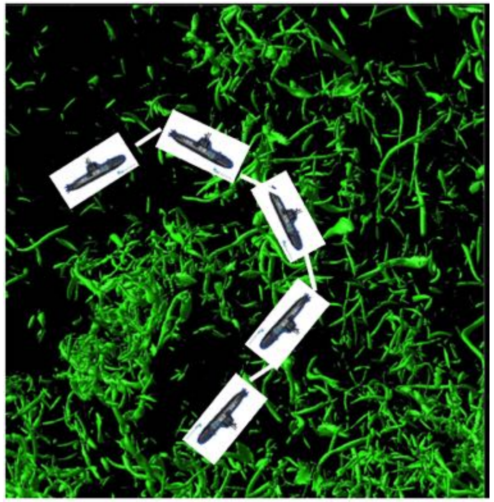
Nudging, Hybrid Monte Carlo, Smart Particles: new tools for old turbulent problems

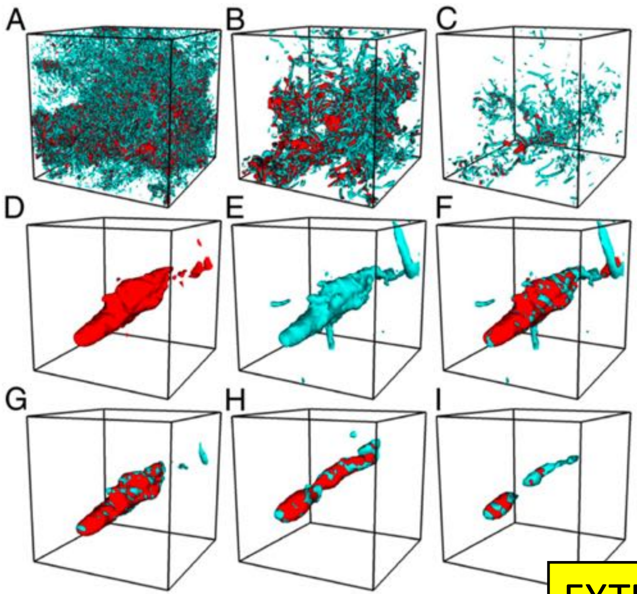
Luca Biferale
Dept. Physics, INFN & CAST
University of Rome 'Tor Vergata'
biferale@roma2.infn.it

