Learning from Smart Lagrangian particles (a journey in Mare Incognitum)

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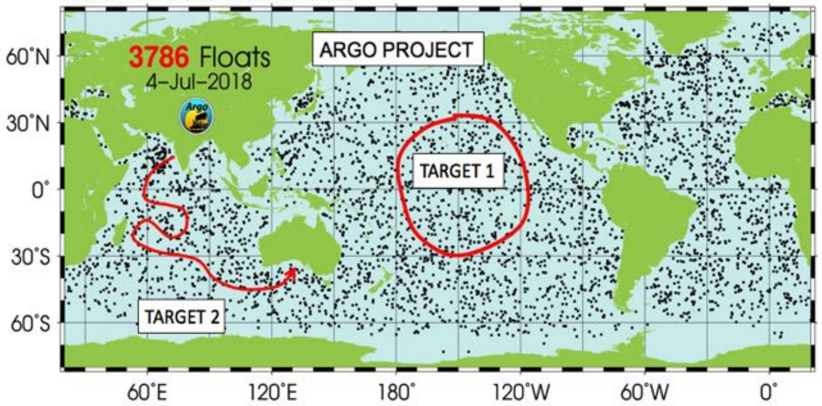
APS-2018

FIG. 2: INSTANTANEOS WORLDWIDE DISTRIBUTION OF DRIFTERS. WE HIGHLIGTHED IN RED TWO POTENTIAL TARGETS: (1) KEEP THE PROBES INSIDE A GIVEN REGION OR (2) OPTIMISING THE NAVIGATION AMONG TWO END-POINTS



Carta Marina *et descriptio septemtrionalium terrarum ac mirabilium rerum in eis contentarum, diligentissime elaborata anno* ***1539*** *Veneciis.* **Olao Magno**

CREDITS: S. Colabrese, G. Marazoglou, P. Clark di Leoni, M. Buzzicotti, F. Bonaccorso (Univ. Tor Vergata, Rome-IT); A. Celani (ICTP Trieste-IT); K. Gustafsson (Univ. Gotheborg, SE); A. Mazzino (Univ. Genova, IT); F. Toschi (TuE , NL)

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CAN WE TEACH **SMART** PROBES (PARTICLES. GLIDERS, DRONES, DRIFTER) TO NAVIGATE IN COMPLEX FLOWS?

CONSTRAINTS. YOU CANNOT:

1) SPEND LARGE AMOUNT OF CHEMICAL/MECHANICAL ENERGY (NO STRONG SELF-PROPULSION)
2) ACCOMPLISH EXTREMELY COMPLEX MANOEVERING
3) HAVE A COMPLETE DESCRIPTION OF THE ENVIRONMENT SURROUNDING YOU

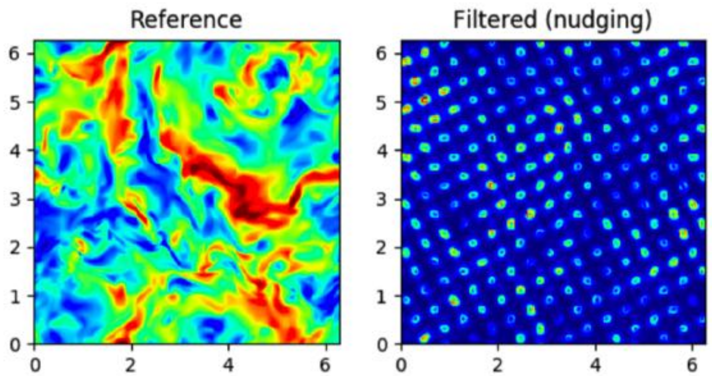
WHY:

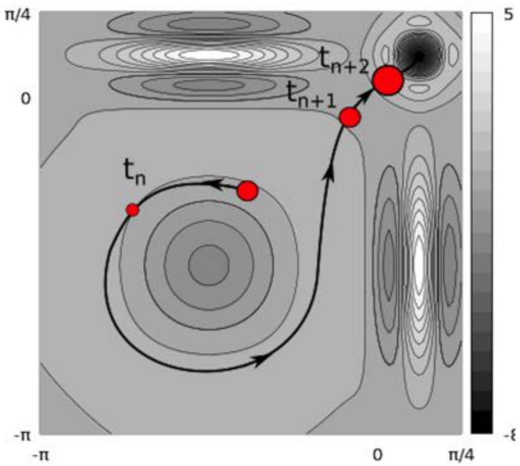
1) TO CONCENTRATE PROBES IN SPECIFIC KEY-FLOW REGIONS: FOR DATA-ASSIMILATION OR FLOW-RECONSTRCUTION

