Numerical Tours

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1 Linear Programming

1.1 Optimal Transport of Distributions

We begin with the following dataset, which represents a heart with random points within a small region:

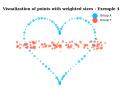


Figure 1: Dataset visualization.

This configuration leads to the transport plan shown in fig. 2a, along with the optimal coupling connection as depicted in fig. 2b.

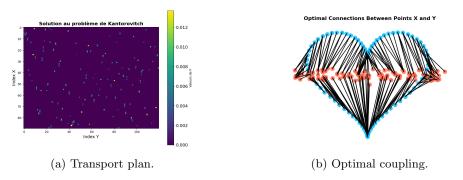


Figure 2: Transport and optimal coupling results.

1.2 Displacement Interpolation

From the optimal transport plan \mathbf{P}^{\star} , we compute the W_2 -geodesic path $(\mu_t)_t$, which is defined as:

$$\mu_t = \sum_{i,j} \mathbf{P}_{i,j}^{\star} \delta_{(1-t)x_i + ty_j}$$

Applying this to our dataset, we obtain the barycenter distributions shown in fig. 3:

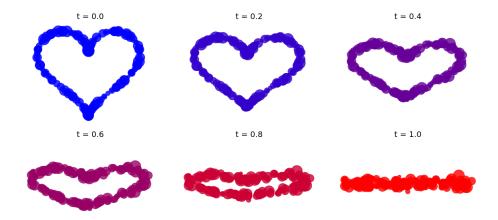


Figure 3: Barycenter distributions.

1.3 Optimal Assignment

In this variation of the dataset, the optimal transport plan becomes a permutation matrix $\mathbf{P}^{\star} = P_{\sigma^{\star}}$, and the heatmap of this matrix is shown in fig. 4a, where two distinct colors are used to represent the plan.

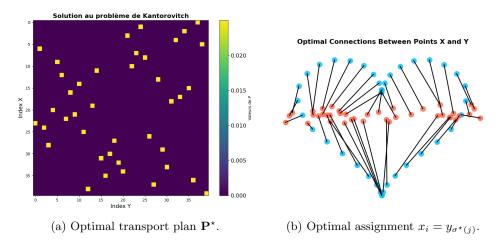


Figure 4: Optimal assignment process.

2 Entropic Regularization of Optimal Transport

2.1 Transport Between Point Clouds

Exercise 1. We consider the following point cloud data:

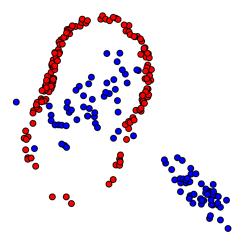


Figure 5: Point cloud visualization.

The optimal transport plan reveals a notable structure, as seen in the following results.

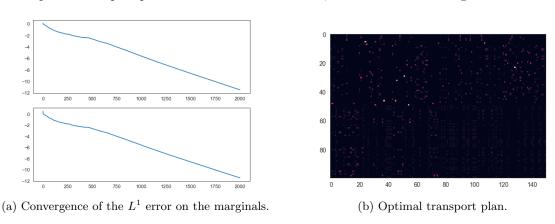


Figure 6: Convergence and optimal transport plan for regularization strength $\varepsilon = 0.01$.

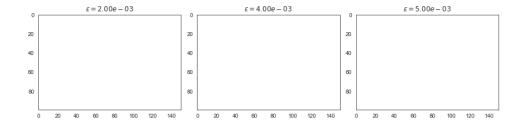
We derive the following relation for the computation of the L^1 error:

$$P^{(l+1)}\mathbb{1} = \operatorname{diag} u^{(l+1)} K v^{(l+1)} = \frac{a}{K v^{()}} \odot K v^{(l+1)}$$

which facilitates efficient calculation of the error.

Exercise 2. We compute the regularized optimal transport for various values of $\varepsilon \in \{0.002, 0.004, 0.005, 0.01, 0.1, 0.3\}$, as shown below:

The smallest value tested without encountering underflow is $\varepsilon_{\rm min}=1.10^{-2}.$



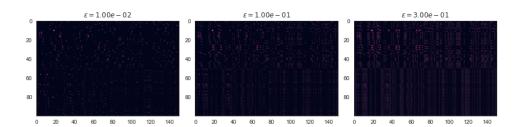


Figure 7: Optimal transport plans for varying ε .

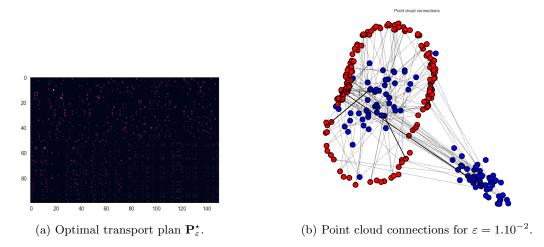


Figure 8: Transport plans and connections.

2.2 Transport Between Histograms

We work with the following data, where the marginals are a mixture of Gaussian and Laplace distributions, as shown in fig. 9. The unnormalized functions are given by:

$$f_1(x) = \exp\left(-\frac{(x-1/2)^2}{2\sigma^2}\right) + 0.6 \exp\left(-\frac{(x-0.65)^2}{2\sigma^2}\right)$$

$$f_2(x) = 0.4 \exp\left(-\frac{|x-0.2|}{\beta}\right) + 0.6 \exp\left(-\frac{|x-0.8|}{\beta}\right)$$
(2.1)

Exercise 3. We use the regularization strength $\varepsilon = (0.03)^2$. The optimal coupling and transport map are given figs. 10a and 10b.

