

# No-collision Transportation Maps

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## Half-space preserving transportation maps

Given a probability measure  $\mu \in \mathcal{P}(\mathbb{R}^d)$  and a Borel measurable map  $T : \mathbb{R}^d \rightarrow \mathbb{R}^d$ , the **push-forward** of  $\mu$  by  $T$  is a probability measure  $T\#\mu$  that is given by

$$(T\#\mu)(B) = \mu(T^{-1}(B)) \quad (B \text{ Borel}).$$

Furthermore, for probability measures  $\mu, \nu \in \mathcal{P}(\mathbb{R}^d)$  and a Borel measurable map  $T : \mathbb{R}^d \rightarrow \mathbb{R}^d$ , we say that  $T$  **transports**  $\mu$  to  $\nu$  if  $\nu = T\#\mu$ .

A natural problem is to search for  $T$  with useful properties. This leads to the theory of *optimal transport*: given a cost  $c(x, y)$  for transporting unit mass from  $x$  to  $y$ , one searches for a transportation (correspondence) that minimizes the cost of transporting  $\mu$  to  $\nu$ :

$$\min_{\nu=T\#\mu} \int_{\mathbb{R}^d} c(x, T(x)) d\mu(x).$$

In this work, our goal is to find a transportation map that satisfies the **no-collision** property: for all  $x_1 \neq x_2 \in \text{supp}(\mu)$ , we have that

$$(1 - \lambda)x_1 + \lambda T(x_1) \neq (1 - \lambda)x_2 + \lambda T(x_2) \quad (\lambda \in (0, 1)).$$

In words, this says that the point-masses will not collide if travelling in a straight line with constant speeds. When solving the optimal transport problem,  $T$  has the no-collision property if  $c(x, y) = h(x - y)$  with  $h$  strictly convex and even; though this is typically quite expensive to calculate exactly.

A map  $T : \Omega \subset \mathbb{R}^d \rightarrow \mathbb{R}^d$  is said to be **half-space preserving** if for every  $x_1 \neq x_2 \in \Omega$ , there exists a direction  $v \in \mathbb{S}^{d-1}$  such that

$$\langle x_2, v \rangle - \langle x_1, v \rangle \geq 0, \quad \langle T(x_2), v \rangle - \langle T(x_1), v \rangle \geq 0,$$

and at least one of the inequalities is strict.

**(Theorem 2.1)** A map  $T : \Omega \subset \mathbb{R}^d \rightarrow \mathbb{R}^d$  is half-space preserving if and only if it has the no-collision property.

## Relation to $k$ - $d$ trees

The data structure we are relying on for this construction are  $k$ - $d$  trees. Each node in the tree represents a collection of points (or a measure) and the two children of each node (except the leaves) is a bipartition of the parent into sets (or measure) of equal size, i.e. half the size. An example of the bipartition can be seen in the figures below.

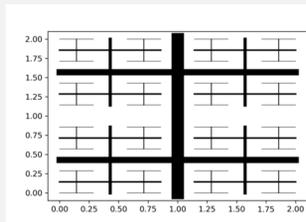


Figure: Bisection on grid

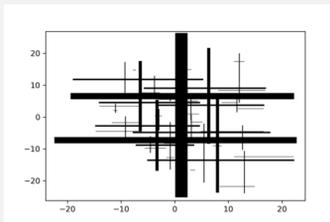


Figure: Bisection on Gaussian

## Map construction via Theorem 2.1

Assume that  $\mu \in \mathcal{P}(\mathbb{R}^d)$  is absolutely continuous and  $\{v_k\}$  is an arbitrary sequence of directions. Denote  $\Omega_0 := \{\mathbb{R}^d\}$ . Since  $\mu$  is absolutely continuous, there exists  $h_1 \in \mathbb{R}^d$  such that

$$\mu(\langle x, v_1 \rangle \leq h_1) = \mu(\langle x, v_1 \rangle > h_1).$$

We then denote  $A_0 := \{\langle x, v_1 \rangle \leq h_1\}$  and  $A_1 := \{\langle x, v_1 \rangle > h_1\}$  to be the two half-planes, with  $\Omega_1 := \{A_0, A_1\}$ .

To every  $x \in A$ , we assign a binary sequence  $s(x)$ , with

$$s(x) = \begin{cases} 0, & x \in A_0 \\ 1, & x \in A_1. \end{cases}$$

Pick a set from  $\Omega_1$ , say  $A_1$ , and find  $h_2$  such that

$$\mu(A_1 \cap \{\langle x, v_2 \rangle \leq h_2\}) = \mu(A_1 \cap \{\langle x, v_2 \rangle > h_2\}),$$

and denote the new sets  $A_{10} := A_1 \cap \{\langle x, v_2 \rangle \leq h_2\}$  and  $A_{11} := A_1 \cap \{\langle x, v_2 \rangle > h_2\}$ ,  $\Omega_2 := \{A_0, A_{10}, A_{11}\}$ . We update the binary sequence for  $x \in A_1$  as follows

$$s(x) = \begin{cases} 10, & x \in A_{10} \\ 11, & x \in A_{11}, \end{cases}$$

and repeat. If the directions  $\{v_k\}$  are chosen appropriately, the sequence  $s(x)$  is a bijection between  $\text{supp}(\mu)$  and  $\{0, 1\}^\infty$ .