PERSPECTIVES ON TURBULENCE - TEXAS A&M UNIVERSITY

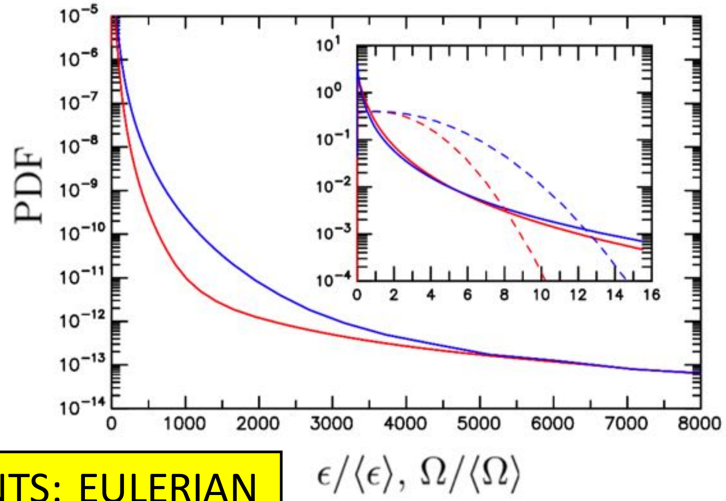
2018



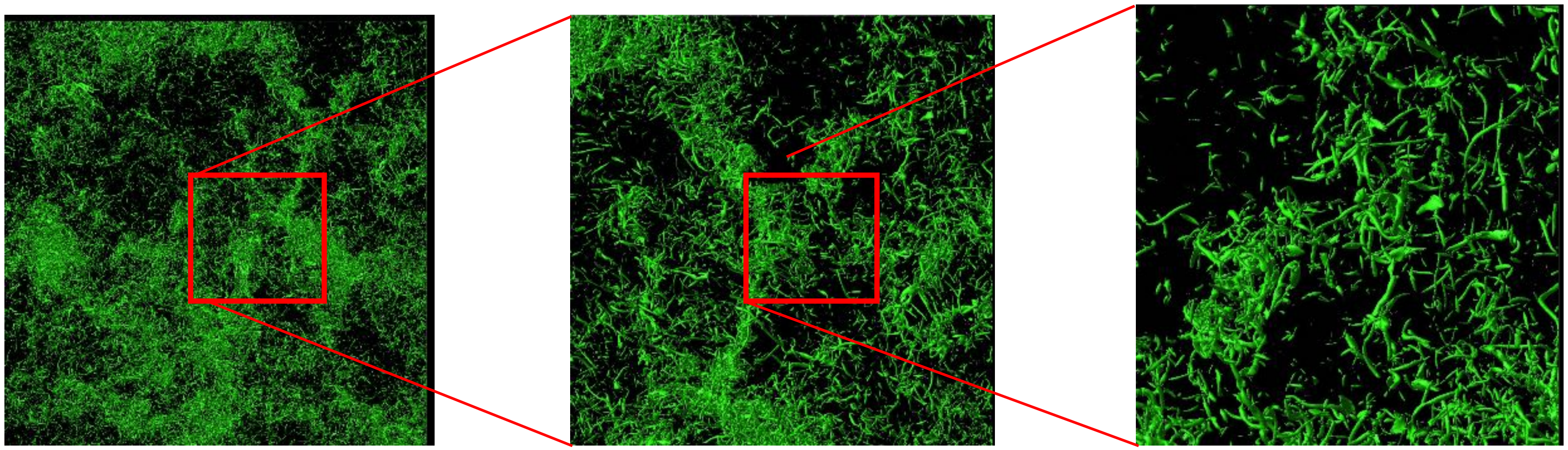
CREDITS: S. Colabrese, G. Marazoglou, P. Clark di Leoni, M. Buzzicotti, F. Bonaccorso (Univ. Tor Vergata, Rome-IT); A. Celani (ICTP Trieste-IT); K. Gustafsson (Univ. Gotheborg, SE); A. Mazzino (Univ. Genova, IT); F. Toschi (TuE , NL); K. Jansen (DESY, GE); J. Frederich, R. Grauer (Univ. Bochum, GE); D. Mestherazy (IBM Zurich, CH); T. Rosenow (Univ. Brandeburg, GE); R. Trpiccione (Univ. Ferrara, IT)



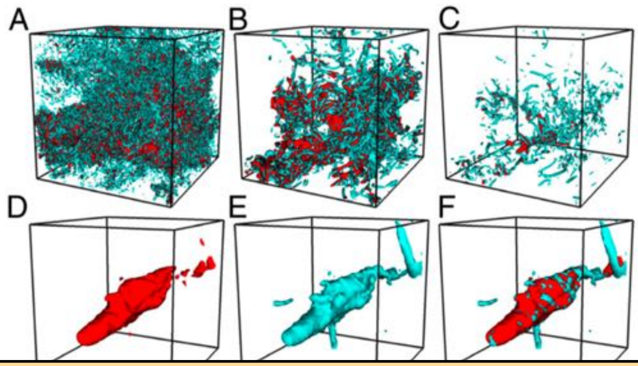
Extreme events in computational turbulence. P. K. Yeung , X. M. Zhai and K.R. Sreenivasan. PNAS 112(41) 12633 (2015)



EXTREME EVENTS: EULERIAN



Watanabe and Gotoh, Phys. Fluids 19, 121701 (2007)