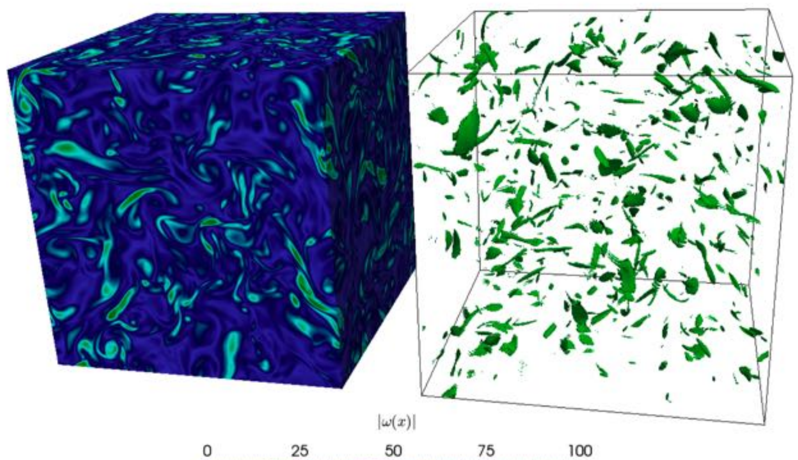
   SEE P. CLARK DI LEONI, L.B., A. MAZZINO: Taming turbulence via spectral and real space Nudging F39.00005 8:52 AM MONDAY

2) TO AVOID/SEARCH EXTREME EVENTS

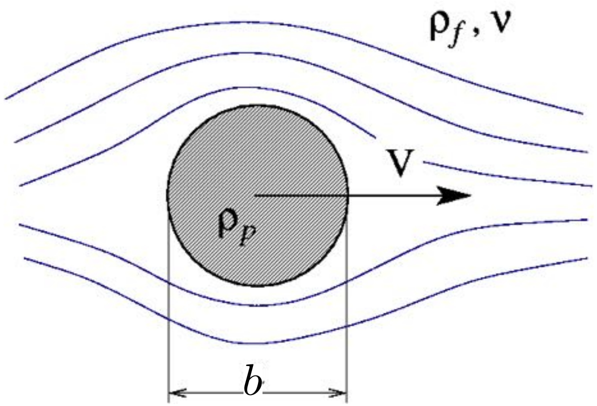
3) TO ACTIVELY REACT ON THE FLOW (TWO-WAY COUPLING). **SEE F. TOSCHI, L.B., M. BUZZICOTTI: The statistical properties of turbulence in presence of smart small-scale forcing L38. 00010 6:02 PM MONDAY**



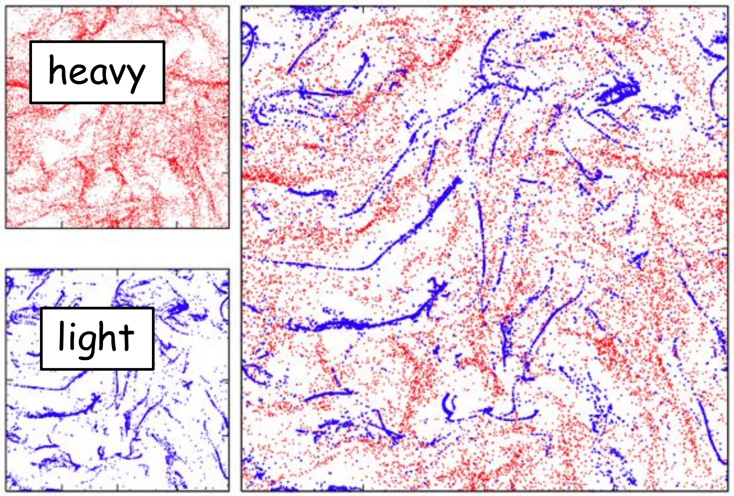




TRACKING PRFERENTIAL STRUCTURES: INERTIAL PARTICLES IN COMPLEX FLOWS



$$\begin{cases} \partial_t \mathbf{v} + \mathbf{v} \cdot \partial_{\mathbf{x}} \mathbf{v} + \partial_{\mathbf{x}} P = \nu \Delta \mathbf{v} \\ \dot{\mathbf{X}}_i = \mathbf{U}_i \\ \dot{\mathbf{U}}_i = -\frac{\mathbf{U}_i - \mathbf{v}}{\tau} + \beta D_t \mathbf{v} - g(1-\beta)\hat{\mathbf{z}} \end{cases}$$



$$\beta = \frac{3\rho_f}{\rho_f + 2\rho_p}$$

$\beta<1$ heavy particles

$\beta>1$ light particles

$$\tau = \frac{b^2}{3\nu\beta}$$

Drag: **Stokes Time**

Preferential concentration

Naive light(heavy) particles accumulate inside(outside) highly vortical regions

M.R. Maxey, J. Fluid Mech. **174**, 441 (1987); G. Falkovich et al, Phys. Rev. Lett. **86**, 2790 (2001)

