

# Predicting shear flow transitions using machine-learning methods

SIAM Conference on Dynamical Systems  
May 24, 2021

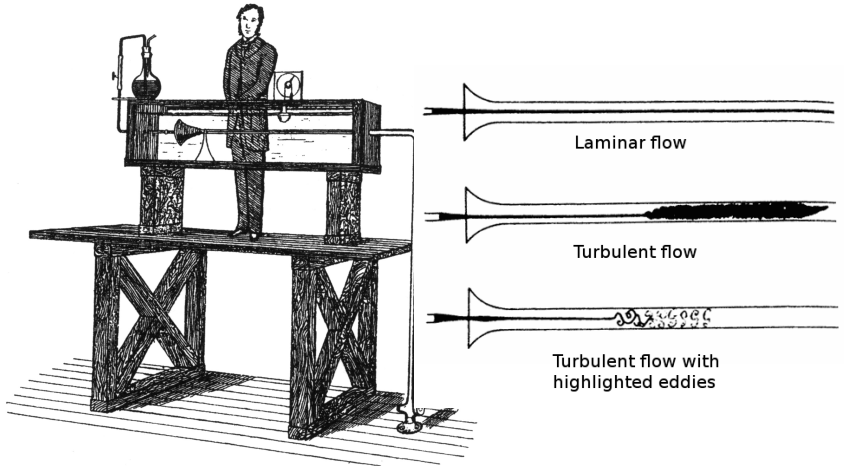
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# Reynolds experiment



Reynolds, Phil. Trans. R. Soc. London, 174 (1884)

# Plane Couette flow

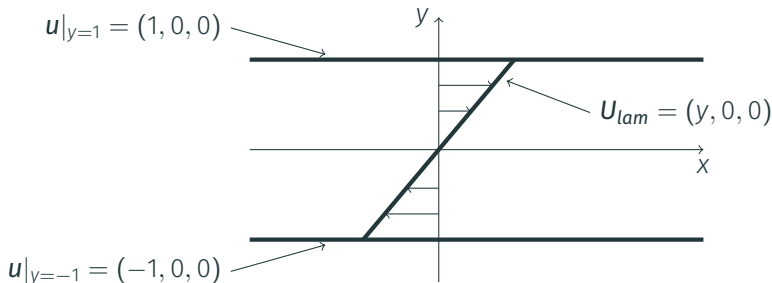
Incompressible Navier–Stokes equation:

$$\partial_t \mathbf{u} + (\mathbf{u} \cdot \nabla) \mathbf{u} = -\nabla p + \frac{1}{Re} \nabla^2 \mathbf{u}$$

$$\nabla \cdot \mathbf{u} = 0$$

Streamwise and spanwise directions: periodic BCs

Wall-normal direction: no-slip BCs



# Moehlis–Faisst–Eckhardt model<sup>1</sup>

Low-dimensional model is obtained by Galerkin projection:

$$\mathbf{u}(x, t) = \sum_{j=1}^9 a_j(t) \mathbf{u}_j(x).$$

9-dimensional system of ODEs:

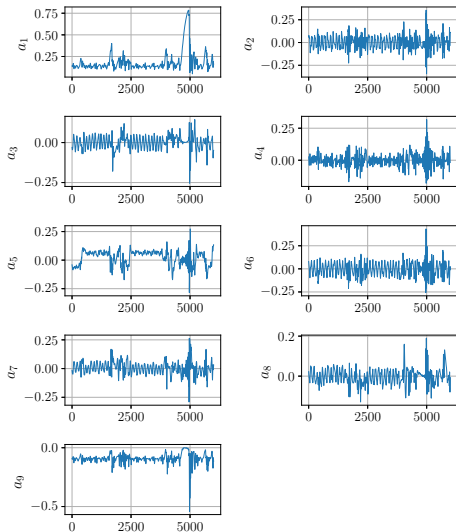
$$\frac{d}{dt} \mathbf{a} = \mathbf{f}(\mathbf{a}; Re, \Gamma_x, \Gamma_z),$$

where  $\mathbf{a}(t) = [a_1(t), \dots, a_9(t)]^T$ .

Parameters:

- Domain wavelengths:  
 $\Gamma_x = 1.75\pi, \Gamma_z = 1.2\pi$
- Reynolds number:  
 $Re \in [200; 500]$

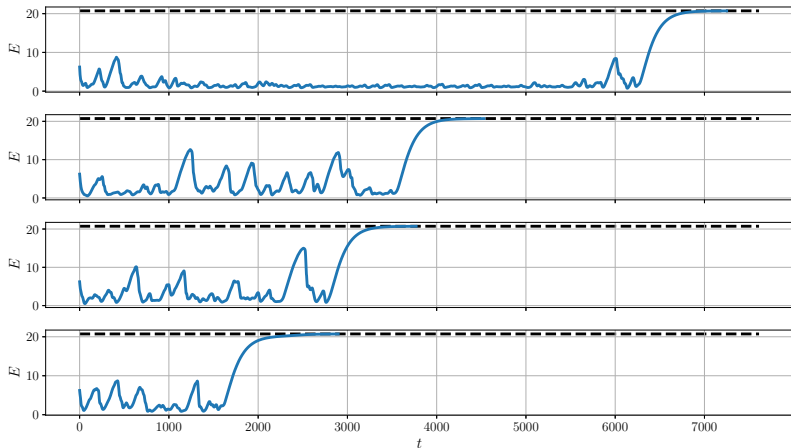
Sustained turbulence:  $Re \gtrsim 320$



<sup>1</sup>Moehlis et al., New J. Phys., 6 56 (2004)

