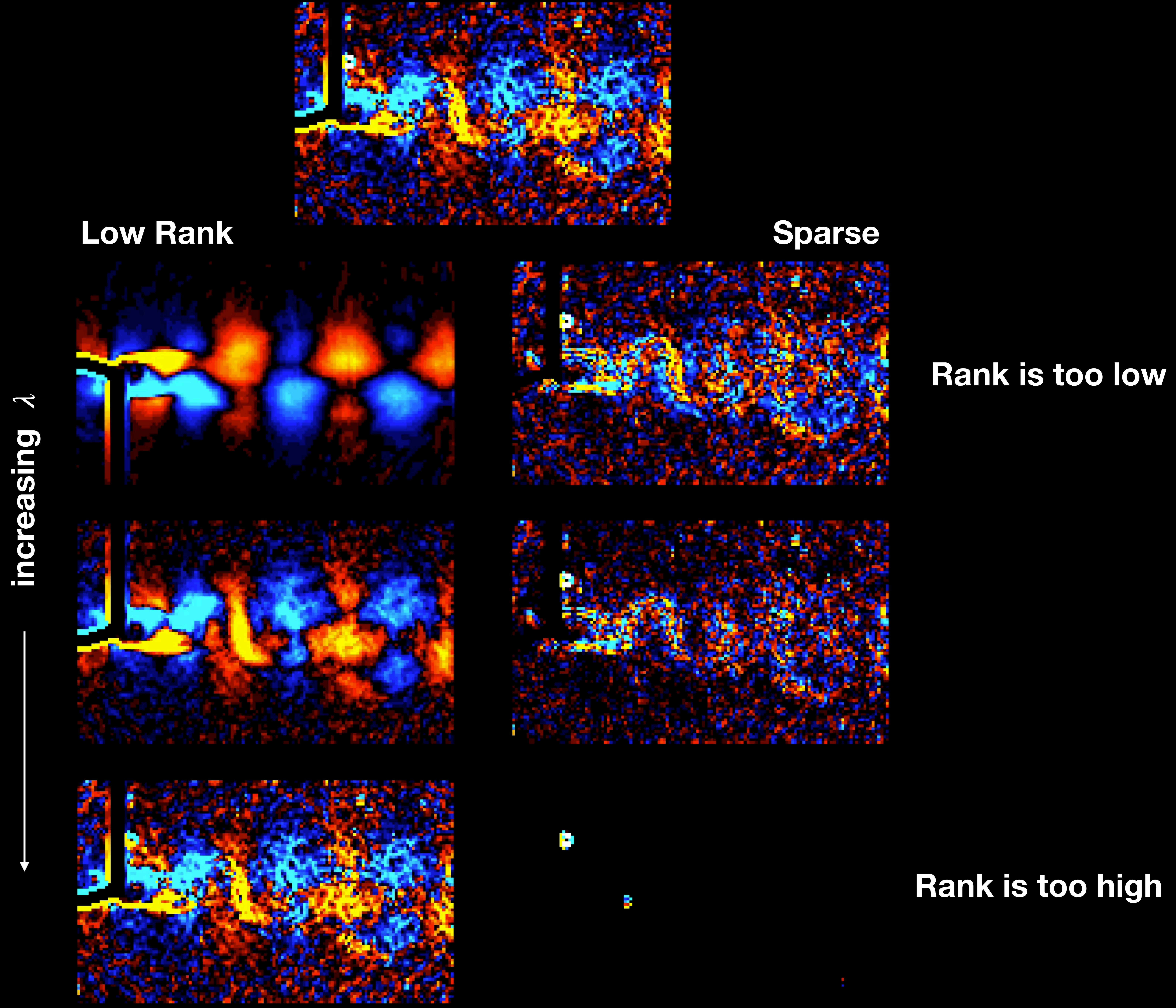


DMD After RPCA



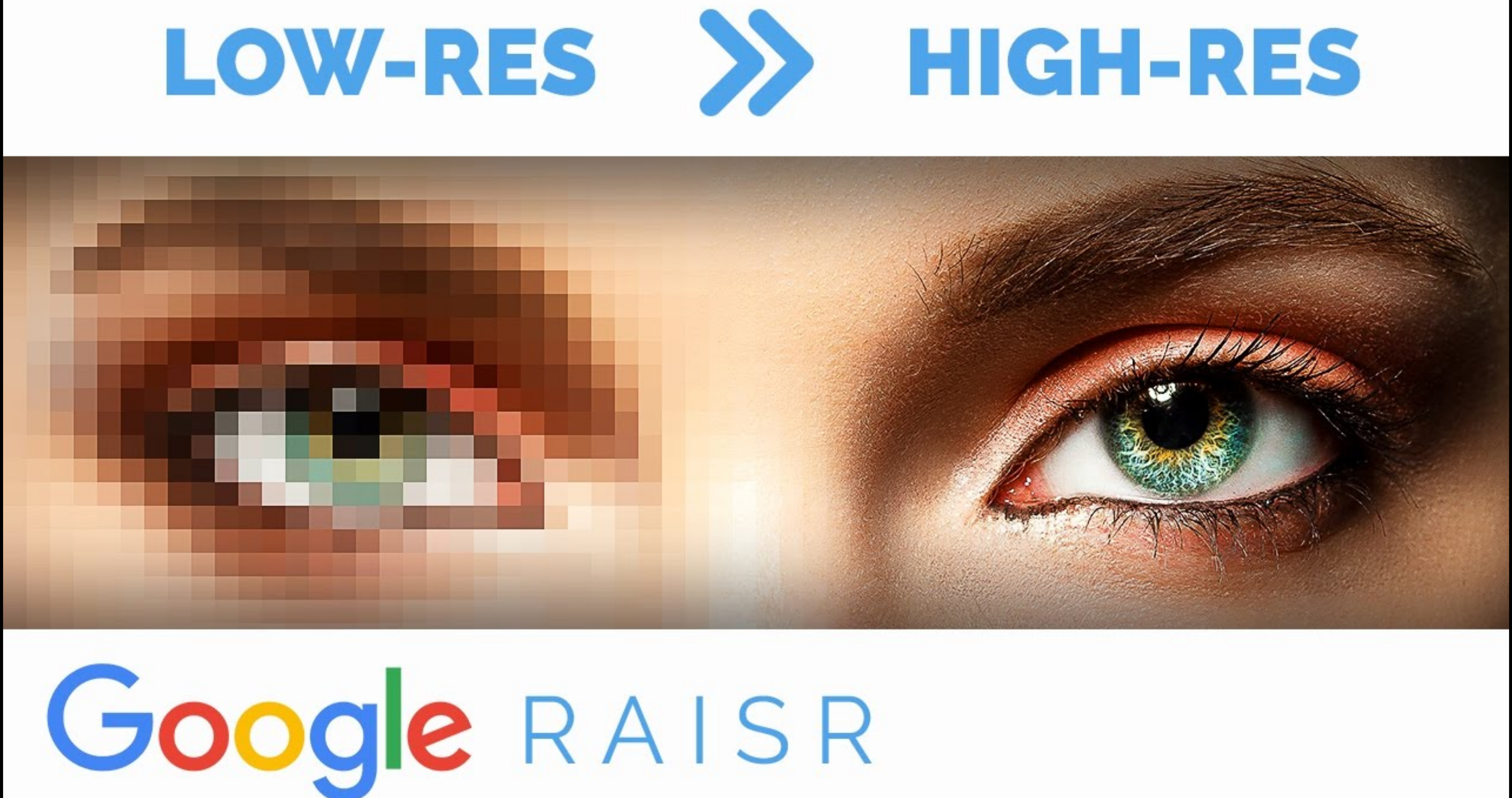
Candes *et al.*, *J. ACM*, 2011
Scherl *et al.*, arXiv:1905.07062, 2019

Cylinder PIV Vorticity (Re = 413)



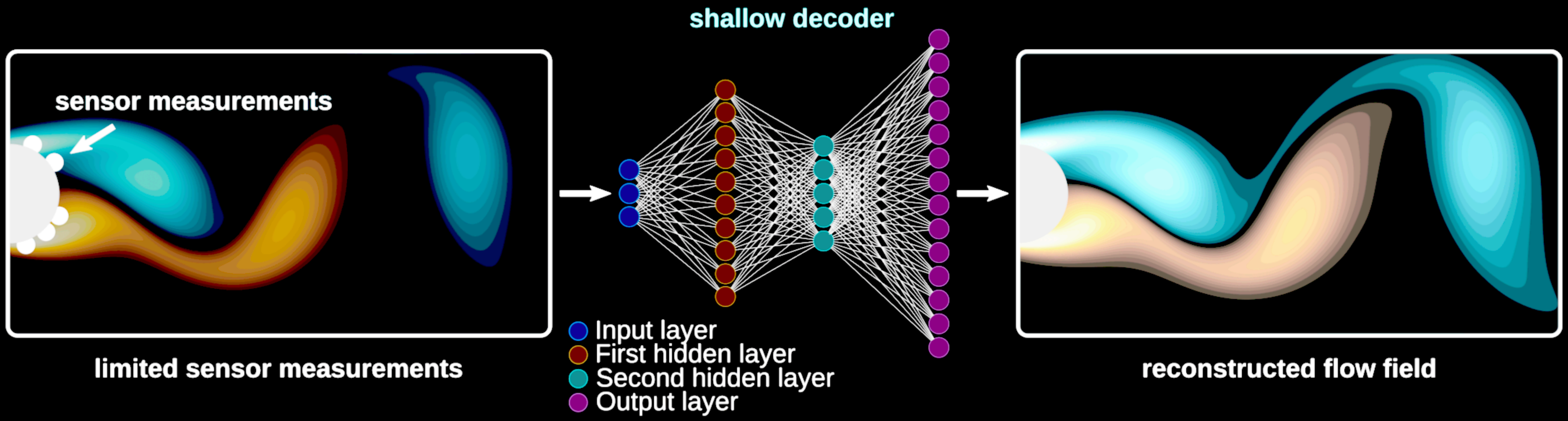
Scherl *et al.*,
arXiv:1905.07062, 2019

SUPER RESOLUTION



SUPER RESOLUTION

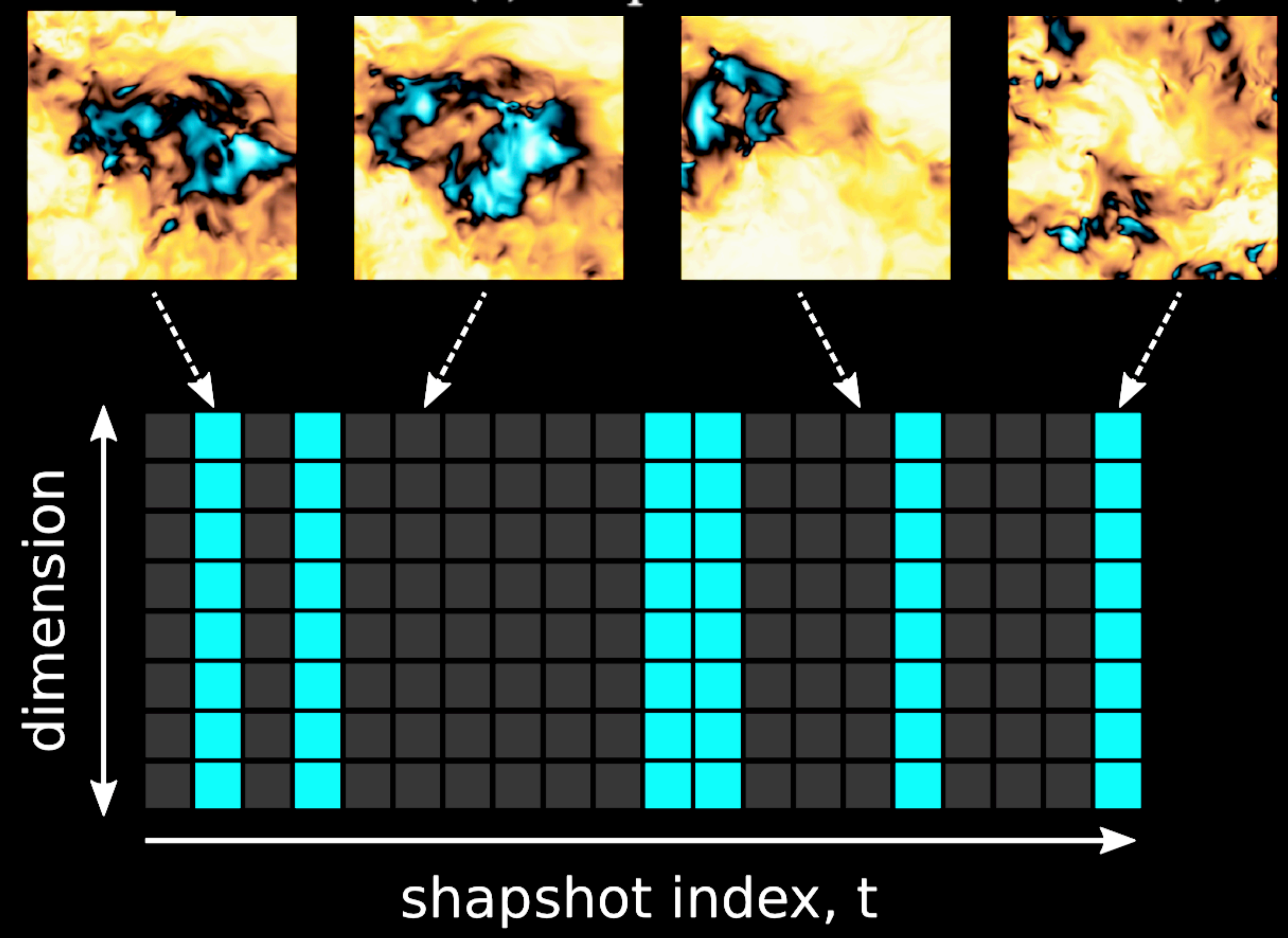
(a) Snapshot (b) Low resolution (c) Shallow Decoder



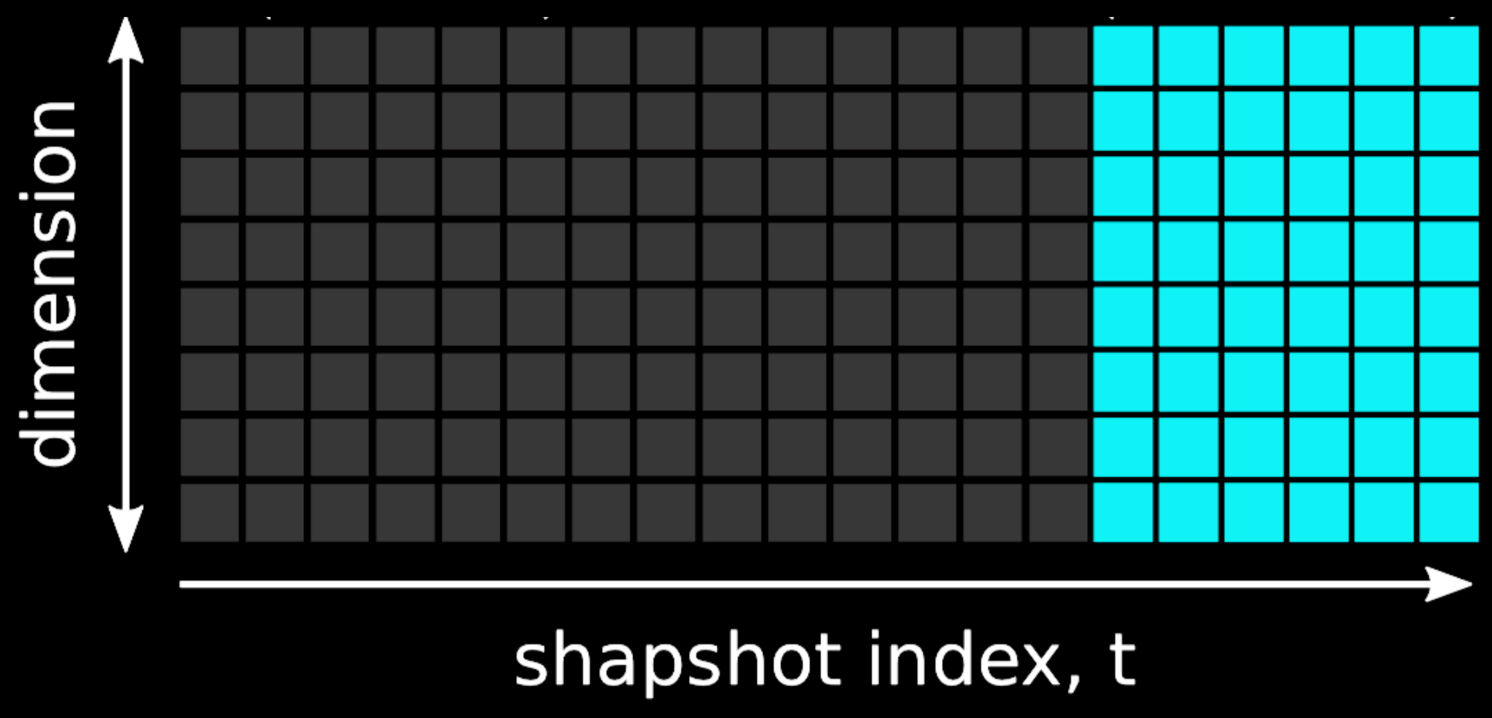
Erichson et al, *arXiv:1902.07358*, 2019

