



# Optimal Transportation for Data Assimilation

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# Optimal Transportation for Data Assimilation

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## DATA ASSIMILATION

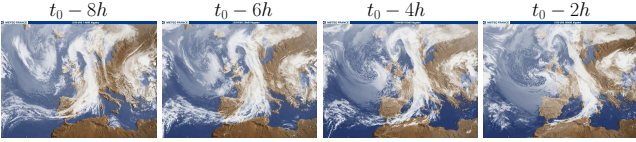
Given

- 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

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

## 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  $\rho_0$  to  $\rho_1$ ,

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

$$\partial_t \rho + \text{div}(\rho \mathbf{v}) = 0$$

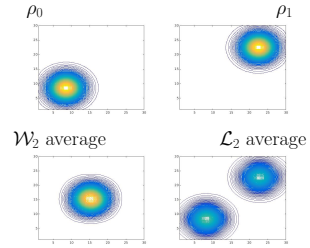
$$\rho(0, x) = \rho_0(x), \rho(1, x) = \rho_1(x)$$

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

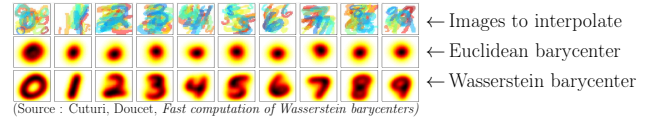
$$\rho_0 \geq 0, \rho_1 \geq 0 \text{ and } \int_{\Omega} \rho_0 = \int_{\Omega} \rho_1 = 1.$$

**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  $\rho$  in the definition of  $\mathcal{W}_2(\rho_0, \rho_1)^2$  at time  $t = 1/2$ .



**Example of use of the Wasserstein distance**

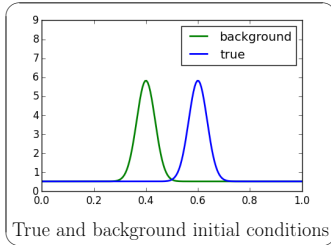
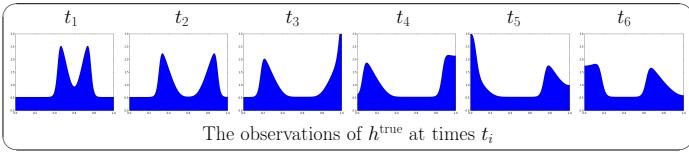


## RESULTS ON A SHALLOW-WATER EQUATION

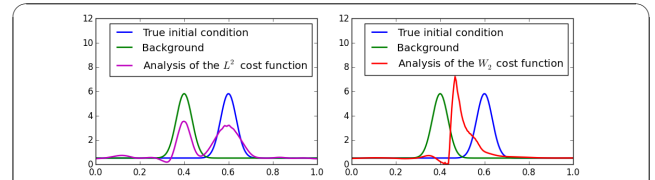
Let the model  $\mathcal{M}$  be a Shallow-Water equation, with initial condition  $(h_0, u_0)$ ,

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

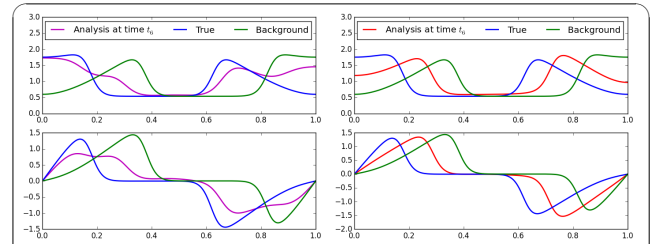
We control the initial condition  $h_0$  only, thanks to the Wasserstein cost function  $\mathcal{J}_W$ . We set  $u_0 = 0$ .



## Results :



Analysis  $h_0$  of the assimilation when using the Euclidean ( $\mathcal{L}^2$ ) or the Wasserstein ( $\mathcal{W}_2$ ) distance.



Values of  $h$  and  $u$  for the background and true states, as well as analysis for Euclidean and Wasserstein distances, at time  $t = t_6$

## SPECIFICITIES ON USING THE WASSERSTEIN DISTANCE

- The Wasserstein distance is only defined for probability measures, *i.e.*  $\rho$  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  $\rho_0$  and  $\rho_1$  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  $\rho_0^n$  to  $\rho_0^{\text{opt}}$ : 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  $\rho_0$ ,

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

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

$$-\text{div}(\rho_0 \nabla \Phi') = \eta'$$

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

