
Principal Geodesic Analysis for Probability Measures under the Optimal Transport Metric: Supplementary Material

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1 Pseudo Geodesic Metric

Let us first recall from [Ambrosio et al., 2006, Section 12.4] that the set of geodesics in the Wasserstein space can be identified to some plans having first marginal equal to $\bar{\mu}$,

$$\mathbf{G}(\bar{\mu}) = \{ \pi \in P_2(\mathcal{X}^2), p_1 \# \pi = \bar{\mu}, (p_1, p_1 + \varepsilon p_2) \# \pi \text{ optimal for some } \varepsilon > 0 \}. \quad (1)$$

Ambrosio et al. [2006, Definition 12.4.1] defined a metric on $\mathbf{G}(\bar{\mu})$,

$$W_{\bar{\mu}}(\pi_1, \pi_2)^2 = \min \left\{ \int_{\mathcal{X}^3} |x_3 - x_2|^2 d\gamma, \gamma \in \Gamma(\pi_1, \pi_2) \right\}, \quad (2)$$

where $\Gamma(\pi_1, \pi_2) \subset P(X^3)$ is the set of a plans verifying $p_{12} \# \gamma = \pi_1$ and $p_{23} \# \gamma = \pi_2$, with $p_{12}(x_1, x_2, x_3) = (x_1, x_2)$ and $p_{13}(x_1, x_2, x_3) = (x_1, x_3)$. If for example π_2 is induced by a mapping T , namely $\pi_2 = (\text{id} \times T) \# \bar{\mu}$, then this metric has the more simple expression [Ambrosio et al., 2006, page 316],

$$W_{\bar{\mu}}(\pi_1, \pi_2) = \left(\int_{\mathcal{X}^2} \|x_2 - T(x_1)\|_{\mathcal{X}}^2 d\pi_1(x_1, x_2) \right)^{1/2}. \quad (3)$$

Interestingly, if we look for the T which minimizes $W_{\bar{\mu}}(\pi_1, \pi_2)$ in Equation (4), we get that the solution is unique $\bar{\mu}$ -almost surely and is equal to the barycentric projection of π_1 . This can be seen by disintegrating π_1 ,

$$W_{\bar{\mu}}(\pi_1, \pi_2)^2 = \int_{\mathcal{X}} \left(\int_{\mathcal{X}} \|x_2 - T(x_1)\|_{\mathcal{X}}^2 d\pi_{1,x_1}(x_2) \right) d\bar{\mu}(x_1). \quad (4)$$

For each x_1 the minimum in the inner integral is achieved indeed for $T(x_1) = \int_{\mathcal{X}} x_2 d\pi_{1,x_1}$, which is the barycentric projection of π_1 . As seen above, if moreover π_1 is an optimal transport plan, then its barycentric projection is an optimal mapping. This observation motivates definition 1, which introduces a quantification of the difference between two vector fields which can be minimized with the barycentric projection.

Definition 1 (Geodesic pseudo metric on $L^2(\bar{\mu}, \mathcal{X})$). *Let u and v in $L^2(\bar{\mu}, \mathcal{X})$. Let Π_o^u be the set of optimal transport plans between $\bar{\mu}$ and $(\text{id} + u) \# \bar{\mu}$, and Π_o^v be the set of optimal transport plans between $\bar{\mu}$ and $(\text{id} + v) \# \bar{\mu}$. We define,*

$$GW_{\bar{\mu}}(u, v) = \inf_{\pi_1 \in \Pi_o^u, \pi_2 \in \Pi_o^v} W_{\bar{\mu}}((p_1, p_2 - p_1) \# \pi_1, (p_1, p_2 - p_1) \# \pi_2)$$

which is the minimal distance between all geodesics starting from $\bar{\mu}$ and going through $(\text{id} + u) \# \bar{\mu}$ at time $t = 1$, and all geodesics starting from $\bar{\mu}$ and going through $(\text{id} + v) \# \bar{\mu}$ at time $t = 1$.

$GW_{\bar{\mu}}$ does not always satisfy the triangular inequality and is thus not a metric on $L^2(\bar{\mu}, \mathcal{X})$. $GW_{\bar{\mu}}$ becomes a metric when Π_o^w contains a unique element for any $w \in L^2(\bar{\mu}, \mathcal{X})$, which is the case for example if $\bar{\mu}$ admits a density. If moreover $\text{id} + u$ and $\text{id} + v$ are optimal mappings, then $\pi_1 = (\text{id} \times (\text{id} + u))\#\bar{\mu}$ and $\pi_2 = (\text{id} \times (\text{id} + v))\#\bar{\mu}$ are the unique optimal plans, and then $GW_{\bar{\mu}}(u, v) = \|v - u\|_{L^2(\bar{\mu}, \mathcal{X})}$. To summarize, these results yield the following Proposition, which motivates the use of the barycentric projection.