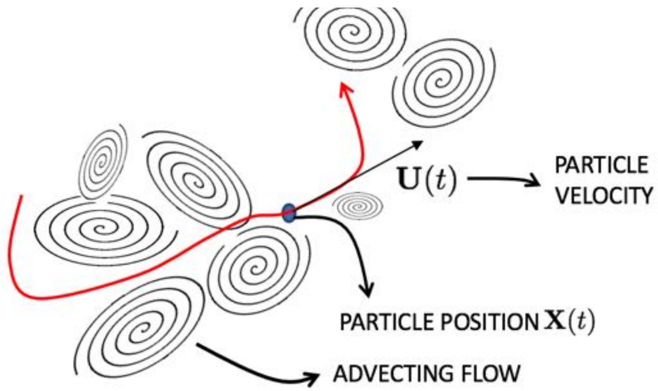
SMART INERTIAL PARTICLES IN COMPLEX FLOWS: HARNESS & CONTROL

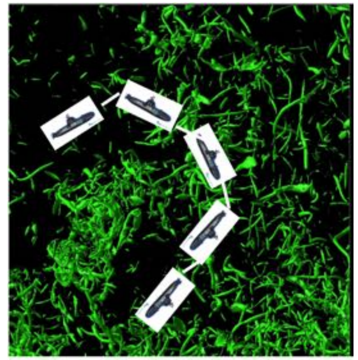
SMART LAGRANGIAN PROBES (ONE-WAY COUPLING): REINFORCEMENT LEARNING TO TRACK PREFERENTIAL VORTICITY STRUCTURES (OR STRAIN, QUADRANTS, HAIRPINS, THERMAL PLUMES…)

$$\begin{cases} \partial_t \mathbf{v} + \mathbf{v}\cdot\partial_{\mathbf{x}}\mathbf{v} + \partial_{\mathbf{x}} P = \nu\Delta\mathbf{v} + \sum_{i=1}^{N_p} \delta(\mathbf{x} - \mathbf{X}_i(t))\mathcal{F} \\ \dot{\mathbf{X}}_i = \mathbf{U}_i \\ \dot{\mathbf{U}}_i = -\frac{\mathbf{U}_i - \mathbf{v}}{\tau} + \beta D_t\mathbf{v} - g(1-\beta)\hat{\mathbf{z}} \end{cases}$$

$$\begin{cases} \beta = \dfrac{3\rho_f}{\rho_f + 2\rho} \quad \rightarrow \quad \dfrac{3\rho_f}{\rho_f + 2\rho[\mathbf{w}, T, c, \ldots]} \\ \tau = \dfrac{r^2}{3\nu\beta} \quad \rightarrow \quad \dfrac{r^2[\mathbf{w}, T, c, \ldots]}{3\nu\beta[\mathbf{w}, T, c, \ldots]} \end{cases}$$

