

# Numerical Optimal Transport

<http://optimaltransport.github.io>

## *Applications*

Gabriel Peyré

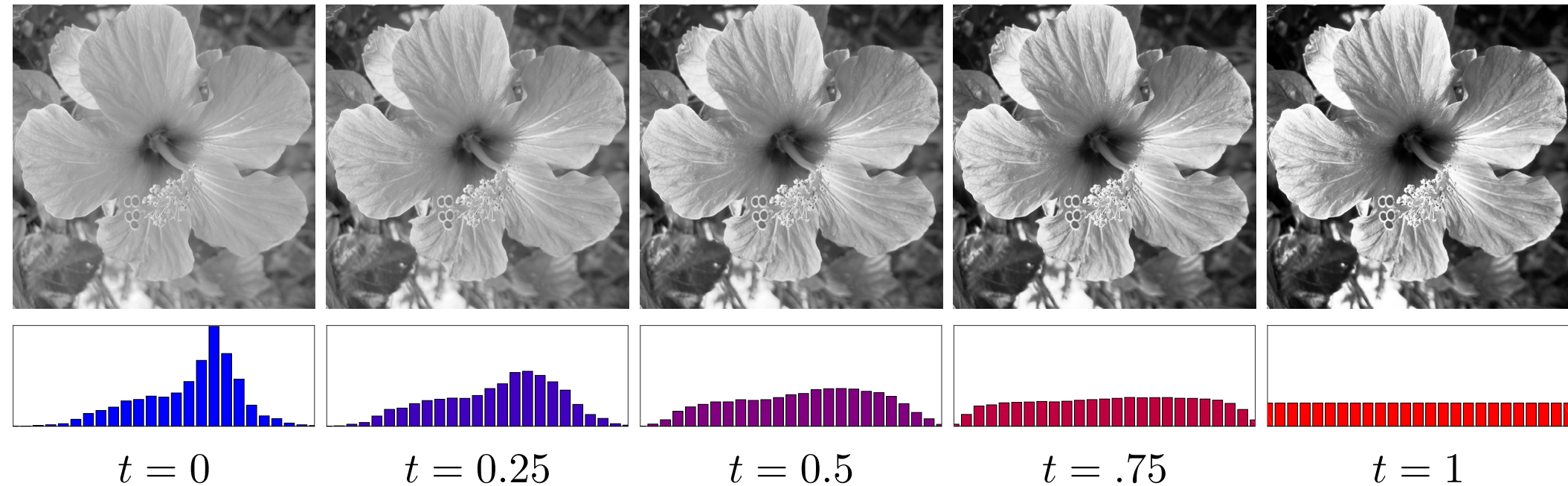
[www.numerical-tours.com](http://www.numerical-tours.com)



