

# On the weighted total variation distance between probability measures

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## Abstract

A short note on the weighted total variation distance for probability measures on  $\mathbb{R}^d$ . Everything is certainly well-known, but I could not find a proper reference.

Given  $\phi : \mathbb{R}^d \rightarrow \mathbb{R}_+$  a non-negative measurable function, we define the weighted total variation distance between two probability measures  $\nu$  and  $\mu$  by

$$d_{TV}^\phi(\nu, \mu) := \int \phi(x) |\nu - \mu|(dx).$$

**Theorem 1.** *The weighted total variation distance satisfies*

$$d_{TV}^\phi(\nu, \mu) = \inf_{\mathcal{L}(X)=\nu, \mathcal{L}(Y)=\mu} \mathbb{E}(\phi(X) + \phi(Y)) \mathbb{1}_{X \neq Y}.$$

*In addition, the Kantorovich duality theorem holds*

$$d_{TV}^\phi(\nu, \mu) = \sup_g \int g(x) (\nu - \mu)(dx),$$

*where the supremum is taken over all the measurable functions  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  s.t.*

$$\forall x, y, \quad |g(x) - g(y)| \leq (\phi(x) + \phi(y)) \mathbb{1}_{x \neq y}. \quad (1)$$

**Remark 2.** *This result states that the weighted total variation distance is equal to the Wasserstein distance  $W_1$  for the following peculiar semi-metric*

$$d(x, y) := (\phi(x) + \phi(y)) \mathbb{1}_{x \neq y}.$$

*See also [CD18, Ch. 5].*

**Remark 3.** *The standard (non-weighted) total variation distance is obtained by choosing  $\phi \equiv 1/2$ . In that case, the result simplifies to*

$$d_{TV}^{1/2}(\nu, \mu) = \inf_{\mathcal{L}(X)=\nu, \mathcal{L}(Y)=\mu} \mathbb{P}(X \neq Y) = \sup_{A \in \mathcal{B}(\mathbb{R}^d)} \nu(A) - \mu(A),$$

*where  $\mathcal{B}(\mathbb{R}^d)$  denotes the Borel sets of  $\mathbb{R}^d$ .*

*Proof. Step 1.* We prove that  $d_{TV}^\phi(\nu, \mu) \leq \sup_g \int g(x)(\nu - \mu)(dx)$ .

Let  $m$  be a non-negative measure such that  $\nu \ll m$  and  $\mu \ll m$  (one can choose  $m = \nu + \mu$ ). The Radon–Nikodym theorem provides non-negative measurable functions  $h_\nu$  and  $h_\mu$  such that

$$\nu(dx) = h_\nu(x)m(dx) \quad \text{and} \quad \mu(dx) = h_\mu(x)m(dx).$$

Let  $B := \{h_\nu \geq h_\mu\}$  and  $\bar{B} := \mathbb{R}^d \setminus B$ . We choose  $g(x) := \phi(x)\mathbb{1}_B(x) - \phi(x)\mathbb{1}_{\bar{B}}(x)$ . It satisfies (1) and

$$\int \phi(x)|\nu - \mu|(dx) = \int g(x)(\nu - \mu)(dx).$$

*Step 2.* We prove that  $\sup_g \int g(x)(\nu - \mu)(dx) \leq \inf_{\mathcal{L}(X)=\nu, \mathcal{L}(Y)=\mu} \mathbb{E}(\phi(X) + \phi(Y))\mathbb{1}_{X \neq Y}$ .

Let  $g$  such that (1) holds. Consider  $\pi$  any coupling between  $\nu$  and  $\mu$ , we have

$$\begin{aligned} \int g(x)\nu(dx) - \int g(y)\mu(dy) &= \int \int (g(x) - g(y))\pi(dx, dy) \\ &\leq \int \int |g(x) - g(y)|\pi(dx, dy) \\ &\leq \int \int (\phi(x) + \phi(y))\mathbb{1}_{x \neq y}\pi(dx, dy). \end{aligned}$$

Taking the infimum of the right-hand side over all the couplings gives the result.

*Step 3.* We prove that  $\inf_{\mathcal{L}(X)=\nu, \mathcal{L}(Y)=\mu} \mathbb{E}(\phi(X) + \phi(Y))\mathbb{1}_{X \neq Y} \leq d_{TV}^\phi(\nu, \mu)$ .

We use the following explicit coupling taken from [Vil09]

$$\pi(dx, dy) := (\nu \wedge \mu)(dx)\delta_x(dy) + \frac{1}{a}(\nu - \mu)_+(dx)(\nu - \mu)_-(dy),$$

where  $a := \int (\nu - \mu)_+ = \int (\nu - \mu)_-$  and  $\nu \wedge \mu := \nu - (\nu - \mu)_+$ . Let  $(X, Y) \sim \pi$ . We have

$$\mathbb{E}\phi(X) = \mathbb{E}\phi(X)\mathbb{1}_{X=Y} + \mathbb{E}\phi(X)\mathbb{1}_{X \neq Y},$$

and denoting by  $\alpha := \int \phi(x)(\nu - \mu)_+(dx)$ , it holds that

$$\begin{aligned} \mathbb{E}\phi(X)\mathbb{1}_{X=Y} &\geq \int \phi(x)(\nu \wedge \mu)(dx) \\ &= \int \phi(x)\nu(dx) - \int \phi(x)(\nu - \mu)_+(dx) \\ &= \mathbb{E}\phi(X) - \alpha. \end{aligned}$$

So  $\mathbb{E}\phi(X)\mathbb{1}_{X \neq Y} \leq \alpha$ . Similarly, let  $\beta := \int \phi(x)(\nu - \mu)_-(dx)$ , a similar argument shows that

$$\mathbb{E}\phi(Y)\mathbb{1}_{X \neq Y} \leq \beta.$$

Altogether, we have

$$\mathbb{E}(\phi(X) + \phi(Y))\mathbb{1}_{X \neq Y} \leq \alpha + \beta = d_{TV}^\phi(\nu, \mu).$$

Combining the three steps ends the proof. □

## References

- [CD18] R. Carmona and F. Delarue. *Probabilistic theory of mean field games with applications. I*. Vol. 83. Probability Theory and Stochastic Modelling. Mean field FBSDEs, control, and games. Springer, Cham, 2018, pp. xxv+713.
- [Vil09] C. Villani. *Optimal transport*. Vol. 338. Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]. Old and new. Springer-Verlag, Berlin, 2009, pp. xxii+973. DOI: 10.1007/978-3-540-71050-9.