CONTROL TOOLS

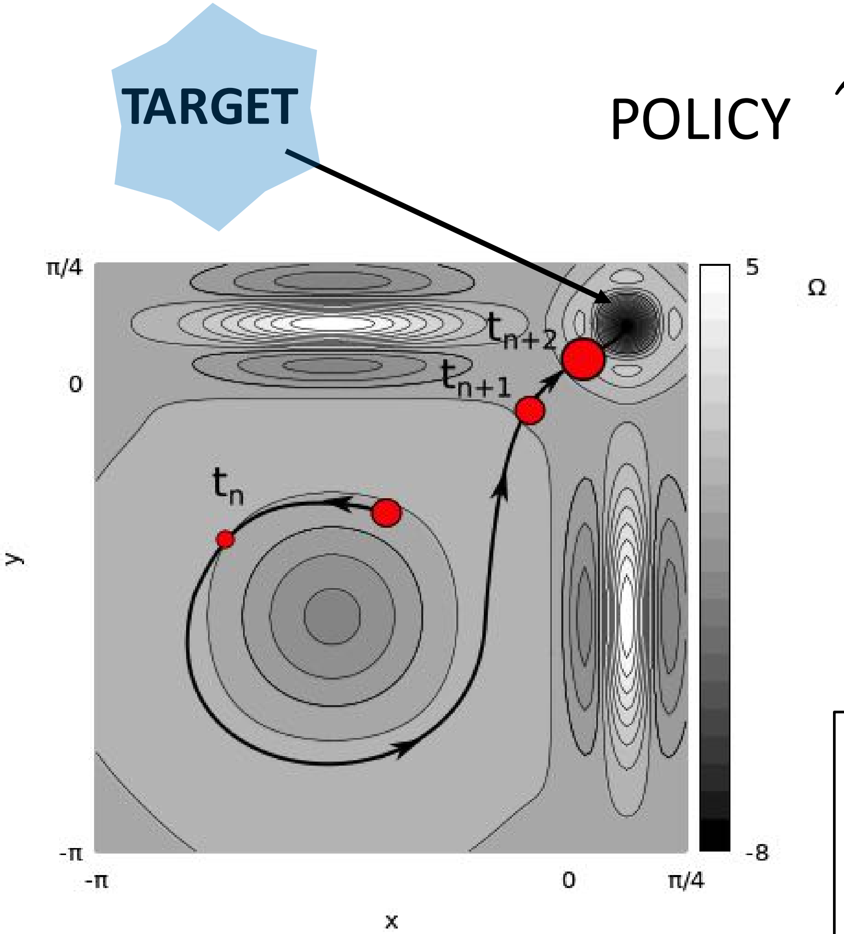


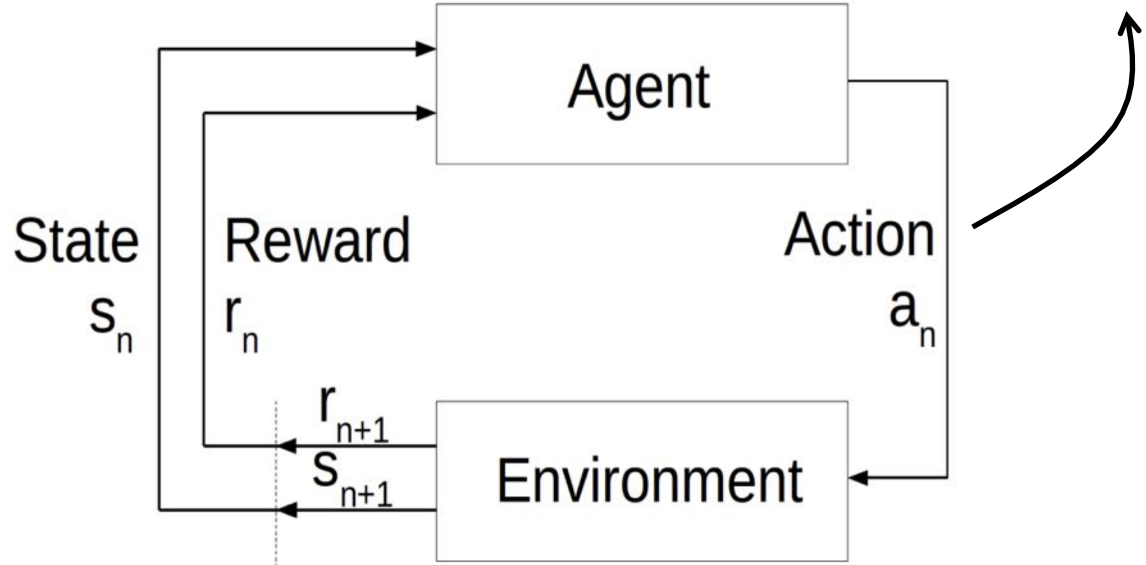


SMART INFLATABLE/DEFLATABLE INERTIAL PARTICLES IN COMPLEX FLOWS

POLICY $\pi : s \to a$

$$\begin{cases} \beta = \frac{3\rho_f}{\rho_f + 2\rho} & \to \frac{3\rho_f}{\rho_f + 2\rho[\mathbf{w}, T, c, \dots]} \\ \tau = \frac{r^2}{3\nu\beta} & \to \frac{r^2[\mathbf{w}, T, c, \dots]}{3\nu\beta[\mathbf{w}, T, c, \dots]} \end{cases}$$