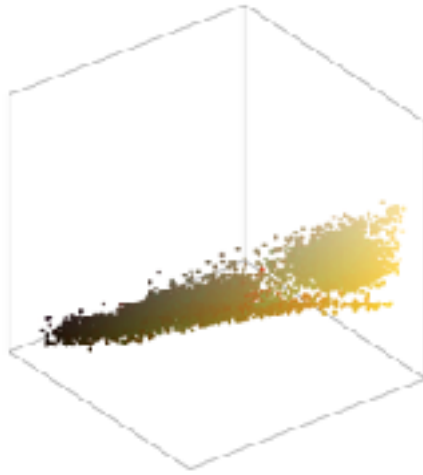
**ENS**  
ÉCOLE NORMALE  
SUPÉRIEURE



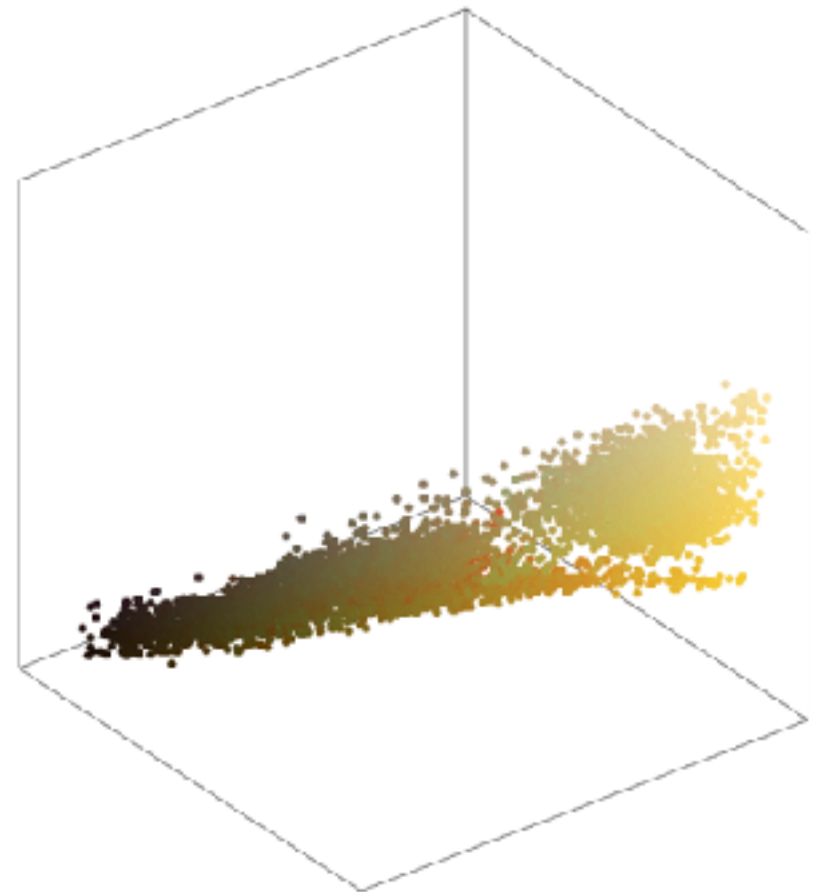
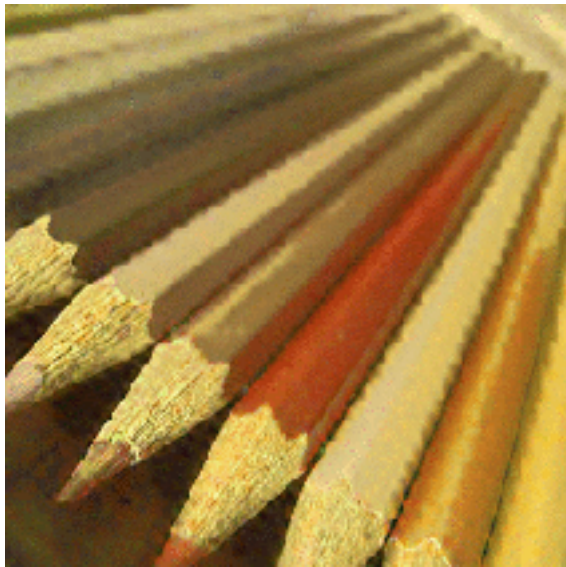
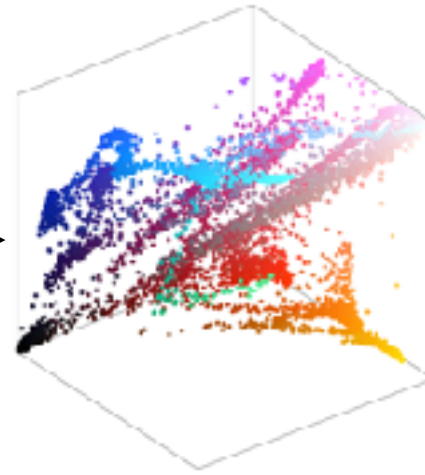
# Grayscale Image Equalization



