

$$W_2^2(P, Q) = \sup_{\phi \in \mathcal{C}_c(X)} \int_X \phi dP + \int_Y \phi^c dQ = \int_X \phi^* dP + \int_Y \phi^{*c} dQ.$$

$$\frac{\delta W_2^2(P, Q)}{\delta P} = \frac{\delta}{\delta P} \left\{ \int_X \phi dP + \int_Y \phi^c dQ \right\}.$$

$$= \int_X \frac{\delta}{\delta P} \phi dP$$

$$= \phi^*.$$

$$P = F_\theta, \quad \frac{\partial F_\theta}{\partial \theta}$$

$$\frac{\partial W_2^2(F_\theta, Q)}{\partial \theta} = \int \phi_{\theta}^* \cdot \nabla_\theta F_\theta(x) dx$$

$$T_\theta(x) = \nabla_x \phi_\theta(x) \quad x \sim \mu, \quad P = \phi^* \text{ optimal potential.}$$

$$\nabla_\theta W_2^2((T_\theta)_\# \mu, Q) =$$

$$\frac{\delta}{\delta P} W_2^2(P, Q) = \phi_P$$

higher order.
↑

First variation:
ℝ^d.

$$F(P) - F(P_0) \approx \int \frac{\delta}{\delta P} F \cdot (P - P_0) + O(W_2^2(P - P_0)).$$

$$\theta' \approx \theta,$$

$$W_2^2((T_{\theta'})_\# \mu, Q) - W_2^2((T_\theta)_\# \mu, Q).$$

$$\approx \int \phi_P \cdot (d(T_{\theta'})_\# \mu - d(T_\theta)_\# \mu).$$

$$= \int \phi_P \circ T_{\theta'} d\mu - \int \phi_P \circ T_\theta d\mu. \quad (\text{sample avg}).$$

$$u_1, \dots, u_m \sim \mu \quad (\text{sample}).$$

$$= \frac{1}{m} \sum_{j=1}^m [\phi^*(T_{\theta'}(u_j)) - \phi^*(T_\theta(u_j))]$$

$$= \frac{1}{n} \sum_{j=1}^n \nabla_{\theta} (\underbrace{\phi^* \circ T_{\theta}}_{\text{Sinkhorn}})(u_j)$$

$$W_2^2(P, Q) \quad \phi^*, \quad \nabla \phi^* = T_P^Q$$

$$\nabla_{\theta} (\phi^* \circ T_{\theta}) = T_P^Q \circ \nabla T_{\theta}.$$

• First variation.

$$F, \text{ gradient}, \quad F(\theta) - F(\theta^*)$$

$$= \underbrace{\langle f, \theta - \theta^* \rangle}_{\text{gradient}} + o(\|\theta - \theta^*\|^2).$$

CS 540 Deep Learning Theorem.