SUPER RESOLUTION

(a) Snapshot (b) Low resolution (c) Shallow Decoder



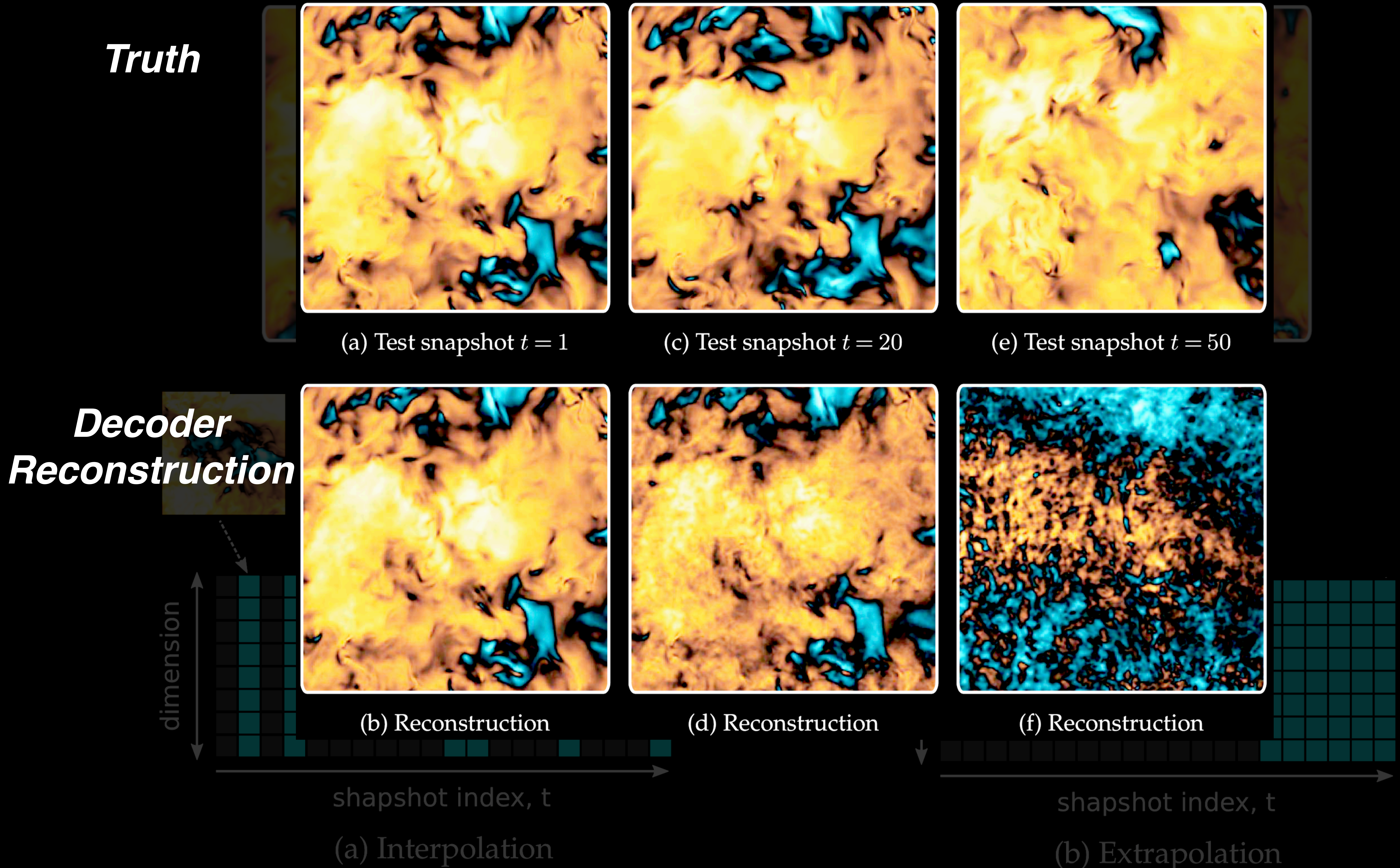
(a) Interpolation



(b) Extrapolation

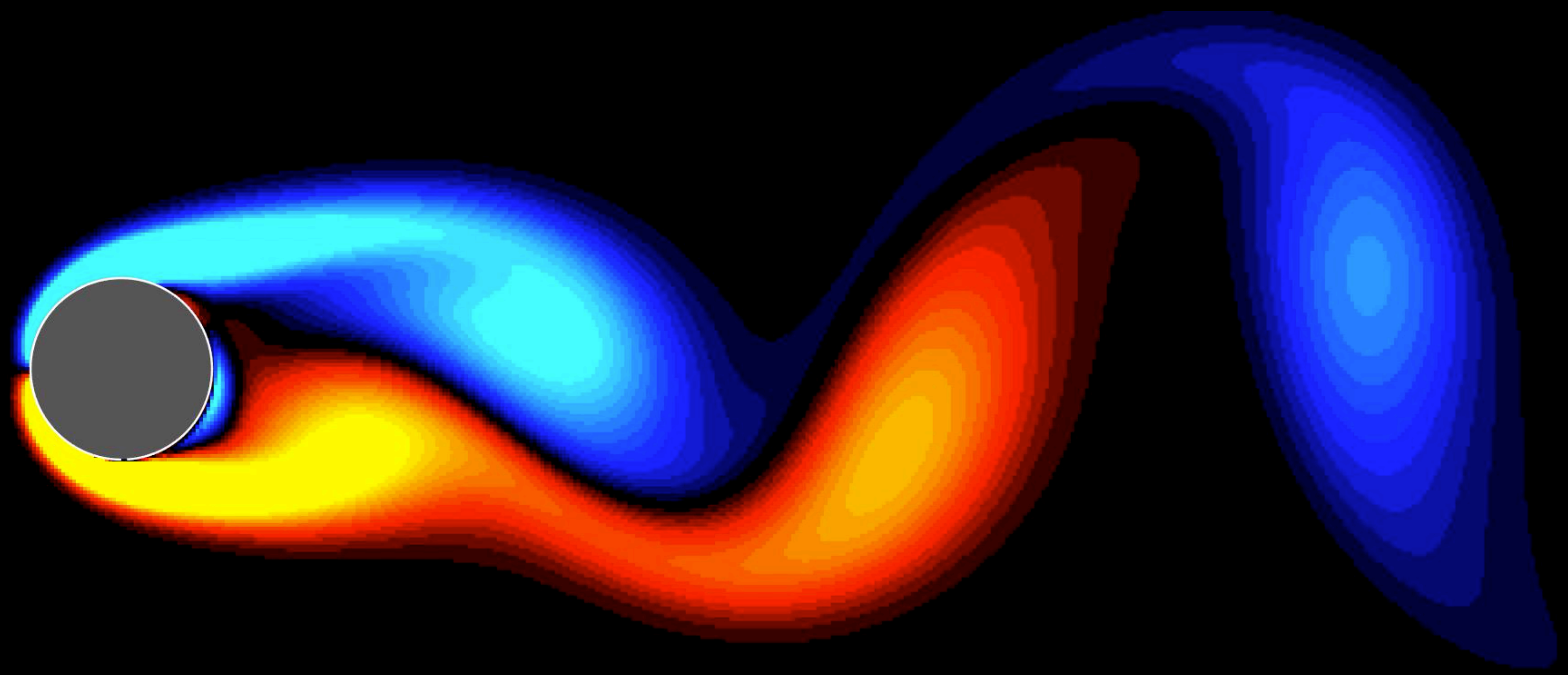
Erichson et al, *arXiv:1902.07358*, 2019

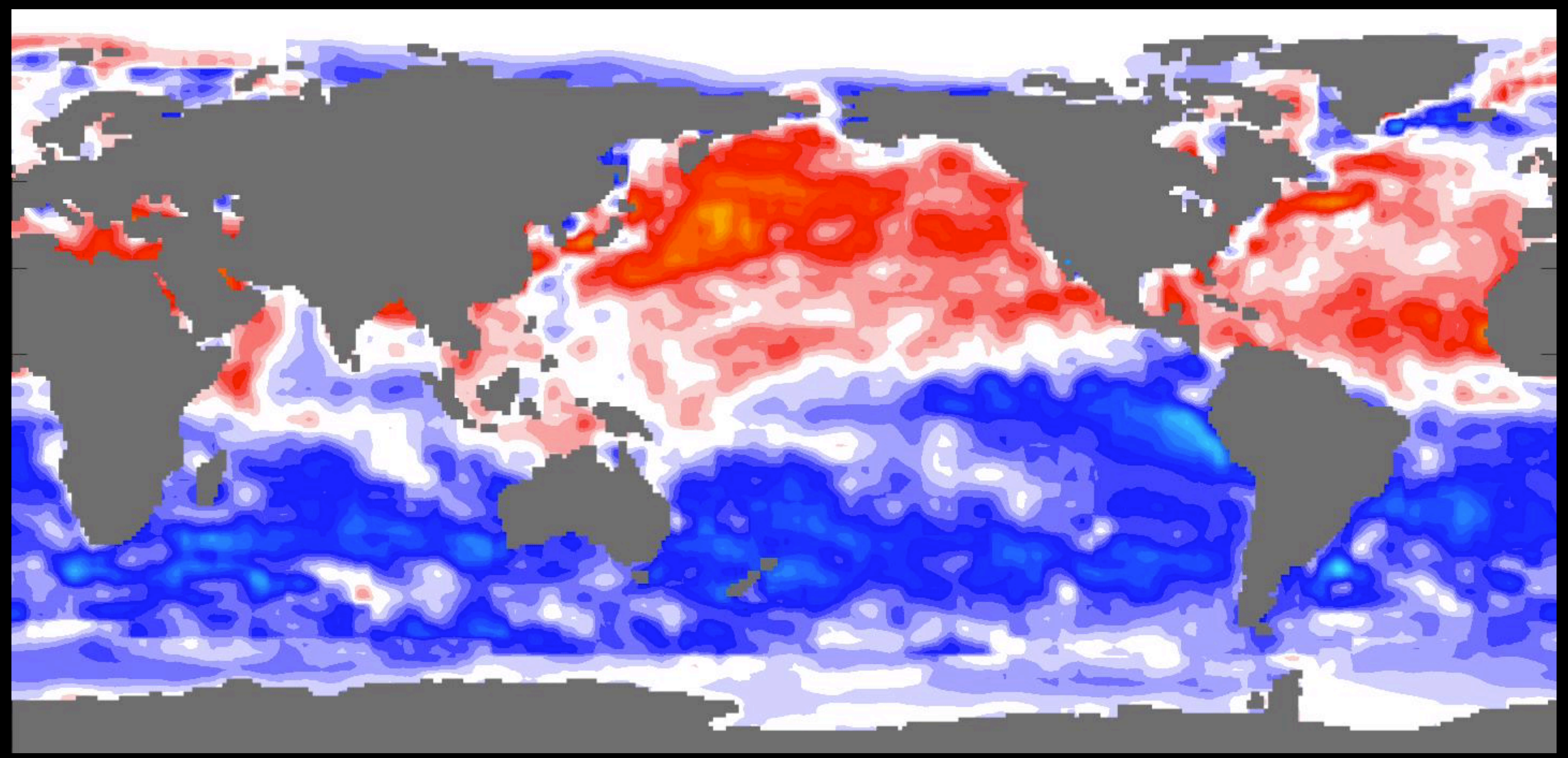
SUPER RESOLUTION

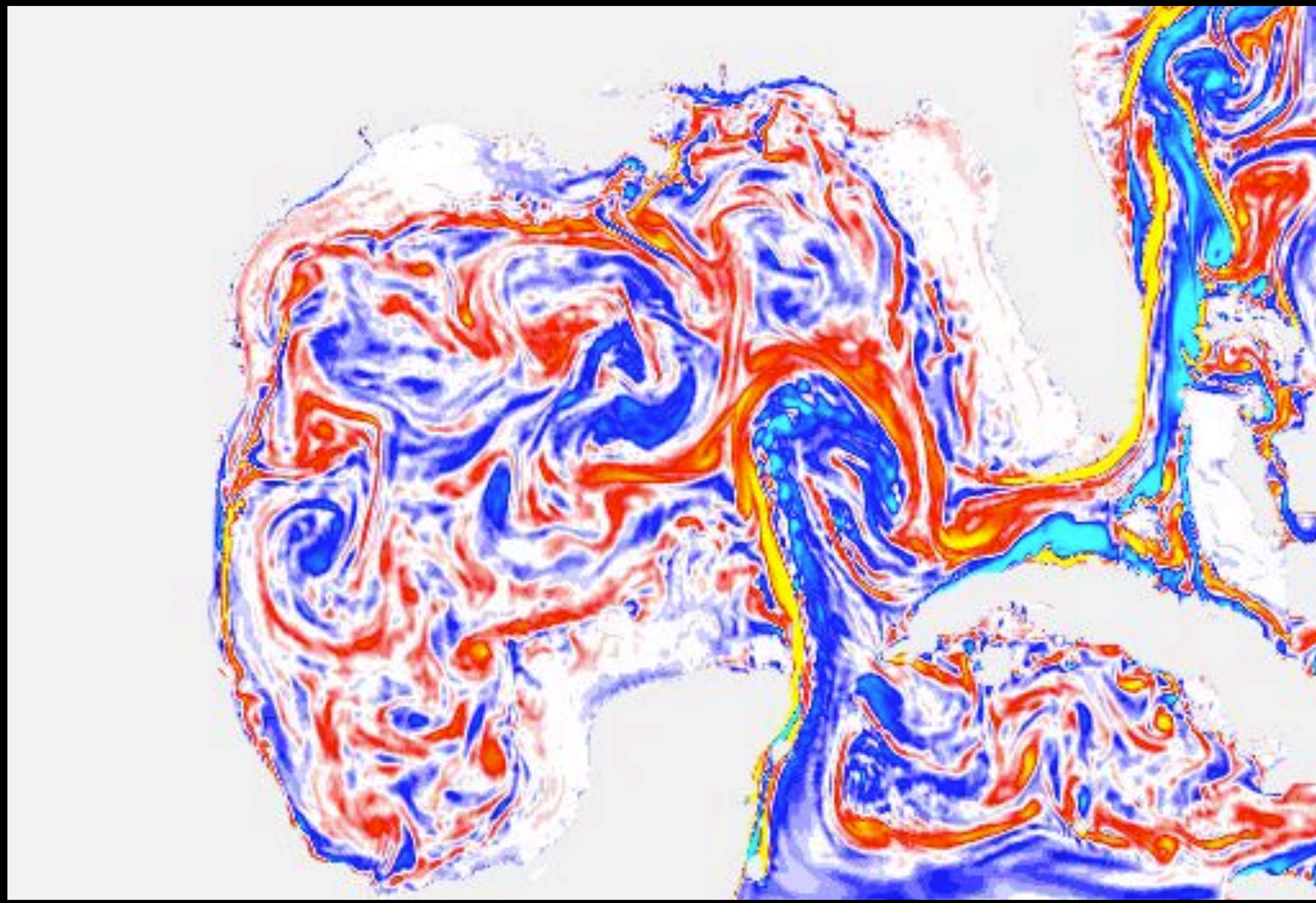


Erichson et al, *arXiv:1902.07358*, 2019

STATISTICAL STATIONARITY

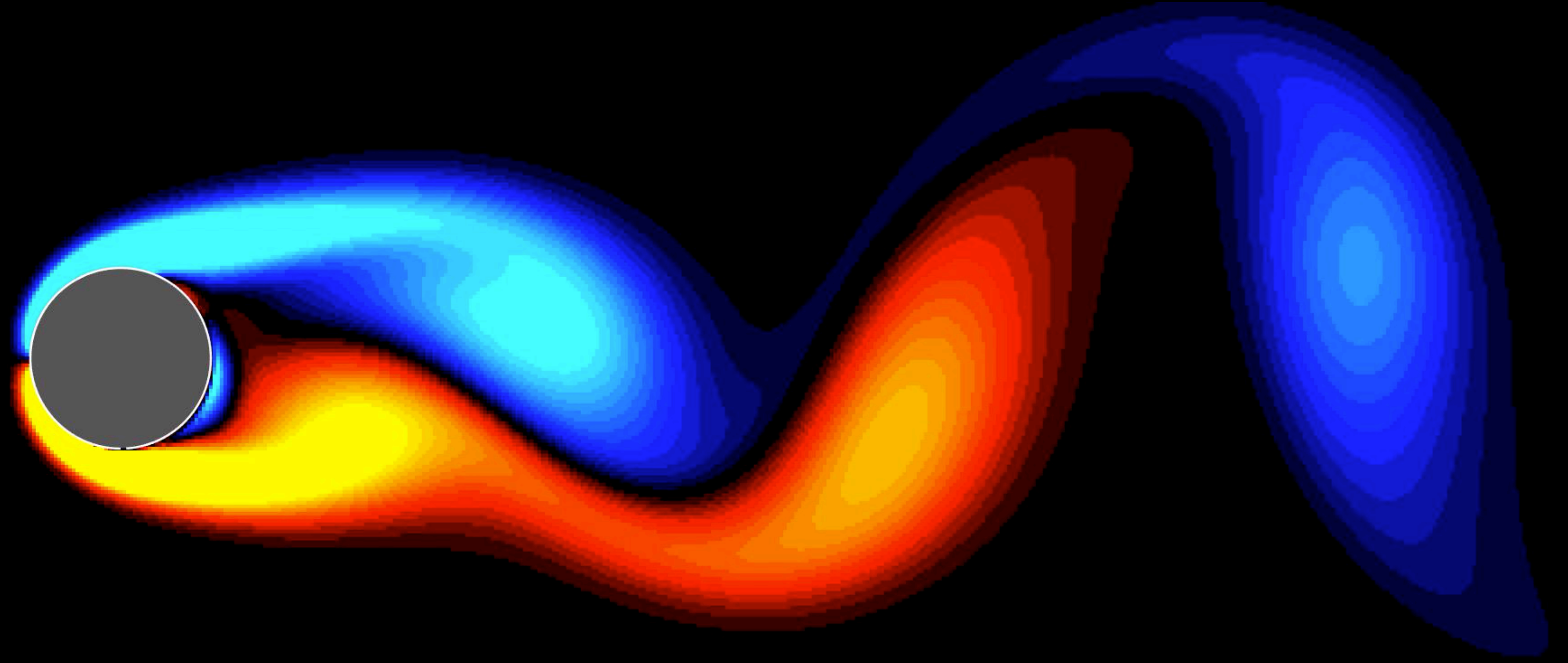


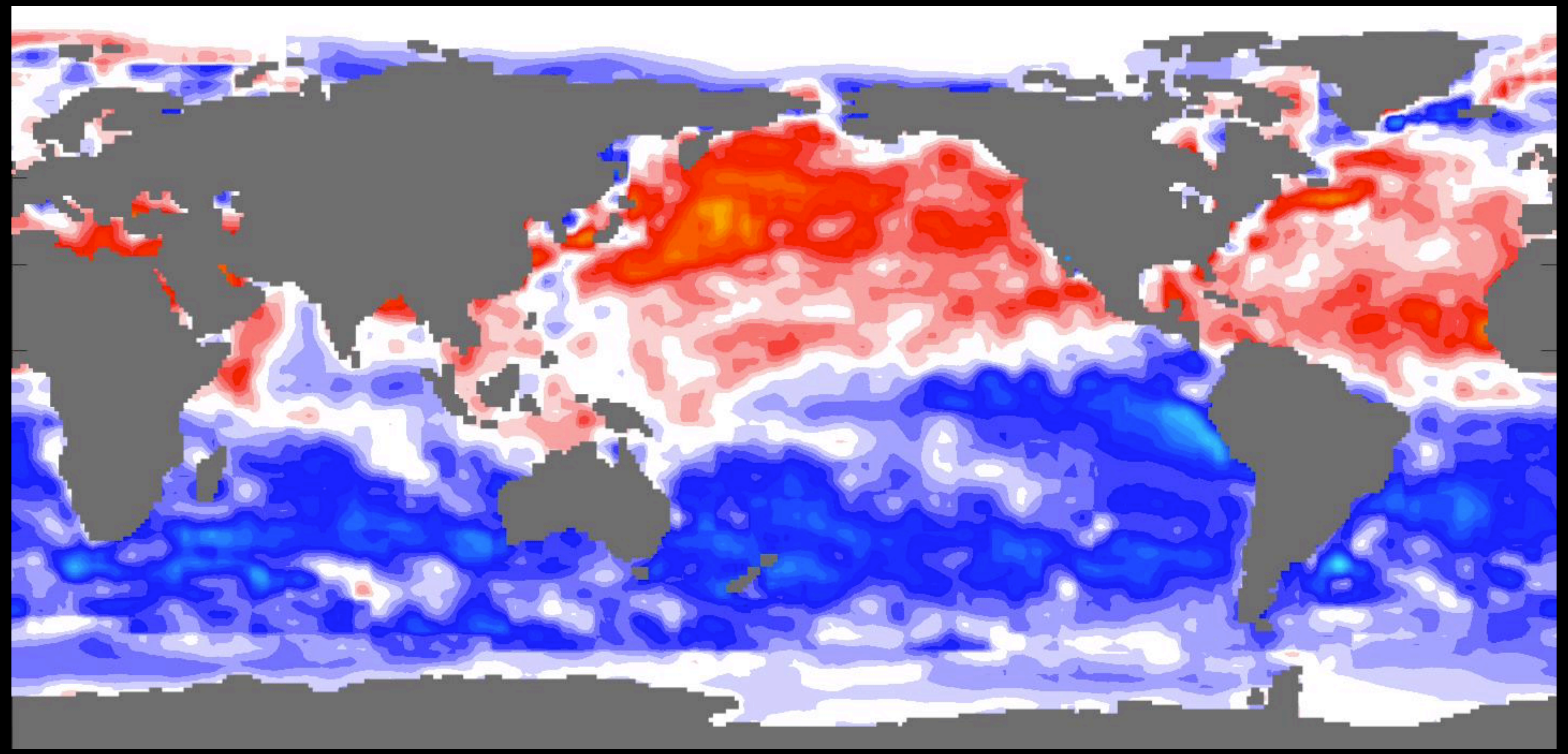


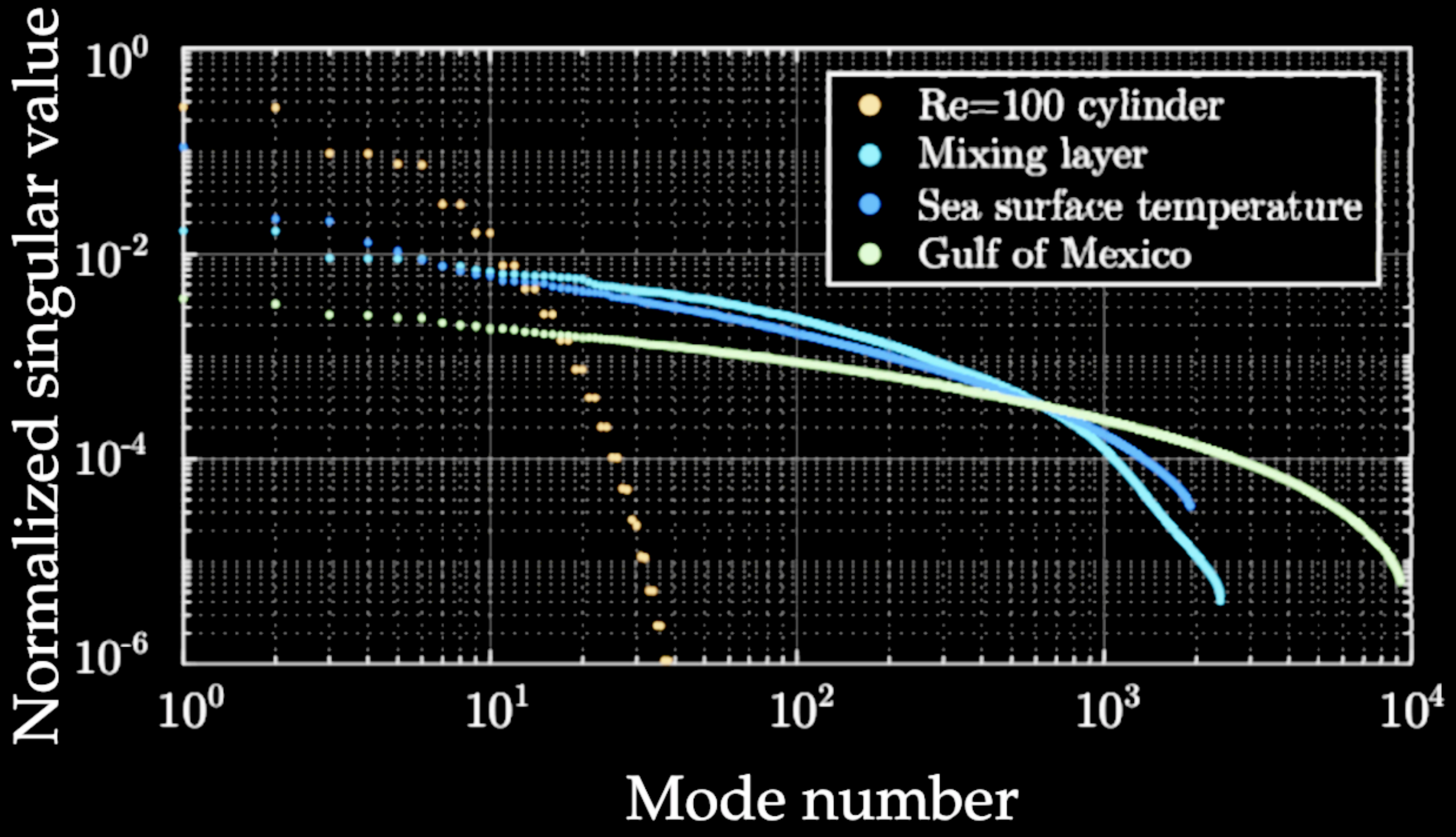


Callaham, Maeda, SLB, *PRF* 2019
[arXiv:1810.06723]

