



Optimal Transportation for Data Assimilation

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Optimal Transportation for Data Assimilation

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DATA ASSIMILATION

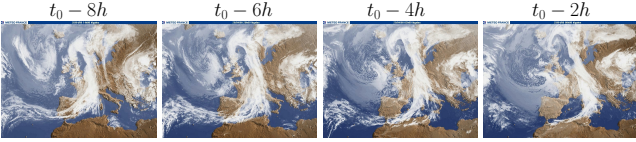
Given

- a physical system and its state $\mathbf{x}(t, x)$;
- **partial** observations of the system (\mathbf{y}_i^o);
- a (numerical) model \mathcal{M} simulating the evolution of \mathbf{x} ;

E.g., for the atmosphere, the state $\mathbf{x}(t, x, y)$ gathers the different variables

- humidity $H(t, x, y)$;
- velocities $\mathbf{u}(t, x, y)$;
- temperature $T(t, x, y)$;
- pressure $p(t, x, y)$.

Can we estimate the initial condition \mathbf{x}_0 of the system?



Variational data assimilation consists in retrieving \mathbf{x}_0 by minimizing

$$\mathcal{J}(\mathbf{x}_0) := \sum_i d\left(\underbrace{\mathcal{H}_i \mathcal{M}_i(\mathbf{x}_0)}_{\text{Mapping of } \mathbf{x}_0 \text{ on the space of } \mathbf{y}_i^o}, \mathbf{y}_i^o\right)^2 + \omega d(\mathbf{x}_0, \mathbf{x}_0^b)^2. \quad (1)$$

It is common for the distance d to be a weighted \mathcal{L}^2 distance. Our main goal to use the Wasserstein distance \mathcal{W}_2 instead, which seems very interesting when dealing with dense data (see right panel). The Wasserstein cost function writes

$$\mathcal{J}_W(\mathbf{x}_0) := \sum_i \mathcal{W}_2\left(\mathcal{H}_i \mathcal{M}_i(\mathbf{x}_0), \mathbf{y}_i^o\right)^2 + \omega \mathcal{W}_2(\mathbf{x}_0, \mathbf{x}_0^b)^2. \quad (2)$$

OPTIMAL TRANSPORTATION AND THE WASSERSTEIN DISTANCE

For two functions $\rho_0(x)$ and $\rho_1(x)$, the square of the **Wasserstein distance** $\mathcal{W}_2(\rho_0, \rho_1)$ is defined as the minimal kinetic energy necessary to transport ρ_0 to ρ_1 ,

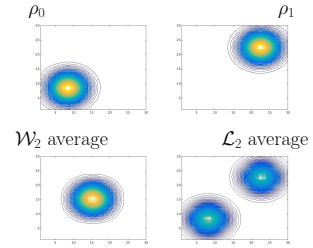
$$\mathcal{W}_2(\rho_0, \rho_1)^2 := \inf_{\begin{subarray}{c} (\rho(t, x), \mathbf{v}(t, x)) \\ \partial_t \rho + \text{div}(\rho \mathbf{v}) = 0 \\ \rho(0, x) = \rho_0(x), \rho(1, x) = \rho_1(x) \end{subarray}} \frac{1}{2} \iint_{[0,1] \times \Omega} \rho |\mathbf{v}|^2 dt dx.$$

For the Wasserstein distance to be well-defined, one needs

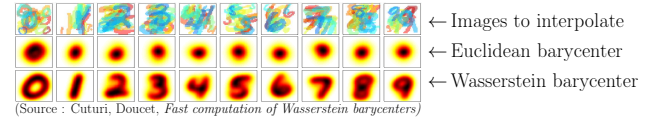
$$\rho_0 \geq 0, \rho_1 \geq 0 \text{ and } \int_{\Omega} \rho_0 = \int_{\Omega} \rho_1 = 1.$$

Average w.r.t the Wasserstein distance

The average, or barycenter, minimizes $\mathcal{W}_2(\rho, \rho_0)^2 + \mathcal{W}_2(\rho, \rho_1)^2$. It is also the optimal ρ in the definition of $\mathcal{W}_2(\rho_0, \rho_1)^2$ at time $t = 1/2$.