Proposition 1. *Let v in $L^2(\bar{\mu}, \mathcal{X})$ and π_o^v an optimal transport plan between $\bar{\mu}$ and $(\text{id} + v)\#\bar{\mu}$. Assume π_o^v is unique and that there exists a solution w to,*

$$w \in \min_{\text{id} + u \in \mathcal{C}_{\bar{\mu}}(\mathcal{X})} GW_{\bar{\mu}}^2(u, v),$$

such that the optimal transport plan π_o^w between $\bar{\mu}$ and $(\text{id} + w)\#\bar{\mu}$ is unique. Then,

$$w = B((p_1, p_2 - p_1)\#\pi_o^v). \quad (5)$$

Proof. Since we assume that the solution w to the minimization problem has the property that there is a unique optimal transport plan between π_o^w between $\bar{\mu}$ and $(\text{id} + w)\#\bar{\mu}$, it is equivalent to restrict to the u which also verify this property. The constraint $u \in \mathcal{C}_{\bar{\mu}}(\mathcal{X}) - \text{id}$ means that $(\text{id} \times (\text{id} + u))\#\bar{\mu}$ is an optimal transport plan between $\bar{\mu}$ and $(\text{id} + u)\#\bar{\mu}$, and then $(p_1, p_2 - p_1)\#\pi_o^u = (\text{id} \times u)\#\bar{\mu}$. This leads to,

$$GW_{\bar{\mu}}^2(u, v) = \min_u \int_{\mathcal{X}^2} \|x_2 - u(x_1)\|_{\mathcal{X}}^2 d(p_1, p_2 - p_1)\#\pi_o^u(x_1, x_2),$$

which is minimum if and only if w is the barycentric projection of $(p_1, p_2 - p_1)\#\pi_o^v$ as discussed earlier. \square

Although we are not able to compute a solution of Equation (7), the last proposition shows that substituting the L^2 norm in Eq. (7) by the pseudo metric defined in definition 1, we have an analytic solution which is simple to obtain through the computation of an optimal transport plan and a barycentric projection. As stated above, this pseudo metric and the $L_{\bar{\mu}}^2$ norm are equal on the subset $\mathcal{C}_{\bar{\mu}}(\mathcal{X}) - \text{id}$ of $L^2(\bar{\mu}, \mathcal{X})$ when $\bar{\mu}$ admits a density.

2 MNIST Principal Components per Digits with our approach

1000 images for each of the digits of the MNIST dataset have been sampled. We display below the first three PCs computed with our approach.

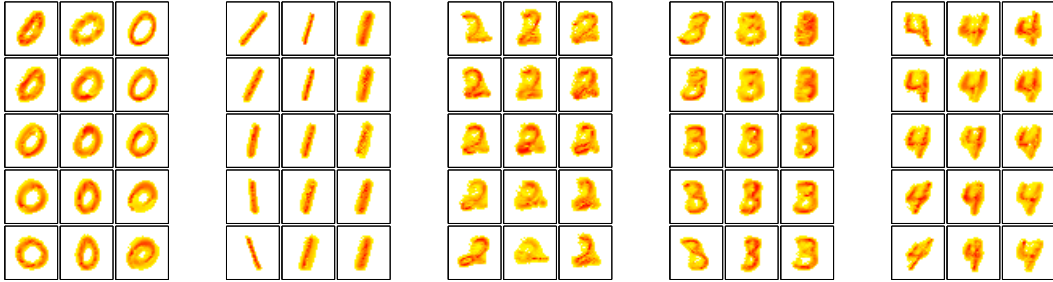


Figure 1: Digits 0,1,2,3,4. The three PCs are sampled at times $t_k = k/4$, $k = 0, \dots, 4$ for each of these digits.



Figure 2: Digits 5,6,7,8,9. The three PCs are sampled at times $t_k = k/4$, $k = 0, \dots, 4$ for each of these digits.

3 MNIST Principal Components per Digits with Wang et al.'s approach (2013)

As above, 1000 images for each of the digits of the MNIST dataset have been sampled. We display below the first three PCs computed using Wang et al.'s approach (2013).