STATISTICAL STATIONARITY

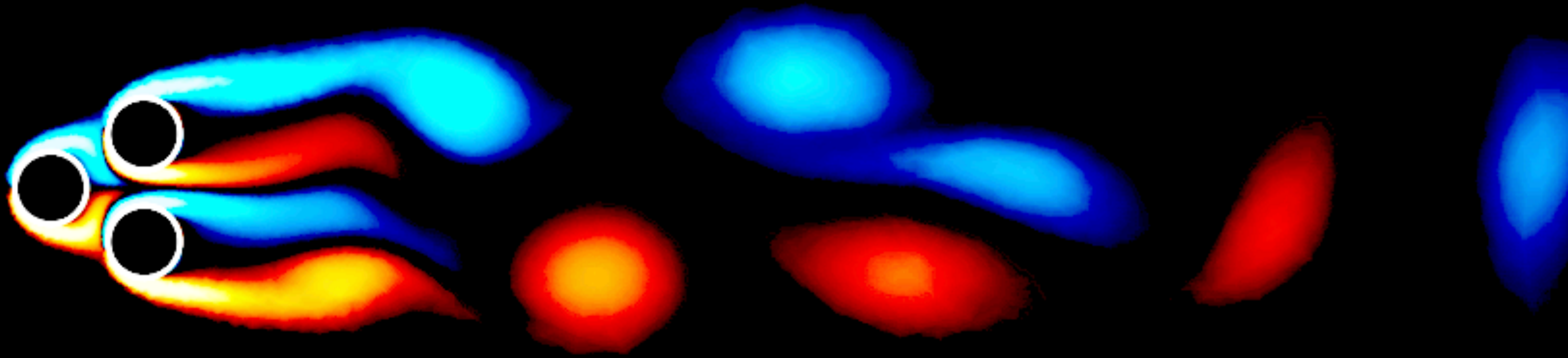




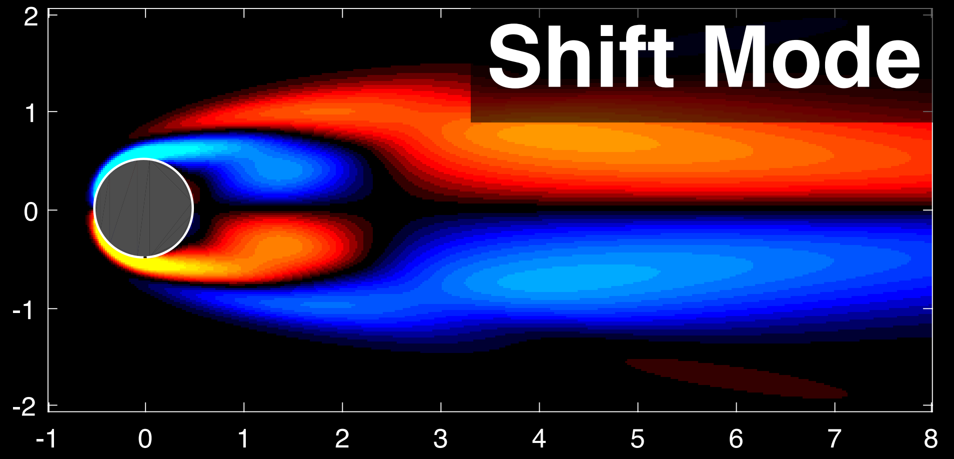


Callaham, Maeda, SLB, *PRF* 2019
[arXiv:1810.06723]

Reduced Order Models



REDUCED ORDER MODELS



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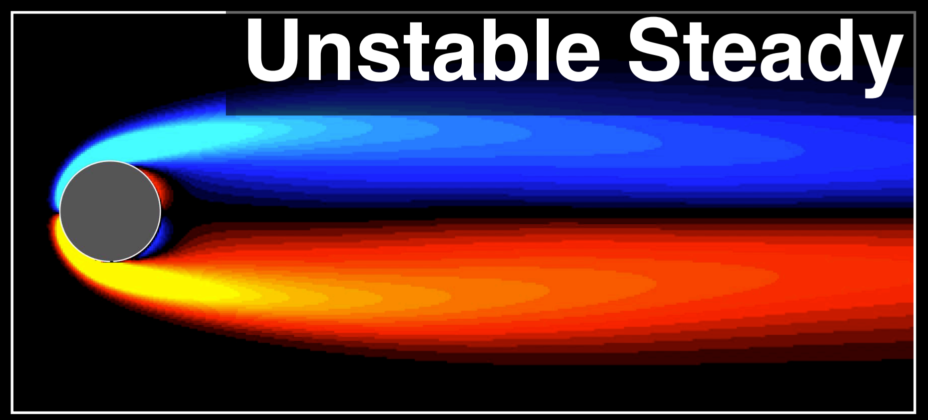

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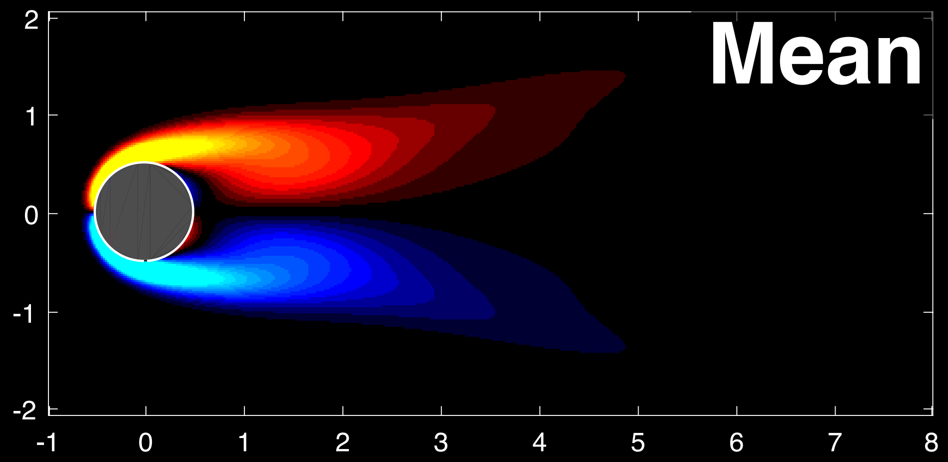
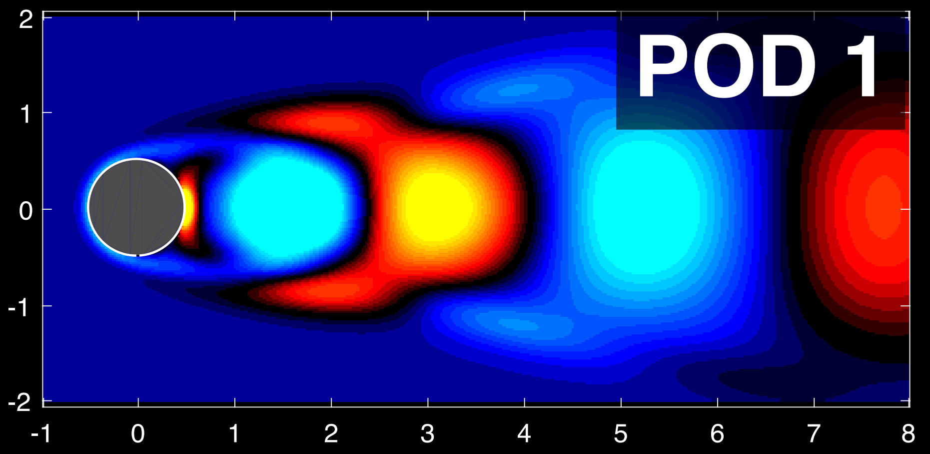
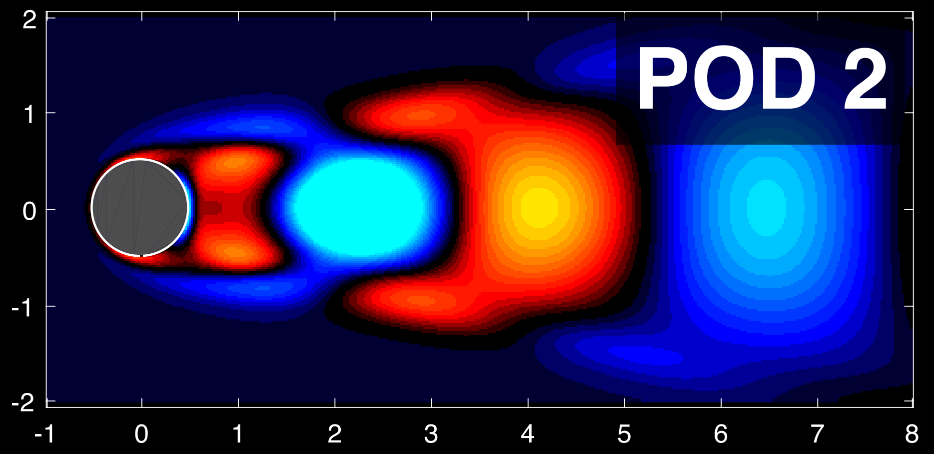
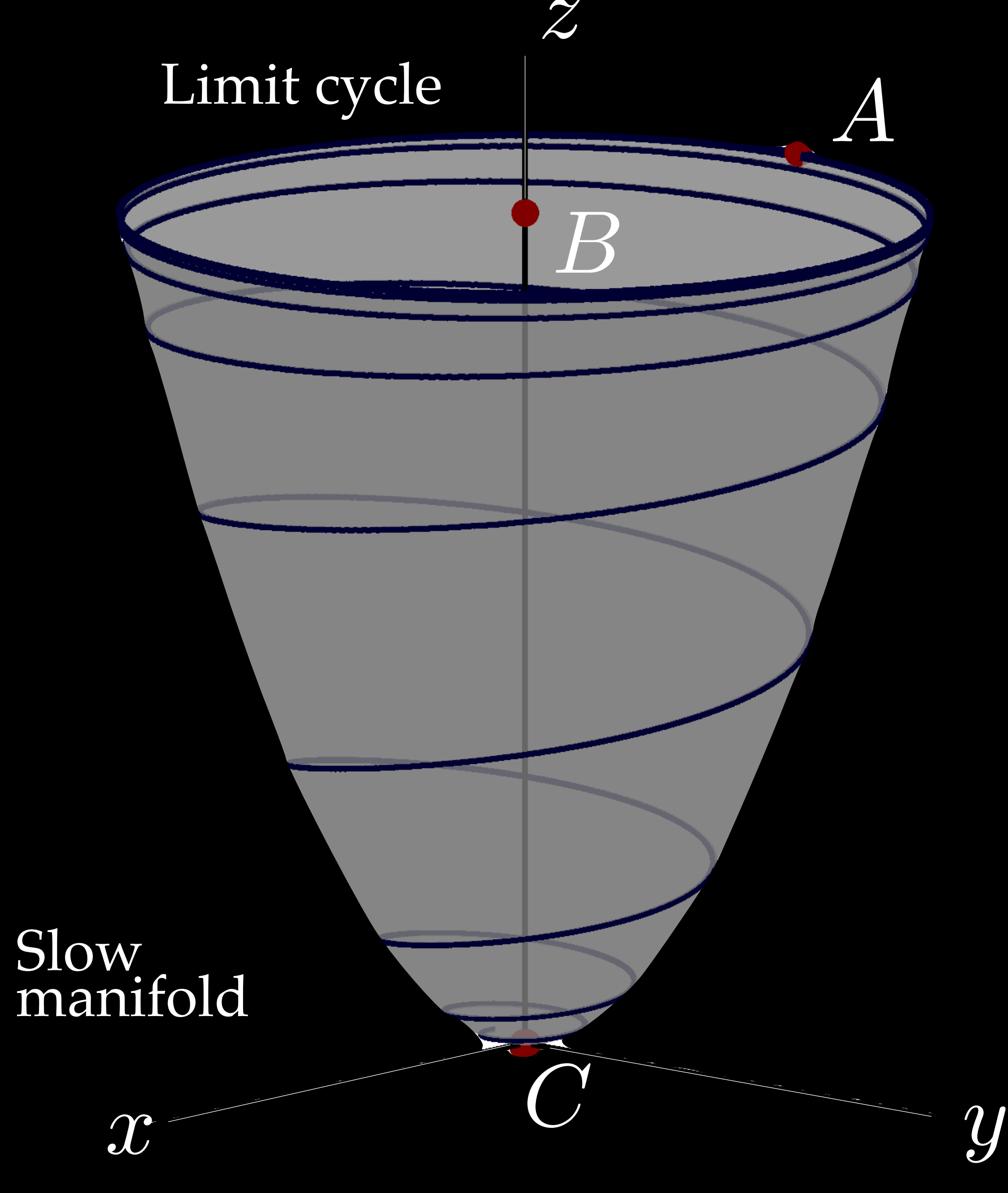
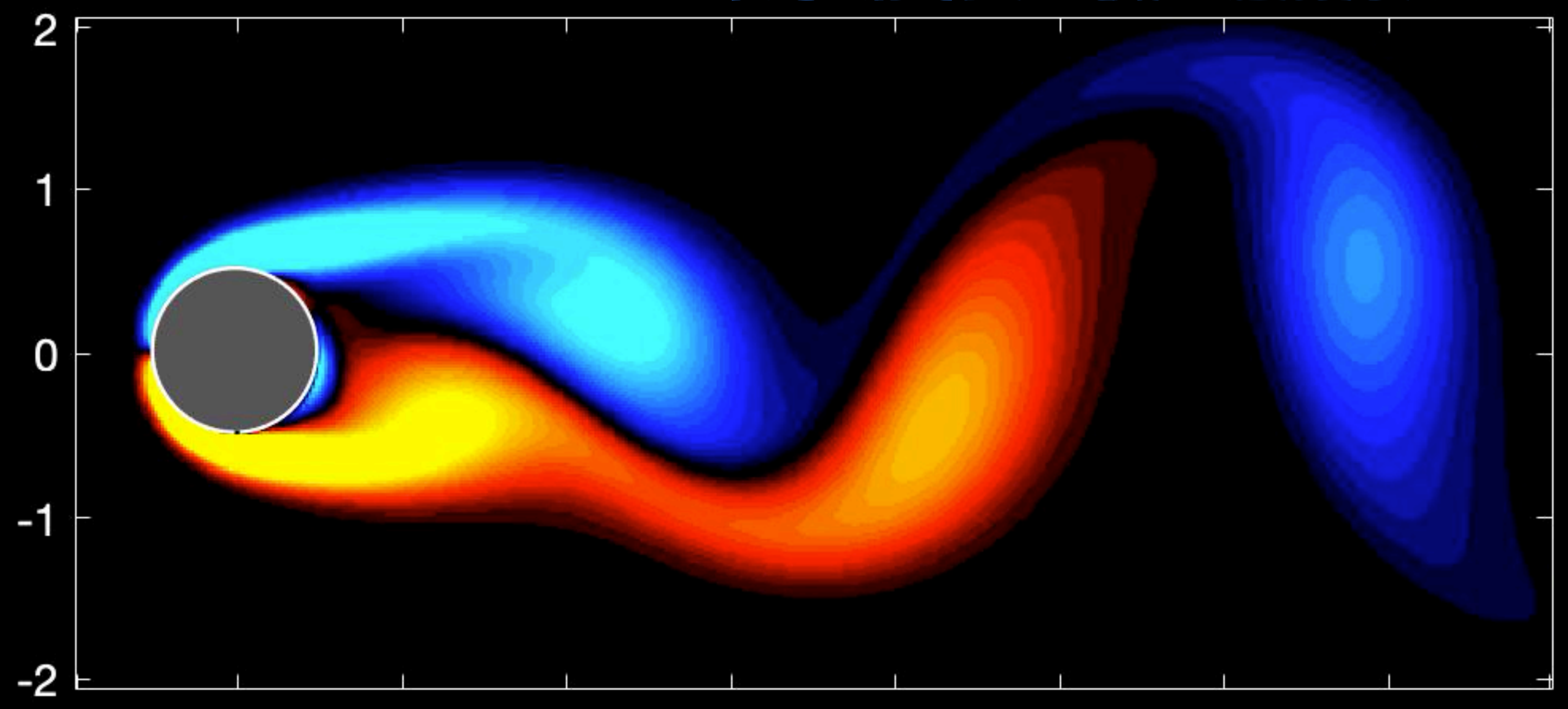






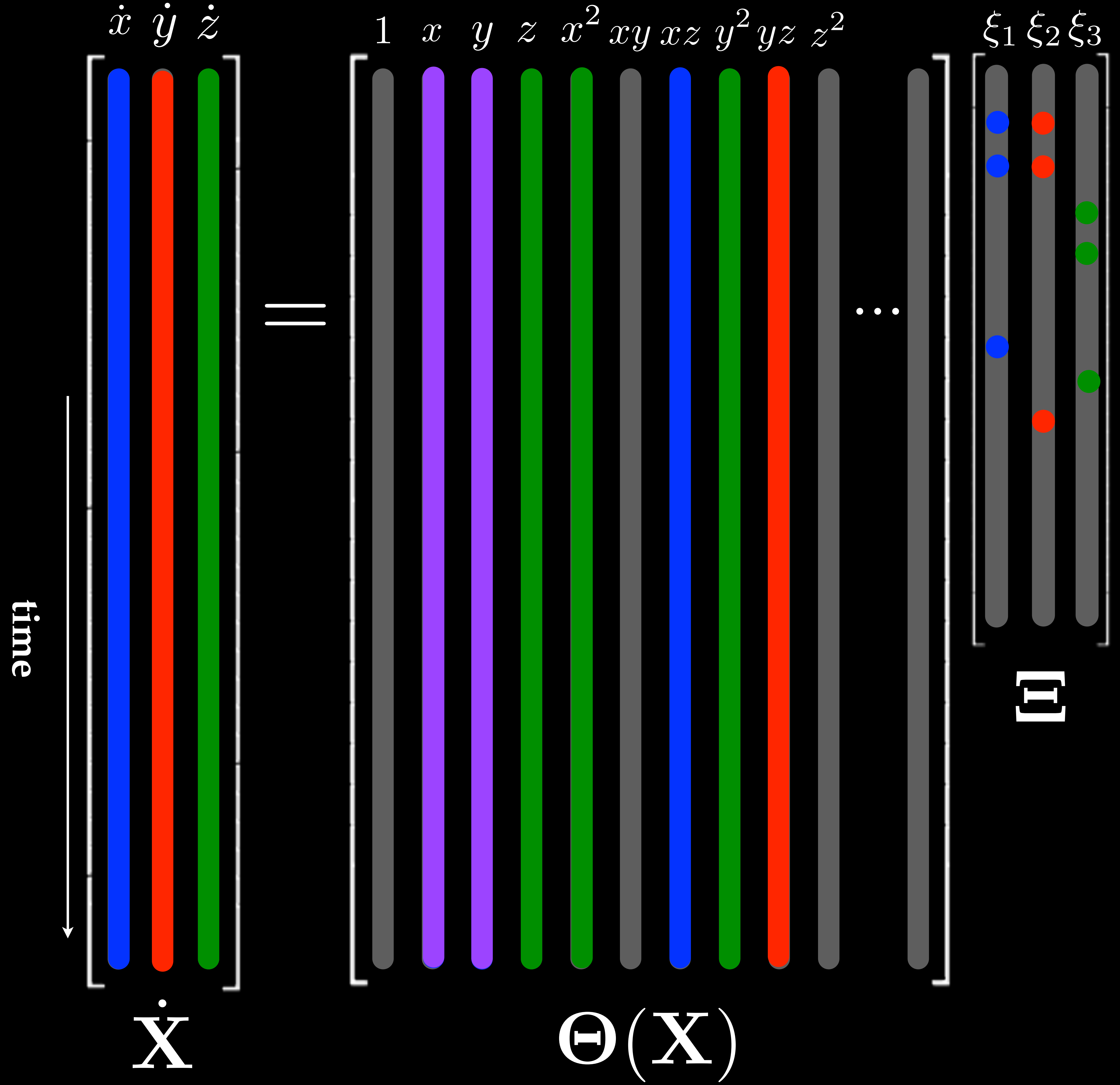


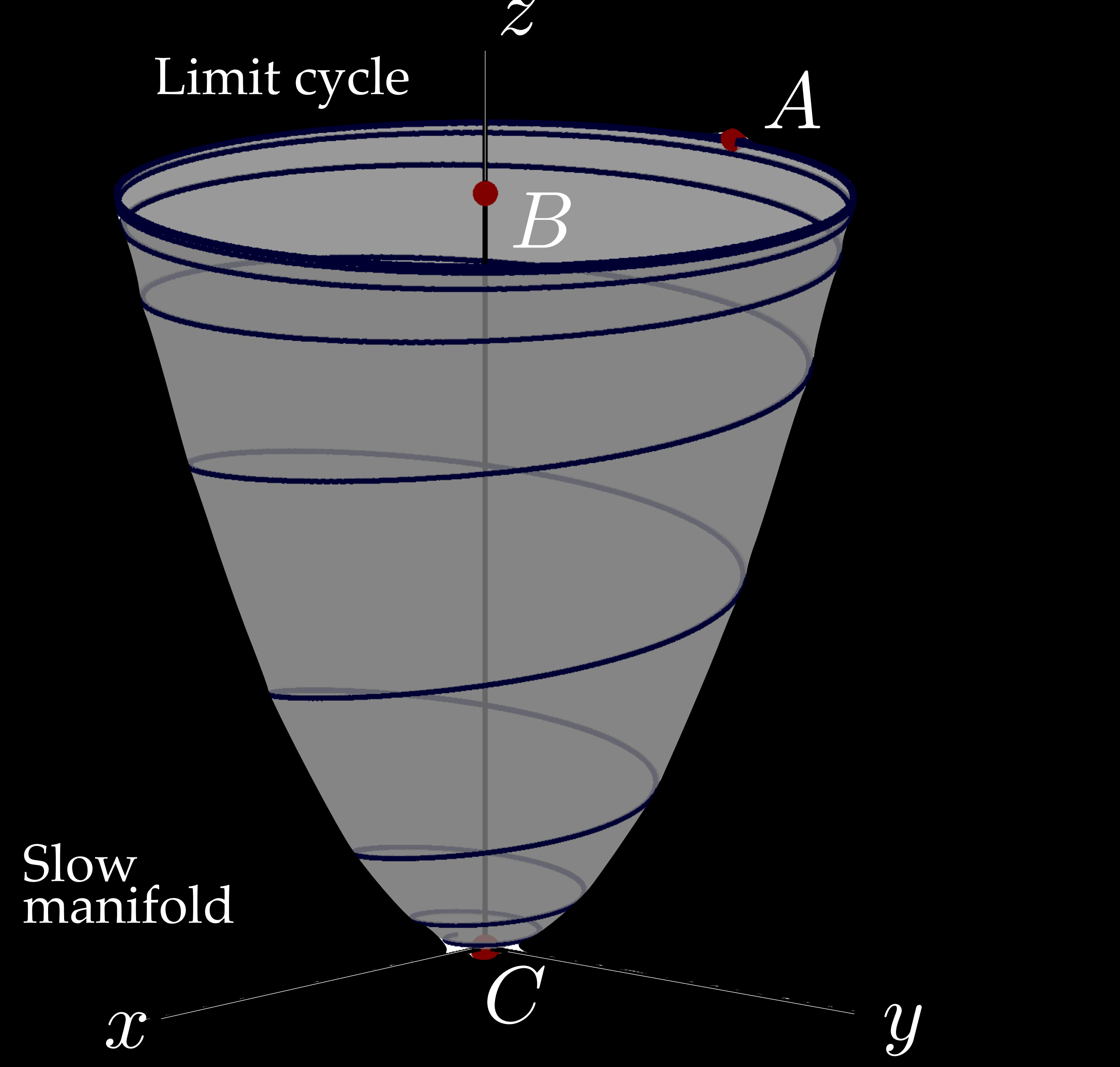
$$
\begin{aligned}
\dot{x} &= \mu x - \omega y + Axz \\
\dot{y} &= \omega x + \mu y + Ayz \\
\dot{z} &= -\lambda(z - x^2 - y^2).
\end{aligned}
$$



Noack *et al.*, JFM 2003.

