

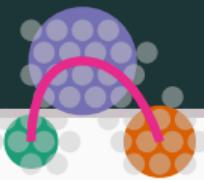
AutoInformation State aggregation

a dynamical point of view

Mauro Faccin
IRD/CEPED, Université de Paris

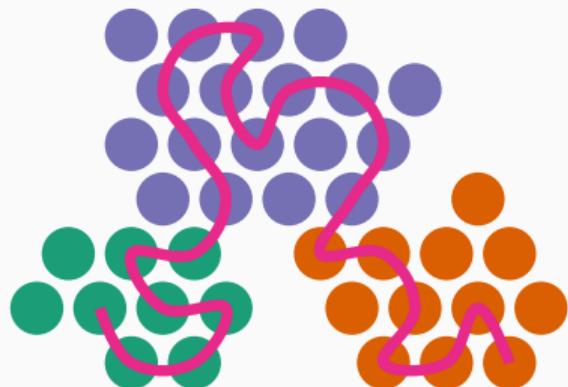


Projected Markov Chain



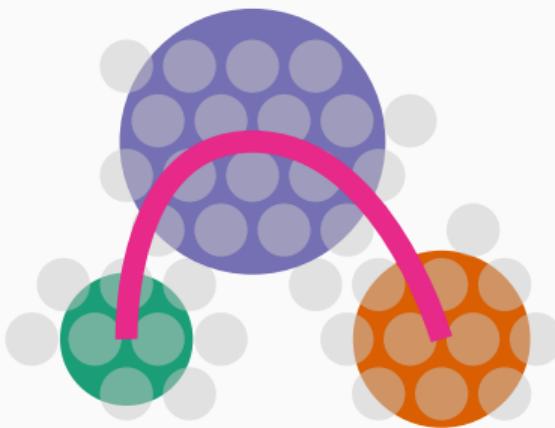
Markov Chain

$\dots, x_{\text{past}}, x_{\text{now}}, x_{\text{future}}, \dots$



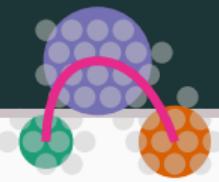
Projection

$\dots, y_{\text{past}}, y_{\text{now}}, y_{\text{future}}, \dots$



Aggregation strategies

Non-linear correlations

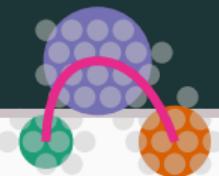


AutoInformation

$$I(y_t; y_{t-\tau})$$

Non-linear correlation
between successive
time-steps

M.F. et al, Journal of Complex Networks, cnx055



AutoInformation

$$I(y_t; y_{t-\tau})$$

Non-linear correlation
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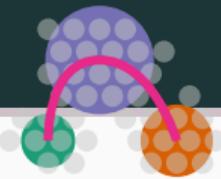
$$I(y_t; y_{t-\tau}) = \boxed{I(y_t; y_{t-\tau}, \dots)} - \boxed{I(y_t; y_{t-2\tau}, \dots | y_{t-\tau})}$$

where τ represents a time-scale parameter.

Maximized by a Markov chain that:

¹ Maximize predictability of the dynamics

² Minimize non-Markovianity (effective memories from the projection)



Random walker covariance

χ_c characteristic function of class c

$$Q = \sum_c \text{Cov}(\chi_c(t), \chi_c(t+1))$$

Auto-covariance of the dynamics on the partition space.

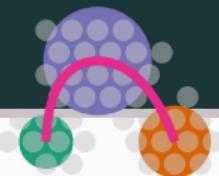
Modularity:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

Linear correlation between consecutive time-steps.

Shen et al. (2010) PRE, 82, 016114

Generative models as particular case



Fitting a generative model (e.g. DC-SBM) to the data through log-likelihood maximization can be seen as maximizing the AutoInformation for paths of lenght $\tau = 1$ (e.g. links).

$$I(Y_t; Y_{t-1}) = H(Y_t) + H(Y_{t-1}) - H(Y_t, Y_{t-1})$$

$$H(Y_t) = - \sum_c \frac{e_c}{2m} \log \frac{e_c}{2m} \quad e_c = \sum_{i \in c, j} A_{ij}$$

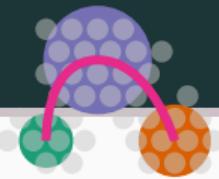
$$H(Y_t, Y_{t-1}) = - \sum_{cd} \frac{e_{cd}}{2m} \log \frac{e_{cd}}{2m} \quad e_{cd} = \sum_{i \in c, j \in d} A_{ij}$$

DC-SBM

$$\mathcal{S} \propto \frac{1}{2} \sum_{cd} e_{cd} \log \frac{e_{cd}}{e_c e_d}$$

In binary symmetric networks

Karrer and Newman (2011), PRE 83, 016107.



