#### Gromov-Hausdorff stable signatures for shapes using persistence

joint with F. Chazal, D. Cohen-Steiner, L. Guibas and S. Oudot

#### Facundo Mémoli

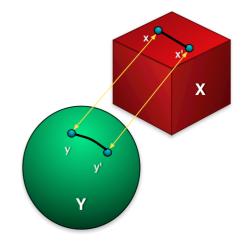
memoli@math.stanford.edu



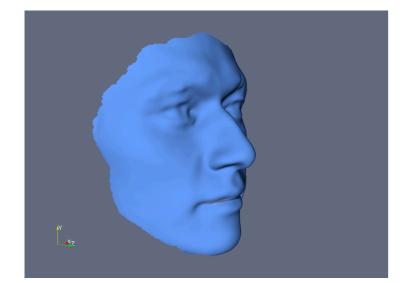


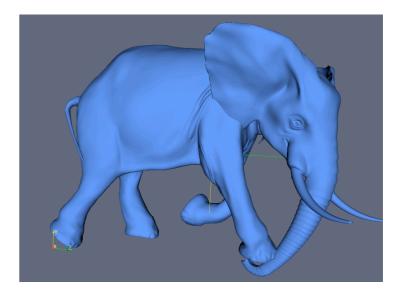
#### Goal

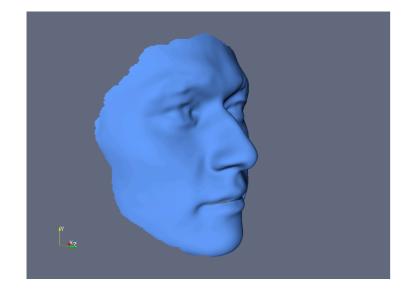
- Shape discrimination is a very important problem in several fields.
- **Isometry invariant** shape discrimination has been approached with different tools, mostly via computation and comparison of **invariant signatures**, **[HK03,Osada-02,Fro90,SC-00]**.
- The **Gromov-Hausdorff distance** (and certain variants) provides a **rig-orous** and well motivated framework for studying shape matching under invariances [**MS04**,**MS05**,**M07**,**M08**].
- However, its direct computation leads to **NP hard** problems (BQAP: bottleneck quadratic assignment problems).

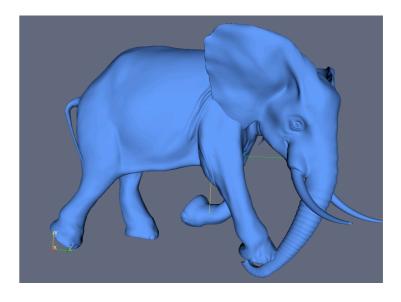


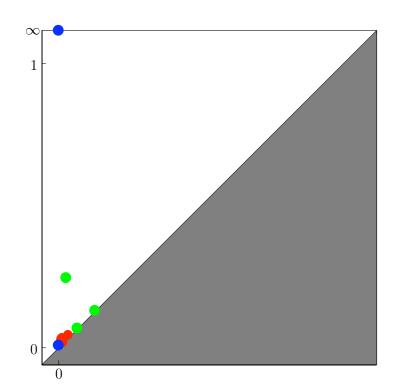
- Most of the effort has gone into finding **lower bounds** for the GH distance that use informative invariant signatures and lead to easier optimization problems [M07,M08].
- Using **persistent topology** [ELZ00], we obtain a new family of signatures and prove that they are **stable** w.r.t the GH distance: i.e., we obtain lower bounds for the GH distance!
- These lower bounds:
  - perform very well in practical application of shape discrimination.
  - lead to BAPs (bottleneck assignment problems) which can be solved in polynomial time.