# Laminarization ( $Re = 300$ )

- Turbulence in shear flows is a “leaky” attractor<sup>2</sup>
- As a result, all trajectories eventually end up with laminarization



<sup>2</sup>Avila *et al.*, *Science* 333, 6039 (2011)

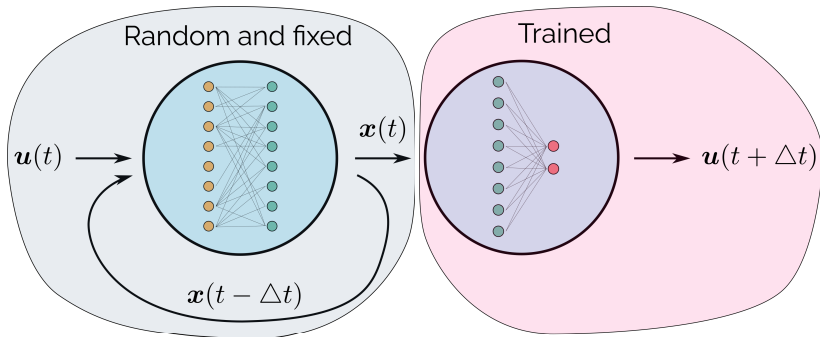
# Echo State Network (ESN)

Echo State Network is a reservoir-computing architecture:

$$\begin{aligned}x(t) &= \tanh(W_{in}u(t) + Wx(t - \Delta t)), \\u(t + \Delta t) &= W_{out}x(t).\end{aligned}$$

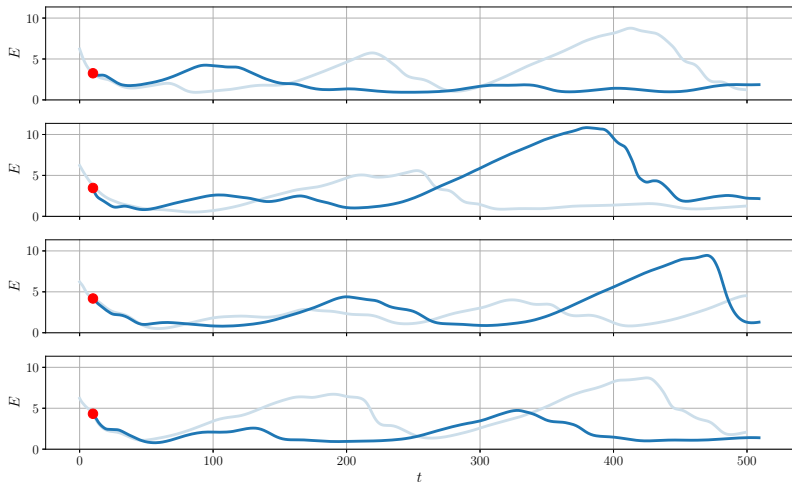
where

- $W_{in}$  and  $W$  are random sparse matrices
- $W_{out}$  is to be trained by solving the normal equation



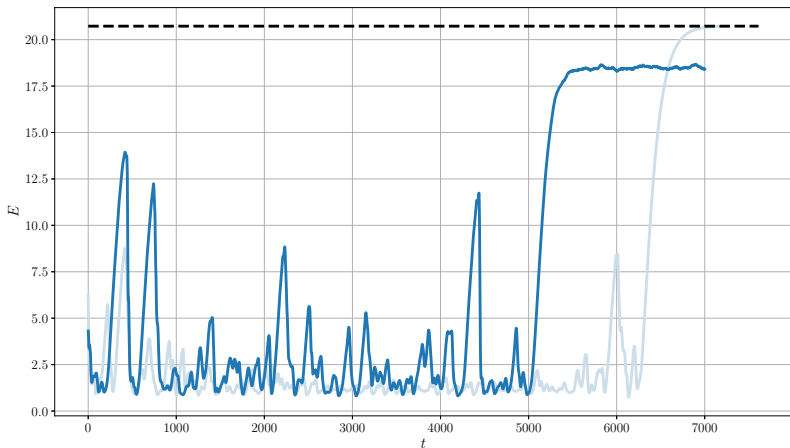
## Short-term prediction ( $Re = 300$ )

Due to the chaotic nature of the original model, the ESN skill for short-term prediction is limited