# Image Color Palette Equalization

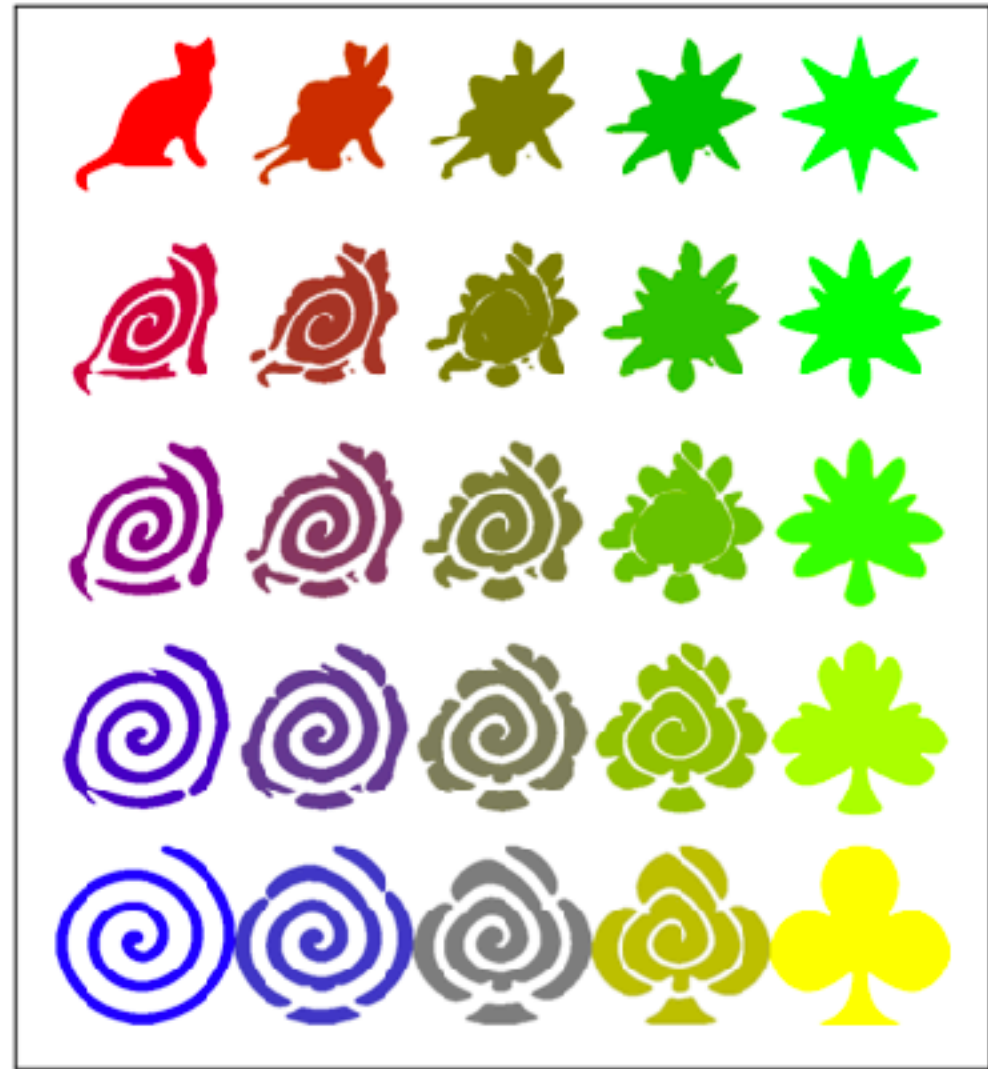
