

Optimal Transport on the Sphere

- Sphere: $S^{d-1} = \{x \in \mathbb{R}^d, \|x\|_2 = 1\}$
- Geodesic Distance on the sphere:

$$\forall x, y \in S^{d-1}, d(x, y) = \arccos(\langle x, y \rangle)$$

Wasserstein distance: Let $p \geq 1, \mu, \nu \in \mathcal{P}_p(S^{d-1})$, then

$$W_p^p(\mu, \nu) = \inf_{\gamma \in \Pi(\mu, \nu)} \int d(x, y)^p d\gamma(x, y).$$

- Complexity *w.r.t* number of samples n : $O(n^3 \log n)$

Wasserstein distance on $\mathcal{P}(\mathbb{R})$:

$$\forall p \geq 1, \forall \mu, \nu \in \mathcal{P}_p(\mathbb{R}), W_p^p(\mu, \nu) = \int_0^1 |F_\mu^{-1}(u) - F_\nu^{-1}(u)|^p du$$

Sliced-Wasserstein distance:

$$\forall \mu, \nu \in \mathcal{P}_p(\mathbb{R}^d), SSW_p^p(\mu, \nu) = \int_{S^{d-1}} W_p^p(P_\#^\theta \mu, P_\#^\theta \nu) d\lambda(\theta),$$

