

# Off-the-Grid Wasserstein Group Lasso

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**Abstract.** In this contribution, we propose a new off-the-grid (i.e. without spatial discretization) solver for a sparse regularization method for multi-canal inverse problems, which integrates a Wasserstein distance between the recovered measures. This solver uses a semidefinite programming (SDP) relaxation based on Lasserre’s hierarchy.

The goal is to estimate two (hopefully sparse, *i.e.* sums of Diracs) positive Radon measures  $(\mu_0, \nu_0)$  on the torus  $\mathbb{T}^d$  from low-resolution noisy measurements of the form  $u = \mathcal{F}\mu_0 + w$  and  $v = \mathcal{F}\nu_0 + \varepsilon$ , where  $\mathcal{F}$  is a linear operator and  $w, \varepsilon$  account for some unknown noises. We assume that  $\mathcal{F}$  is a convolution with a low-pass filter, so that without loss of generality, we may consider a Fourier transform  $(\mathcal{F}\mu)_k = \int_{\mathbb{T}^d} e^{-2i\pi\langle k, x \rangle} d\mu(x)$ , for  $k \in \Omega_c \stackrel{\text{def.}}{=} \llbracket -f_c, f_c \rrbracket^d$ . In practice, the sought after sources  $(\mu, \nu)$  are linked to physical or biological phenomena, and one wishes to constrain the relative positions of the spikes in both measures. The classical approach (often called the group-Lasso problem) is to use a vectorial total variation norm, which imposes that  $\mu$  and  $\nu$  share the same support. This constraint is often too strong, and following [1] we propose to relax this assumption by rather penalizing their respective Wasserstein “distance”. This distance is defined, for some cost  $C(x, y)$ , by  $W_C(\mu, \nu) = \min_{\gamma_1=\mu, \gamma_2=\nu} \int C(x, y) d\gamma(x, y)$  where  $(\gamma_1, \gamma_2)$  are the two marginals of the transport plan  $\gamma$ , which is a positive measure over the product space  $\mathbb{T}^d \times \mathbb{T}^d$ . The sources are thus estimated by solving the following infinite dimensional optimization problem

$$\min_{\mu, \nu \in \mathcal{M}_+(\mathbb{T}^d)} \frac{1}{2} \|u - \mathcal{F}\mu\|^2 + \frac{1}{2} \|v - \mathcal{F}\nu\|^2 + \lambda |\mu|(\mathbb{T}^d) + \lambda |\nu|(\mathbb{T}^d) + \tau W_C(\mu, \nu). \quad (1)$$

Instead of considering a fixed spatial discretization, we rather search for the Fourier moments of the transport plan  $\gamma$ . For  $\ell \geq f_c$ , we consider  $z_{(s,t)} \stackrel{\text{def.}}{=} \int_{\mathbb{T}^d \times \mathbb{T}^d} e^{-2i\pi\langle s, x \rangle} e^{-2i\pi\langle t, y \rangle} d\gamma(x, y)$  for  $s, t \in \llbracket -\ell, \ell \rrbracket^d$ , and  $R_\ell(z) = (z_{(s-s', t-t')})_{s, s', t, t' \in \llbracket 0, \ell \rrbracket^d}$ . We denote by  $\hat{C}$  the Fourier coefficients of  $C$ . Let also  $z_1 = z_{(\cdot, 0)}$ ,  $z_2 = z_{(0, \cdot)}$  and  $z_0 = z_{(0, 0)}$ . Then the sequence of SDP problems

$$\min_{z \in \mathbb{C}^{|\Omega_c|}} \frac{1}{2} \|u - z_1\|^2 + \frac{1}{2} \|v - z_2\|^2 + 2\lambda z_0 + \tau \langle \hat{C}, z \rangle \quad \text{s.t.} \quad R_\ell(z) \succeq 0 \quad (\mathcal{P}_\ell)$$

can be shown to define a “Lasserre” hierarchy of increasingly tighter relaxations of (1), and in many cases, one can recover the support of a solution of (1) from a solution of  $(\mathcal{P}_\ell)$ . Note that when  $\lambda = 0$  and as  $\tau \rightarrow 0$ , solving (1) defines a low-frequency approximation of the celebrated optimal transport problem. In this talk, I will outline the theoretical aspects of the relaxation  $(\mathcal{P}_\ell)$ , explain efficient tailored numerical solvers and showcase numerical illustrations.

## References

- [1] Wasserstein regularization for sparse multi-task regression. Janati et al. AISTATS 2019.

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