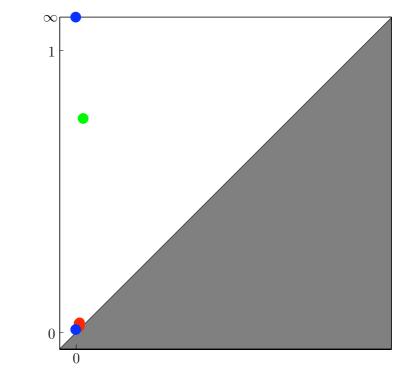


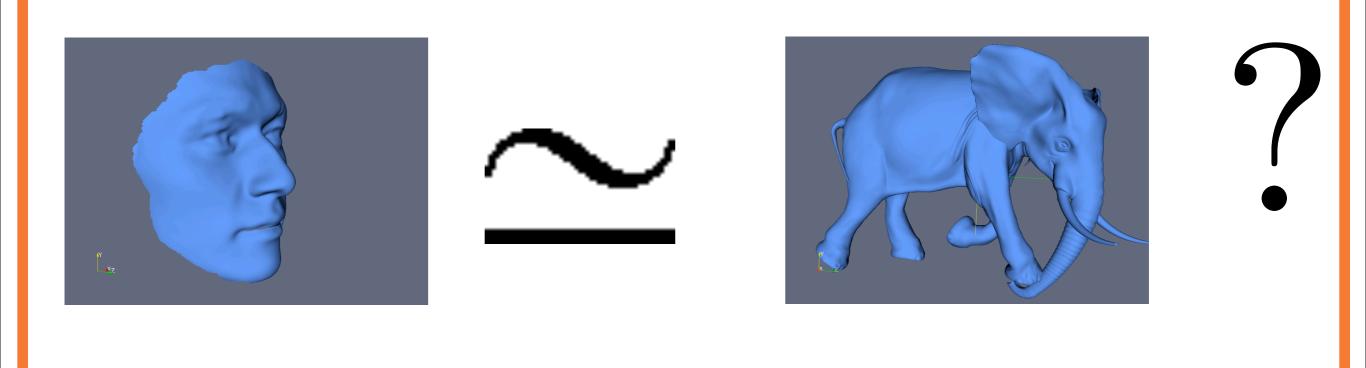


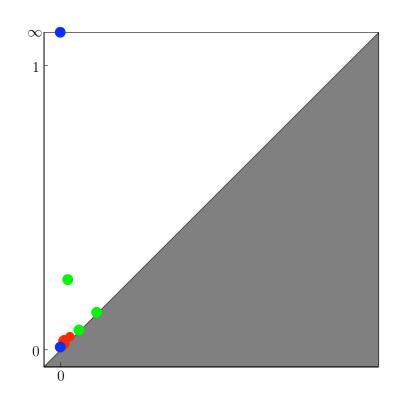




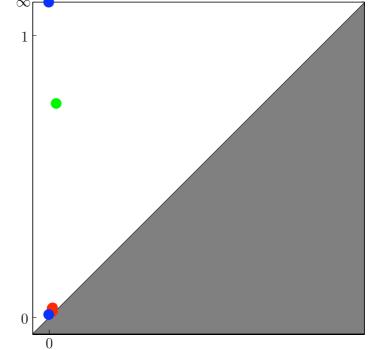


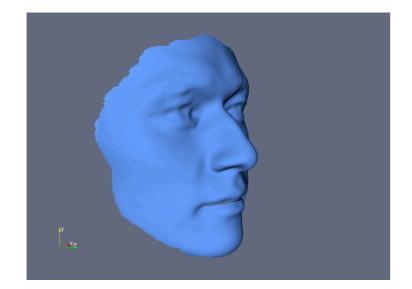


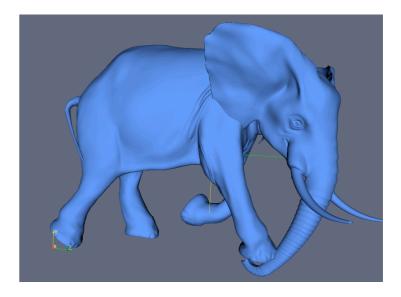