Sparse Identification of Nonlinear Dynamics (SINDy)





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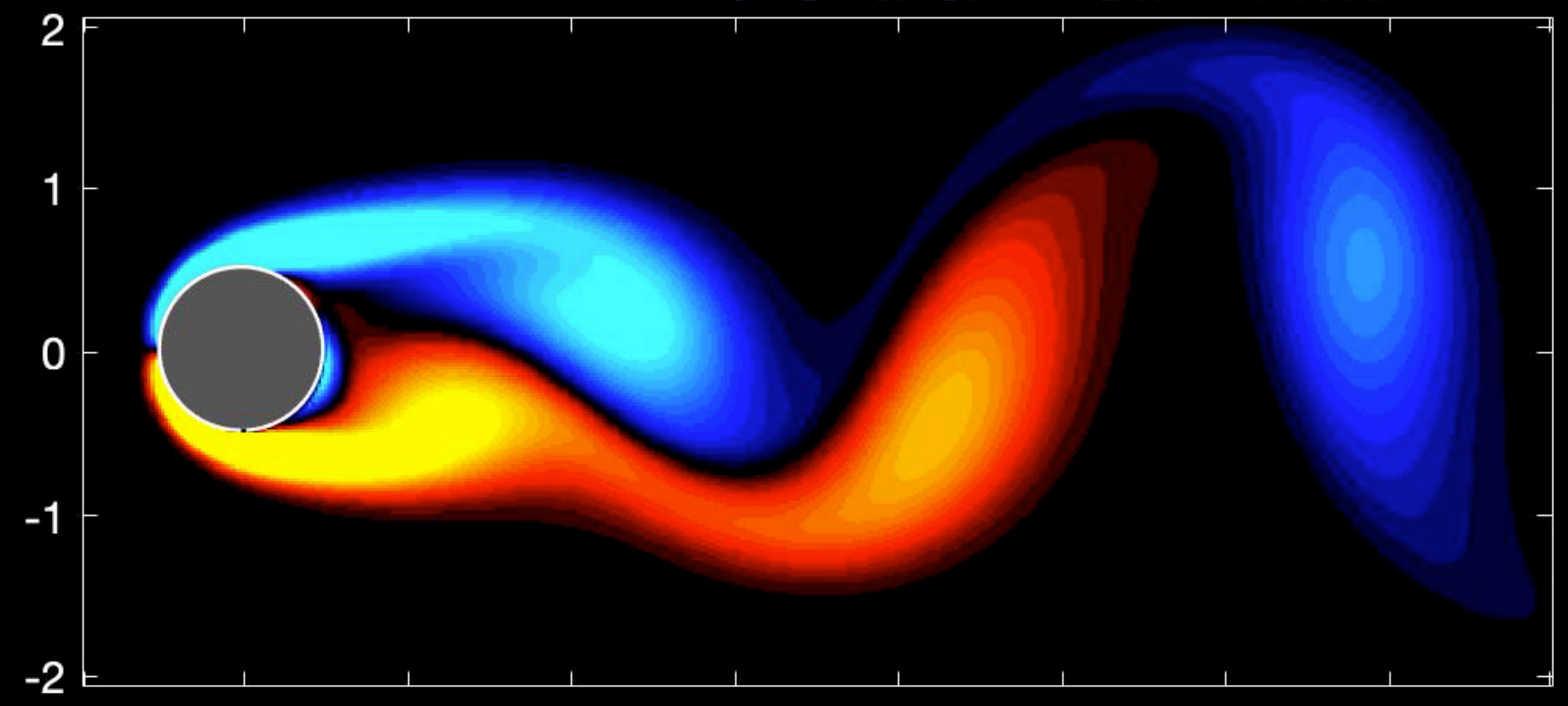
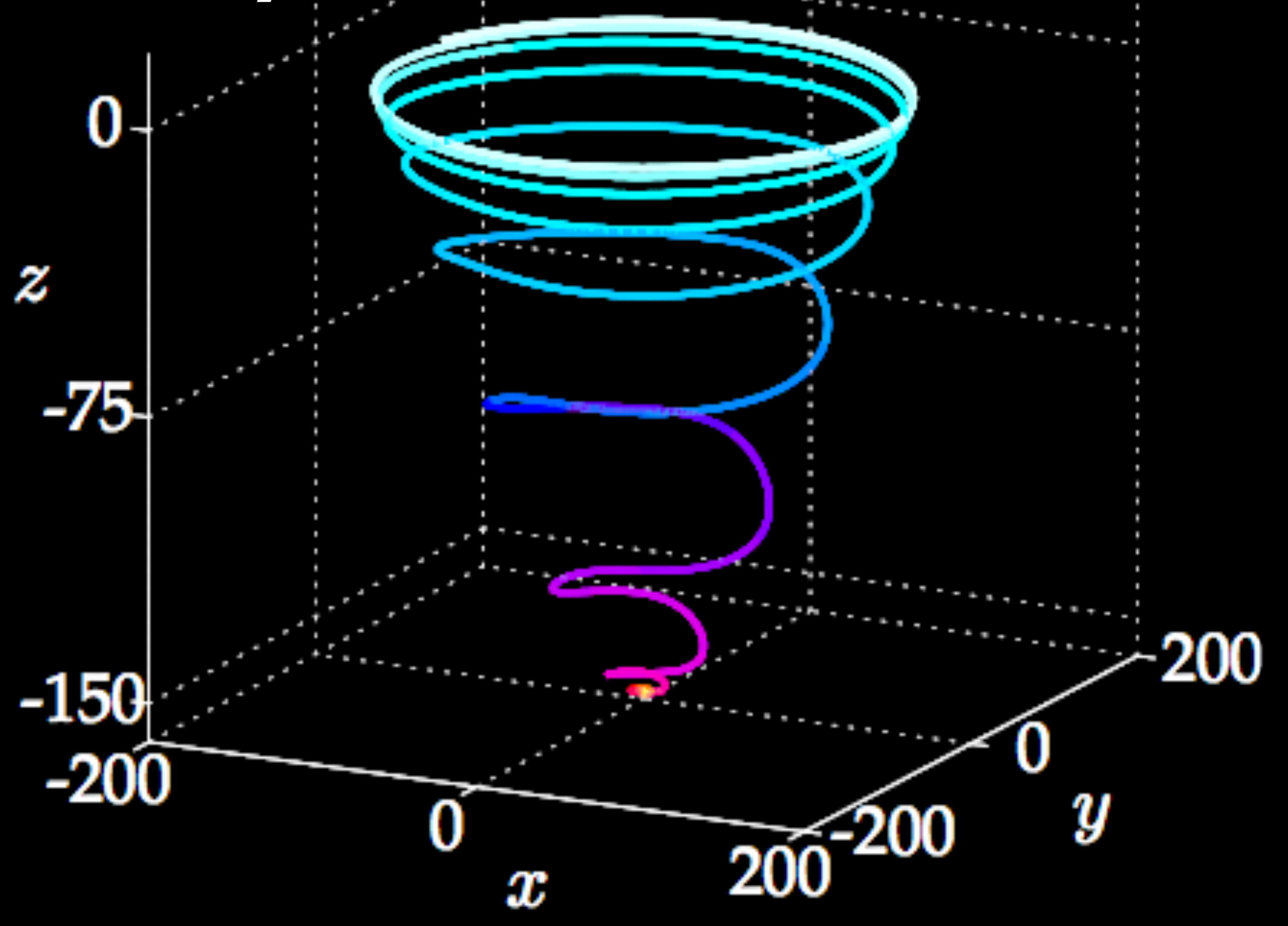


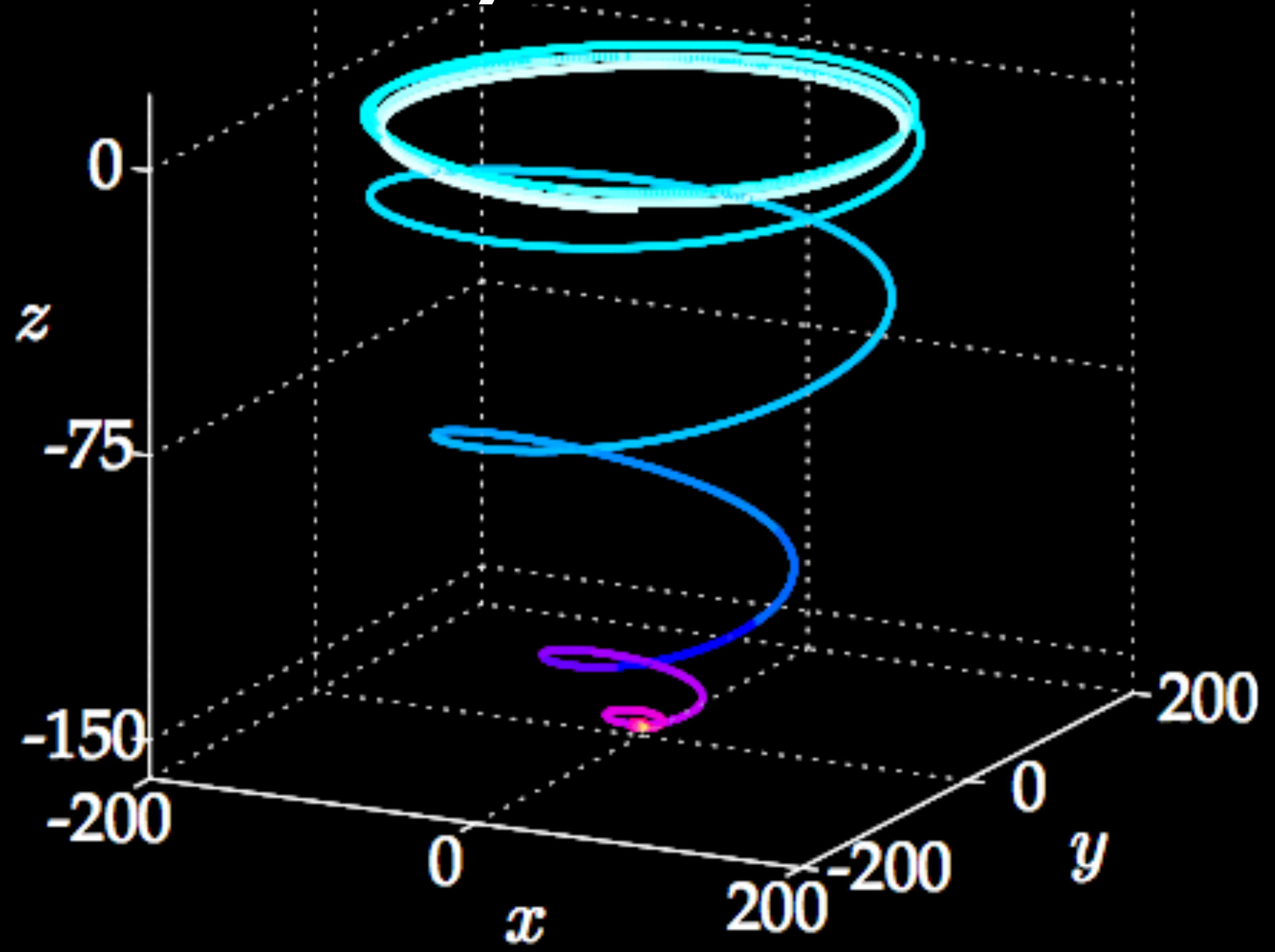
SLB, Proctor, Kutz, *PNAS* 2016.

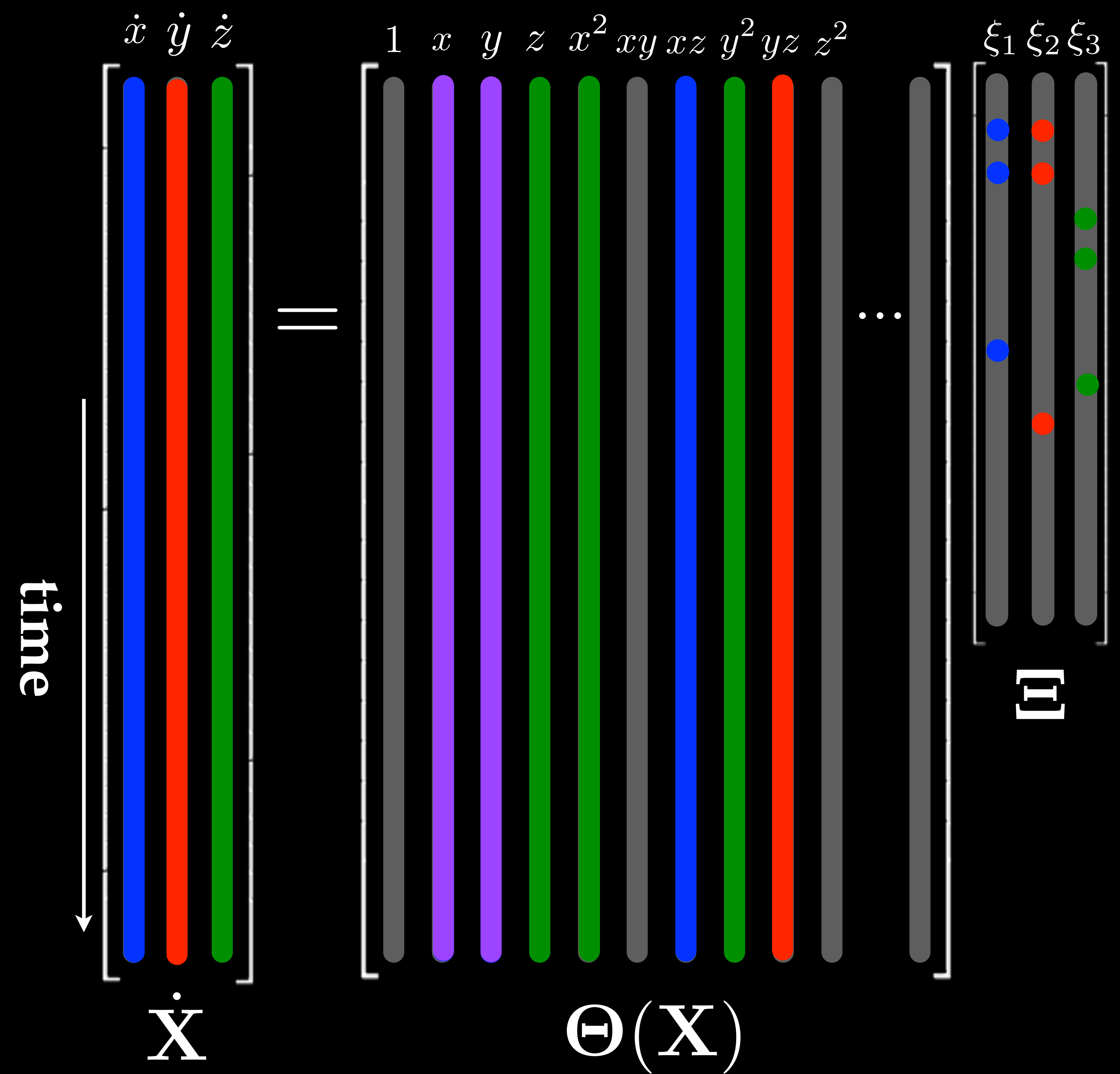
Sparse Identification of Nonlinear Dynamics (SINDy)