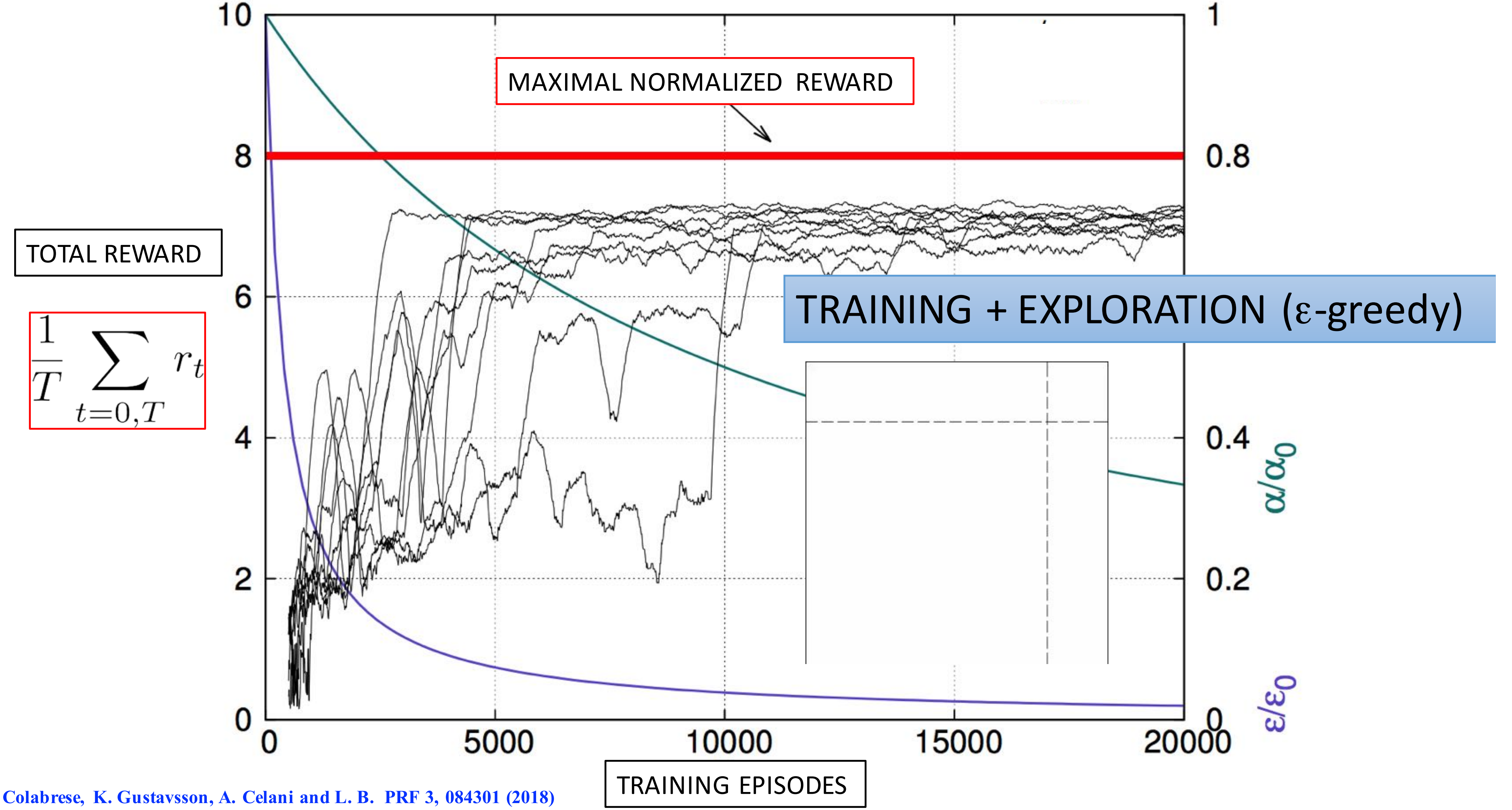




<u>Reinforcement learning</u> is a framework to find a good (optimal) POLICY for achieving given long-term tasks. It is widely used in artificial intelligence and machine learning. It is based on the interaction between a decision-maker (in our case the inertial particle) and the environment. The decision maker can change its behaviour in response to inputs from the system (in our case the flow). By trial and error the decision maker progressively learns how to behave optimally.