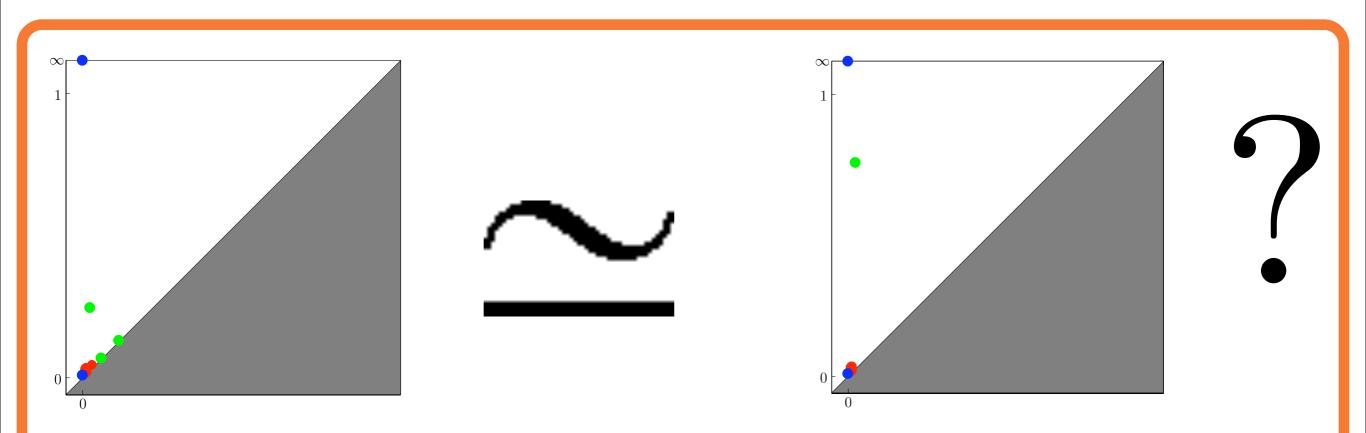




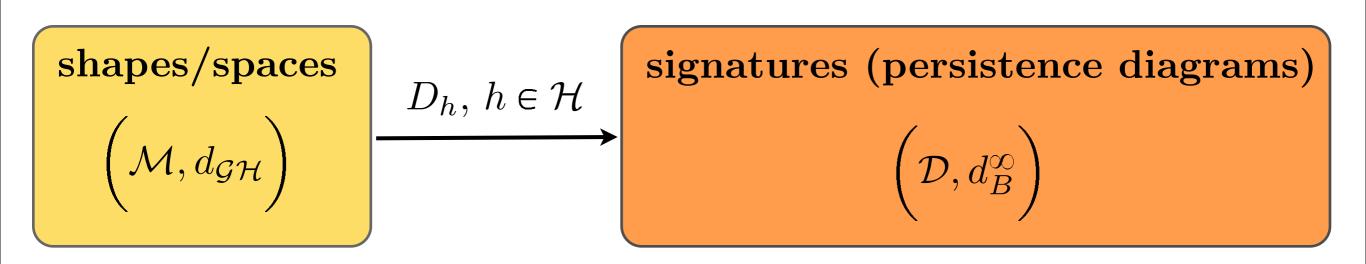




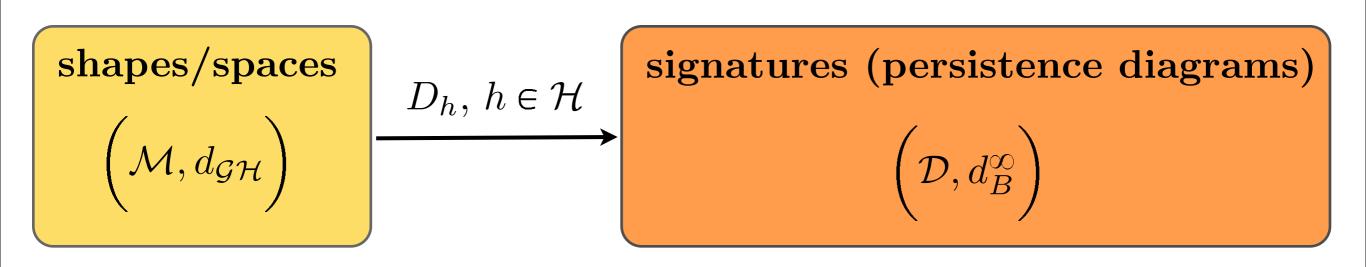




- $\mathcal{M}$ : collection of all shapes (finite metric spaces).
- $\mathcal{D}$ : collection of all signatures (persistence diagrams).