AutoInformation

$$I(y_t; y_{t-\tau})$$

Non-linear correlation
between successive time-steps

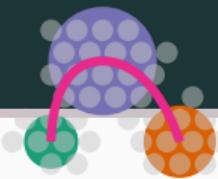
The parameter τ selects the *time-scale* of the aggregation.

Maximizing in a naive way is not possible, one need to fix the number of classes or apply some **model selection**.
E.g. a entropic Lagrange multiplier:

$$\mathcal{I}_{\alpha\tau} = I(y_t; y_{t-\tau}) - \alpha H(y_t)$$

 Didactic Examples.

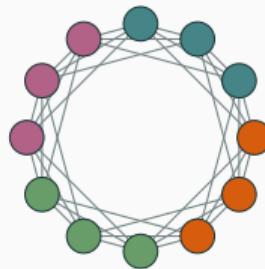
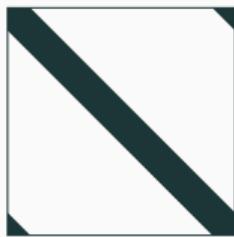
Example 0: One cycle



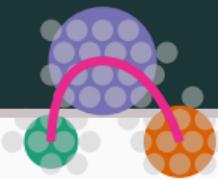
A regular ring lattice with N nodes, each connected with k neighbours.

How many classes?

Adj:



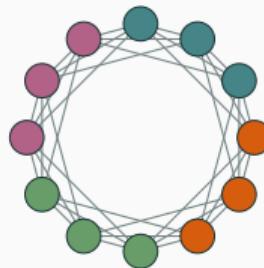
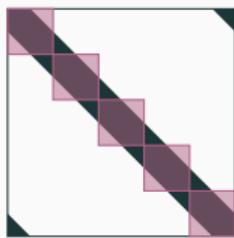
Example 0: One cycle



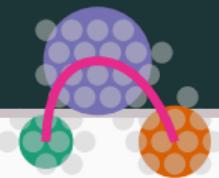
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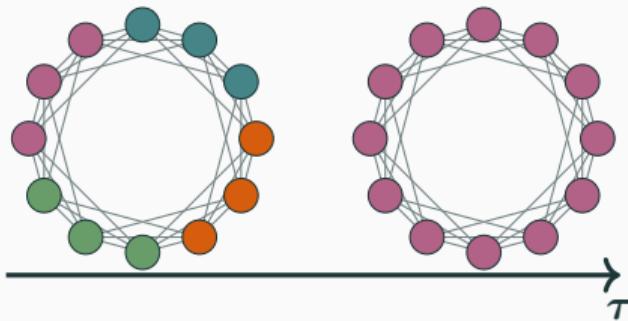
Example 0: One cycle



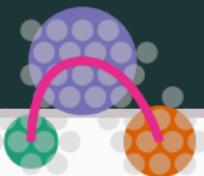
A regular ring lattice with N nodes, each connected with k neighbours.

How many classes?

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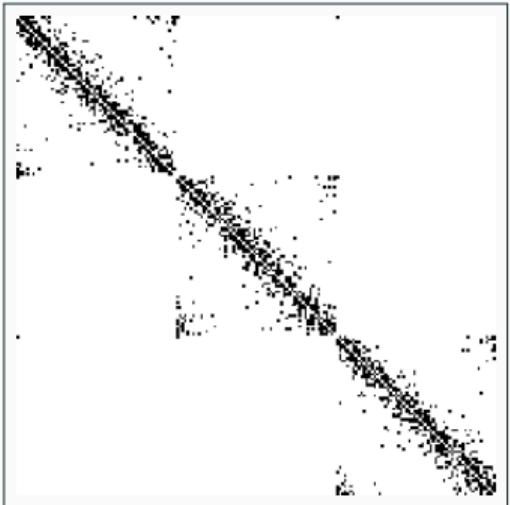