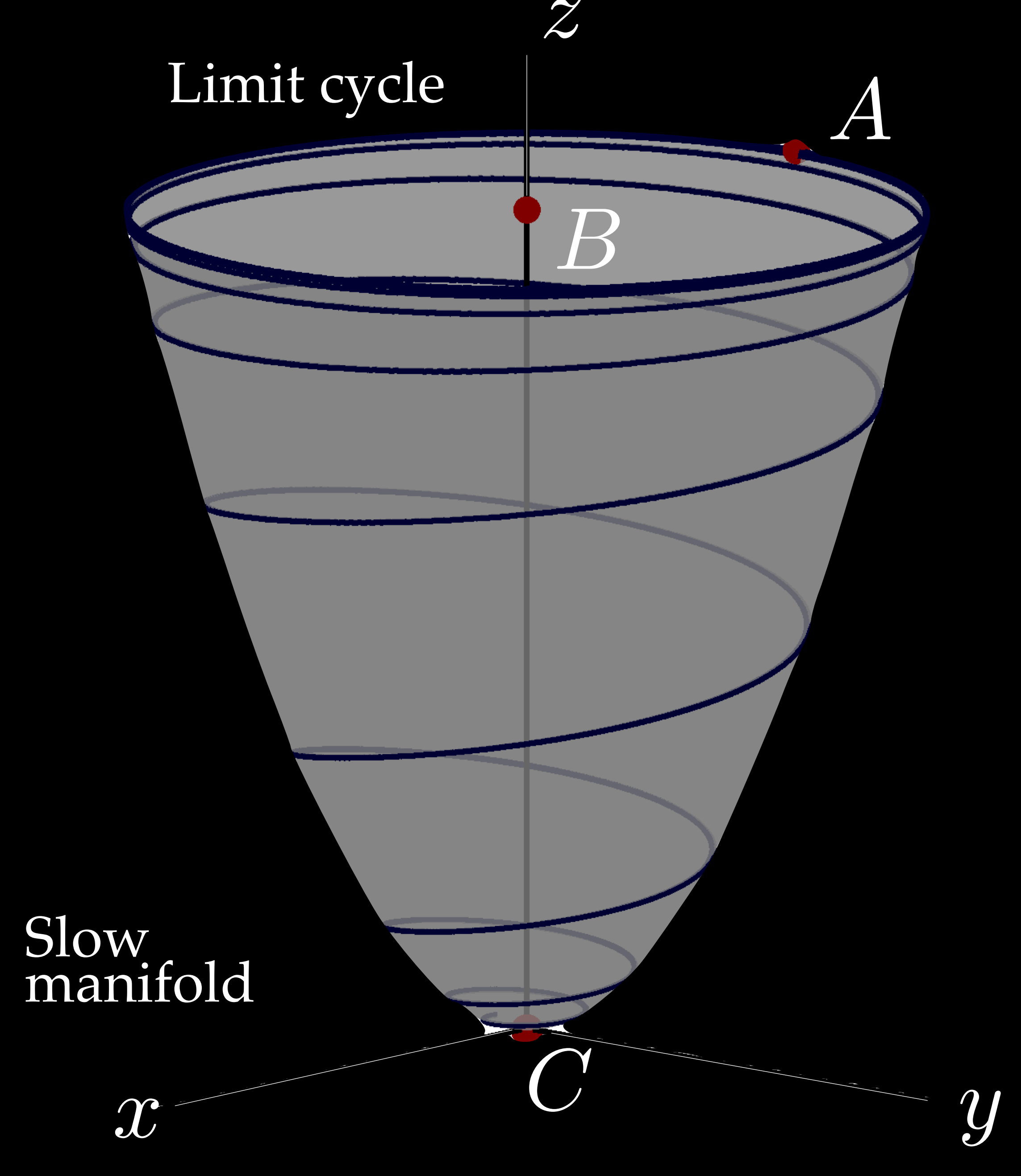
Full System



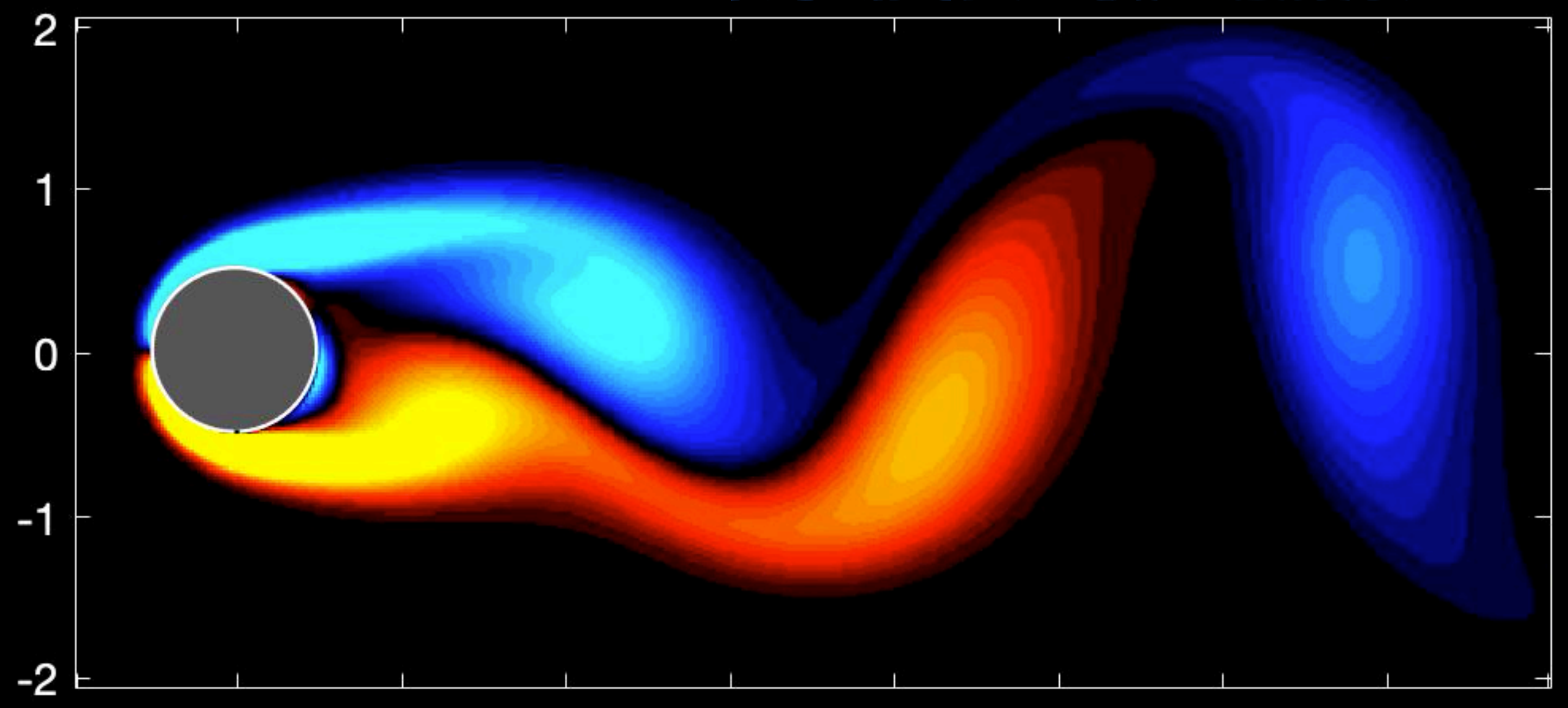
Identified System





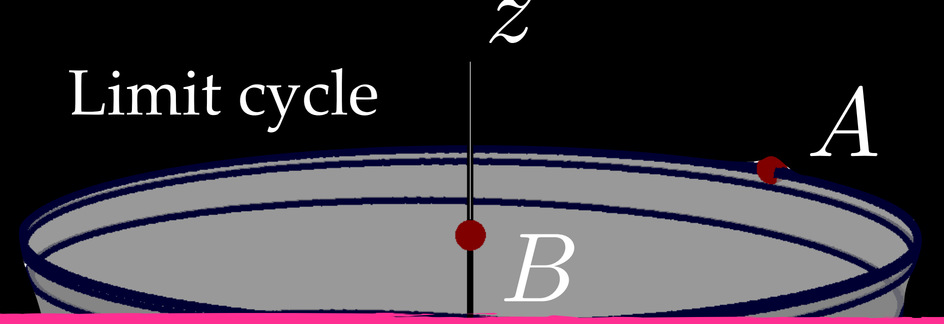


$$\begin{aligned}\dot{x} &= \mu x - \omega y + Axz\\ \dot{y} &= \omega x + \mu y + Ayz\\ \dot{z} &= -\lambda(z - x^2 - y^2).\end{aligned}$$

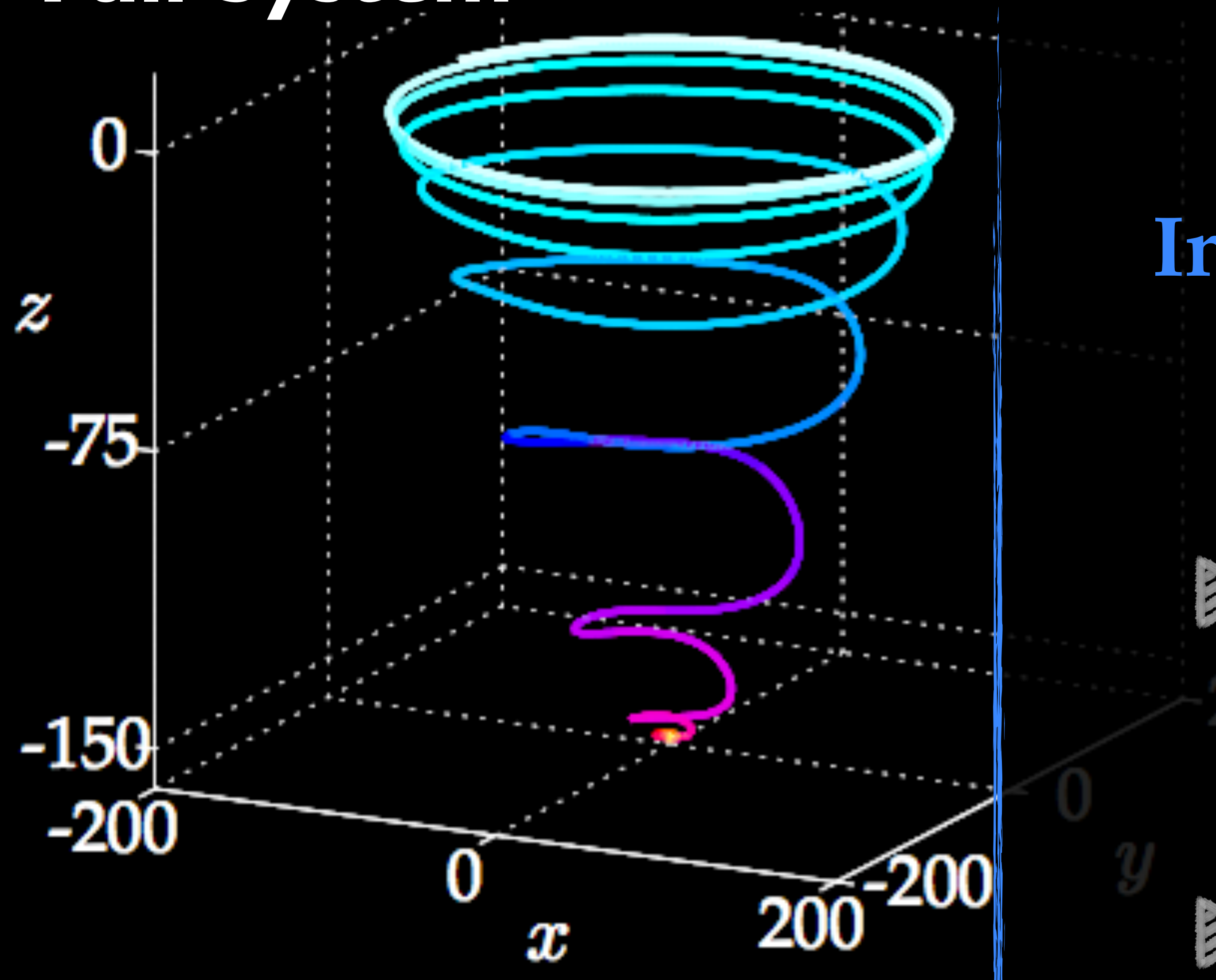


SLB, Proctor, Kutz, *PNAS* 2016.
Loiseau & SLB, *JFM* 838, 2018

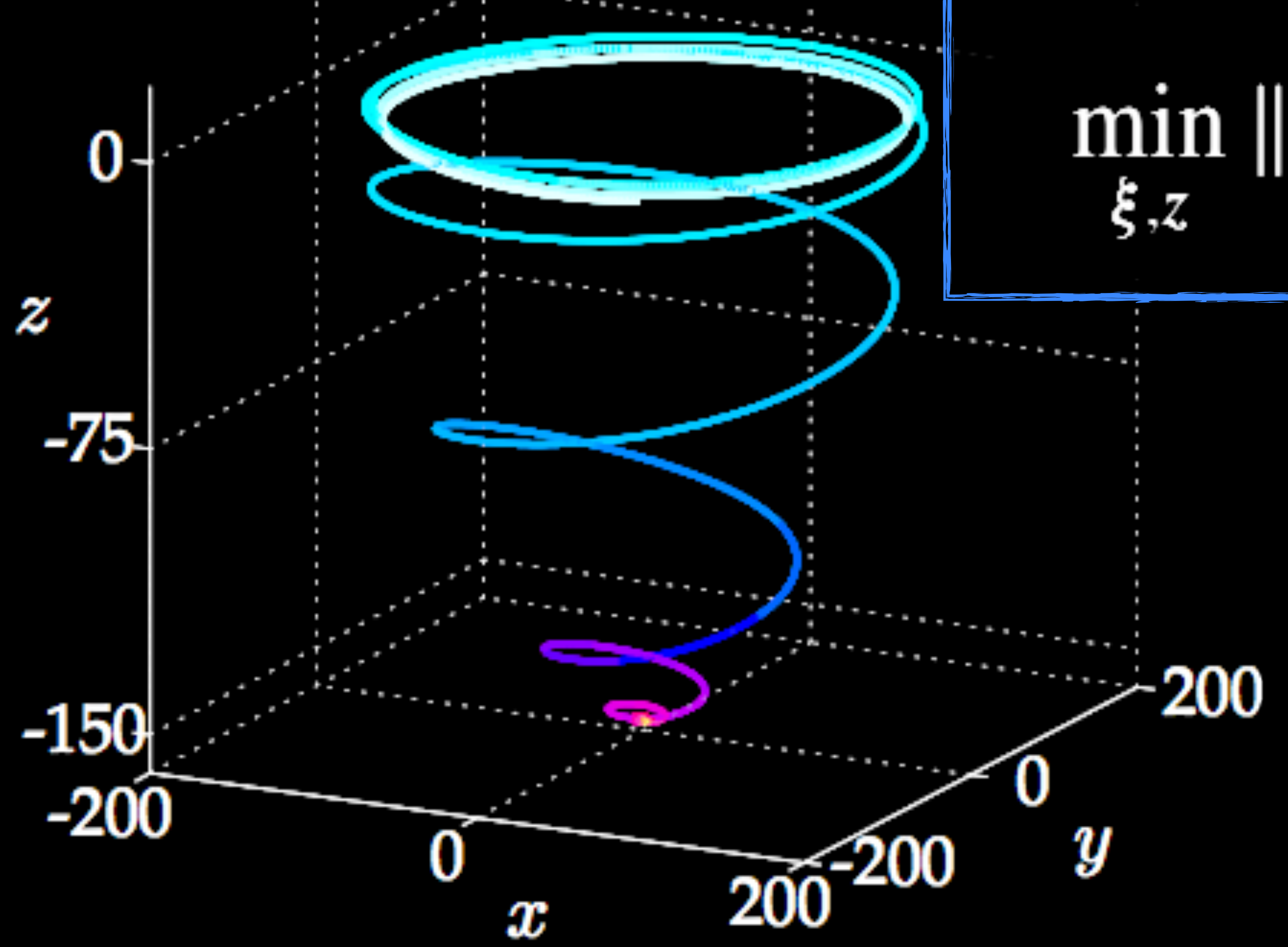
Sparse Identification of Nonlinear Dynamics (SINDy)



Full System



Identified System



Innovation 1: Enforcing known constraints

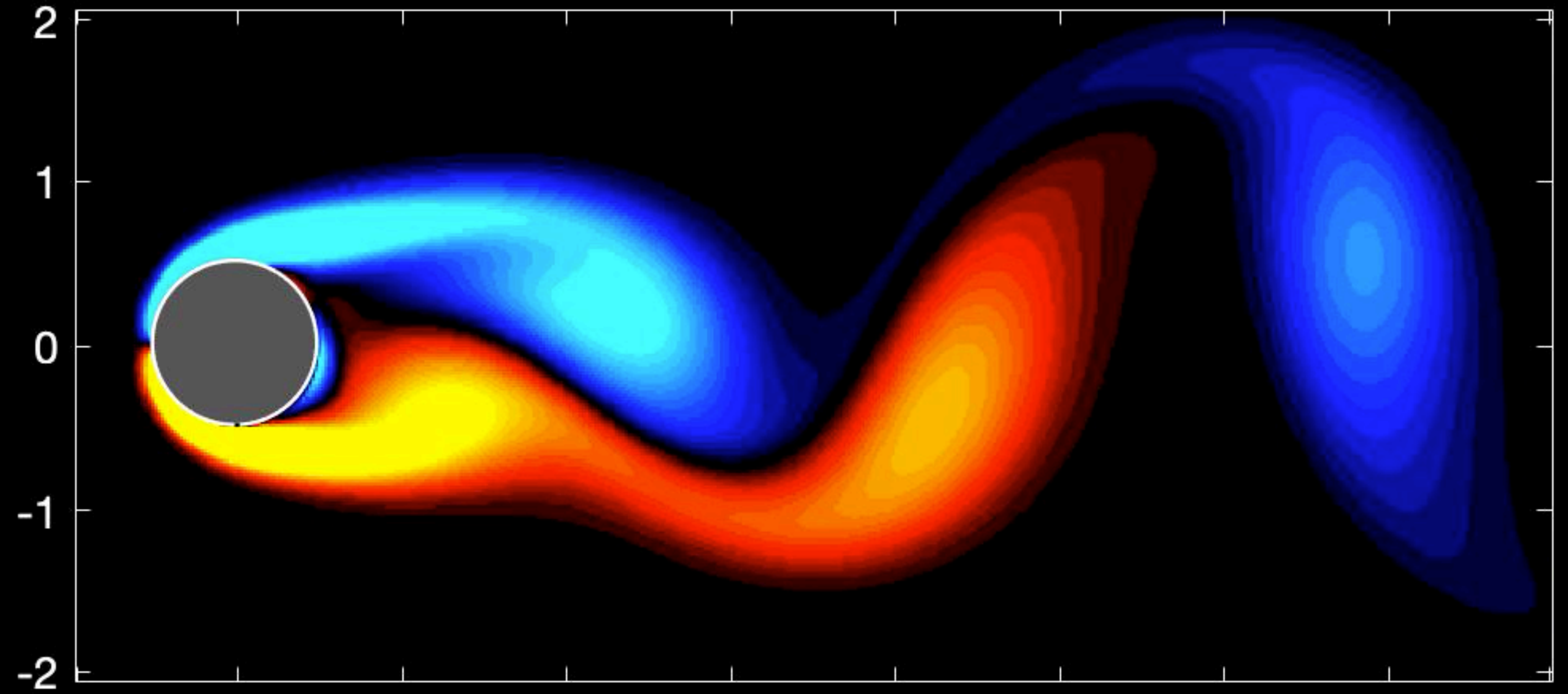
- Skew-symmetric quadratic nonlinearities to enforce energy conservation
- Improved stability

$$\min_{\xi, z} \|\Theta(X)\Xi - \dot{X}\|_2^2 + z^T(C\xi - d)$$

Innovation 2: Higher-order Nonlinearities

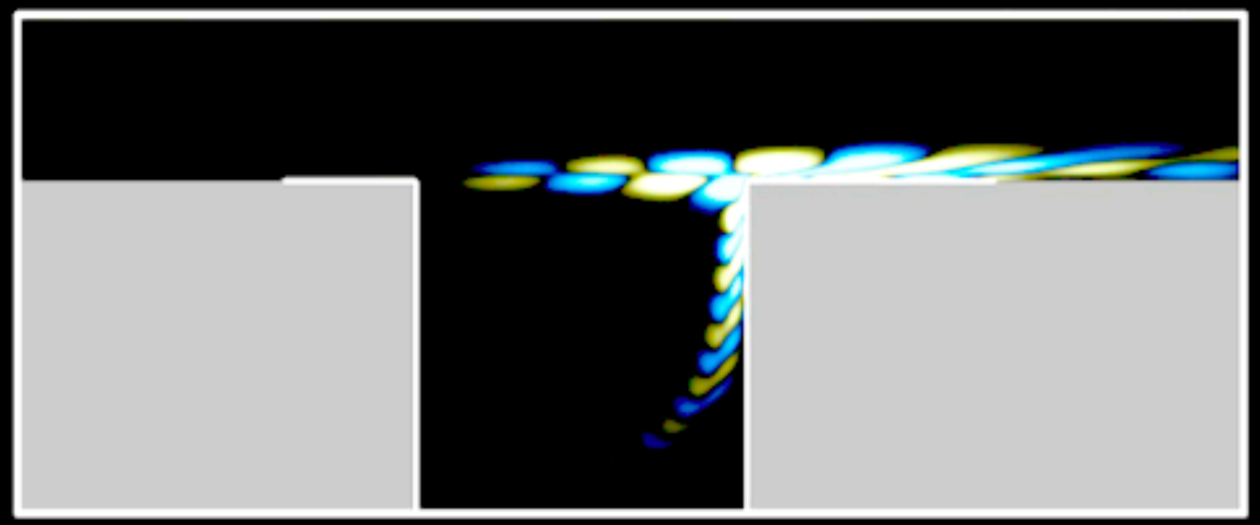
- Cubic, Quintic, Septic terms approximate truncated terms in Galerkin expansion

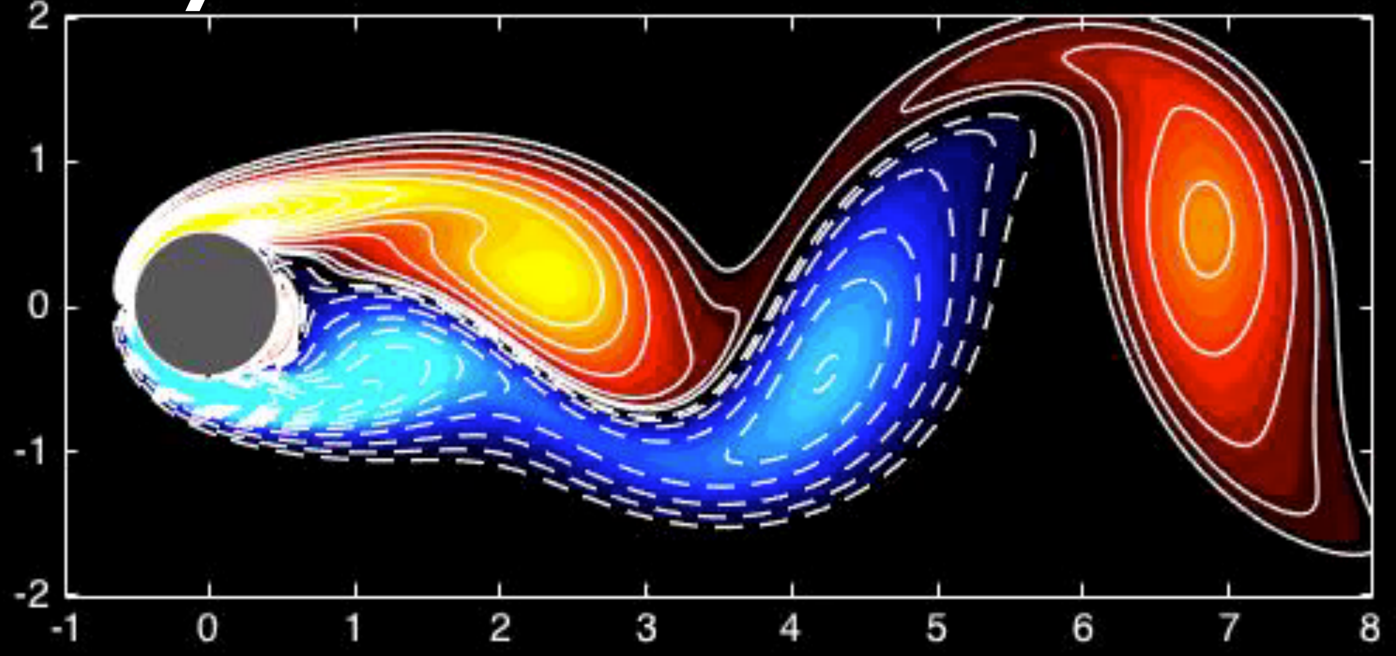
$$\begin{aligned} \dot{x} &= \mu x - \omega y + Axz \\ \dot{y} &= \omega x + \mu y + Ayz \\ \dot{z} &= -\lambda(z - x^2 - y^2). \end{aligned}$$