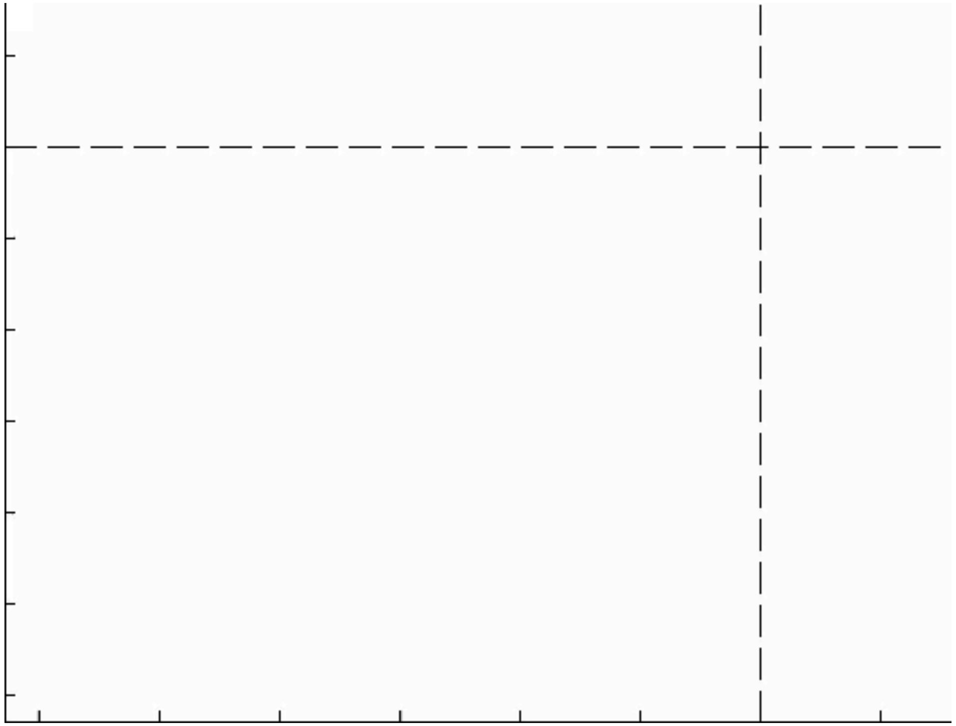
Sutton Barto (2017. Reinforcement Learning: An Introduction. (Cambridge University Press, 2017)

S. Colabrese, K. Gustavsson, A. Celani and L. B. Smart Inertial Particles. PRF 3, 084301 (2018)
S. Colabrese, K. Gustavsson, A. Celani and L. B. Flow navigation by smart microswimmers via reinforcement learning. Phys. Rev. Lett. 118 (15), 158004 (2017)