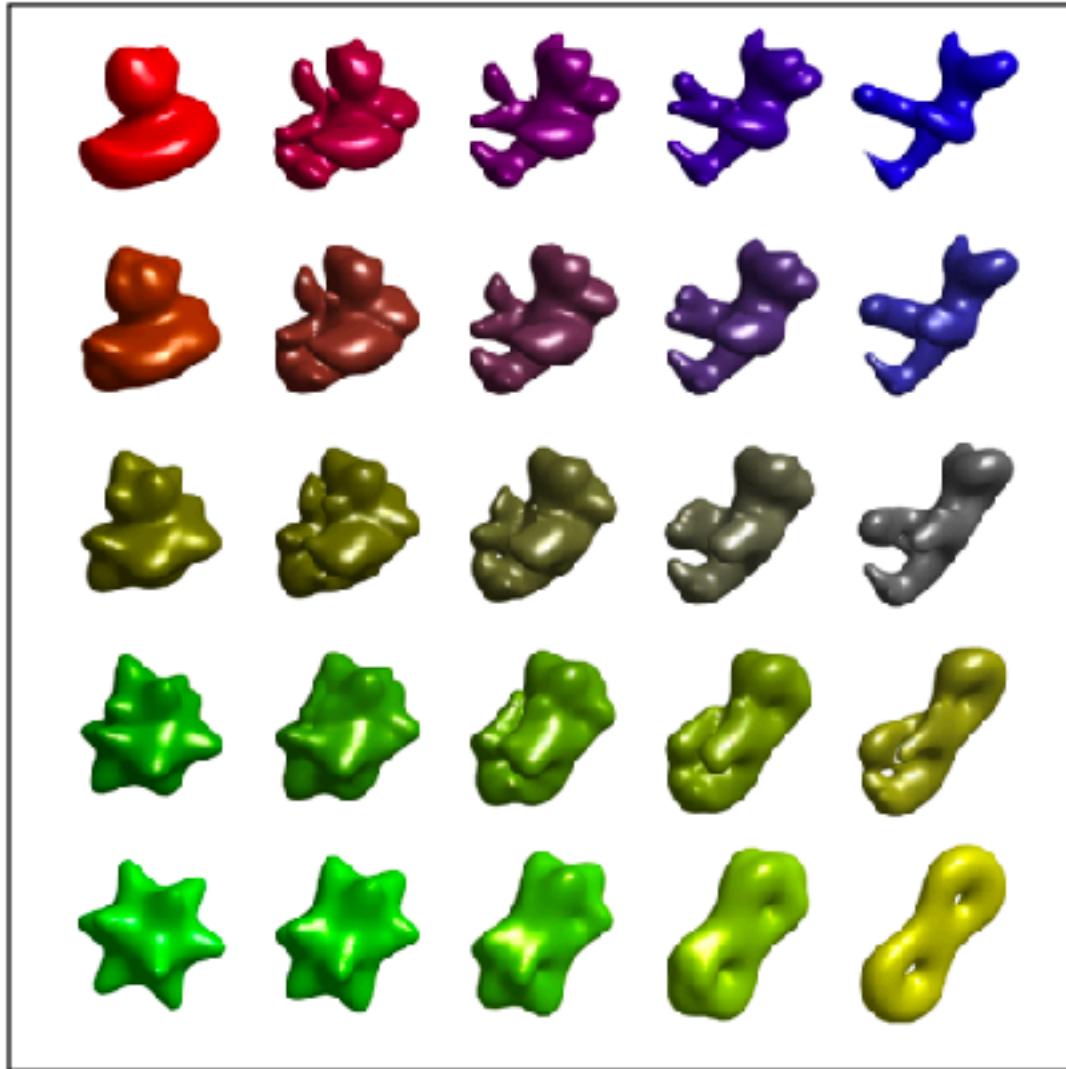