Example 1: Range dependant graphs

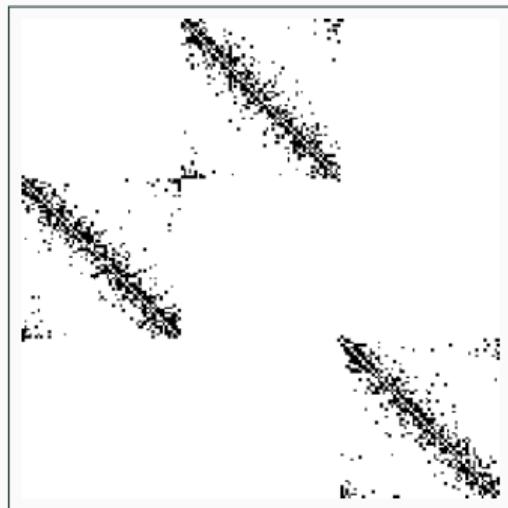
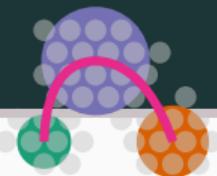


$$p_{ij} = \alpha_{c_i c_j} \cdot (\gamma_{c_i c_j})^{d_{ij}}$$
$$\alpha_{c_i c_j}, \gamma_{c_i c_j} \in [0, 1]$$

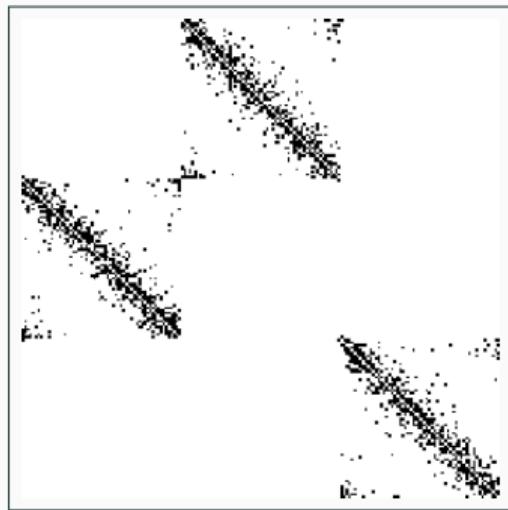
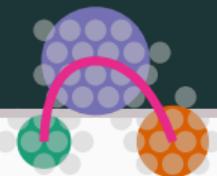
with d_{ij} a (normalized) distance between nodes aligned on a cycle.



Example 1: Range dependent graphs



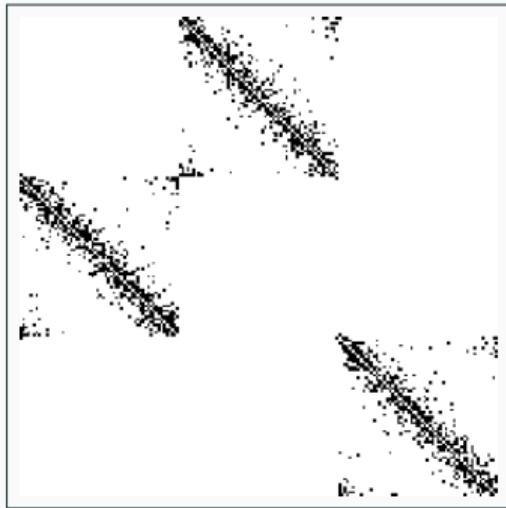
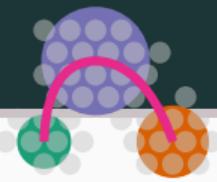
Example 1: Range dependent graphs



DC-SBM



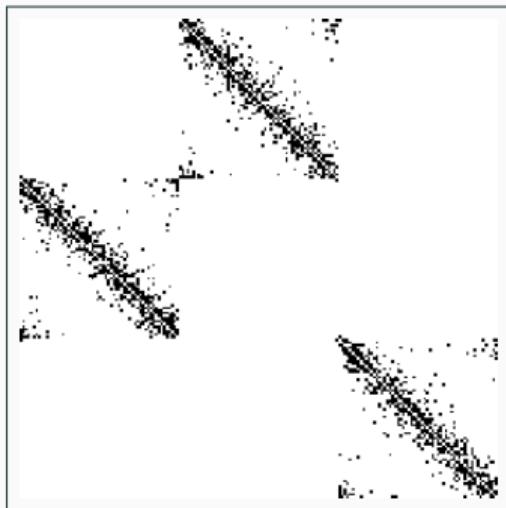
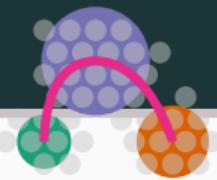
Example 1: Range dependent graphs