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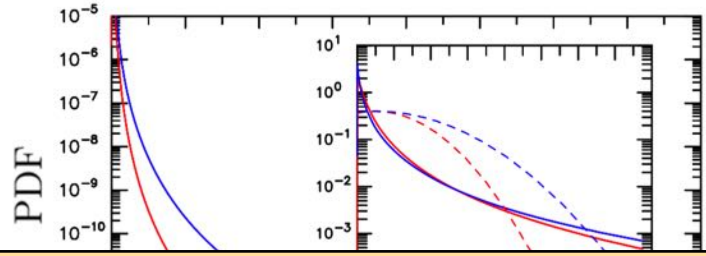
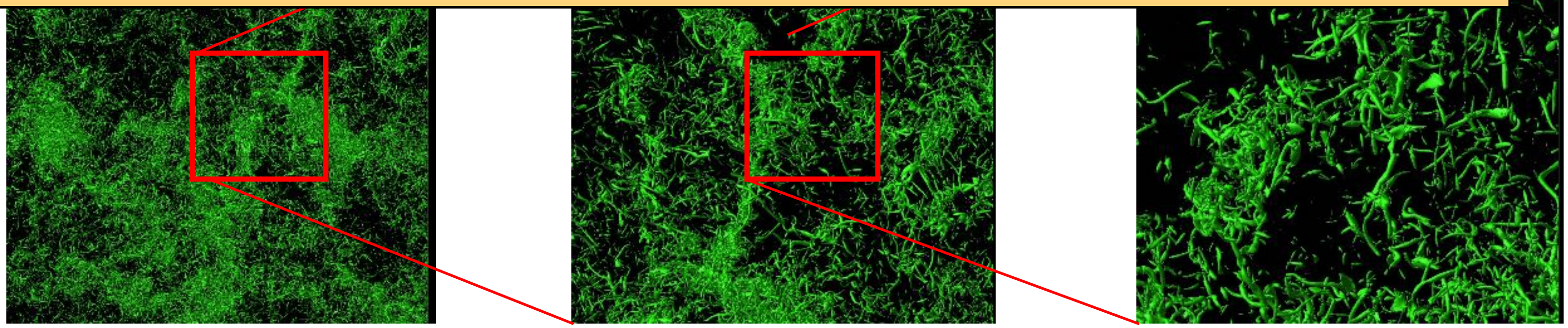


1. IS IT POSSIBILE TO PREFERENTIALLY TRACK INTENSE (LARGE- OR SMALL-SCALE) STRUCTURES?

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

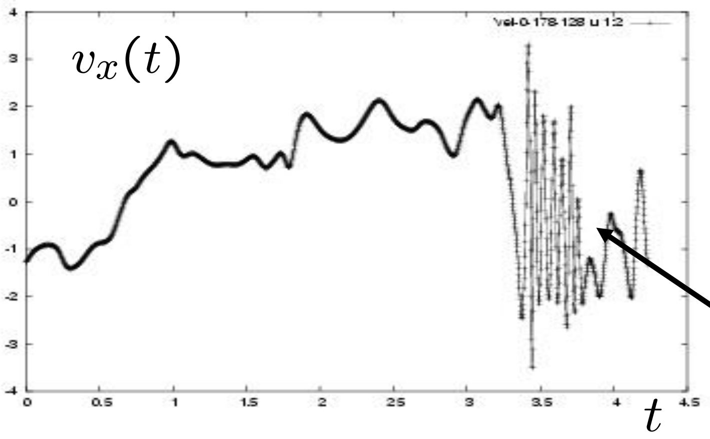
3. CAN WE IDENTIFY THE KEY DEGREES-OF-FREEDOM TO RECONSTRUCT THE FLOW (KEY FLOW STRUCTURES)?

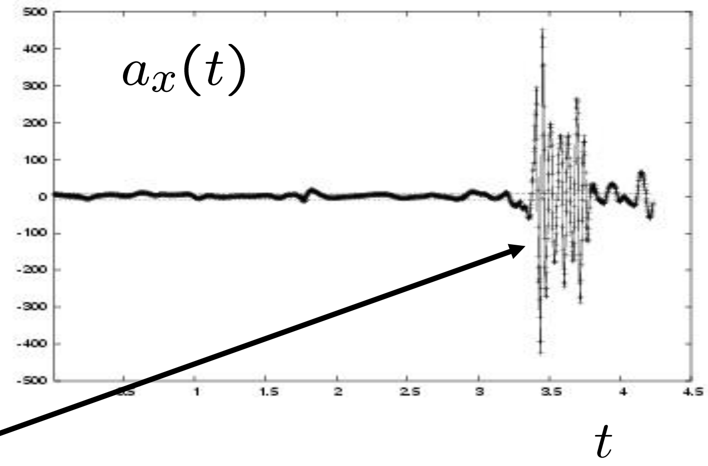
4. ARE THERE REYNOLDS-INDEPENDENT TURBULENT FINGERPRINTS? IF YES: IS IT BETTER TO WORK AT LOW REYNOLDS AND HIGH STATISTICS OR VICEVERSA?