where $P^\theta(x) = \langle x, \theta \rangle$ and λ is the uniform distribution on S^{d-1} .

- Complexity *w.r.t* number of samples n : $O(Ln(\log n + d))$ with L the number of projections $\theta_1, \dots, \theta_L$
- Use Euclidean projections: not suitable to the sphere

Contributions

- New Sliced-Wasserstein discrepancy on the sphere
- New Spherical Radon transform
- Density Estimation, Sliced-Wasserstein autoencoders

Recipe of Spherical Sliced-Wasserstein

- Projections on geodesics: great circles = intersections between S^{d-1} and 2-planes
- 2-planes modeled via the Stiefel manifold

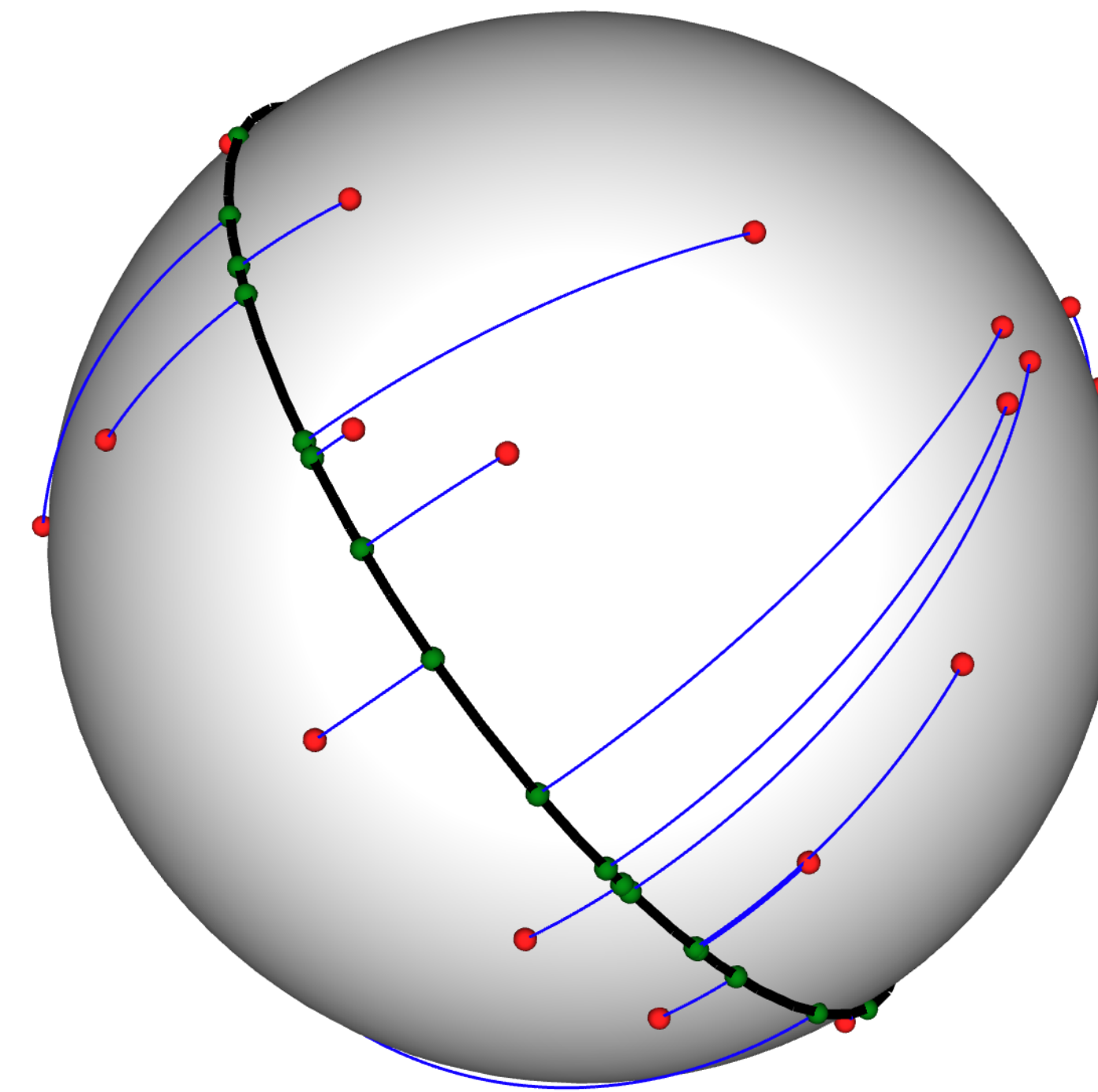
$$\mathbb{V}_{d,2} = \{U \in \mathbb{R}^{d \times 2}, U^T U = I_2\}$$