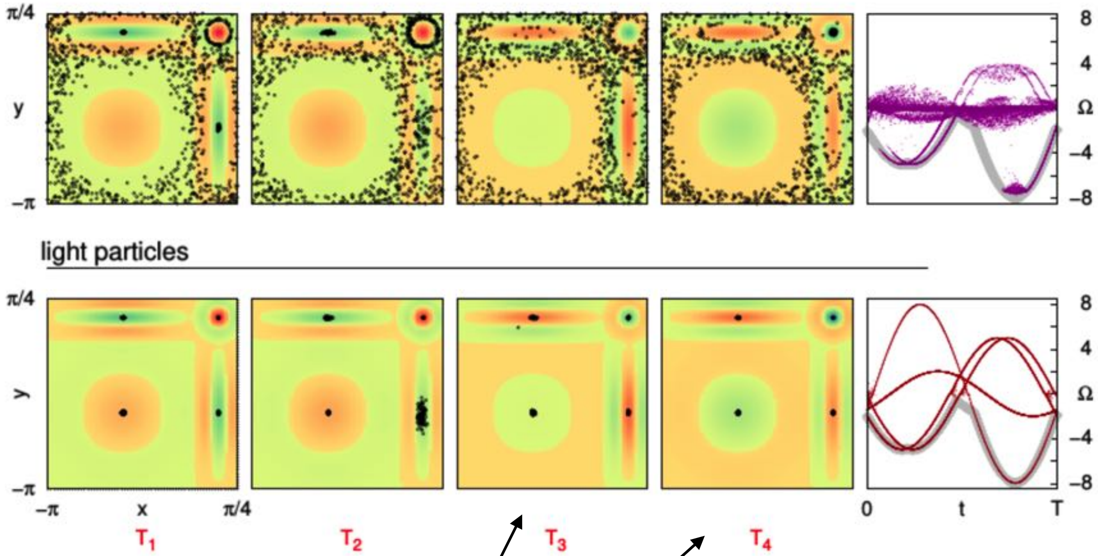


S. Colabrese, K. Gustavsson, A. Celani and L. B. PRF 3, 084301 (2018)

SMART INERTIAL PARTICLES TRAINED TO FOLLOW HIGHEST VORTICITY REGION IN A TIME DEPENDENT FLOW



SMART PARTICLES



NAÏVE LIGTH PARTICLES

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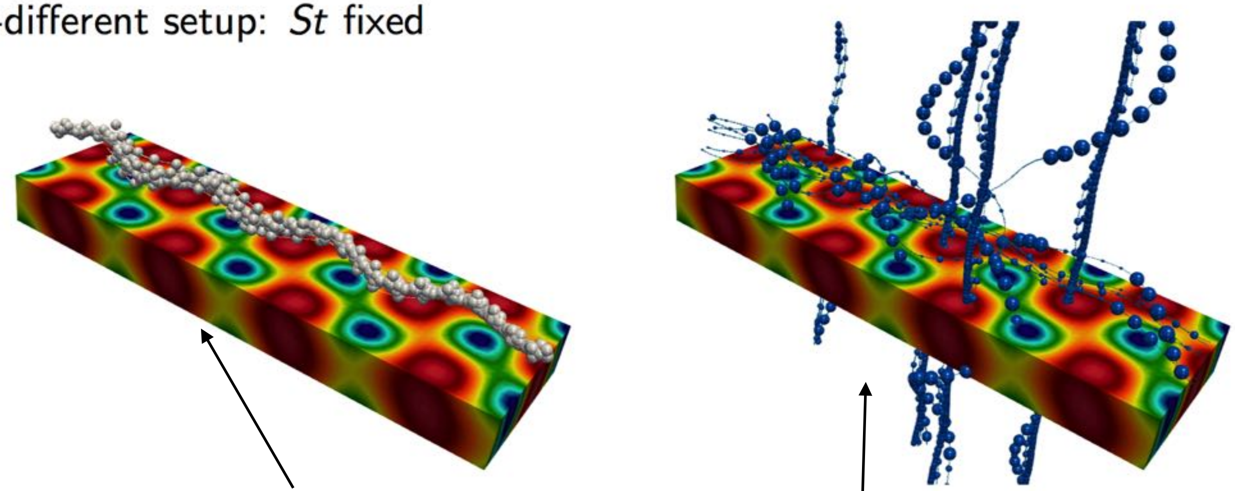
ASYMMETRIC ABC FLOW

$$\boldsymbol{u}(\boldsymbol{x}) = (C\cos y + A\sin z, A\cos z + B\sin x, B\cos x + C\sin y) \ [4A=2B=C=1]$$

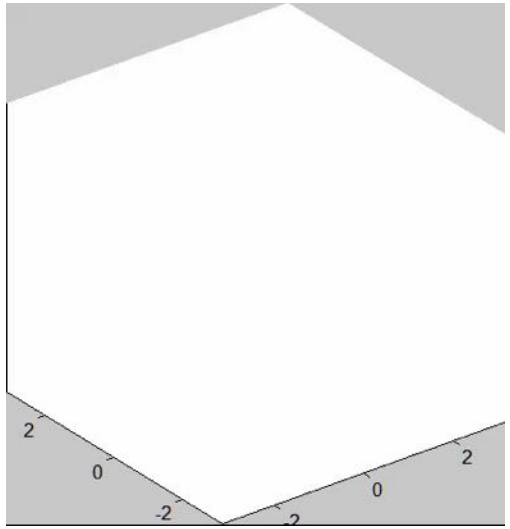
Task: Optimize long-term vorticity $|\boldsymbol{\Omega}|$ by perception of Ω_z or Ω_x

-different setup: *St* fixed



Light particles distribute on minor vortices

Smart particle learns to target principal vortices



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Advecting flow

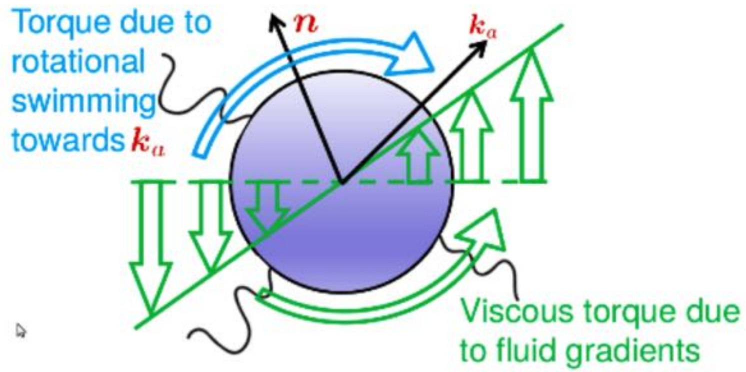
Swimming intensity

Swimming direction

- $\dot{\boldsymbol{x}} = \boldsymbol{u} + \Phi\, \boldsymbol{n}$
- $\dot{\boldsymbol{n}} = \underbrace{\frac{1}{2\Psi}[\boldsymbol{k}_a - (\boldsymbol{k}_a \cdot \boldsymbol{n})\boldsymbol{n}]}_{\text{Particle torque}} + \underbrace{\frac{1}{2}\boldsymbol{\omega} \times \boldsymbol{n}}_{\text{Flow torque}}$