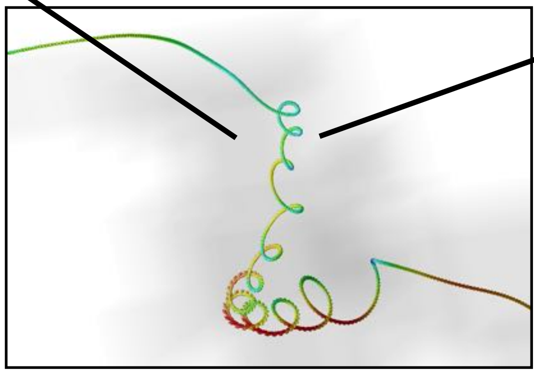


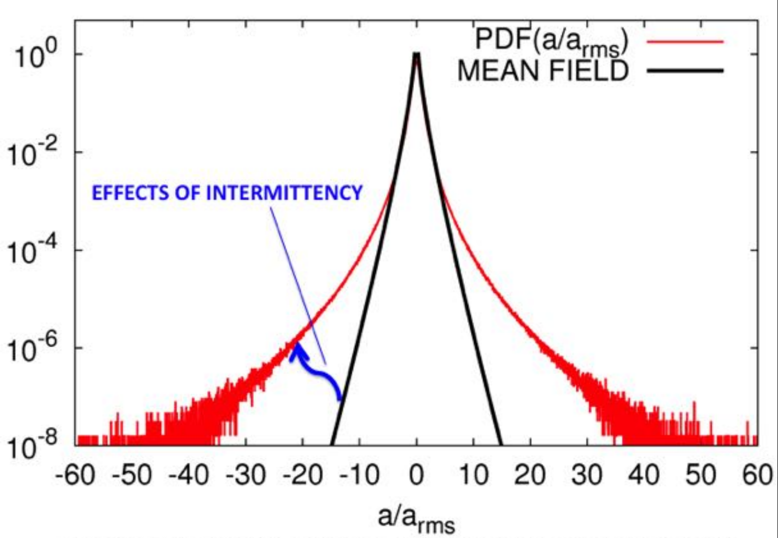
Watanabe and Gotoh, Phys. Fluids 19, 121701 (2007)

EXTREME EVENTS: LAGRANGIAN





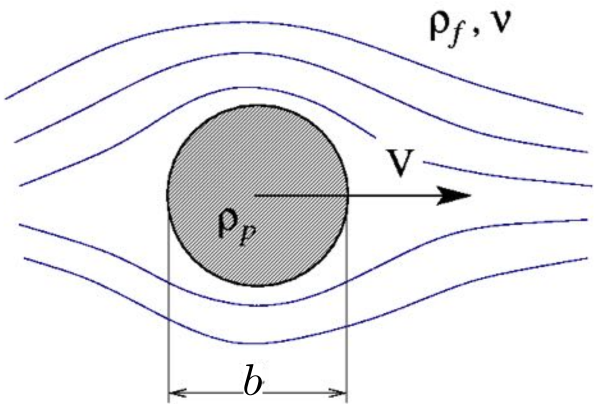




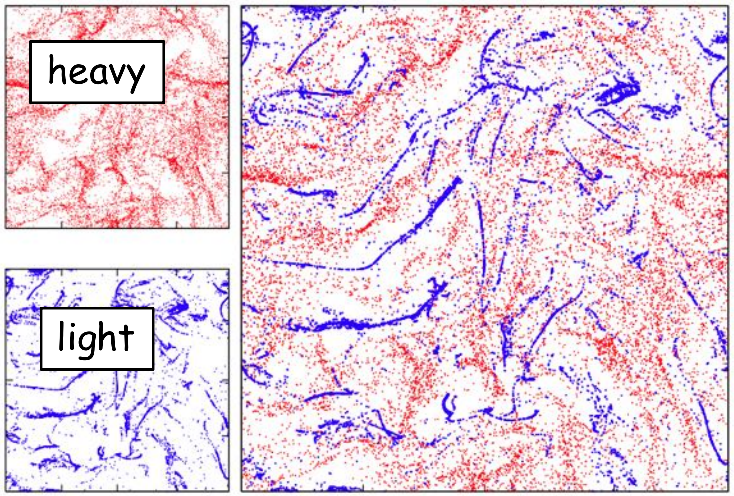
ACCELERATION PROBABILITY DISTRIBUTION FUNCTION (PDF) AT RE ~ 10^5 [Bi04]
COMPARED WITH THE PREDICTION FROM MEAN FIELD (KOLMOGOROV THEORY)