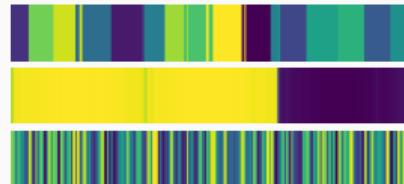
DC-SBM
spectral



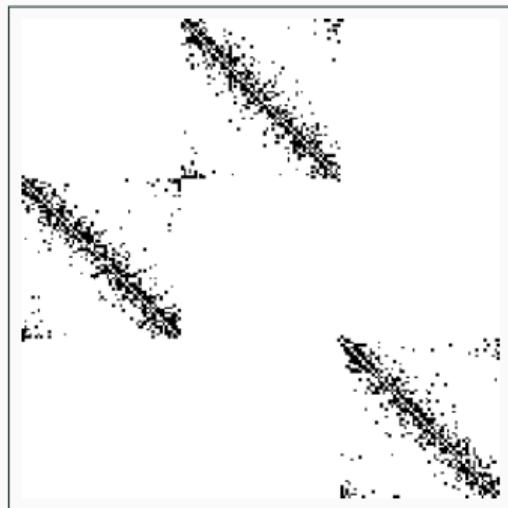
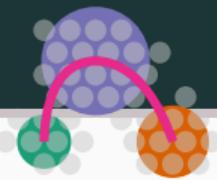
Example 1: Range dependent graphs



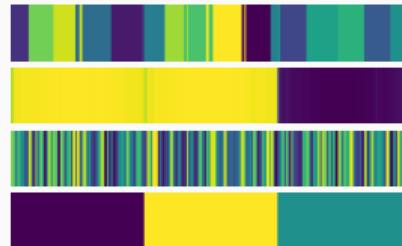
DC-SBM
spectral
AutoInfo $\tau = 1$



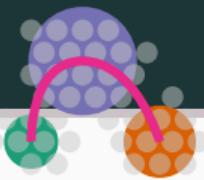
Example 1: Range dependent graphs



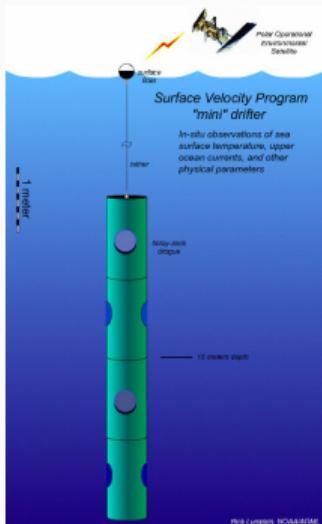
DC-SBM
spectral
AutoInfo $\tau = 1$
AutoInfo $\tau = 5$