Optimal  
transport





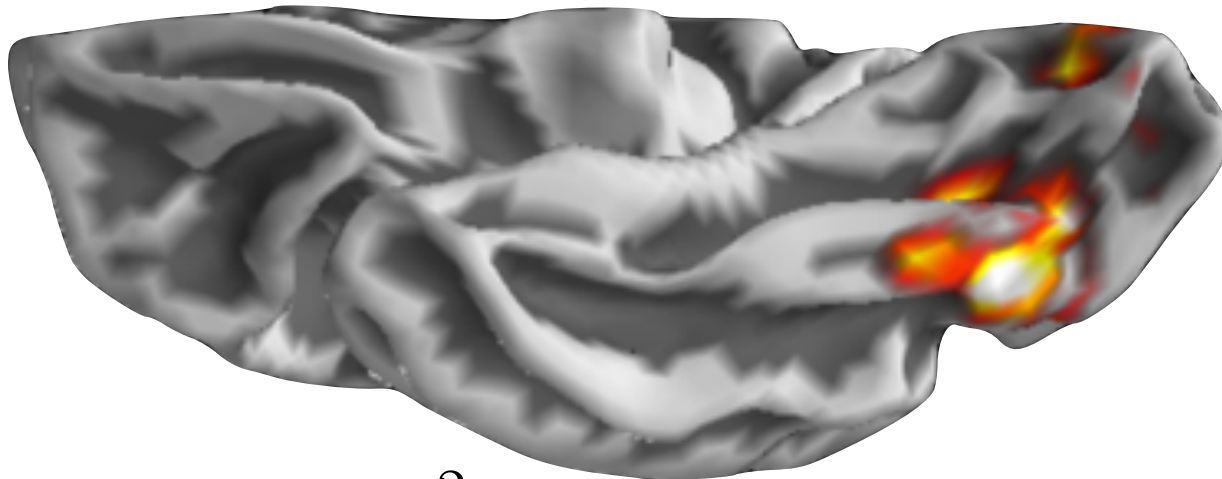
# Shape Interpolation



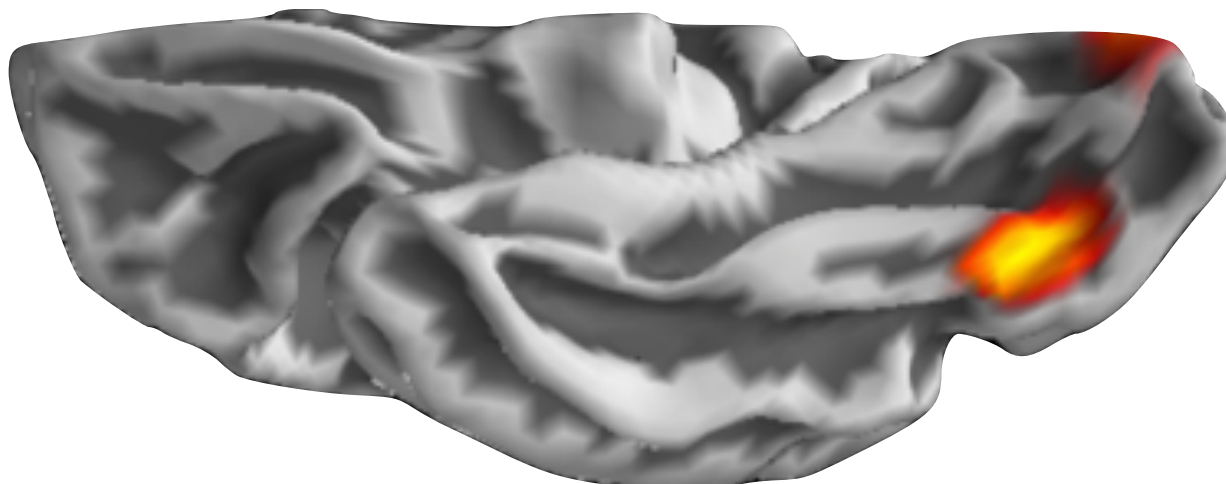


# MRI Data Processing [with A. Gramfort]

Ground cost  $c = d_M$ : geodesic on cortical surface  $M$ .



$L^2$  barycenter



$W_2^2$  barycenter

# Gradient Flows Simulation



<https://www.youtube.com/watch?v=tDQw21ntR64>

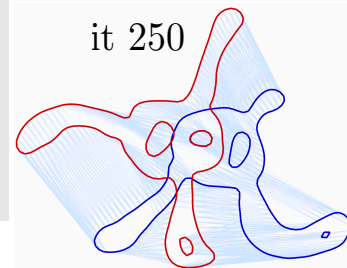
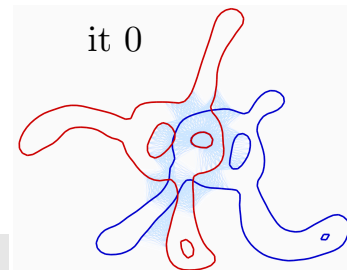
Tim Whittaker (New Zealand)



# OT Loss for Diffeomorphic Registration

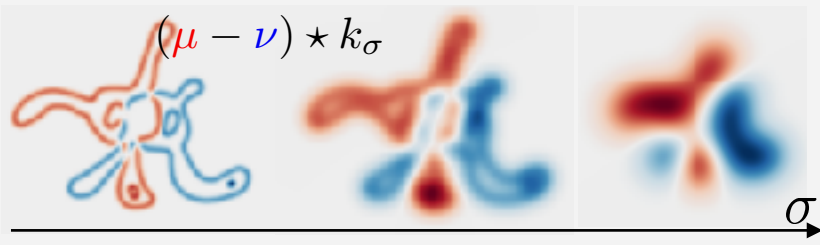
*Joint work with J. Feydy, B. Charier, F-X. Vialard.*

Shape registration:  $\min_{\varphi \text{ diffeo}} D(\varphi(\mu), \nu) + R(\varphi)$   
loss                      regularity