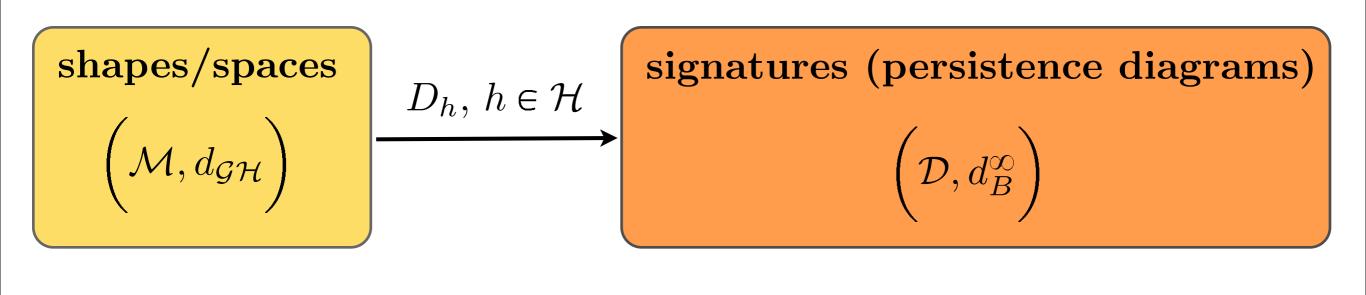


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X, Y

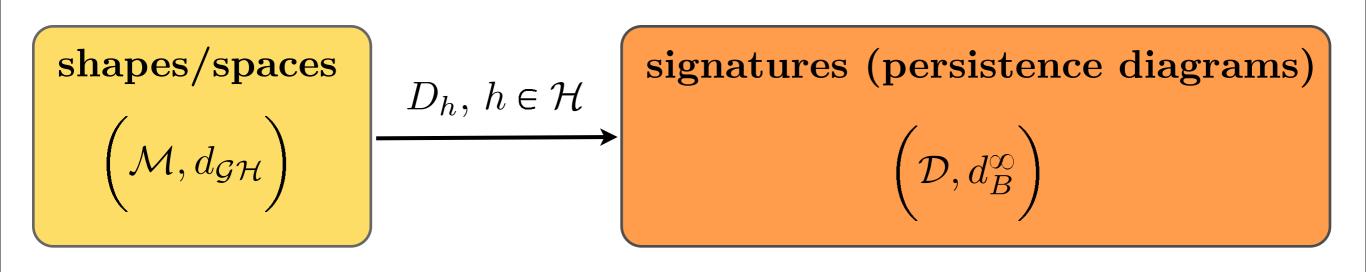
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X, Y

 $D_h(X), D_h(Y) \qquad h \in \mathcal{H}$ 

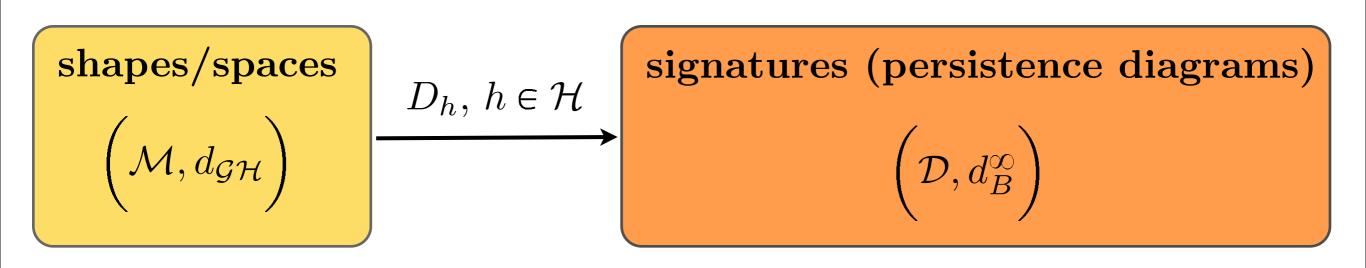
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$$X, Y$$
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## $d_{\mathcal{GH}}(X,Y)$