Example 2. Ocean buoys



VOS Crew Deploy Next Generation SVP Drifter
Photo by: GDP



Global Drifter Program



GDP Array

AOML Drifter Data Assembly Center
Mon, 04 Oct 2021

No. of Buoys = 1471

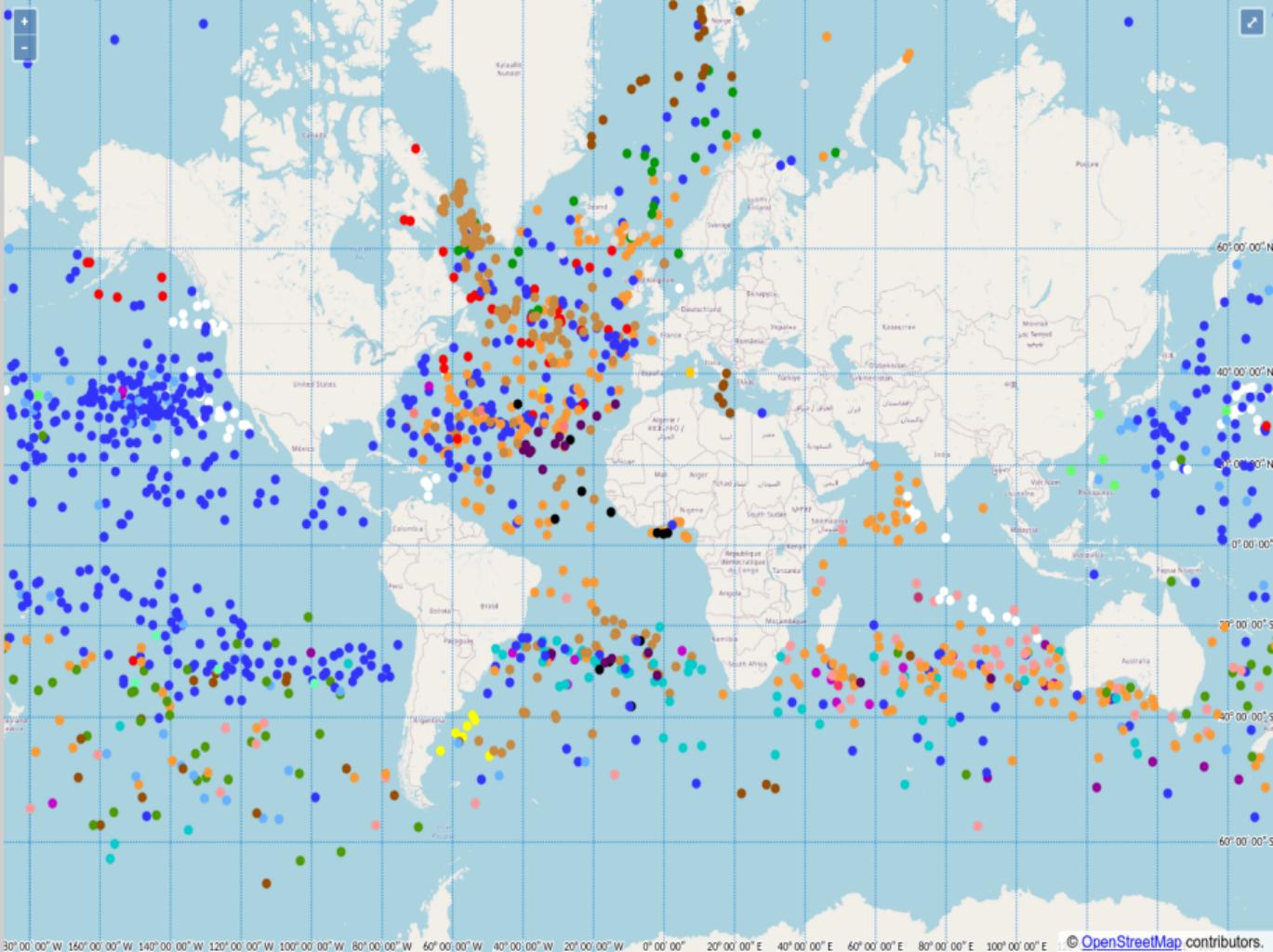
ID WMO

Search...

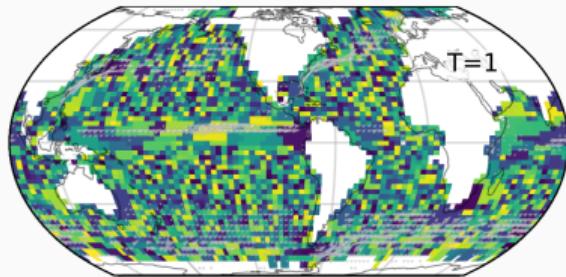
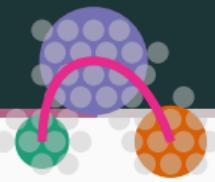
Map Viewing Options

- Deploying Country
- Buoy Type
- Buoy Drogue Status

Deploying Country	
Argentina (7)	Australia (48)
Barbados (3)	Brazil (12)
Canada (40)	Chile (4)
China (6)	Denmark (1)
France (272)	Germany (12)
Iceland (23)	India (3)
Indonesia (1)	Italy (51)
Japan (11)	Korea Rep. of (63)
New Zealand (52)	Netherlands (14)
Portugal (19)	Seychelles (1)
South Africa (59)	Spain (2)
Tonga (1)	UK (153)
USA (539)	Unknown (74)