Preferred direction

Strenght of the flow torque



Free Particle parameters

If
$\Phi \to 0,\ \Psi \to \infty$
passive swimmer

Flow properties

Direction to be modified depending on ω

S. Colabrese, K. Gustavsson, A. Celani and L. B. Flow navigation by smart microswimmers via reinforcement learning. Phys. Rev. Lett. 118 (15), 158004 (2017) & Finding efficient swimming strategies in a three-dimensional chaotic flow by reinforcement learning. EPJE 40 (12), 110 (2017)

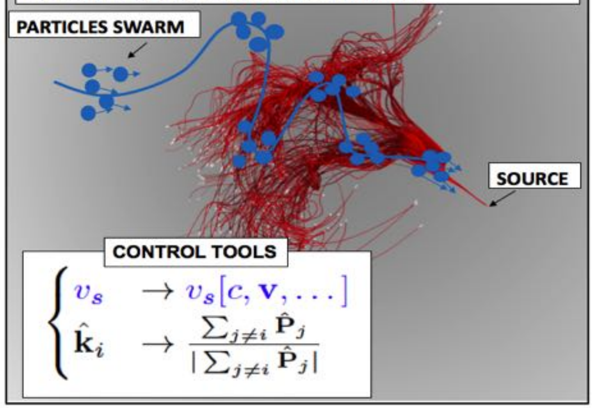
1. IS IT POSSIBILE TO **PREFERENTIALLY TRACK** INTENSE (LARGE- OR SMALL-SCALE) STRUCTURES?

2. CAN WE INVENT IN-SILICO EXPERIMENTS TO ENGINEER A (LAGRANGIAN) WAY TO **CONTROL/STUDY** TURBULENCE?

3. CAN WE IDENTIFY THE **KEY DEGREES-OF-FREEDOM** TO **RECONSTRUCT** THE FLOW (KEY FLOW STRUCTURES)?

4. CAN WE TRAIN A **SWARM** OF AGENTS TO PERFORM FIELD-TAXIS IN COMPLEX FLOWS?

FIG. 4: COLLECTIVE FIELD-TAXIS WITHOUT GRADIENT-SENSING WHERE EACH AGENT CONTROLS ITS SWIMMING INTENSITY AND PREFERRED DIRECTION (AVERAGING THE ONE OF THE SWARM, SEE INSET). RED TRAJECTORIES COME FROM A DIRECT NUMERICAL SIMULATION OF TURBULENT DISPERSION [Bi14]. THE SWARM PATH IS AN ARTISTIC REPRESENTATION.



$$\begin{cases} v_s & \rightarrow v_s[c, \mathbf{v}, \dots] \\ \hat{\mathbf{k}}_i & \rightarrow \dfrac{\sum_{j\neq i} \hat{\mathbf{P}}_j}{|\sum_{j\neq i} \hat{\mathbf{P}}_j|} \end{cases}$$

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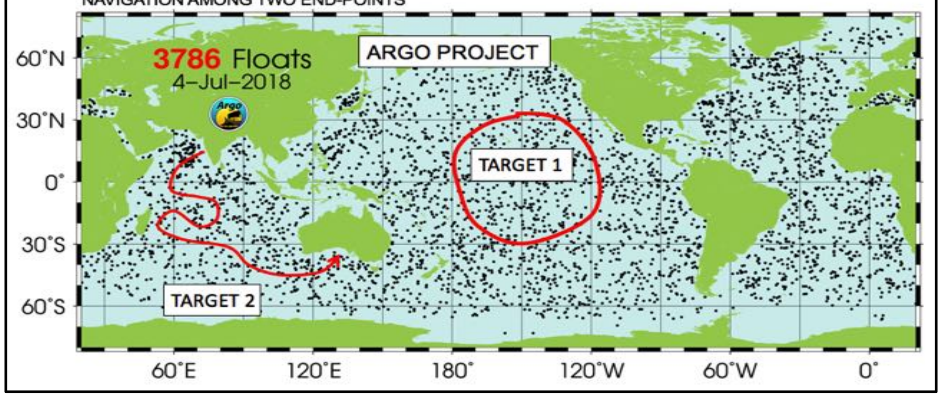

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PC Di Leoni, A Mazzino, L B. Inferring flow parameters and turbulent configuration with physics-informed data assimilation and spectral nudging. Physical Review Fluids 3 (10), 104604 (2018)

Finding efficient swimming strategies in a three-dimensional chaotic flow by reinforcement learning. K Gustavsson, L.B., A Celani, S Colabrese. EPJE 40 (12), 110 (2017)