- Geodesic projection: $P^U(x) = \operatorname{argmin}_{z \in S^1} d(x, Uz)$
- Wasserstein distance on the circle: $\forall \mu, \nu \in \mathcal{P}(S^1)$, (Delon et al., 2010; Rabin et al., 2011)

$$W_p^p(\mu, \nu) = \inf_{\alpha \in \mathbb{R}} \int_0^1 |F_\mu^{-1}(u) - (F_\nu - \alpha)^{-1}(u)|^p du,$$

$$W_2^2(\mu, \operatorname{Unif}(S^1)) = \int_0^1 |F_\mu^{-1}(t) - t - \hat{\alpha}|^2 dt, \quad \hat{\alpha} = \int x d\mu(x) - \frac{1}{2}.$$

Spherical Sliced-Wasserstein



Spherical Sliced-Wasserstein

Let $p \geq 1, \mu, \nu \in \mathcal{P}_p(S^{d-1})$ absolutely continuous *w.r.t.* Lebesgue measure,

$$SSW_p^p(\mu, \nu) = \int_{\mathbb{V}_{d,2}} W_p^p(P_\#^U \mu, P_\#^U \nu) d\sigma(U),$$

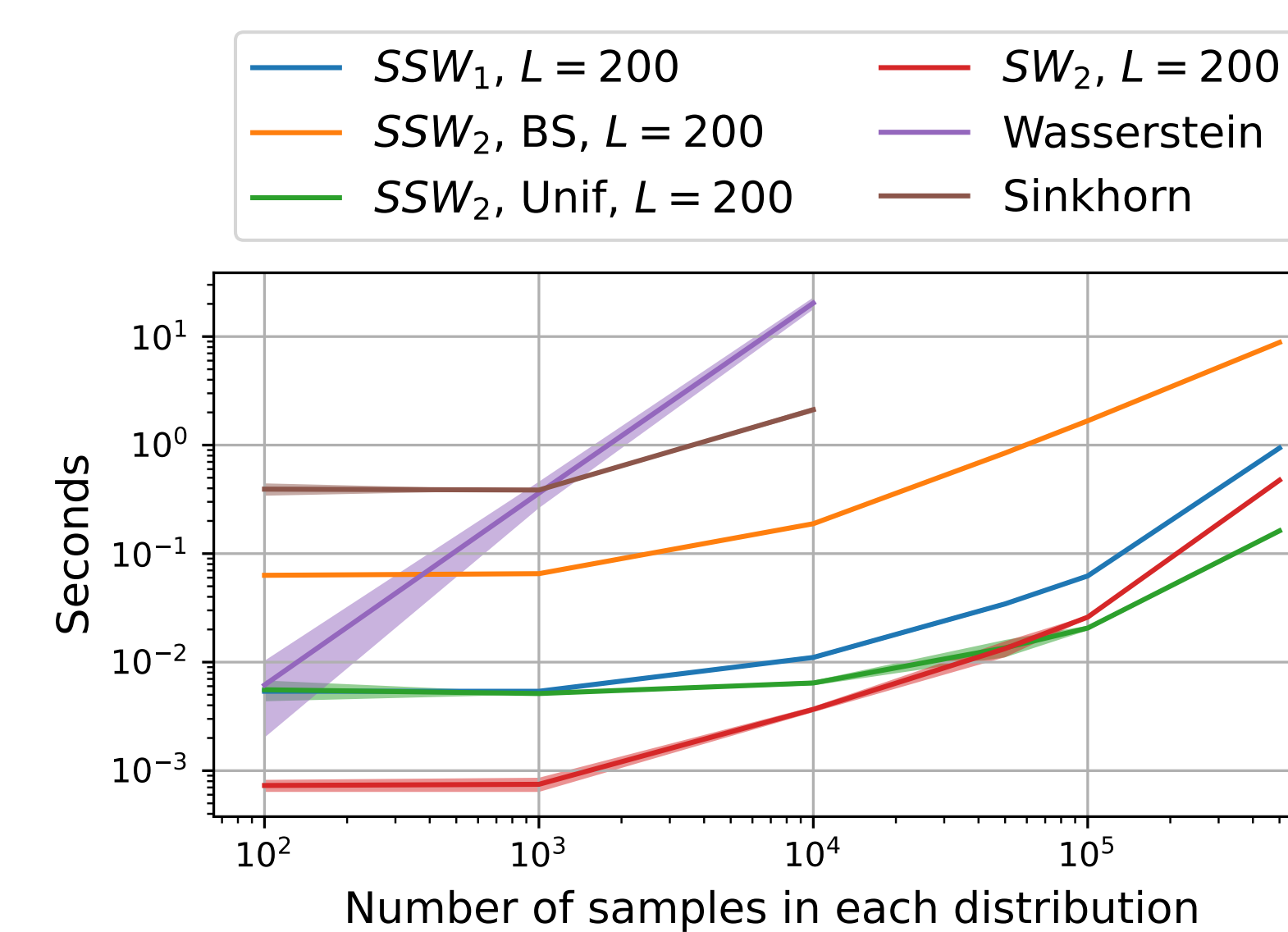
with σ the uniform distribution over $\mathbb{V}_{d,2}$.

	SW	SSW
Closed-form of W	Line	(Great)-Circle
Projection	$P^\theta(x) = \langle x, \theta \rangle$	$P^U(x) = \frac{U^T x}{\ U^T x\ _2}$
Integration	S^{d-1}	$\mathbb{V}_{d,2}$