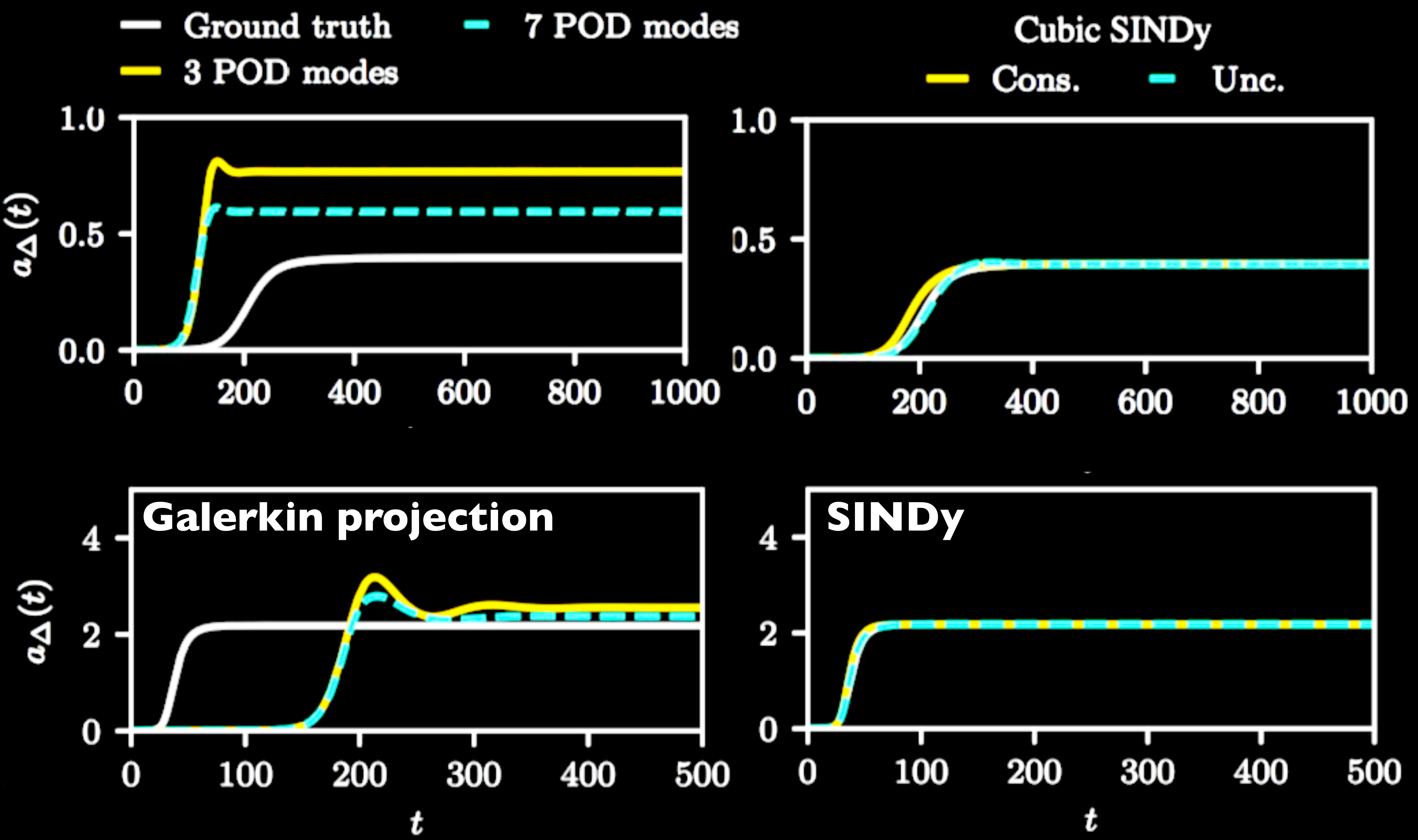


SLB, Proctor, Kutz, *PNAS* 2016.
Loiseau & SLB, *JFM* 838, 2018

Constrained Sparse Galerkin Regression





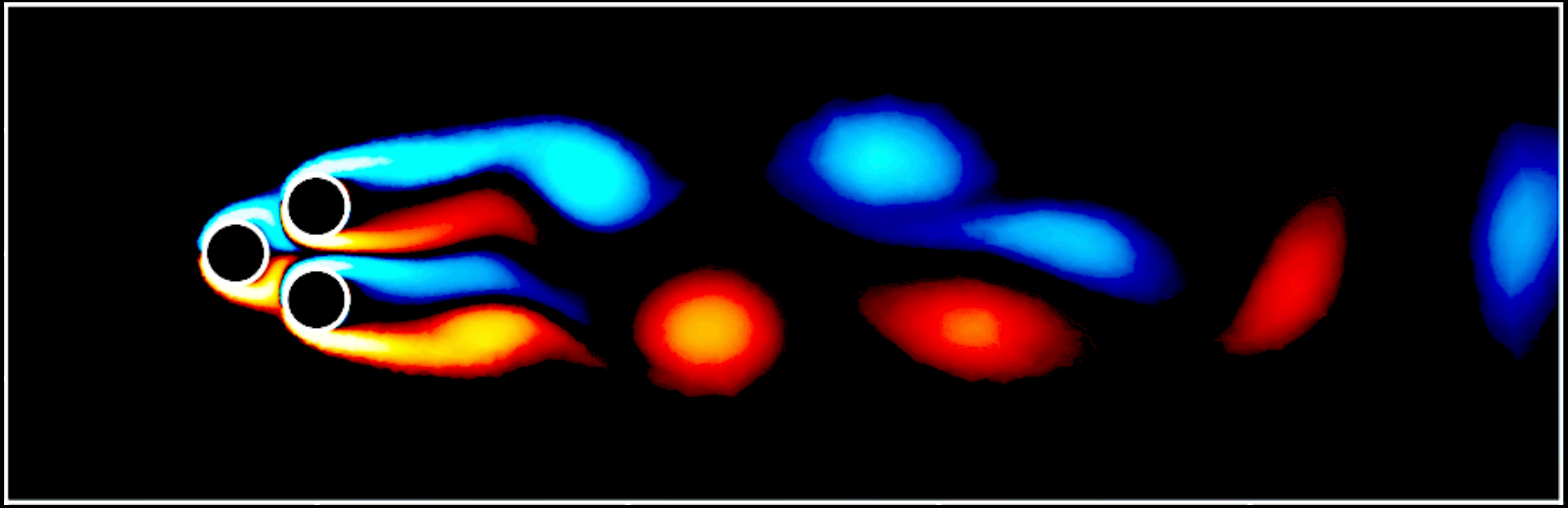


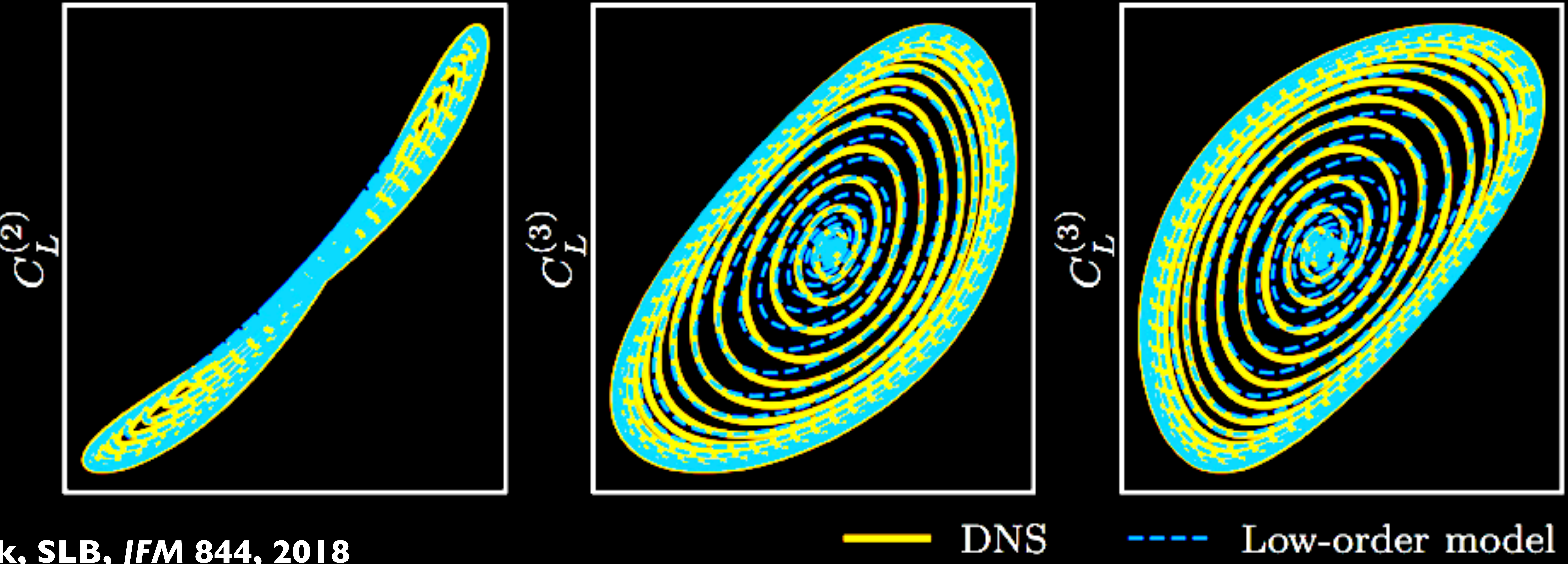
$$\ddot{x} - \underbrace{\left(0.2 - 0.24x^2 - 0.15\dot{x}^2\right)}_{k(x,\dot{x})}\dot{x} + 1.26x = 0$$

Spring-Mass Damper with Nonlinear Damping!

Loiseau & SLB, *JFM* 838, 2018

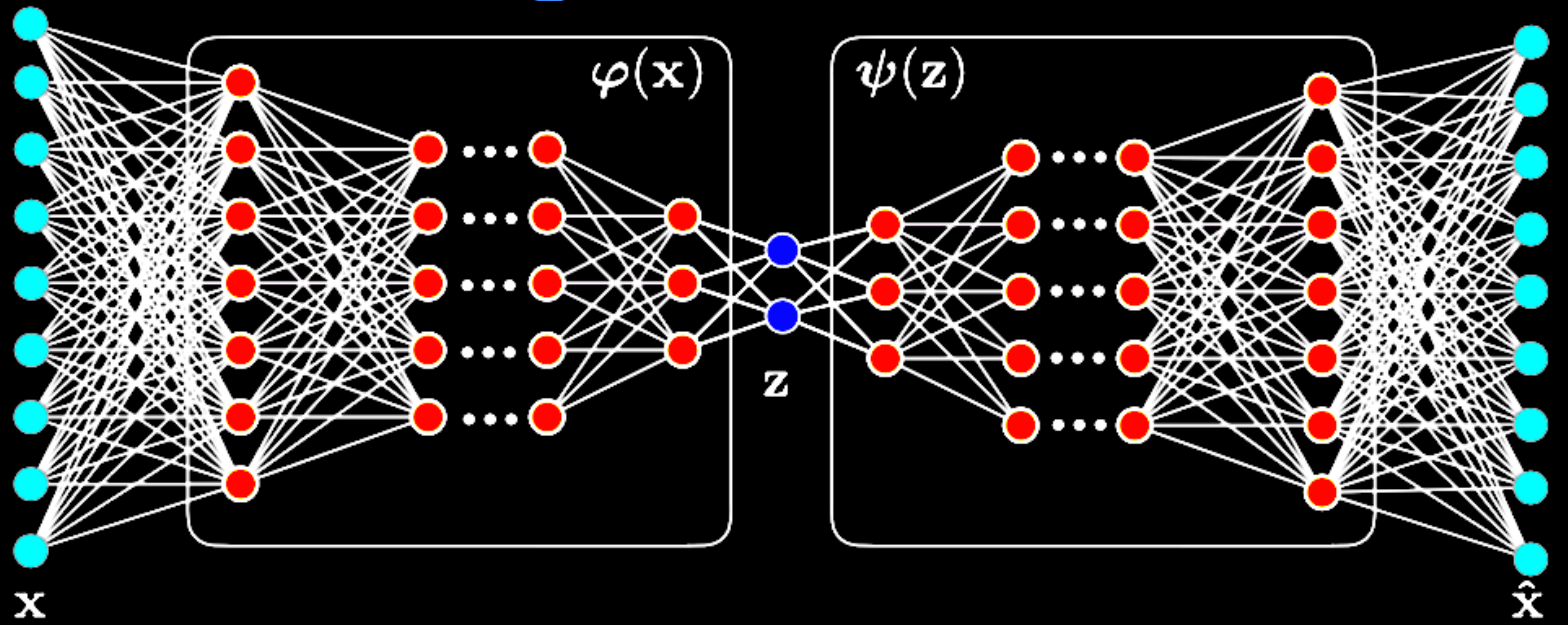
More Complex Flow: Fluidic Pinball





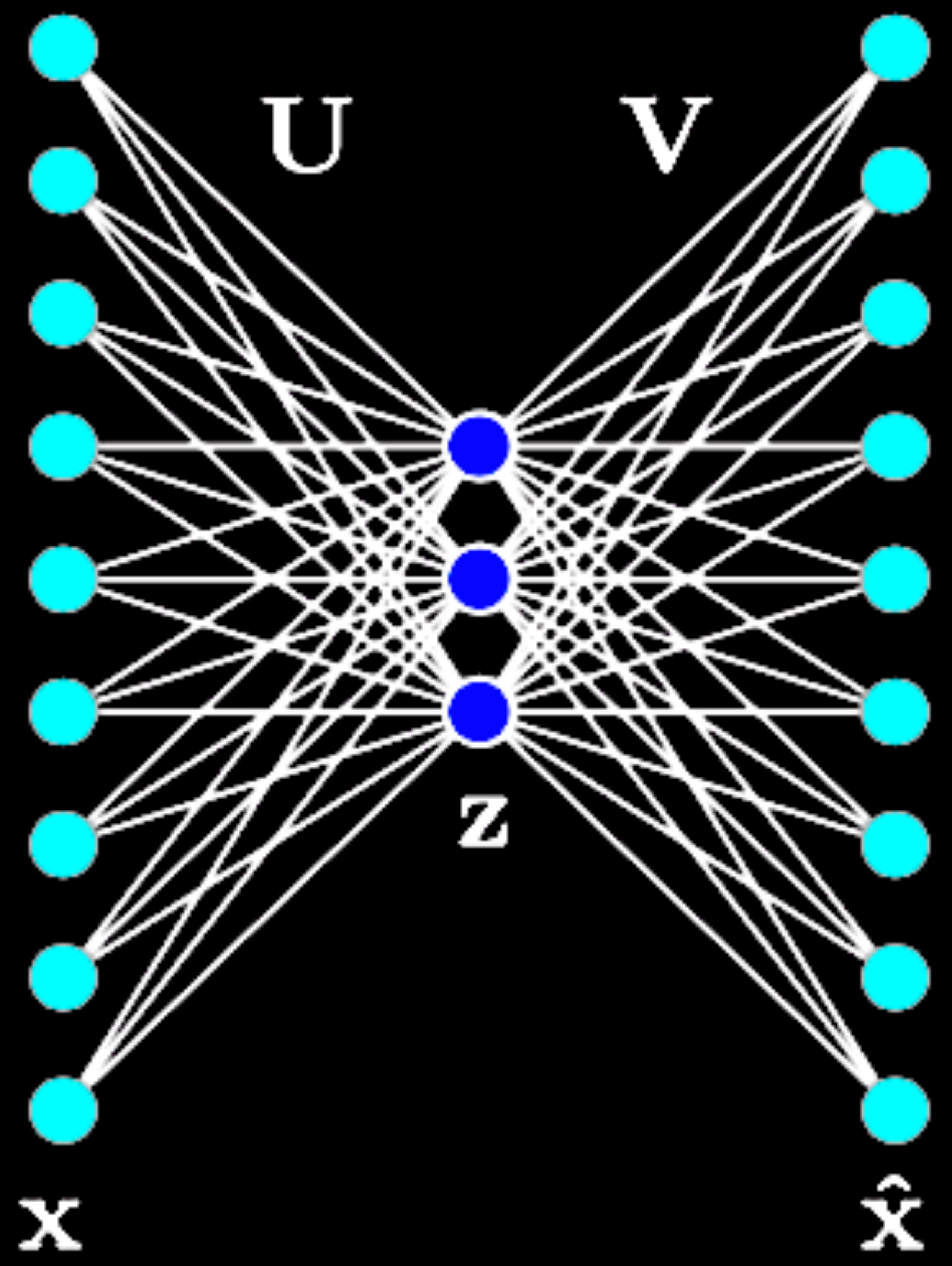
Loiseau, Noack, SLB, *JFM* 844, 2018

LATENT VARIABLES

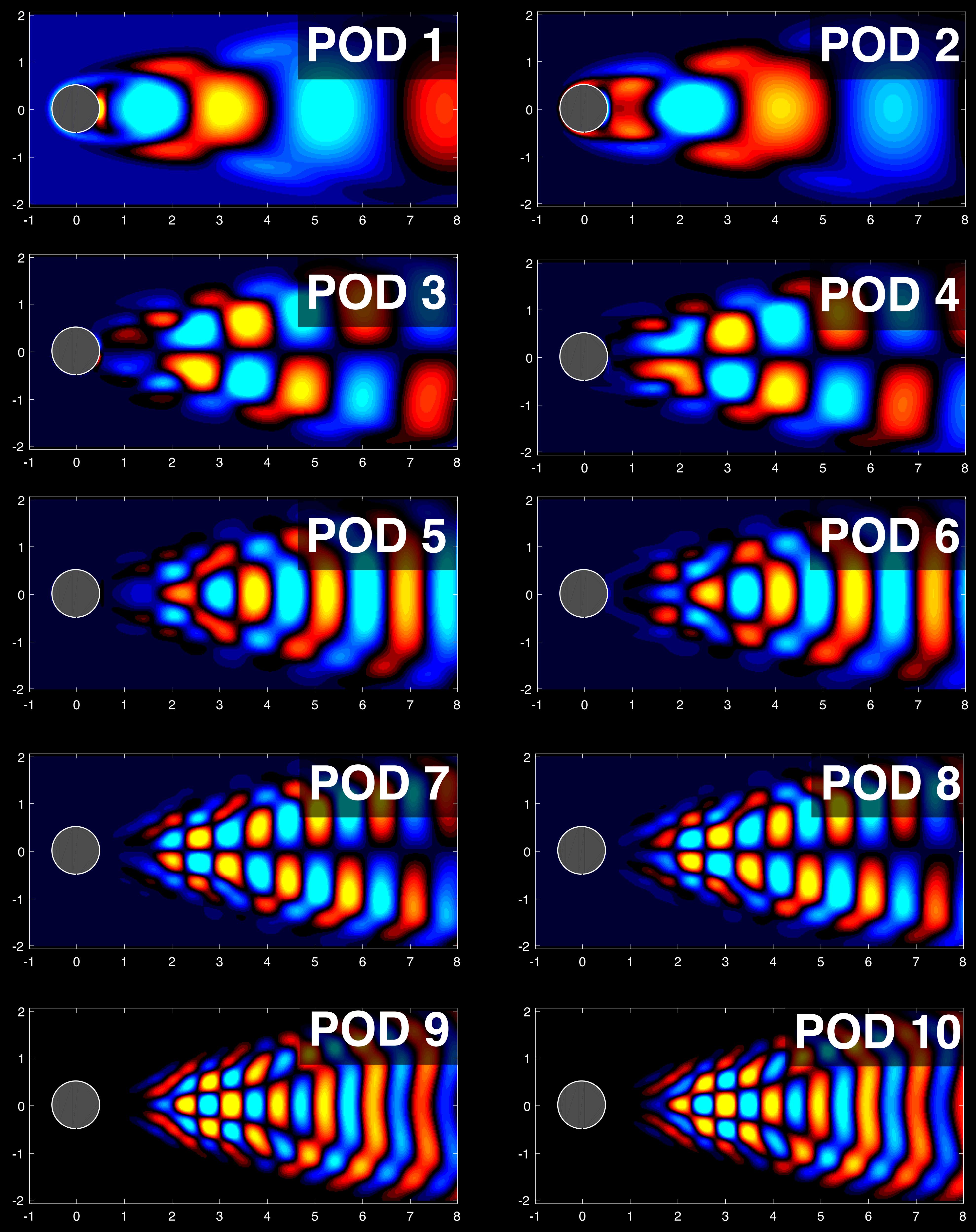


D
E
LEARNING
P

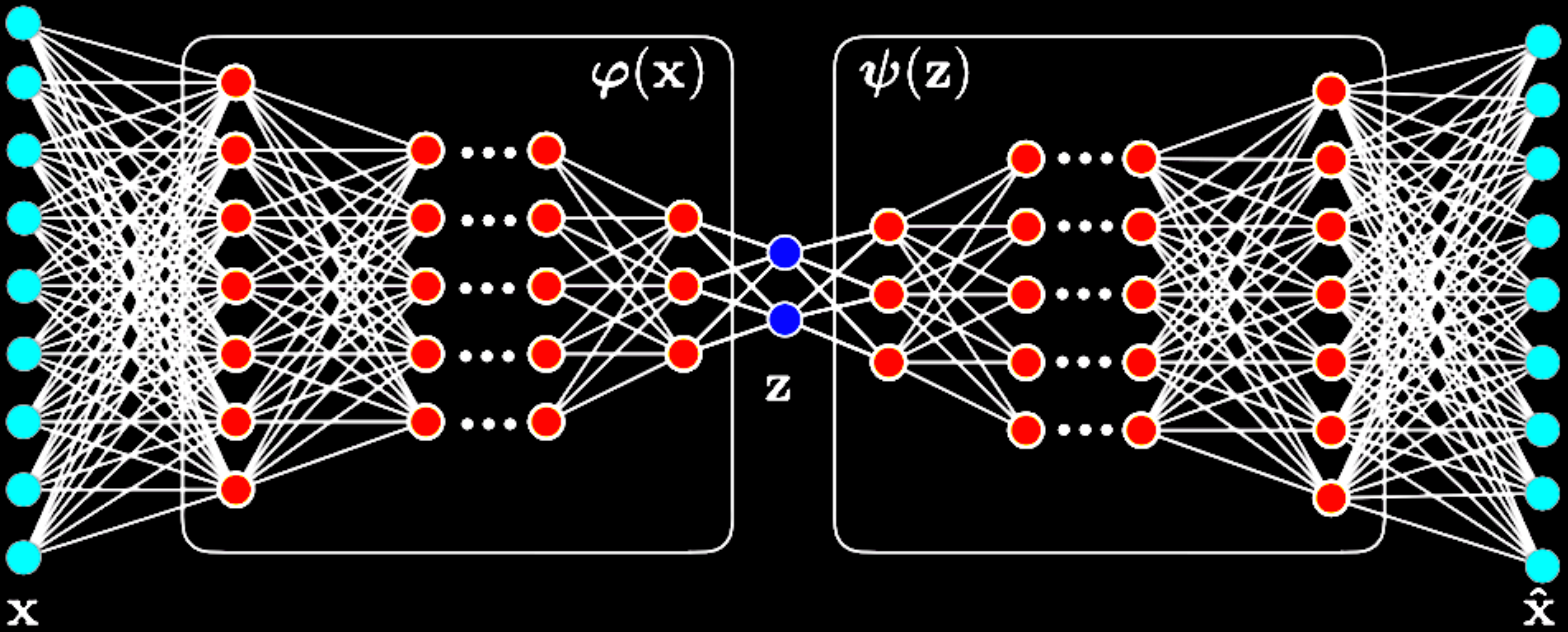
Autoencoder (Shallow, Linear)