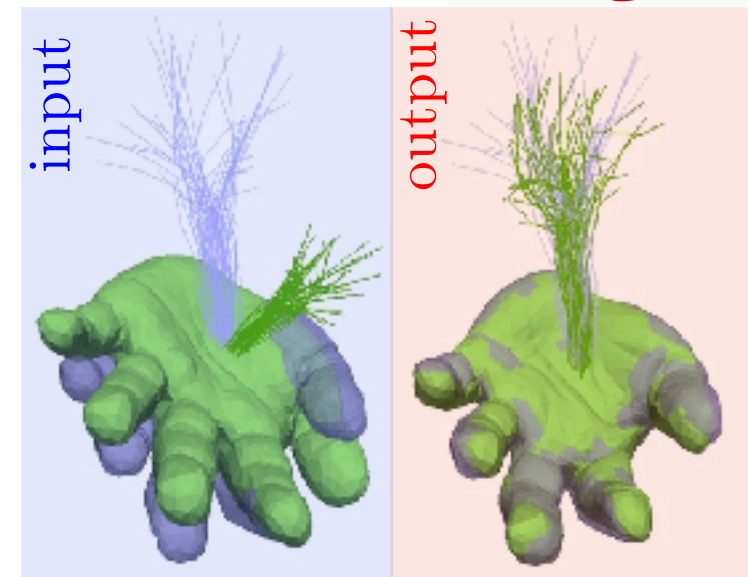
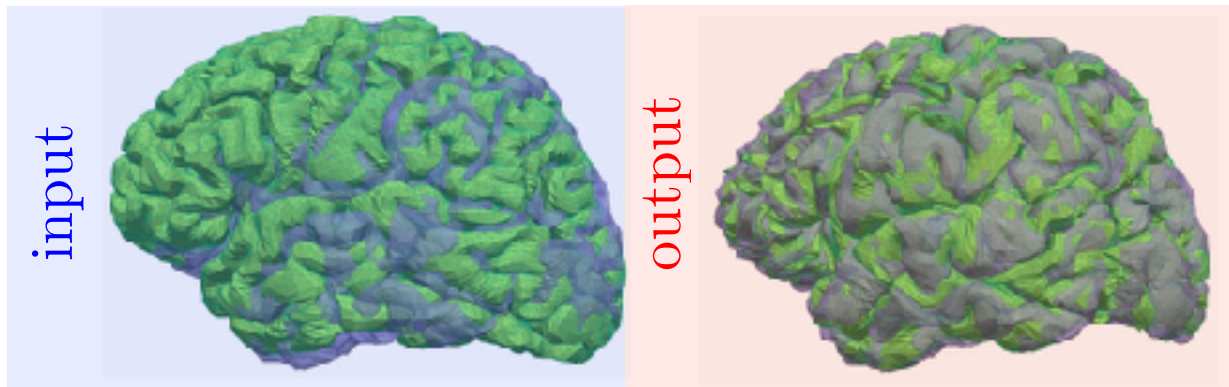
Hilbertian loss (MMD/RKHS):

$$D(\mu, \nu) = \|k_\sigma \star (\mu - \nu)\|_{L^2}^2$$



Sinkhorn divergence:

$$D(\mu, \nu) = \bar{W}_\varepsilon(\mu, \nu)$$



- Do not use OT for registration ... but as a loss.
- Sinkhorn's iterates "propagate" a small bandwidth kernel.
- Automatic differentiation: game changer for advanced loss and models.