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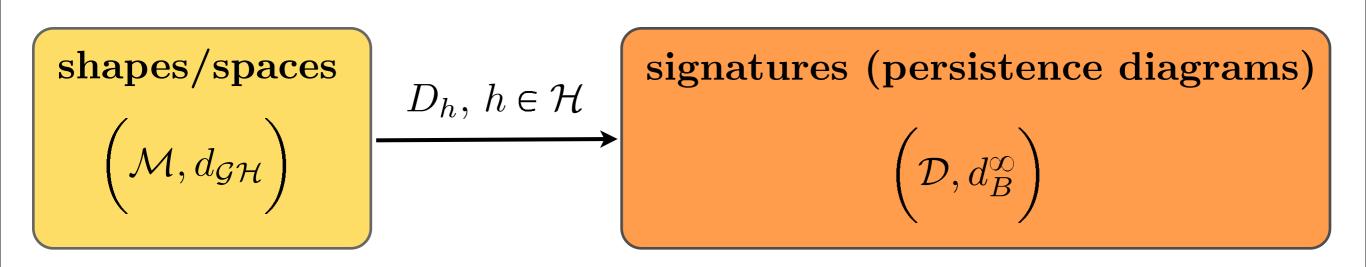


X, Y

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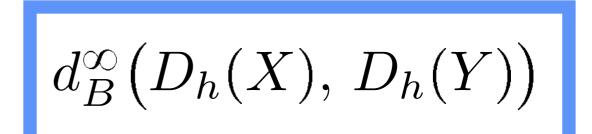
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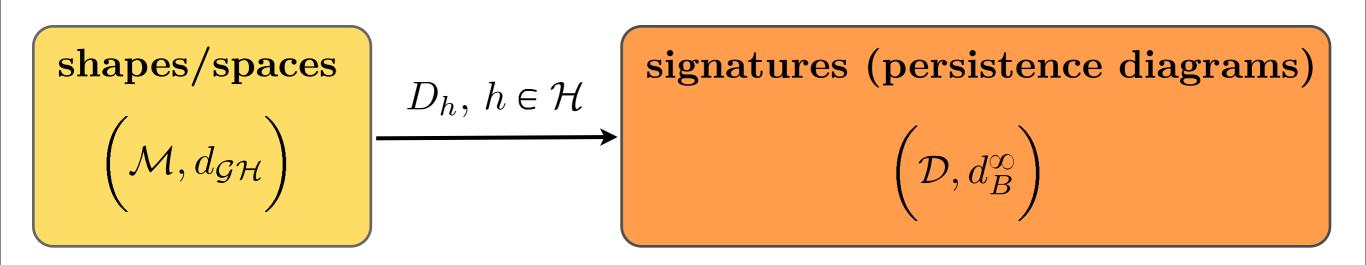
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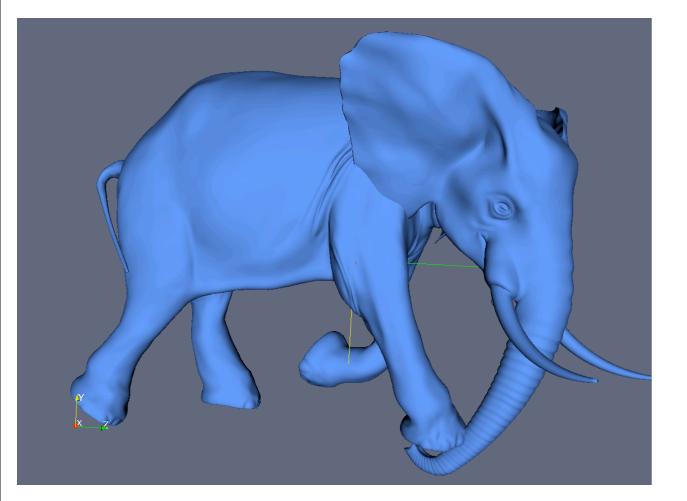
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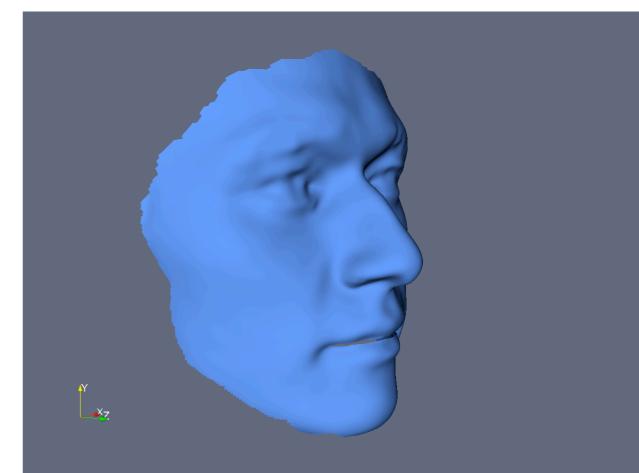