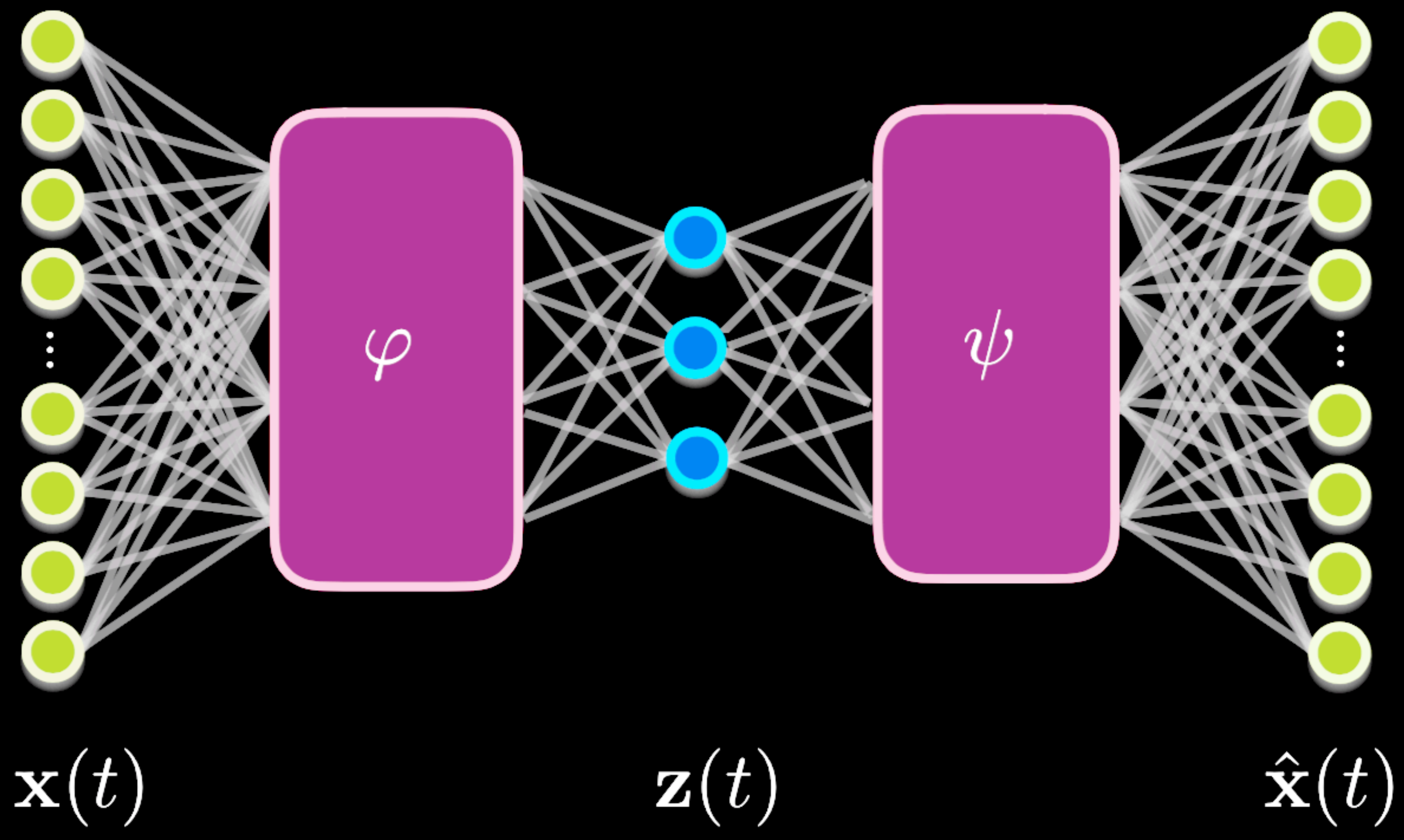
Principal
Component
Analysis

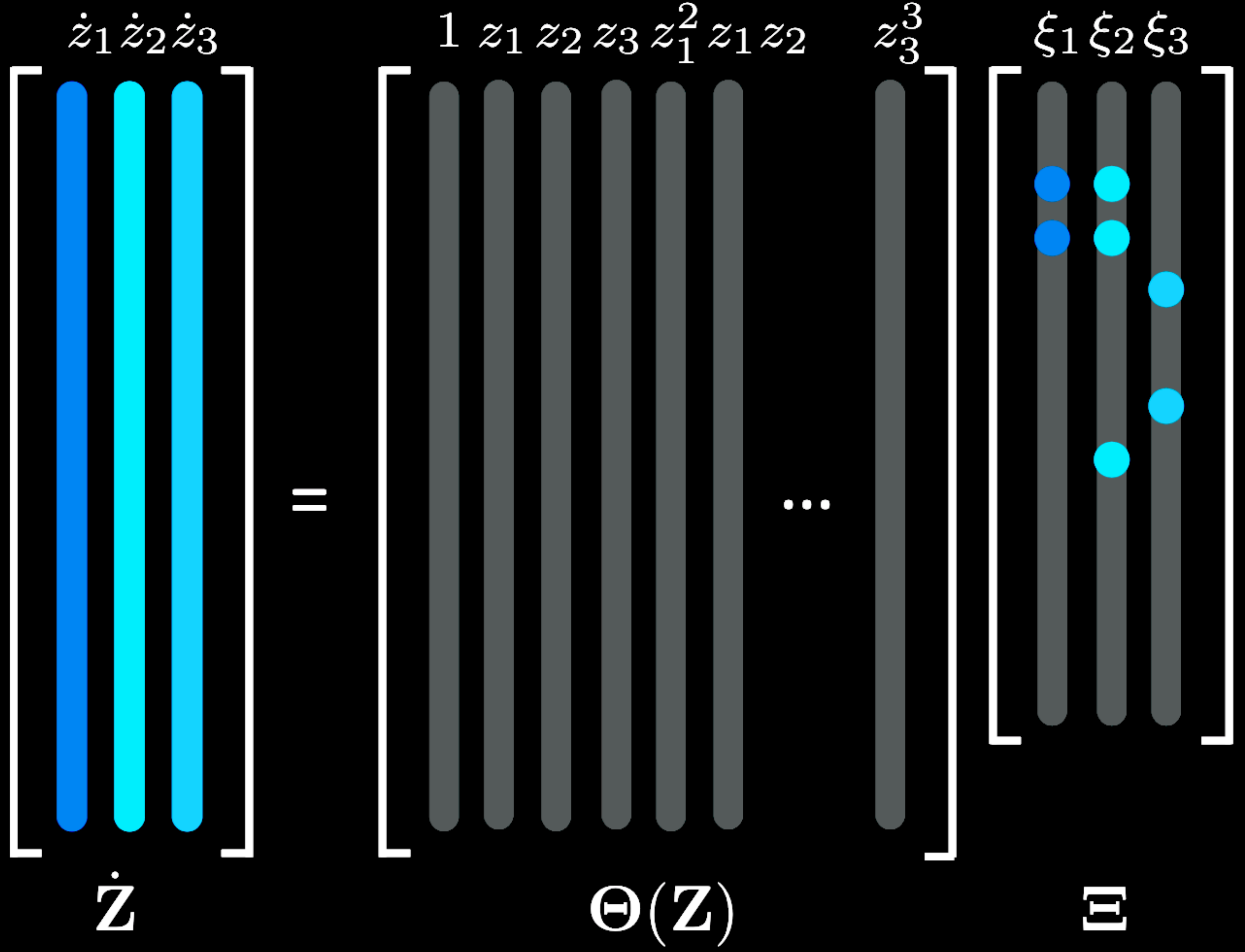


Autoencoder (Deep)



SINDY + Autoencoder



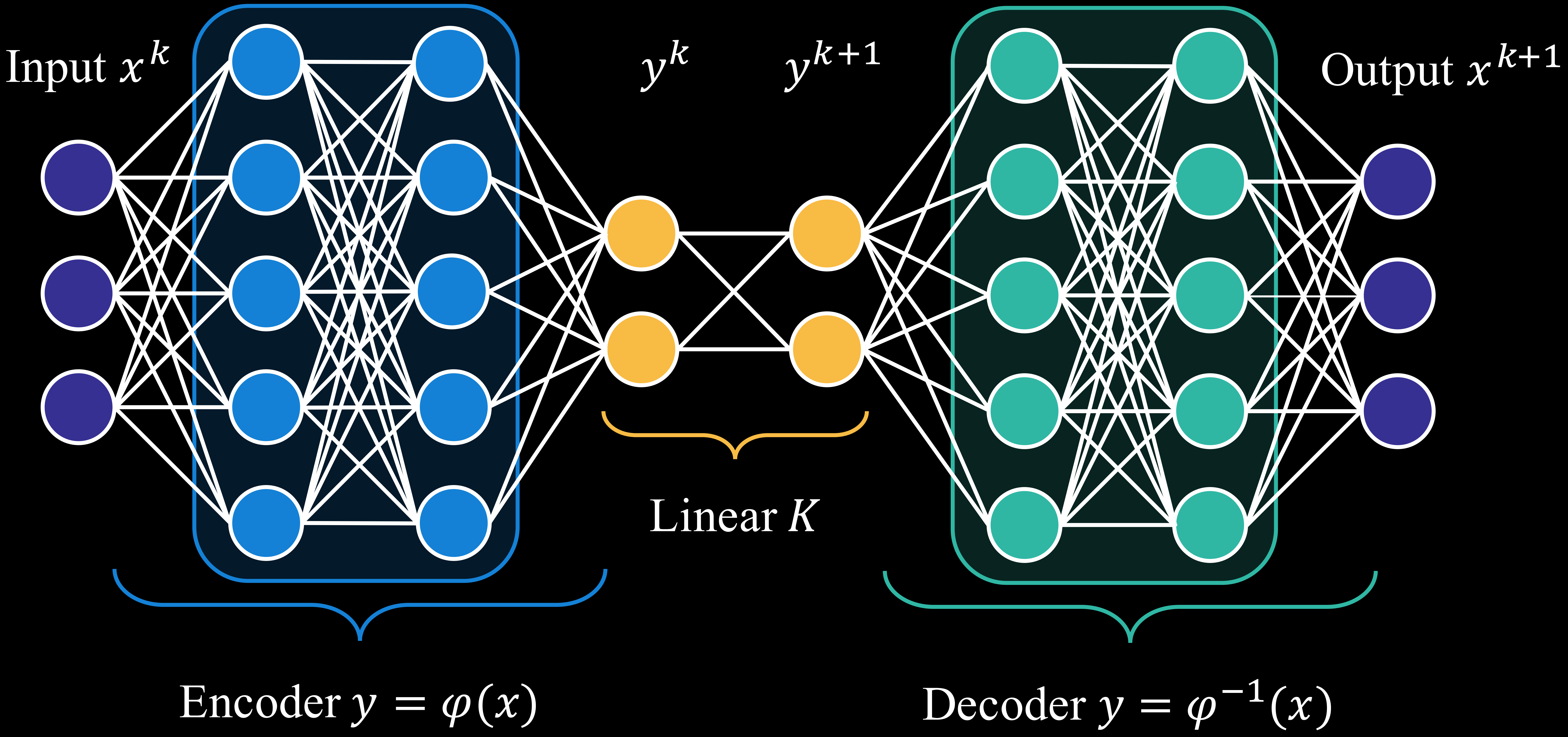


$$\dot{\mathbf{z}}_i = \nabla_{\mathbf{x}}\varphi(\mathbf{x}_i)\dot{\mathbf{x}}_i \qquad \boldsymbol{\Theta}(\mathbf{z}_i^T) = \boldsymbol{\Theta}(\varphi(\mathbf{x}_i)^T)$$

$$\underbrace{\|\mathbf{x}-\psi(\mathbf{z})\|_2^2}_{\text{reconstruction loss}} + \underbrace{\lambda_1 \left\|\dot{\mathbf{x}} - (\nabla_{\mathbf{z}}\psi(\mathbf{z}))\left(\boldsymbol{\Theta}(\mathbf{z}^T)\boldsymbol{\Xi}\right)\right\|_2^2}_{\text{SINDy loss in } \dot{\mathbf{x}}} + \underbrace{\lambda_2 \left\|(\nabla_{\mathbf{x}}\mathbf{z})\,\dot{\mathbf{x}} - \boldsymbol{\Theta}(\mathbf{z}^T)\boldsymbol{\Xi}\right\|_2^2}_{\text{SINDy loss in } \dot{\mathbf{z}}} + \underbrace{\lambda_3 \|\boldsymbol{\Xi}\|_1}_{\text{SINDy regularization}}$$

Champion, Lusch, Kutz, Brunton. *PNAS*, 2019

Neural Network to Find Koopman Eigenfunctions

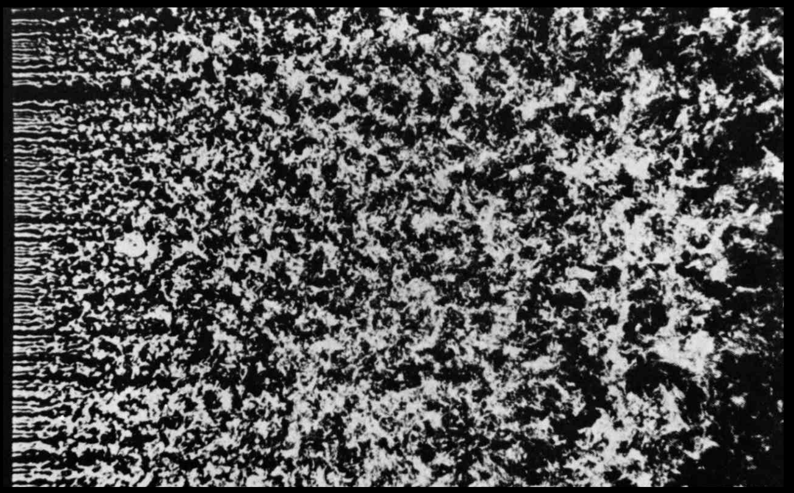
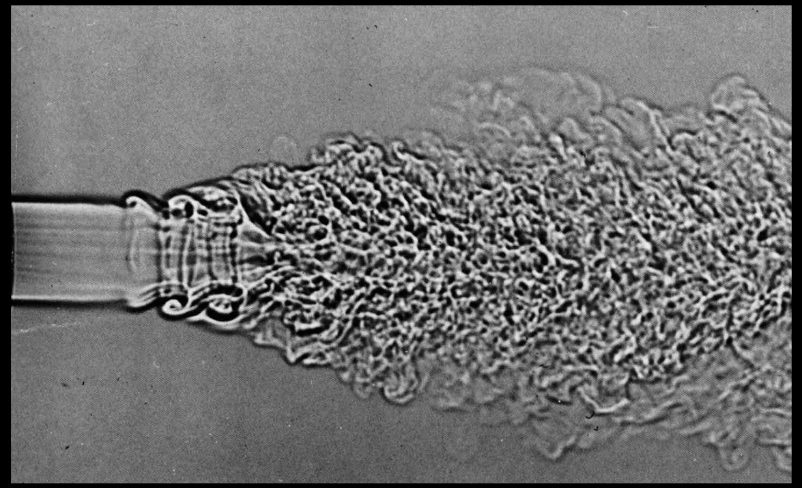
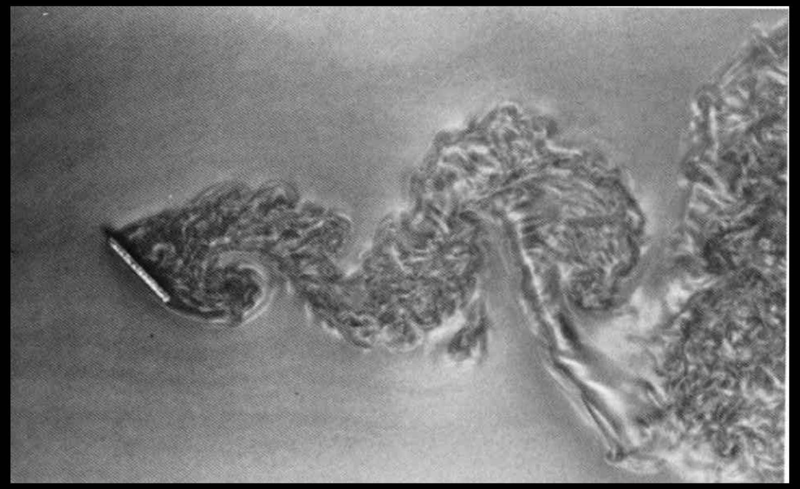
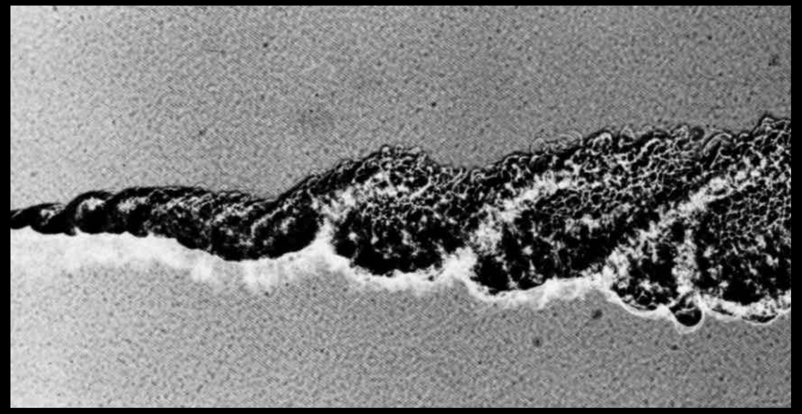
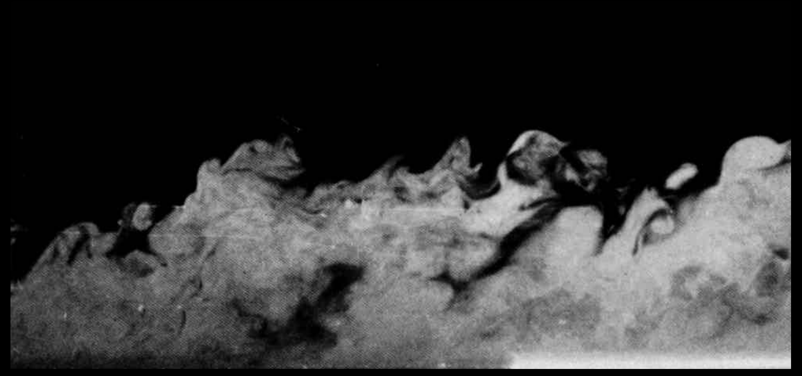


