## A PROOFS

**Proof for Definition 1** We write a proof in the case where  $\mathcal{E} = \{\mathbb{R}^d\}$ . If K > 1, the proof can be applied independently on each set of the partition.

Let  $(f_n)_{n \in \mathbb{N}}$  be such that  $f_n(0) = 0$  for all  $n \in \mathbb{N}$  and

$$W_2\left[(\nabla f_n)_{\sharp}\mu,\nu\right] \leq \frac{1}{n+1} + \inf_{f \in \mathcal{F}_{\ell,L}} W_2\left[(\nabla f)_{\sharp}\mu,\nu\right].$$

Let  $x_0 \in \operatorname{supp}(\mu)$ . Then there exists C > 0 such that for all  $n \in \mathbb{N}$ ,  $\|\nabla f_n(x_0)\| \leq C$ . Indeed, suppose this is not true. Take r > 0 such that  $V := \mu[B(x_0, r)] > 0$ . By Prokhorov theorem, there exists R > 0 such that  $\nu[B(0, R)] \geq 1 - \frac{V}{2}$ . Then for C > 0 large enough, there exists an  $n \in \mathbb{N}$  such that:

$$W_{2}^{2}[(\nabla f_{n})_{\sharp}\mu,\nu] = \min_{\pi \in \Pi(\mu,\nu)} \int \|\nabla f_{n}(x) - y\|^{2} d\pi(x,y)$$
  

$$\geq \int \|\nabla f_{n}(x) - \operatorname{proj}_{B(0,R)} [\nabla f_{n}(x)] \|^{2} d\mu(x)$$
  

$$\geq \int_{B(x_{0},r) \cap \operatorname{supp}(\mu)} \|\nabla f_{n} - \operatorname{proj}_{B(0,R)} [\nabla f_{n}] \|^{2} d\mu$$
  

$$\geq \frac{1}{2} V \min_{\substack{x \in B(x_{0},r) \\ y \in B(0,R)}} \|\nabla f_{n}(x) - y\|^{2}$$
  

$$\geq \frac{1}{2} V(C - Lr - R)$$

which contradicts the definition of  $f_n$  when C is sufficiently large.

Then for  $x \in \mathbb{R}^d$ ,

$$\|\nabla f_n(x)\| \le L \|x - x_0\| + \|\nabla f_n(x_0)\| \le L \|x - x_0\| + C.$$

Since  $(\nabla f_n)_{n \in \mathbb{N}}$  is equi-Lipschitz, it converges uniformly (up to a subsequence) to some function g by Arzelà–Ascoli theorem. Note that g is L-Lipschitz.

Let  $\epsilon > 0$  and let  $N \in \mathbb{N}$  such that  $n \ge N \Rightarrow$  $\|\nabla f_n - g\|_{\infty} \le \epsilon$ . Then for  $n \ge N$  and  $x \in \mathbb{R}^d$ ,

$$|f_n(x)| = \left| \int_0^1 \langle \nabla f_n(tx), x \rangle \, dt \right| \le ||x|| (||g||_\infty + \epsilon)$$

so that  $(f_n(x))$  converges up to a subsequence. Let  $\phi, \psi$  be two extractions and  $\alpha, \beta$  such that  $f_{\phi(n)}(x) \to \alpha$ and  $f_{\psi(n)}(x) \to \beta$ . Then

$$\begin{aligned} |\alpha - \beta| &= \lim_{n \to \infty} \left| \int_0^1 \langle \nabla f_{\phi(n)}(tx) - \nabla f_{\psi(n)}(tx), x \rangle \, dt \right| \\ &\leq \lim_{n \to \infty} \|x\| \|\nabla f_{\phi(n)} - \nabla f_{\psi(n)}\|_{\infty} = 0. \end{aligned}$$

This shows that  $(f_n)_{n \in N}$  converges pointwise to some function  $f_*$ . In particular,  $f_*$  is convex. For  $x \in \mathbb{R}^d$ , using Lebesgue's dominated convergence theorem,

$$f_{\star}(x) = \lim_{n \to \infty} f_n(x) = \lim_{n \to \infty} \int_0^1 \langle \nabla f_n(tx), x \rangle \, dt$$
$$= \int_0^1 \left\langle \lim_{n \to \infty} \nabla f_n(tx), x \right\rangle \, dt = \int_0^1 \langle g(tx), x \rangle \, dt$$

so  $f_{\star}$  is differentiable and  $\nabla f_{\star} = g$ . Using Lebesgue's dominated convergence theorem, uniform (hence pointwise) convergence of  $(\nabla f_n)_{n \in \mathbb{N}}$  to  $\nabla f_{\star}$  shows that  $(\nabla f_n)_{\sharp} \mu \rightarrow (\nabla f_{\star})_{\sharp} \mu$ . Then classical optimal transport stability theorems *e.g.* (Villani, 2009, Theorem 5.19) show that

$$W_2\left[(\nabla f_\star)_{\sharp}\mu,\nu\right] = \lim_{n \to \infty} W_2\left[(\nabla f_n)_{\sharp}\mu,\nu\right]$$
$$= \inf_{f \in \mathcal{F}_{\ell,L}} W_2\left[(\nabla f)_{\sharp}\mu,\nu\right],$$