If  $\nu$  is another absolutely continuous measure, then the same directions and subsets will give us the binary sequence  $r(x)$ . Then, the transportation map from  $\mu$  to  $\nu$  is simply  $t = r^{-1} \circ s$ .

**(Theorem 2.2)** With some reasonable assumptions on  $\mu$  and  $\nu$ , and the way the directions  $\{v_k\}$  are chosen, it can be shown that  $t$  is a.e. Borel measurable from  $\text{int}(\text{supp}(\mu))$  to  $\text{int}(\text{supp}(\nu))$ , and also a.e. continuous.

## Runtime comparisons

- Construction of a no-collision map via  $k$ - $d$  trees costs  $O(n \log(n))$ , where  $n$  is the number of points.
- When the cost is separable under addition, [1] propose a clever back-and-forth approach that achieves  $O(n \log(n))$  on the dual problem using  $c$ -transforms. However, the algorithm requires a regular grid discretization and is not suitable for discrete measures with irregular support.
- In the quadratic cost case, [2] achieves near-linear complexity, with  $\tilde{O}(n\epsilon^{-3}(C \log(n)\epsilon^{-1})^d)$ , though it might not have the no-collision property.

## Experimental results: Transporting points in $\mathbb{R}^2$

The algorithm for constructing the map  $T$  was coded in both the Python and C programming languages. It was tested for  $n = 64, 256, 1024, 4096$  points in Python, and up to  $4^{12}$  points in C to measure speed. The repository for the Python coded can be found by scanning the QR code on the poster.

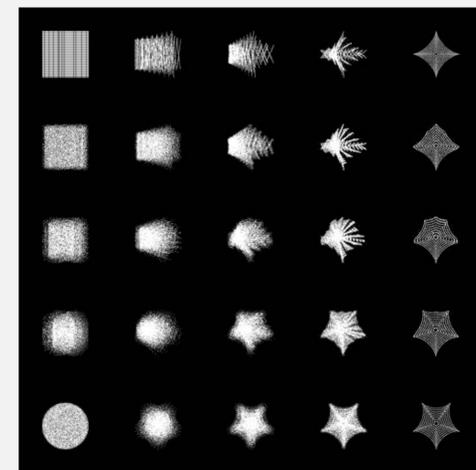


Figure: Barycentres of four starting shapes (shown in corners) at various weights

Further work for implementation:

- To be run on NVIDIA GPUs with the CUDA architecture
- For higher dimensions using the GPU version
- For fractional weights on points

Note: For the tables below,  $C(x, x + y) = \|y\|_p^q$ ,  $p = 1, 2, \infty$ ,  $q = 1, 2$ .

Cost	Method	$n$			
		64	256	1024	4096
$\ \cdot\ _2^2$	OT	0.97	1.02	1.23	1.14
	HV (ratio)	1.49 (1.54×)	1.23 (1.21×)	1.32 (1.07×)	1.16 (1.02×)
	SH (ratio)	0.98 (1.02×)	1.05 (1.03×)	1.26 (1.03×)	1.16 (1.02×)
	LEX (ratio)	6.52 (6.72×)	6.59 (6.46×)	7.00 (5.72×)	7.13 (6.27×)
$\ \cdot\ _2$	OT	1.01	0.77	0.78	0.84
	HV (ratio)	1.15 (1.13×)	0.83 (1.08×)	0.81 (1.04×)	0.85 (1.02×)
	SH (ratio)	1.04 (1.02×)	0.80 (1.03×)	0.81 (1.04×)	0.87 (1.04×)
	LEX (ratio)	2.25 (2.22×)	2.18 (2.83×)	2.27 (2.92×)	2.31 (2.75×)
$\ \cdot\ _1^2$	OT	1.27	1.47	1.22	1.09
	HV (ratio)	1.74 (1.38×)	1.75 (1.19×)	1.37 (1.13×)	1.15 (1.05×)
	SH (ratio)	1.28 (1.01×)	1.49 (1.01×)	1.25 (1.03×)	1.10 (1.01×)
	LEX (ratio)	9.42 (7.44×)	10.37 (7.07×)	11.27 (9.27×)	11.13 (10.21×)
$\ \cdot\ _\infty^2$	OT	1.39	1.23	1.06	1.00
	HV (ratio)	1.79 (1.29×)	1.49 (1.21×)	1.19 (1.12×)	1.05 (1.05×)
	SH (ratio)	1.41 (1.01×)	1.26 (1.02×)	1.08 (1.03×)	1.03 (1.02×)
	LEX (ratio)	6.58 (4.75×)	5.97 (4.85×)	5.89 (5.57×)	5.97 (5.94×)

Table: Average costs of sets of points sampled from  $\mathcal{N}(0, 1)$  to a new set of points sampled from  $\mathcal{N}(0, 1)$  (then transformed to a 3:1 aspect ratio and rotated 90° counter-clockwise) measured in various cost functions

## References

- [1] M. Jacobs and F. Léger, "A fast approach to optimal transport: the back-and-forth method," *Preprint*, 2019, arXiv:1905.12154 [math.OC]. [Online]. Available: <https://arxiv.org/abs/1905.12154>
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- [4] R. Flamary and N. Courty, "POT Python Optimal Transport library," 2017. [Online]. Available: <https://github.com/rflamary/POT>