$$X, Y$$
  $D_h(X), D_h(Y)$   $h \in \mathcal{H}$ 

$$d_{\mathcal{GH}}(X,Y) \geqslant d_B^{\infty}(D_h(X), D_h(Y))$$

### Shapes as metric spaces





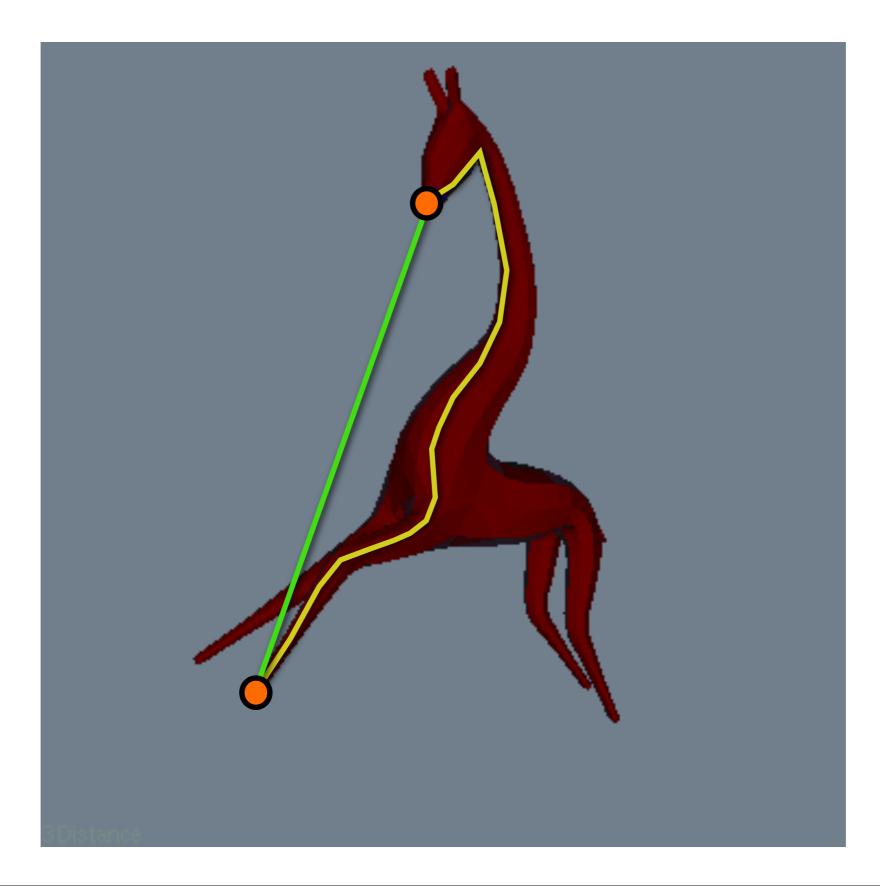
#### Shapes as metric spaces

 $\begin{pmatrix} 0 & d'_{12} & d'_{13} & d'_{14} & \cdots \\ d'_{12} & 0 & d'_{23} & d'_{24} & \cdots \\ d'_{13} & d'_{23} & 0 & d'_{34} & \cdots \\ d'_{14} & d'_{24} & d'_{34} & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$ 