Properties

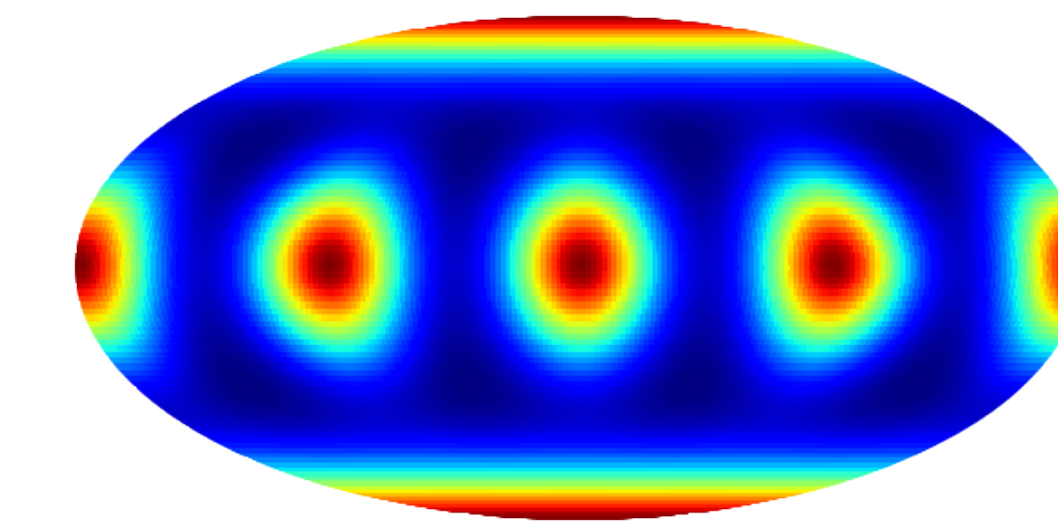
- Pseudo-distance
- Related with a Spherical Radon transform: For all $x \in S^{d-1}, z \in S^1$,
 $\tilde{R}f(z, x) = \int_{S^{d-1}} f(x) 1_{\{P^U(x)=z\}} d\tilde{\sigma}(x)$.
- Sample complexity independent *w.r.t.* the dimension
- Computational complexity:

$$O(Ln(d + \log(\frac{1}{\epsilon}) + \log n))$$

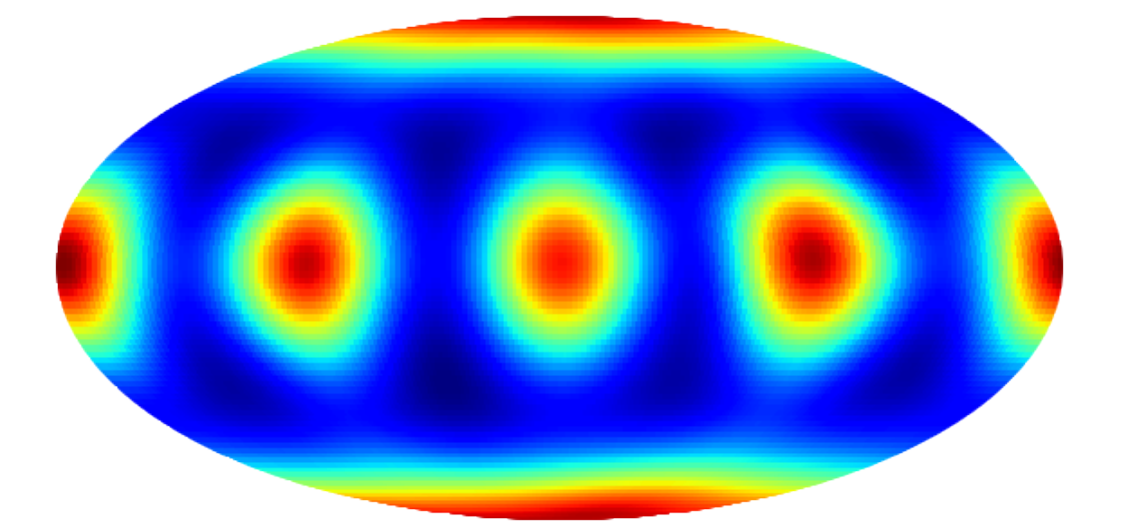


Experiments

Gradient Flow.