*i.e.*  $f_{\star}$  is a minimizer.

**Proof of Theorem 1** For  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$ ,  $\nabla f_{\sharp}\mu = \sum_{i=1}^{n} a_i \delta_{\nabla f(x_i)}$ . Writing  $z_i = \nabla f(x_i)$ , we wish to minimize  $W_2^2 \left( \sum_{i=1}^{n} a_i \delta_{z_i}, \nu \right)$  over all the points  $z_1, \ldots, z_n \in \mathbb{R}^d$  such that there exists  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$  with  $\nabla f(x_i) = z_i$  for all  $i \in [n]$ . Following (Taylor, 2017, Theorem 3.8), there exists such a f if, and only if, there exists  $u \in \mathbb{R}^n$  such that for all  $k \in [K]$  and for all  $i, j \in I_k$ ,

$$u_{i} \geq u_{j} + \langle z_{j}, x_{i} - x_{j} \rangle + \frac{1}{2(1 - \ell/L)} \left( \frac{1}{L} \| z_{i} - z_{j} \|^{2} + \ell \| x_{i} - x_{j} \|^{2} - 2 \frac{\ell}{L} \langle z_{j} - z_{i}, x_{j} - x_{i} \rangle \right).$$

Then minimizing over  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$  is equivalent to minimizing over  $(z_1, \ldots, z_n, u)$  under these interpolation constraints.

The second part of the theorem is a direct application of (Taylor, 2017, Theorem 3.14).

**Proof of Proposition 1** Let  $f : \mathbb{R} \to \mathbb{R}$ . Then  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$  if and only if it is convex and *L*-smooth on each set  $E_k, k \in \llbracket K \rrbracket$ , *i.e.* if and only if for any  $k \in \llbracket K \rrbracket$ ,  $0 \leq f''|_{E_k} \leq L$ .

For a measure  $\rho$ , let us write  $F_{\rho}$  and  $Q_{\rho}$  the cumulative distribution function and the quantile function (*i.e.* the generalized inverse of the cumulative distribution function). Then  $Q_{\nabla f_{\sharp}\mu} = \nabla f \circ Q_{\mu}$ .

Using the closed-form formula for the Wasserstein distance in dimension 1, the objective we wish to minimize (over  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$ ) is:

$$W_2^2(f'_{\sharp}\mu,\nu) = \int_0^1 \left[f' \circ Q_{\mu}(t) - Q_{\nu}(t)\right]^2 dt.$$

Suppose  $\mu$  has a density w.r.t the Lebesgue measure. Then by a change of variable, the objective becomes

$$\int_{-\infty}^{+\infty} \left[ f'(x) - Q_{\nu} \circ F_{\mu}(x) \right]^2 d\mu(x) = \| f' - \overline{\pi} \|_{L^2(\mu)}^2.$$

Indeed,  $Q_{\nu} \circ F_{\mu}$  is the optimal transport map from  $\mu$  to  $\nu$ , hence its own barycentric projection. The result

follows.

Suppose now that  $\mu$  is purely atomic, and write  $\mu = \sum_{i=1}^{n} a_i \delta_{x_i}$  with  $x_1 \leq \ldots \leq x_n$ . For  $0 \leq i \leq n$ , put  $\alpha_i = \sum_{k=1}^{i} a_k$  with  $\alpha_0 = 0$ . Then

$$W_{2}^{2}(f_{\sharp}'\mu,\nu) = \sum_{i=1}^{n} \int_{\alpha_{i-1}}^{\alpha_{i}} (f'(x_{i}) - Q_{\nu}(t))^{2} dt$$
  
$$= \sum_{i=1}^{n} a_{i} \left[ f'(x_{i}) - \frac{1}{a_{i}} \left( \int_{\alpha_{i-1}}^{\alpha_{i}} Q_{\nu}(t) dt \right) \right]^{2}$$
  
$$+ \int_{\alpha_{i-1}}^{\alpha_{i}} Q_{\nu}(t)^{2} dt - \frac{1}{a_{i}} \left( \int_{\alpha_{i-1}}^{\alpha_{i}} Q_{\nu}(t) dt \right)^{2}.$$