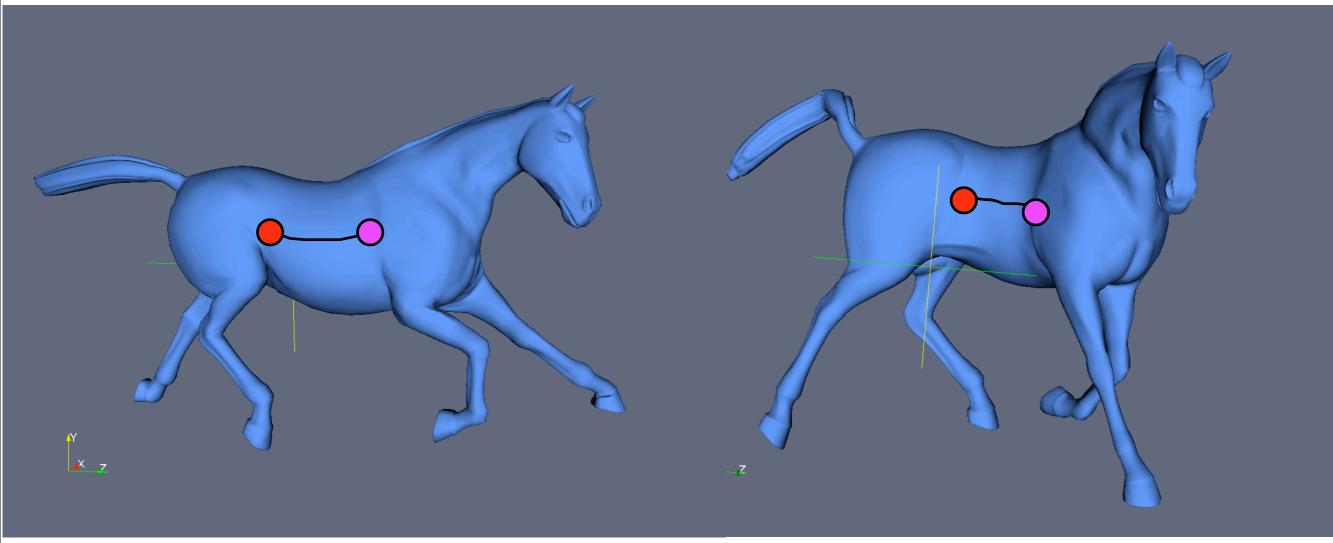
 $\begin{pmatrix} 0 & d_{12} & d_{13} & d_{14} & \dots \\ d_{12} & 0 & d_{23} & d_{24} & \dots \\ d_{13} & d_{23} & 0 & d_{34} & \dots \\ d_{14} & d_{24} & d_{34} & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$ 

then use Gromov-Hausdorff distance..

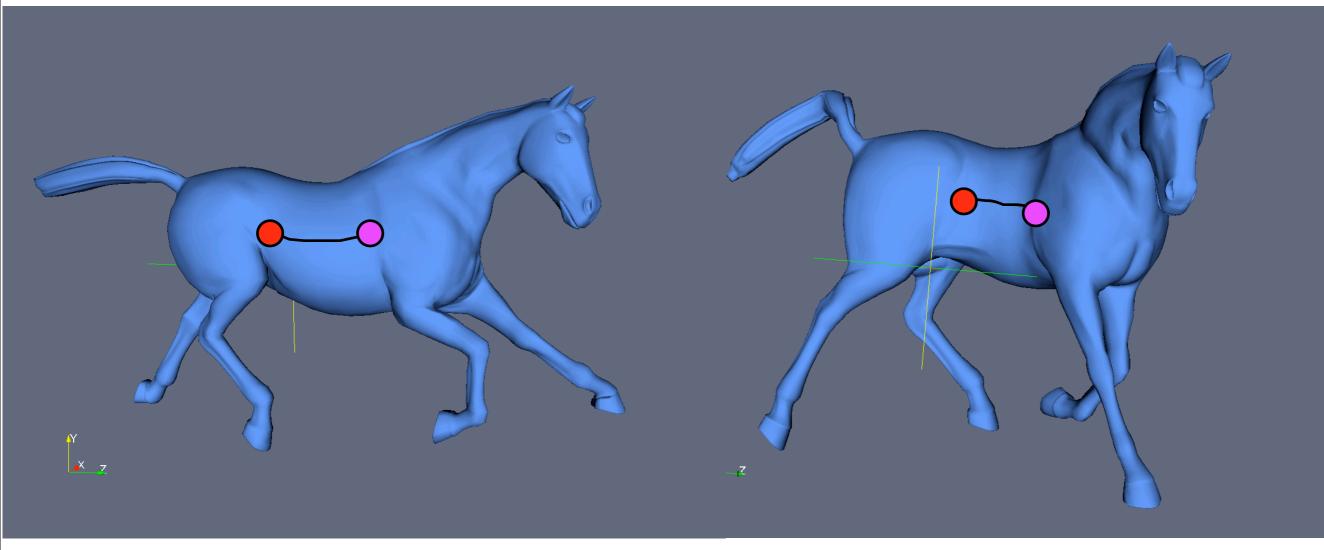
### Choice of the metric: geodesic vs Euclidean