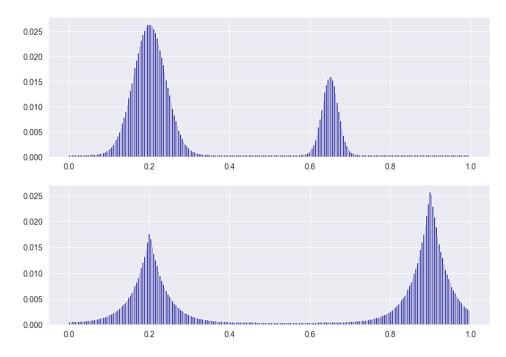


Figure 9: Histograms of the marginal distributions.

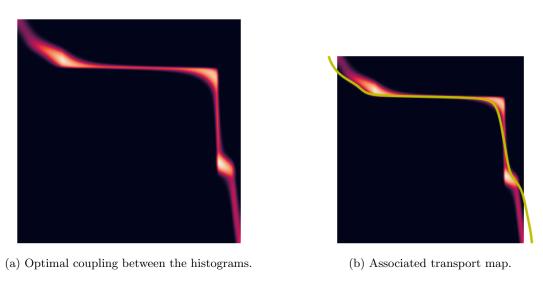


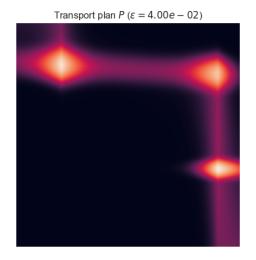
Figure 10: Coupling and transport map for $\varepsilon = (0.03)^2$.

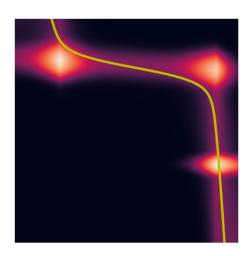
Bonus exercise. Figure 11 shows the coupling and transport map for a lower regularization strength ε .

2.3 Wasserstein barycenters

We use the data fig. 12 and regularization parameter $\varepsilon = (0.04)^2$.

Exercise 4. Figure 13 shows the result.





- (a) Optimal coupling between the histograms.
- (b) Associated transport map.

Figure 11: Coupling and transport map for $\varepsilon = (0.03)^2$.

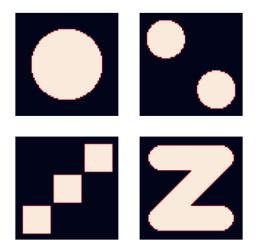


Figure 12: Bitmap image data.

Exercise 5. We compute Wasserstein barycenters for bilinear interpolation weights $t, s \in \{0, 0.25, 0.5, 0.75, 1.0\}$ – see fig. 14.

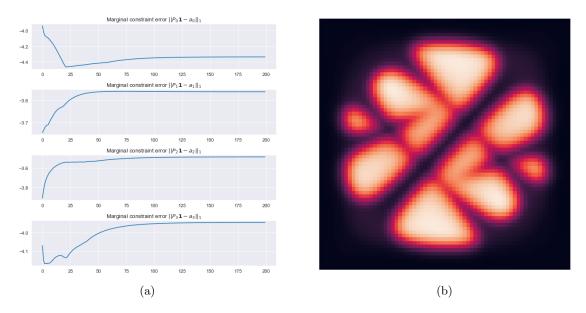


Figure 13: Convergence and result of the Bregman algorithm to compute the Wasserstein barycenters of the images in fig. 12.

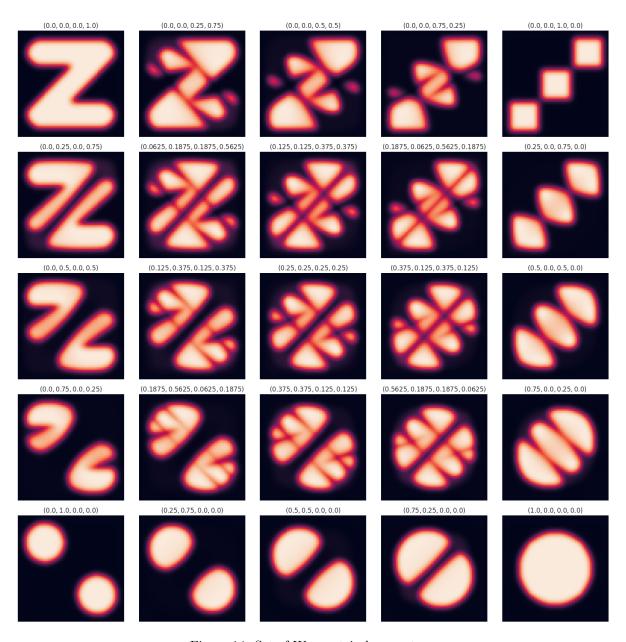


Figure 14: Set of Wasserstein barycenters.