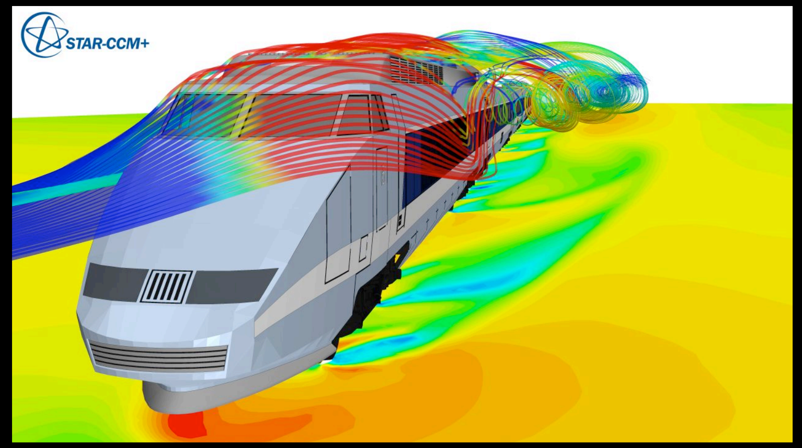
Related work on Deep Learning Koopman:

- **Mardt, Pasquali, Wu, and Noé, *Nat. Comm.* 2018**
  arXiv:1710.06012, 2017
- **Wehmeyer and Noé, *J. Chem. Phys.* 2018**
  arXiv:1710.11239, 2017
- **Yeung, Kundu, Hodas,**
  arXiv:1708.06850, 2017
- **Takeishi, Kawahara, and Yairi, *NeurIPS* 2017**
  arXiv:1710.04340
- **Otto and Rowley, *SIADS 2019***
  arXiv:1712.01378

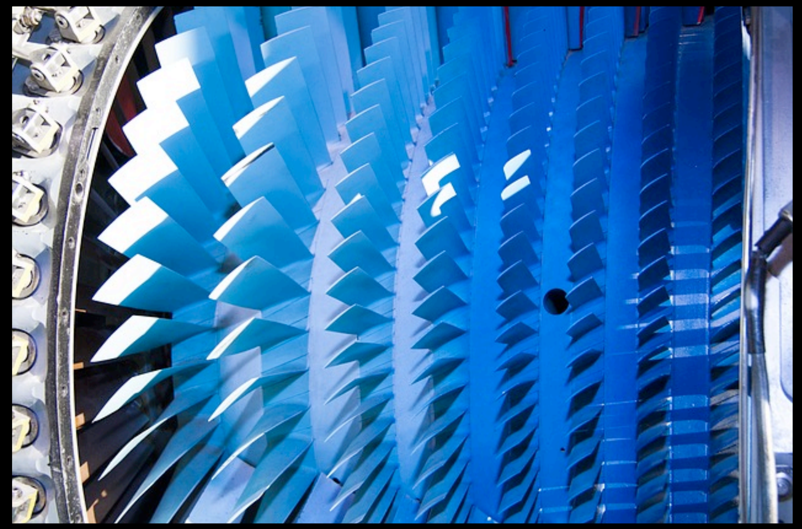
Lusch, Kutz, Brunton, *Nat. Comm.* 2018

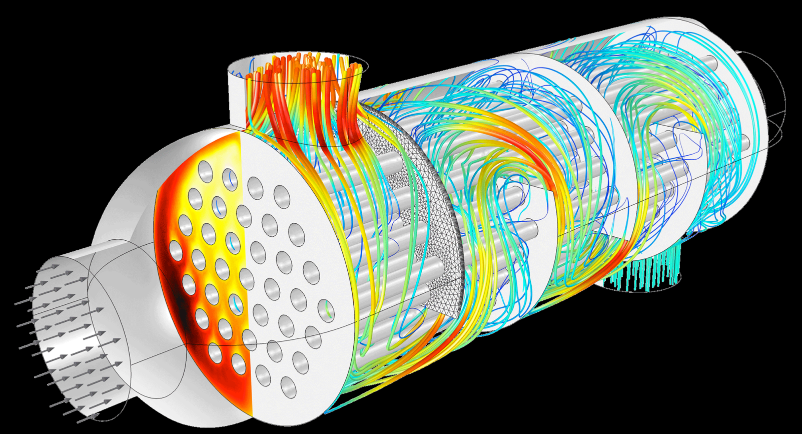
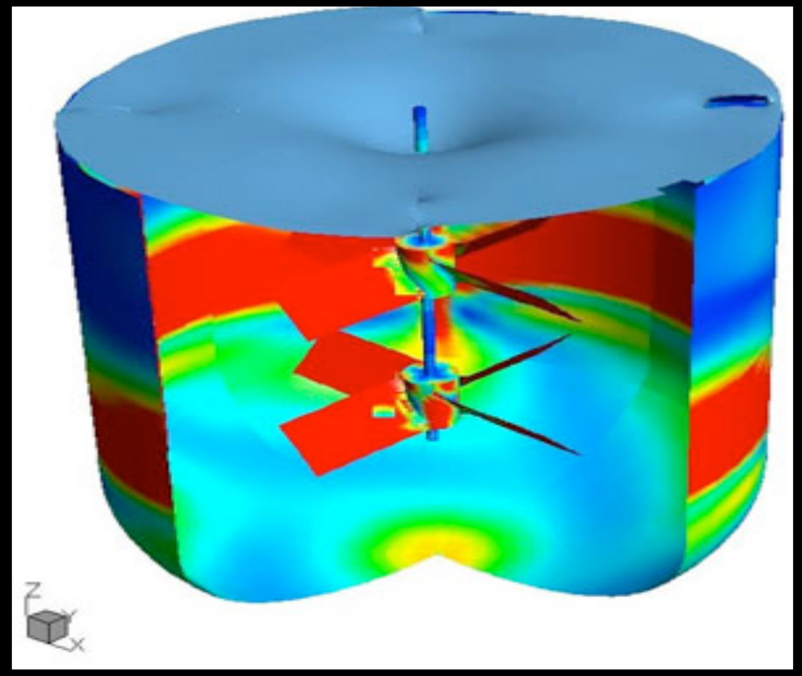
FLOW CONTROL

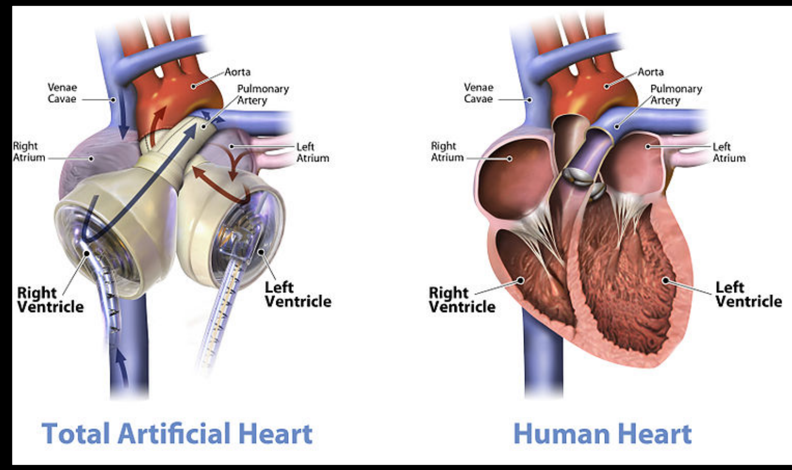










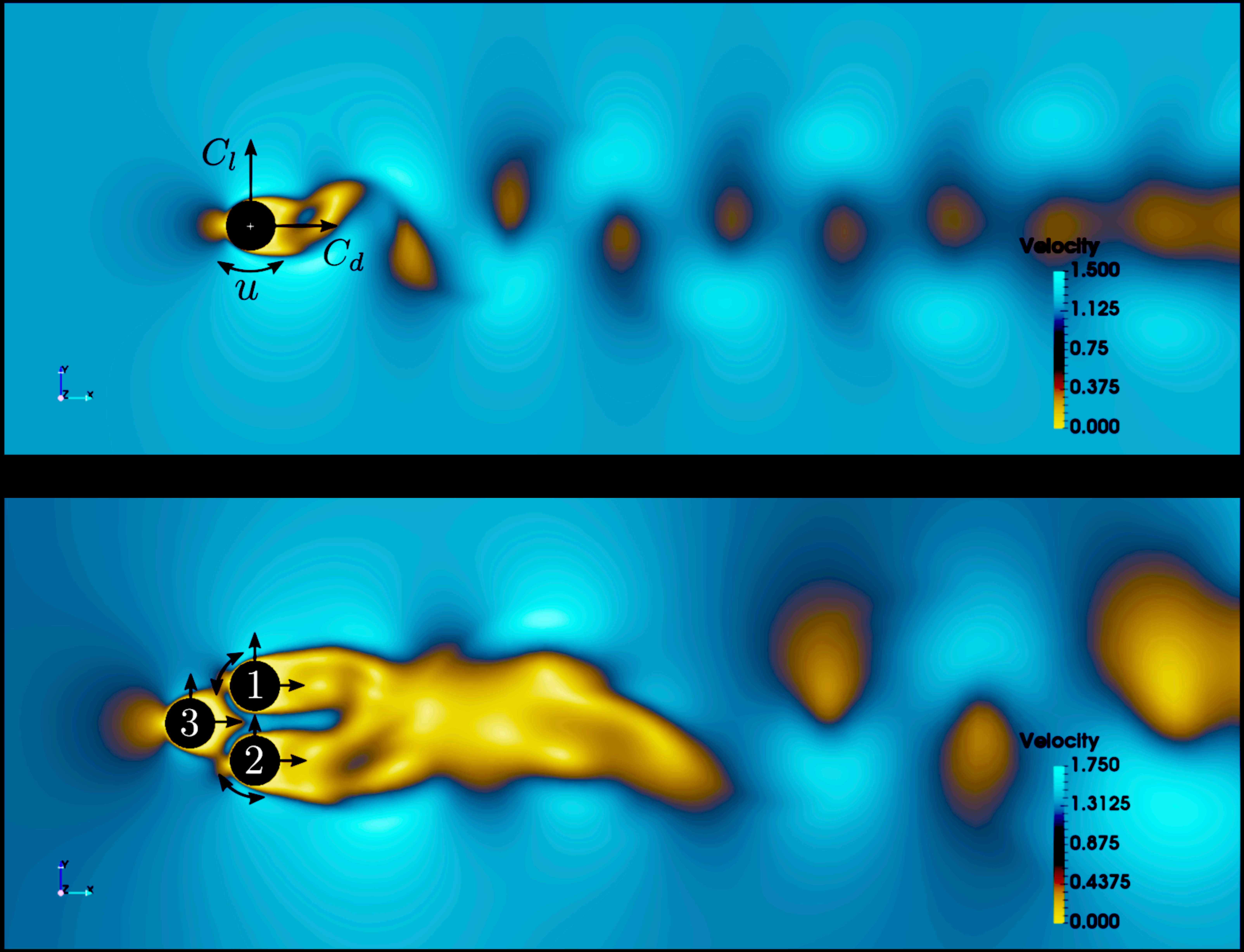




SLB, Noack, *AMR*, 2015
Duriez, SLB, Noack, Springer *2016*

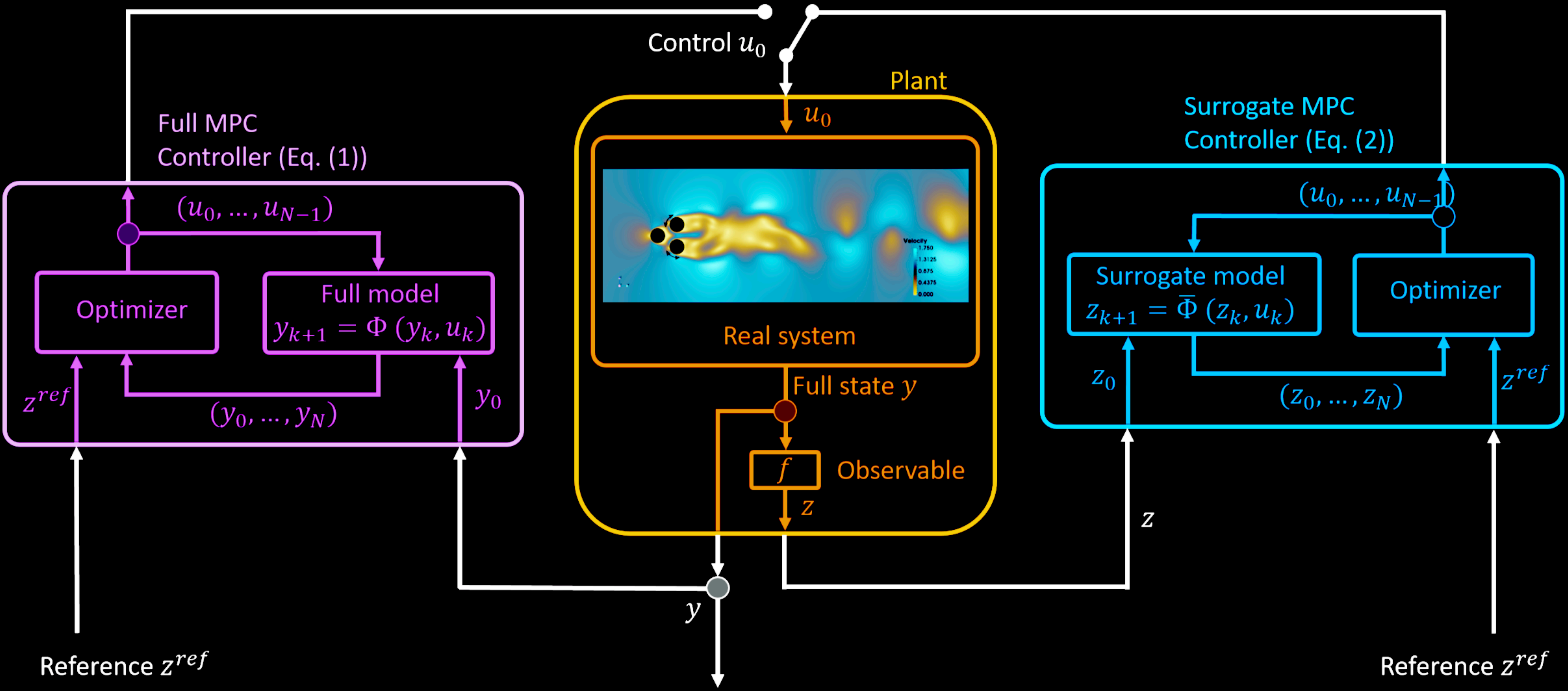
FLOW CONTROL

Deep MPC for Fluid Flow Control



Bieker, Peitz, et al., *arXiv*, 2019.

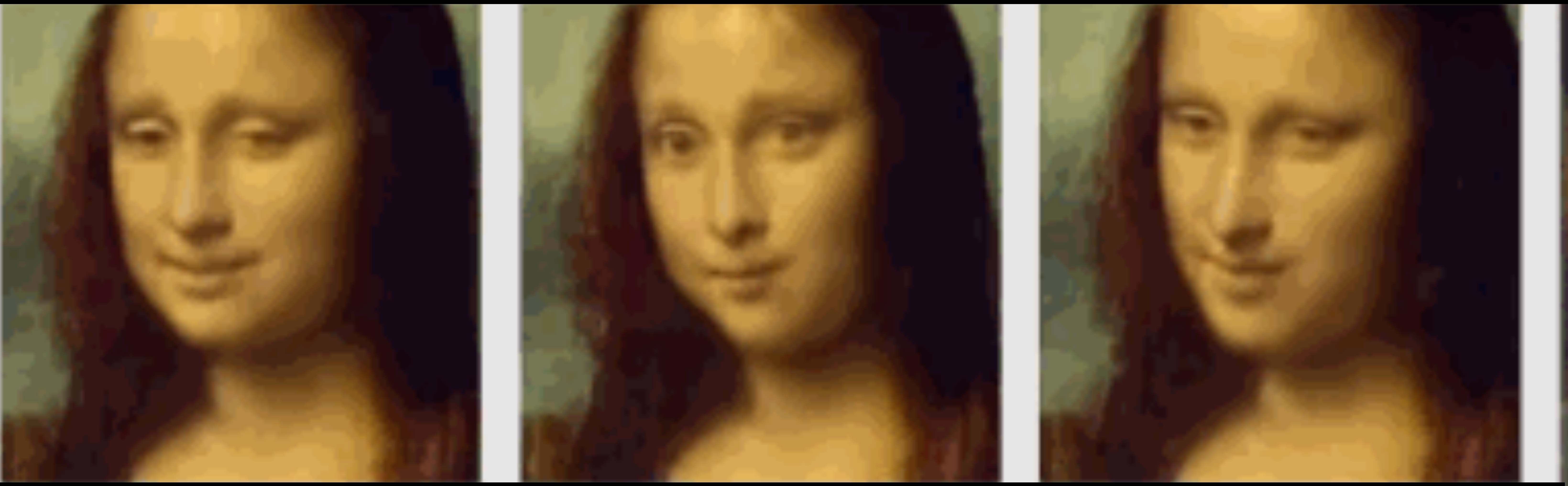
Deep MPC for Fluid Flow Control



Bieker, Peitz, et al., *arXiv*, 2019.

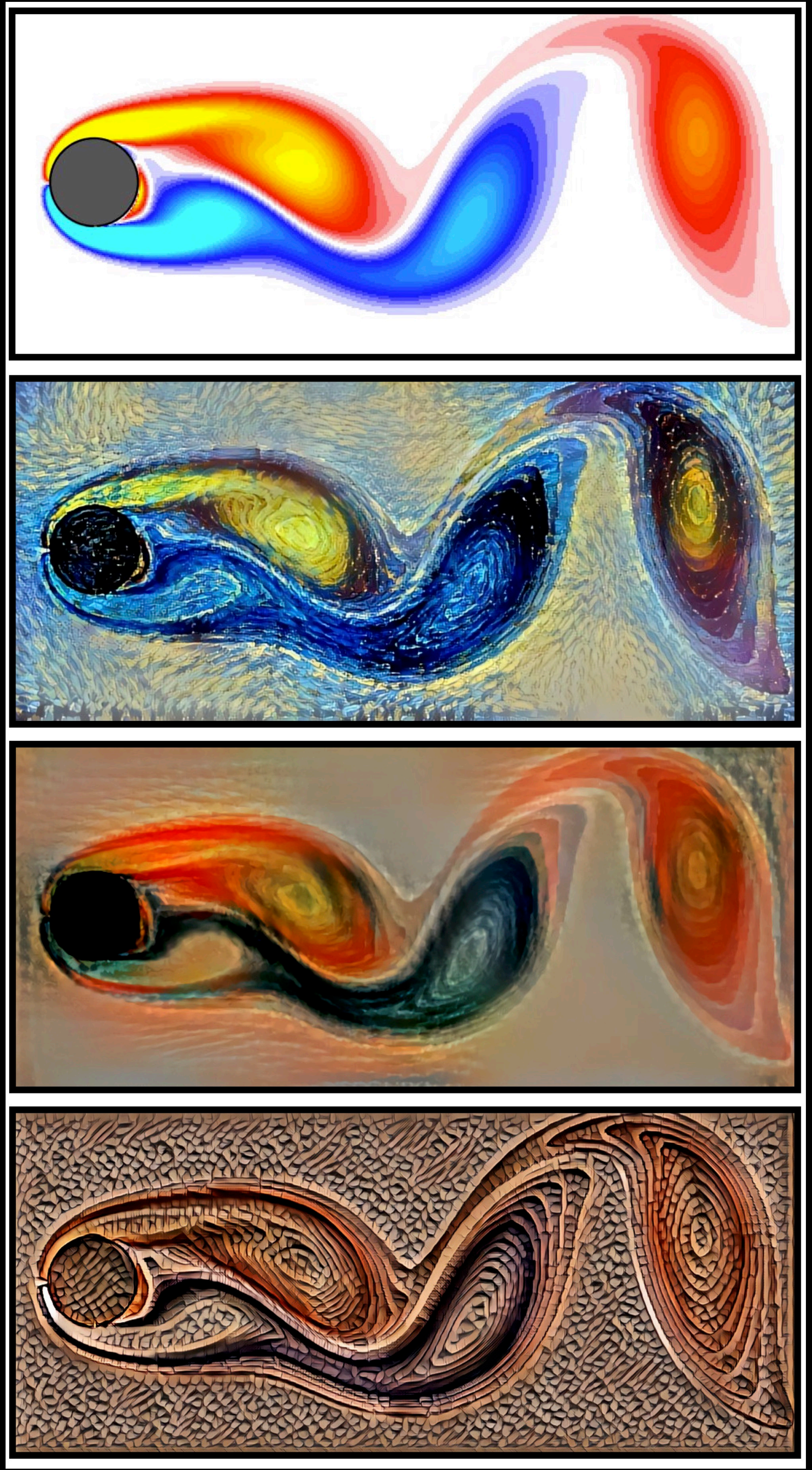
INSPIRATION FROM BIOLOGY

GENERATIVE FLUID DYNAMICS



Samsung AI Center and Skolkovo Institute of Science and Technology

Deep dream of Arcimbaldo’s *La Primavera*
By Calhoun Press



dreamscopeapp.com


QUESTIONS
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