Example of use of the Wasserstein distance

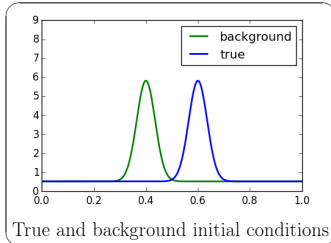
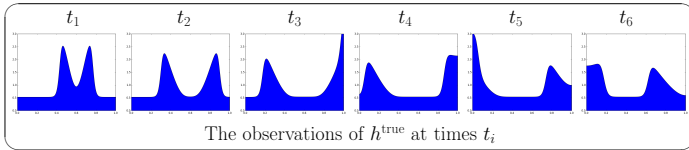


RESULTS ON A SHALLOW-WATER EQUATION

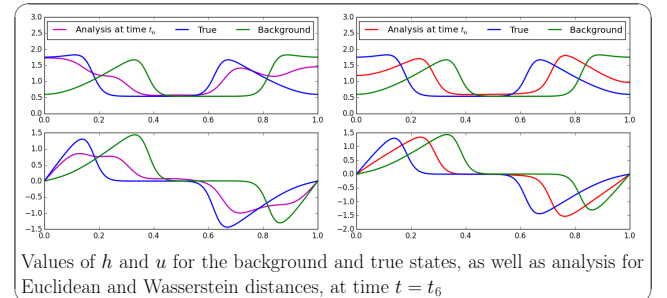
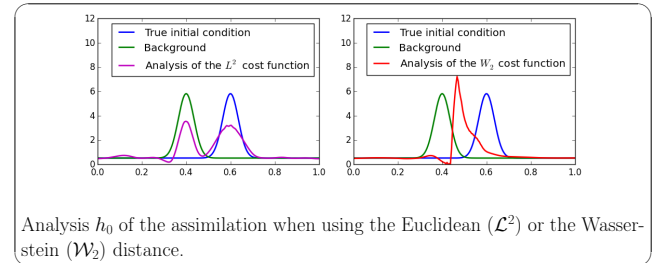
Let the model \mathcal{M} be a Shallow-Water equation, with initial condition (h_0, u_0) ,

$$\mathcal{M}: \begin{cases} \frac{\partial h}{\partial t} + \text{div}(\rho u) = 0 \\ \frac{\partial u}{\partial t} + u \cdot \nabla u = -g \nabla h. \end{cases}$$

We control the initial condition h_0 only, thanks to the Wasserstein cost function \mathcal{J}_W . We set $u_0 = 0$.



Results :



SPECIFICITIES ON USING THE WASSERSTEIN DISTANCE

- The Wasserstein distance is only defined for probability measures, i.e. ρ s.t.

$$\rho \geq 0 \text{ and } \int_{\Omega} \rho = 1$$

Relaxations of the latter constraint are possible, however complex;

- the \mathcal{W}_2 interpolation works well if ρ_0 and ρ_1 are of distinct support;
- when $\mathcal{J}(\rho_0^n) \rightarrow \min_{\rho_0} \mathcal{J}(\rho_0)$, then there is only **weak convergence** of ρ_0^n to ρ_0^{opt} : oscillations or diracs can occur!
- Computing the Wasserstein distance is expensive [Peyré, Papadakis, Oudet, 2013];

- The minimization of \mathcal{J}_W is performed through a gradient descent, using the Wasserstein gradient, arising from the use of the following Wasserstein scalar product depending on ρ_0 ,

$$\text{For } \eta, \eta' \text{ s.t. } \int_{\Omega} \eta = \int_{\Omega} \eta' = 0$$

$$\text{Let } \Phi, \Phi' \text{ s.t. } \begin{cases} -\text{div}(\rho_0 \nabla \Phi) = \eta \text{ (with Neumann BC)} \\ -\text{div}(\rho_0 \nabla \Phi') = \eta' \end{cases}$$

$$\text{Then } \langle \eta, \eta' \rangle_W = \int_{\Omega} \rho_0 \nabla \Phi \cdot \nabla \Phi' dx.$$