Since  $\sum_{i=1}^{n} \int_{\alpha_{i-1}}^{\alpha_{i}} Q_{\nu}(t)^{2} dt - \frac{1}{a_{i}} \left( \int_{\alpha_{i-1}}^{\alpha_{i}} Q_{\nu}(t) dt \right)^{2}$  does not depend on f, minimizing  $W_{2}^{2}(f_{\sharp}'\mu,\nu)$  over  $f \in \mathcal{F}_{\ell,L,\mathcal{E}}$  is equivalent to solve

$$\min_{f \in \mathcal{F}_{\ell,L,\mathcal{E}}} \sum_{i=1}^n a_i \left[ f'(x_i) - \frac{1}{a_i} \left( \int_{\alpha_{i-1}}^{\alpha_i} Q_{\nu}(t) dt \right) \right]^2.$$

There only remains to show that  $\overline{\pi}(x_i) = \frac{1}{a_i} \int_{\alpha_{i-1}}^{\alpha_i} Q_{\nu}(t) dt$ . Using the definition of the conditional expectation and the definition of  $\pi$ :

$$\begin{split} \overline{\pi}(x_i) &= \frac{1}{a_i} \int_{-\infty}^{+\infty} y \, \mathbf{1}\{x = x_i\} \, d\pi(x, y) \\ &= \frac{1}{a_i} \int_{-\infty}^{+\infty} y \, \mathbf{1}\{x = x_i\} \, d(Q_\mu, Q_\nu)_{\sharp} \mathscr{L}^1|_{[0,1]} \\ &= \frac{1}{a_i} \int_0^1 Q_\nu(t) \, \mathbf{1}\{Q_\mu(t) = x_i\} \, dt \\ &= \frac{1}{a_i} \int_{\alpha_{i-1}}^{\alpha_i} Q_\nu(t) \, dt. \end{split}$$

**Proof of Proposition 2** Since  $\mathcal{E} = \{\mathbb{R}^d\}$ , and using the triangular inequality for the Wasserstein distance,

$$\begin{aligned} \left| W_{2}(\mu,\nu) - \widehat{W}_{2}(\mu,\nu) \right| &= \left| W_{2}(\mu,\nu) - W_{2}(\mu,\nabla\hat{f}_{n\,\sharp}\mu) \right| \\ &\leq W_{2} \left( \nabla\hat{f}_{n\,\sharp}\mu,\nu \right) \\ &\leq W_{2} \left( \nabla\hat{f}_{n\,\sharp}\mu,\nabla\hat{f}_{n\,\sharp}\hat{\mu}_{n} \right) \quad (4) \\ &+ W_{2} \left( \nabla\hat{f}_{n\,\sharp}\hat{\mu}_{n},\hat{\nu}_{n} \right) \quad (5) \end{aligned}$$

$$+ W_2\left(\hat{\nu}_n,\nu\right). \tag{6}$$

We now successively upper bound terms (4), (5), (6). Since  $\nabla \hat{f}_n$  is *L*-Lispchitz, almost surely:

$$(4) = W_2\left(\nabla \hat{f}_{n\sharp} \mu, \nabla \hat{f}_{n\sharp} \hat{\mu}_n\right) \le L W_2\left(\mu, \hat{\mu}_n\right) \underset{n \to \infty}{\longrightarrow} 0$$

since almost surely,  $\hat{\mu}_n \rightharpoonup \mu$  and  $\mu$  has compact support, cf. (Santambrogio, 2015, Theorem 5.10). For the same reason, almost surely:

$$(6) = W_2\left(\hat{\nu}_n, \nu\right) \xrightarrow[n \to \infty]{} 0$$

Finally, since  $f_{\star} \in \mathcal{F}_{\ell,L,\mathcal{E}}$  and  $\nabla \hat{f}_n$  is an optimal SSNB potential, it almost surely holds:

$$(5) = W_2\left(\nabla \hat{f}_{n\sharp}\hat{\mu}_n, \hat{\nu}_n\right) \le W_2\left(\nabla f_{\star\sharp}\hat{\mu}_n, \hat{\nu}_n\right)$$
$$\xrightarrow[n \to \infty]{} W_2\left(\nabla f_{\star\sharp}\mu, \nu\right) = 0$$

because  $(\hat{\mu}_n, \hat{\nu}_n) \rightarrow (\mu, \nu)$ , and by definition of  $f_{\star}$ ,  $\nabla f_{\star \sharp} \mu = \nu$ .