Target: Mixture of vMF

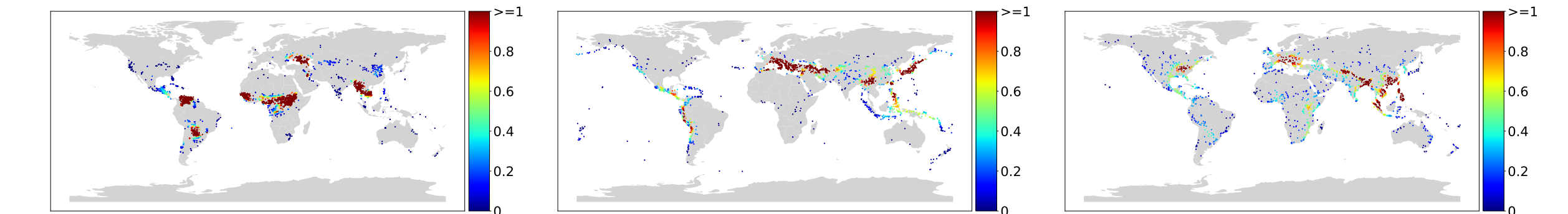


KDE estimate of 500 particles

Density Estimation. Learn a normalizing flow T such that

$$\operatorname{argmin}_T SSW_2^2(T_\# \mu, p_Z), \quad p_Z = \operatorname{Unif}(S^{d-1})$$

Density of μ : $\forall x \in S^{d-1}, f_\mu(x) = p_Z(T(x)) |\det J_T(x)|$



Fire

Earthquake

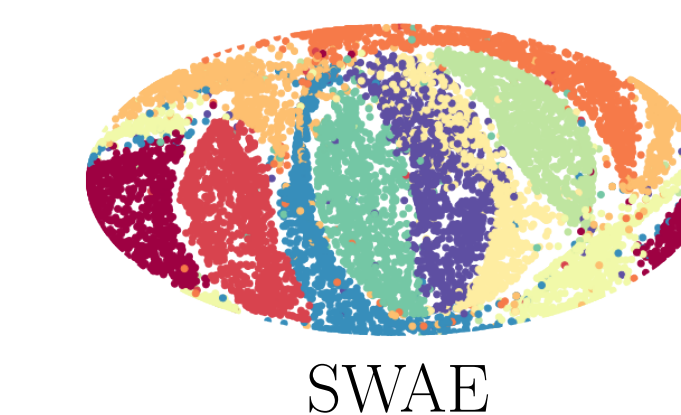
Flood

	Earthquake	Flood	Fire
SSW	0.84±0.07	1.26±0.05	0.23±0.18
SW	0.94±0.02	1.36±0.04	0.54±0.37
Stereo	1.91±0.1	2.00±0.07	1.27±0.09

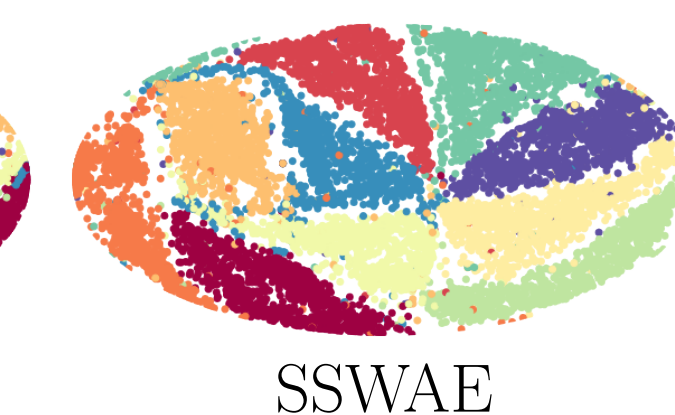
Negative test log likelihood.

SSWAE.

$$\mathcal{L}(f, g) = \int c(x, g(f(x))) d\mu(x) + \lambda SSW_2^2(f_\# \mu, p_Z),$$



SSWAE



SSWAE

Method / Prior	Unif(S^{10})
SSWAE	14.91 ± 0.32
SWAE	15.18 ± 0.32
WAE-MMD IMQ	18.12 ± 0.62
WAE-MMD RBF	20.09 ± 1.42
SAE	19.39 ± 0.56
Circular GSVAE	15.01 ± 0.26

FID (Lower is better).

References

- Julie Delon, Julien Salomon, and Andrei Sobolevski. Fast transport optimization for monge costs on the circle. *SIAM Journal on Applied Mathematics*, 70(7):2239–2258, 2010.
- Julien Rabin, Julie Delon, and Yann Gousseau. Transportation distances on the circle. *Journal of Mathematical Imaging and Vision*, 41(1):147–167, 2011.