L.B., G Boffetta, A Celani, A Lanotte, F Toschi. Particle trapping in three-dimensional fully developed turbulence Physics of Fluids 17 (2), 021701 (2005)
La Porta, G.A. Voth, A.M. Crawford, J. Alexander et al. Fluid particle accelerations in fully developed turbulence. Nature, 409(6823), 1017 (2001)
N. Mordant, P. Metz, O. Michel and J.F. Pinton. Measurement of Lagrangian velocity in fully developed turbulence. Phys. Rev. Lett. 87(21), 214501 (2001)
F. Toschi and E. Bodenschatz. Lagrangian Properties of Particles in Turbulence. Annu. Rev. Fluid Mech. 41, 375 (2009)

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)

OLD QUESTIONS:

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. ARE THERE REYNOLDS-INDEPENDENT TURBULENT FINGERPRINTS? IF YES: IS IT BETTER TO WORK AT LOW REYNOLDS AND HIGH STATISTICS OR VICEVERSA?

NEW TOOLS:

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

2. SMART LAGRANGIAN PROBES (TWO-WAY COUPLING): AD-HOC FEEDBACK ON THE FLOW STRUCTURES TO CONTROL TURBULENCE

3. NUDGING: AN EQUATION-INFORMED TOOL TO ASSIMILATE AND RECONSTRUCT TURBULENCE DATA

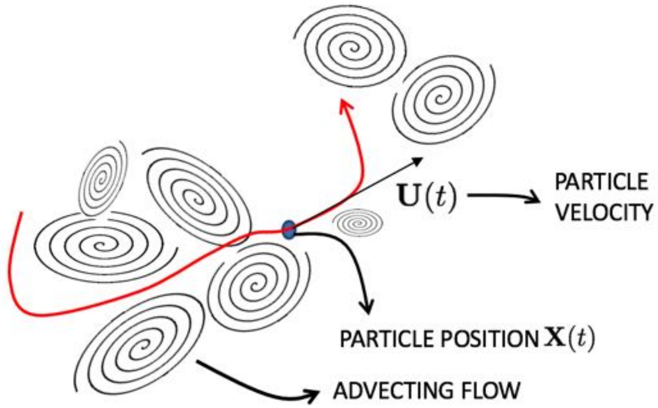
4. HYBRID-MONTE-CARLO FOR MARTIN-SIGGIA-ROSE STOCHASTIC PDES: A TOOL TO PREFERENTIALLY FOCUS ON INTENSE-AND-RARE FLUCTUATIONS (INSTANTONS) AT SMALL REYNOLDS