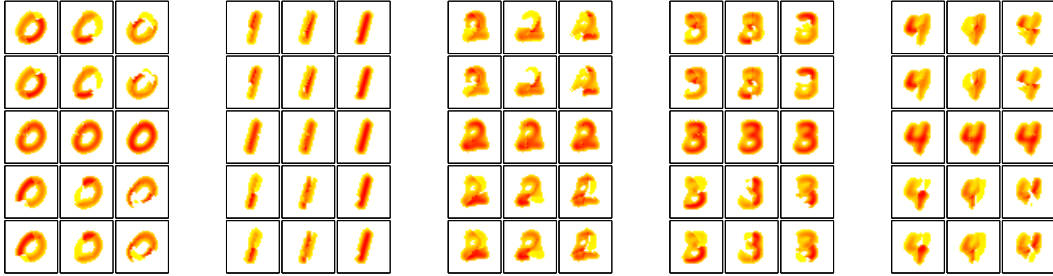


Figure 3: Digits 0,1,2,3,4. The three PCs are sampled at times $t_k = k/4$, $k = 0, \dots, 4$ for each of these digits.

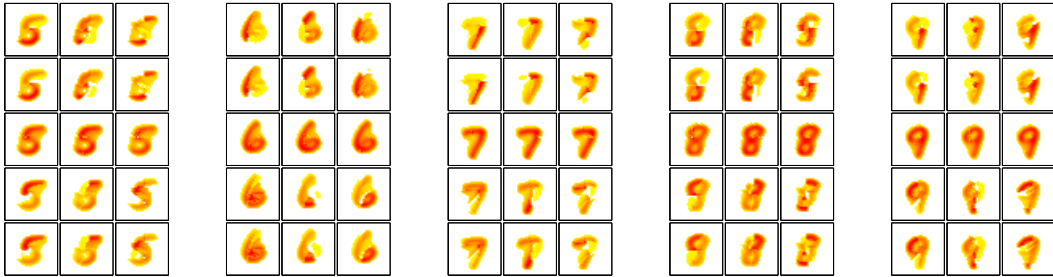


Figure 4: Digits 5,6,7,8,9. The three PCs are sampled at times $t_k = k/4$, $k = 0, \dots, 4$ for each of these digits.

4 Algorithm Pseudo Code

Algorithm 1 Compute the $(n + 1)^{\text{th}}$ generalized geodesic principal component

1: **Input:** For $i \leq N$: $X_i \in \mathbb{R}^{d \times n_i}$, $a_i \in \mathbb{R}_+^{n_i}$ in the simplex. $Y \in \mathbb{R}^{d \times p}$, $b \in \mathbb{R}_+^p$ in the simplex. $K \in \mathbb{N}$, gradient step size $\beta > 0$, parameter $\lambda > 0$. V_1 and V_2 initial random matrices in $\mathbb{R}^{d \times p}$ with small norms.

2: **while** not converged **do**

3: For all i and $t_k = k/K$, form $M_{Z_{t_k} X_i}$ and solve Eq. (9).

4: For all i , compute the optimal projection time $t_i^\#$ and the corresponding optimal plan $P_i^\#$.

5: For all i , compute the gradients of m_i as in Eq. (13).

6: Update

$$V_1 \leftarrow V_1 - \beta \left(\sum_{i=1}^N \nabla_1 m_i^{V_1 V_2} + \lambda \nabla_1 \Omega \right), \quad V_2 \leftarrow V_2 - \beta \left(\sum_{i=1}^N \nabla_2 m_i^{V_1 V_2} + \lambda \nabla_2 \Omega \right)$$

7: Project V_1 and V_2 on $\text{span}(V_1^{(1)} + V_2^{(1)}, \dots, V_1^{(n)} + V_2^{(n)})^\perp$ in the L_μ^2 sense.

8: Compute the optimal plans P_1^* and P_2^* as in Eq. (14).

9: Update V_1 and V_2 through Eq. (15):

$$V_1 \leftarrow -(Y - V_1)P_1^{*T} \text{diag}(b^{-1}) - Y, \quad V_2 \leftarrow (Y + V_2)P_2^{*T} \text{diag}(b^{-1}) - Y.$$

10: **end while**

References

- Luigi Ambrosio, Nicola Gigli, and Giuseppe Savaré. *Gradient flows: in metric spaces and in the space of probability measures*. Springer, 2006.
- Wei Wang, Dejan Slepčev, Saurav Basu, John A Ozolek, and Gustavo K Rohde. A linear optimal transportation framework for quantifying and visualizing variations in sets of images. *International journal of computer vision*, 101(2):254–269, 2013.