# Bag of Words

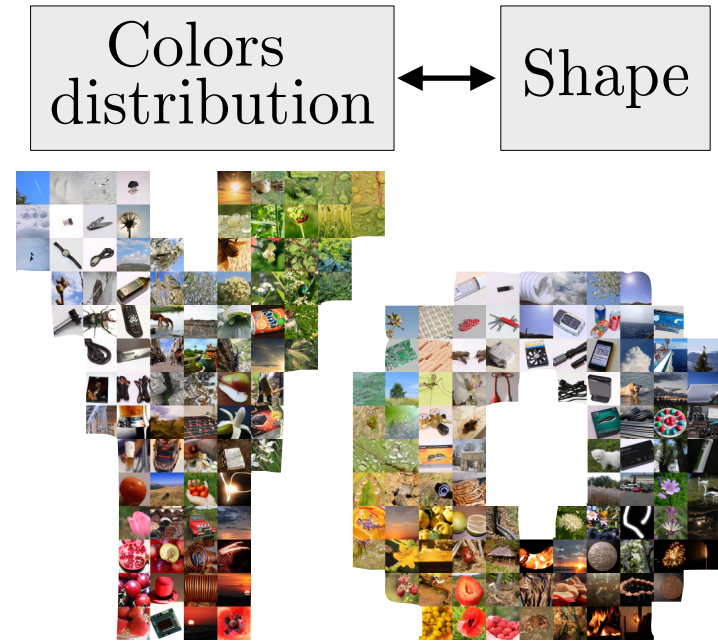
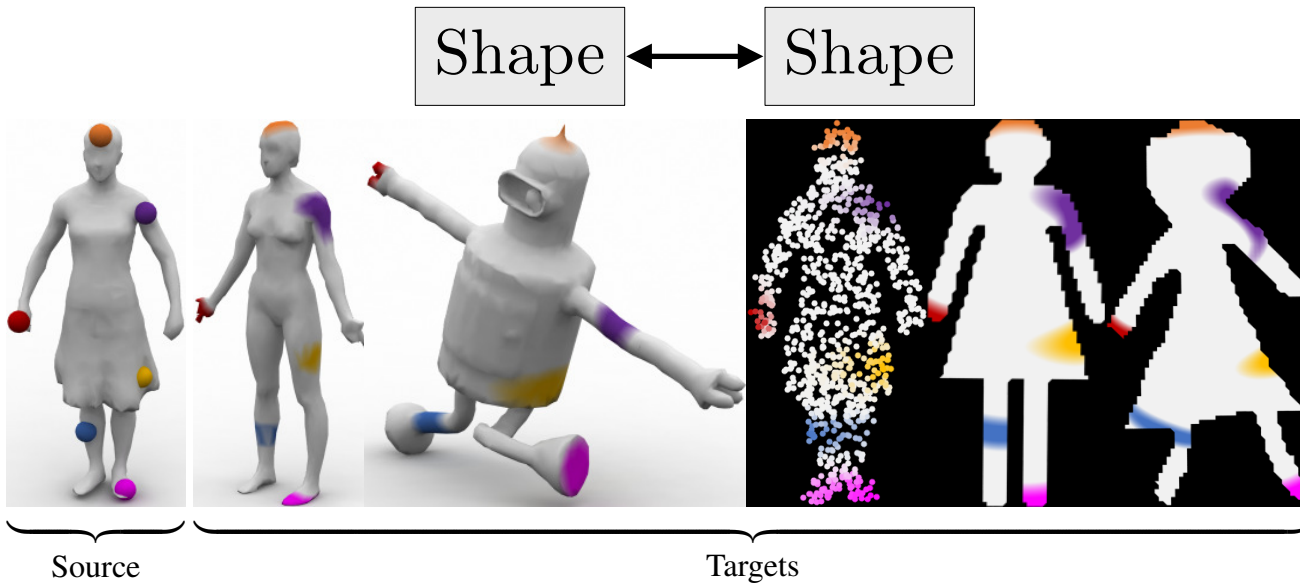


**[Kusner'15]**  $\text{dist}(D_1, D_2) = W_2(\mu, \nu)$



# Shapes Analysis with Gromov-Wasserstein

Use  $T$  to define registration between:



Shapes  
 $(X_s)_s$

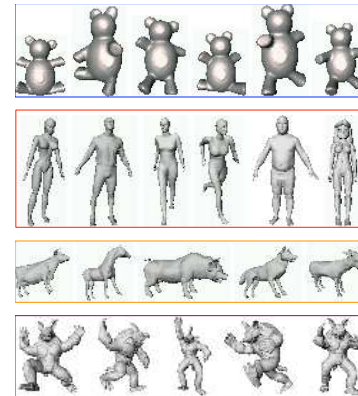
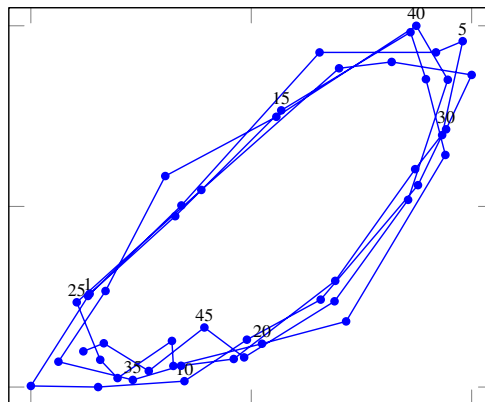
Geodesic distances  
 $d_s = (D_{X_s}(x_i, x_{i'}))_{i,i'}$

GW distances  
 $(GW_\epsilon(d_s, d_{s'}))_{s,s'}$

MDS  
Visualization



MDS in 2-D



MDS in 3-D