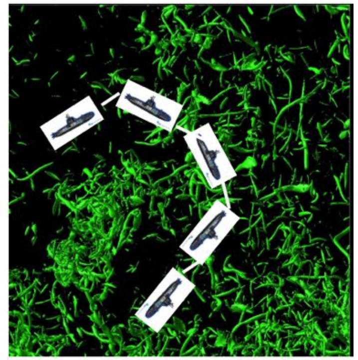
SMART INERTIAL PARTICLES IN COMPLEX FLOWS

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

CONTROL TOOLS

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

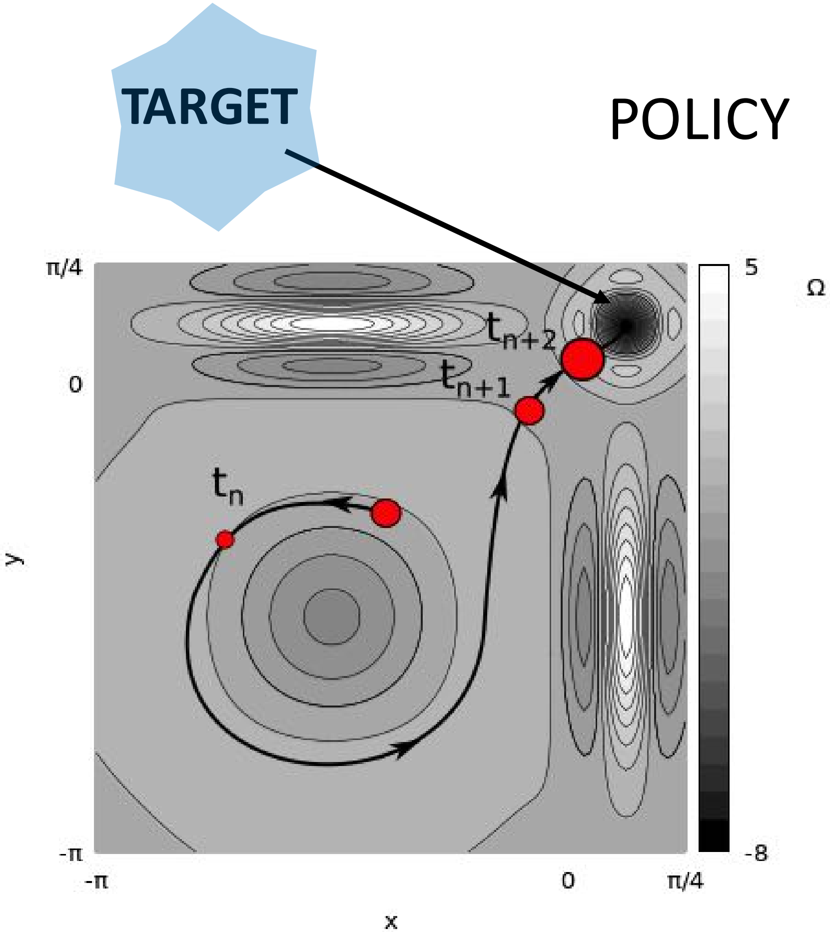


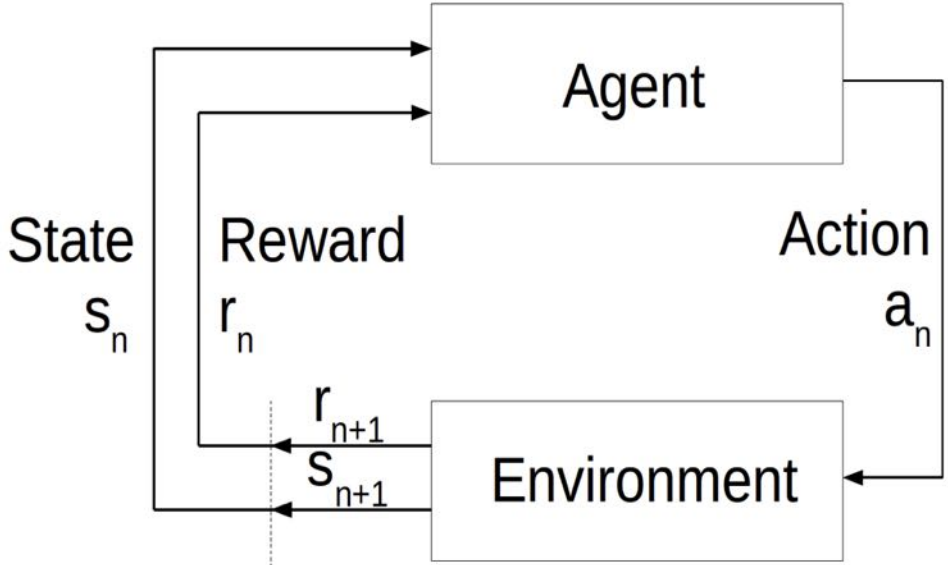


SMART INFLATABLE/DEFLATABLE INERTIAL PARTICLES IN COMPLEX FLOWS

POLICY $\pi : s \to a$

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



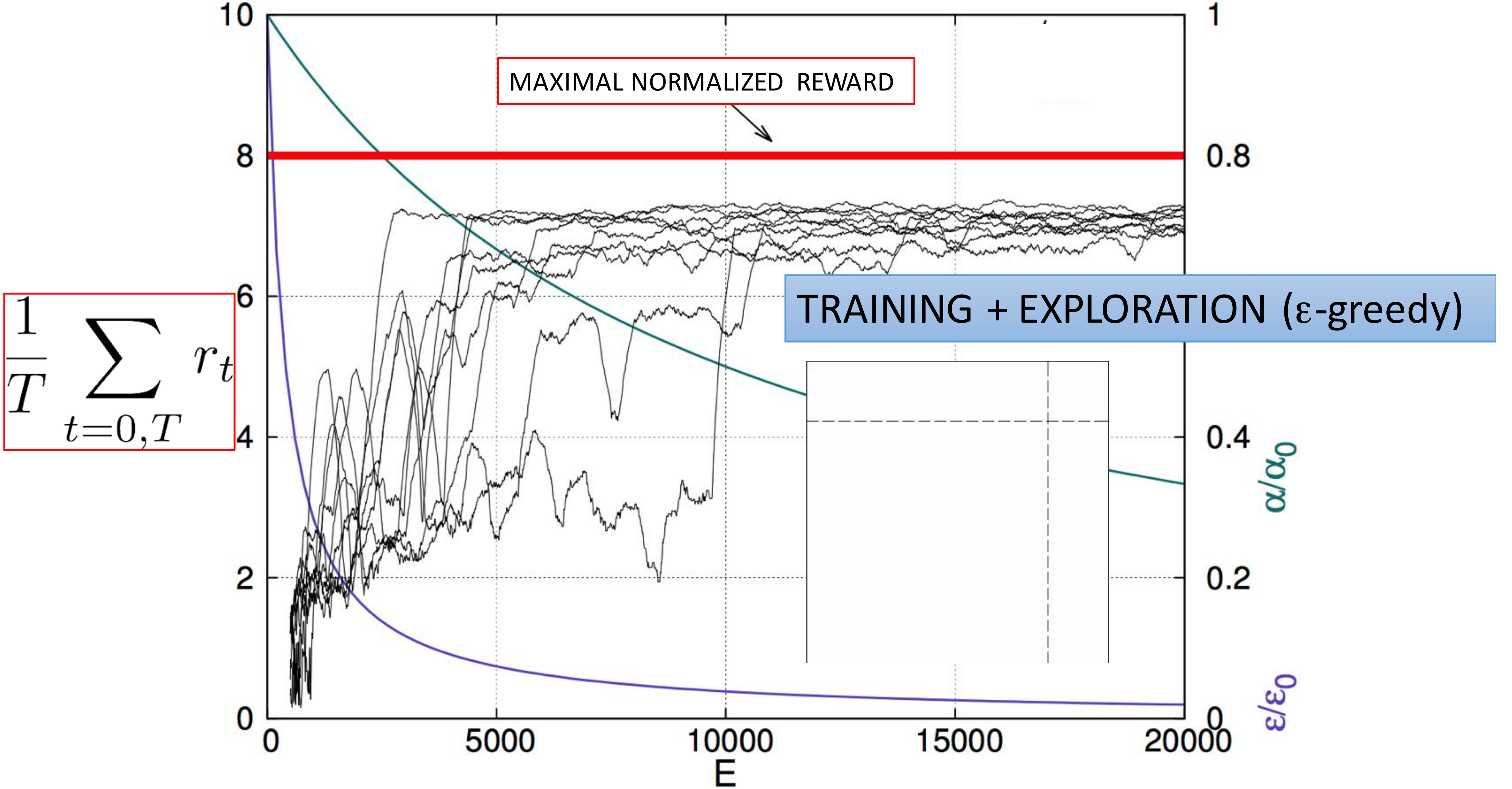


S. Colabrese, K. Gustavsson, A. Celani and L. B. Smart Inertial Particles. PRF 3, 084301 (2018)

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

Reinforcement learning 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)



MAXIMAL NORMALIZED REWARD
TRAINING + EXPLORATION (ε-greedy)
$\frac{1}{T}\sum_{t=0,T} r_t$
α/α_0
$\varepsilon/\varepsilon_0$
E
0
5000
10000
15000
20000
10
8
6
4
2
0
1
0.8
0.4
0.2
0

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