# Long-term prediction ( $Re = 300$ )

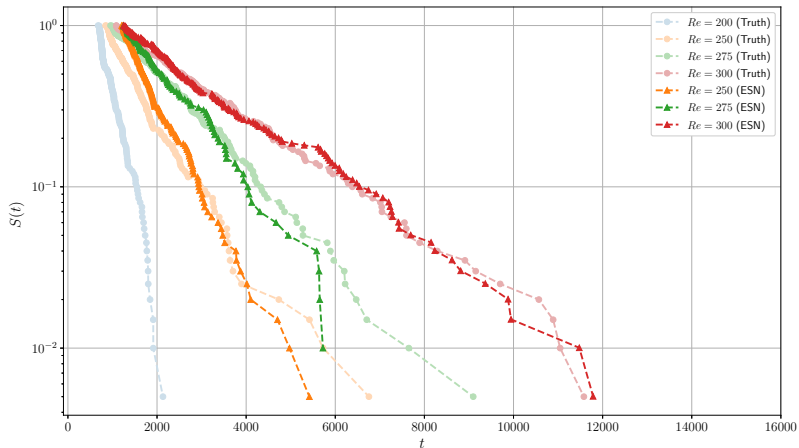
- ESN is able to “learn” the laminarization dynamics without experiencing laminarization during the training
- Moreover, ESN is able to replicate the laminar solution





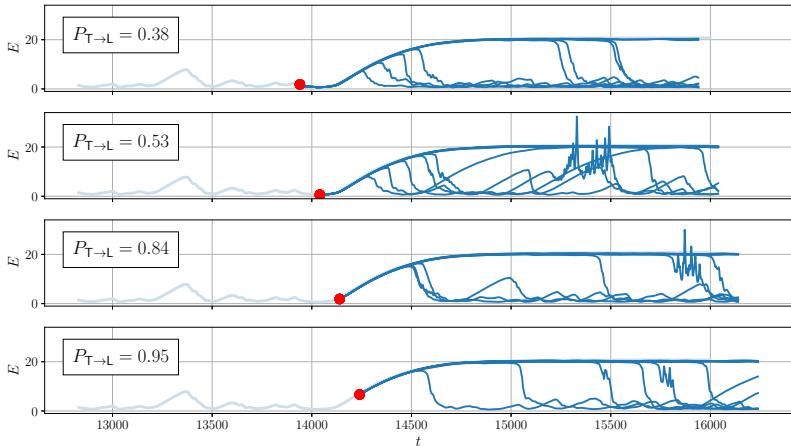
# Lifetime distribution

- ESN can successfully replicate the lifetime statistics
- Its skill may degrade depending on the time series used for training



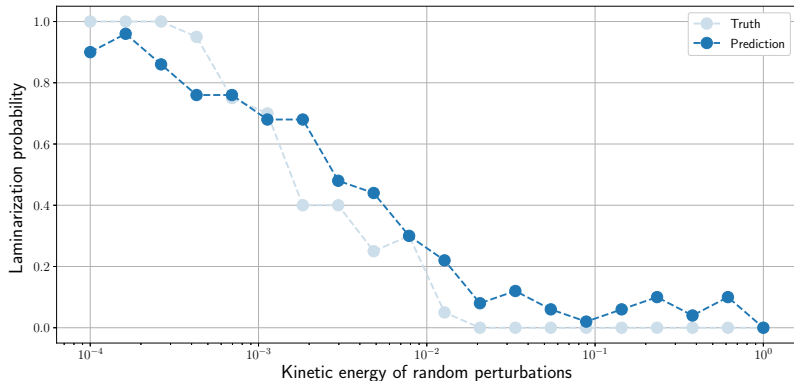
# Turbulent-to-laminar transition ( $Re = 500$ )

- Ensemble approach can be used to estimate the probability of turbulent-to-laminar transition
- The probability grows as the initial condition gets closer to the laminarization event



# Laminar-to-turbulent transition ( $Re = 500$ )

- Robustness of the laminar state to finite-amplitude perturbations is important for assessing laminar-to-turbulent transition
- **Laminarization probability** is the probability that a random perturbation decays as a function of its kinetic energy<sup>3</sup>
- ESN can successfully replicate the laminarization probability



<sup>3</sup>Pershin, Beaume, Tobias, J. Fluid Mech. 895, A16 (2020)

# Conclusion

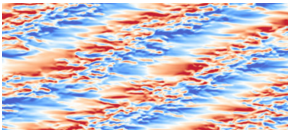
PP2 Poster Session II (Wednesday, 9:30am):

Assessing the Control of Finite-Amplitude Instabilities

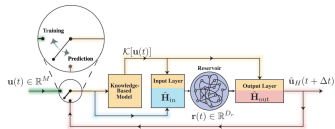
via a Probabilistic Protocol: Application to Transitional Flows

Cedric Beaume, Anton Pershin, Steven Tobias

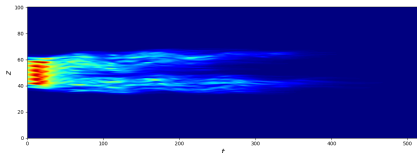
(a) Spatially extended flows?<sup>4</sup>



(b) Physics-informed ESN?<sup>5</sup>



(c) Optimal control using reservoir computing?



<sup>4</sup>Chantry *et al.*, *J. Fluid Mech.* **791**, R8 (2016)

<sup>5</sup>Pathak *et al.*, *Chaos* **28**, 041101 (2018)