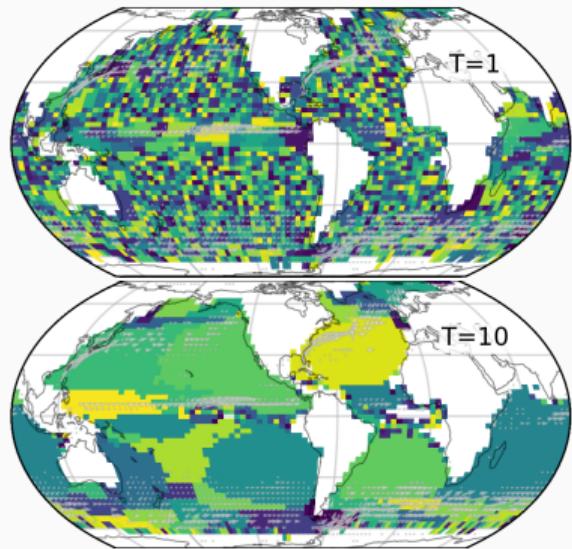
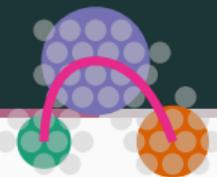


Example 3. Ocean buoys



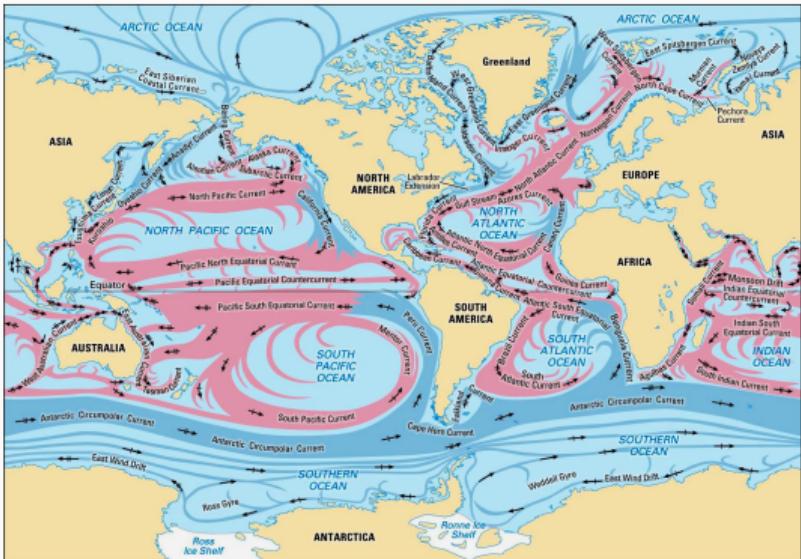
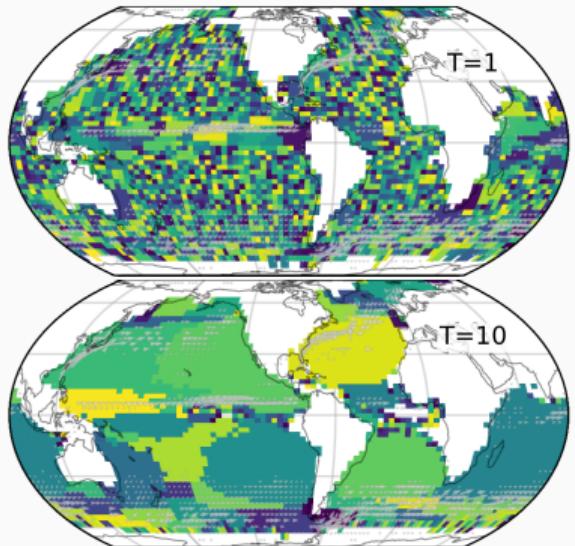
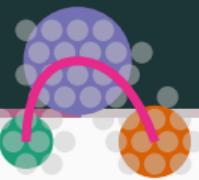
Each time step lasts 16 days.

Example 3. Ocean buoys



Each time step lasts 16 days.

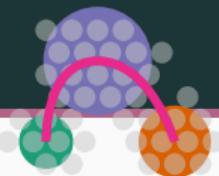
Example 3. Ocean buoys



Each time step lasts 16 days.

Finally...

Questions?



Joint work with:



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 UCLouvain



M Schaub

 RWTHAACHEN
UNIVERSITY

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Code at:

 <https://maurofaccin.github.io/aisa>