### Invariance to isometric deformations (change in pose)



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#### geodesic distance remains approximately constant

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 $\begin{pmatrix} 0 & d_{12} & d_{13} & d_{14} & \dots \\ d_{12} & 0 & d'_{23} & d_{24} & \dots \\ d_{13} & d_{23} & 0 & d_{34} & \dots \\ d_{14} & d_{24} & d_{34} & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix} \simeq \begin{pmatrix} 0 & d'_{12} & d'_{13} & d'_{14} & \dots \\ d'_{12} & 0 & d'_{23} & d'_{24} & \dots \\ d'_{13} & d'_{23} & 0 & d'_{34} & \dots \\ d'_{14} & d'_{24} & d'_{34} & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$ 

#### geodesic distance remains approximately constant

For finite sets A and B, a subset  $C \subset A \times B$  is a *correspondence* (between A and B) if and only if

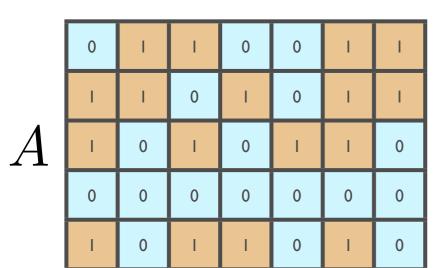
- $\forall a \in A$ , there exists  $b \in B$  s.t.  $(a, b) \in R$
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Let  $\mathcal{C}(A, B)$  denote all possible correspondences between sets A and B.

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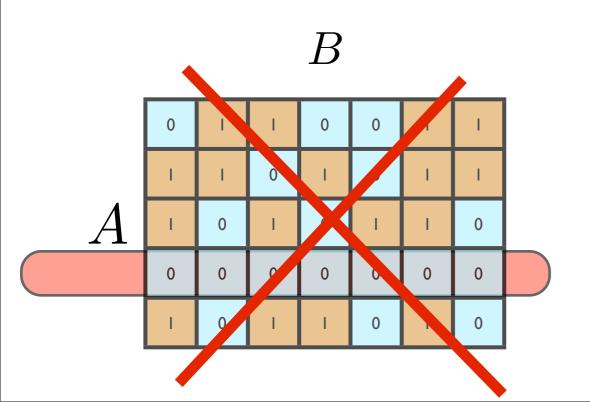
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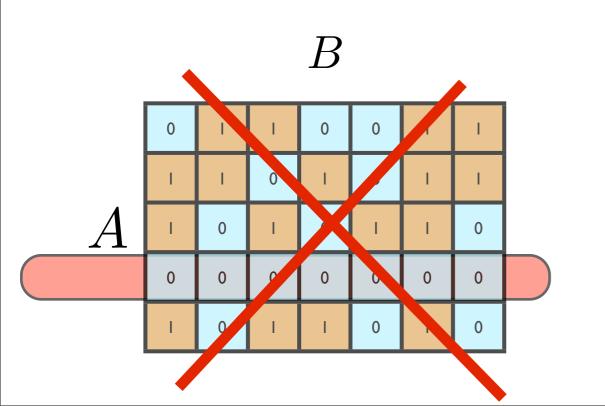


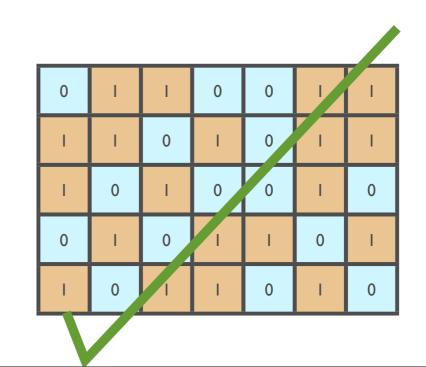
0	I	I	0	0	I	I
I.	I	0	I	0	I	I
I	0	I	0	0	I	0
0	I	0	I	I	0	I
I	0	I	I	0	I	0

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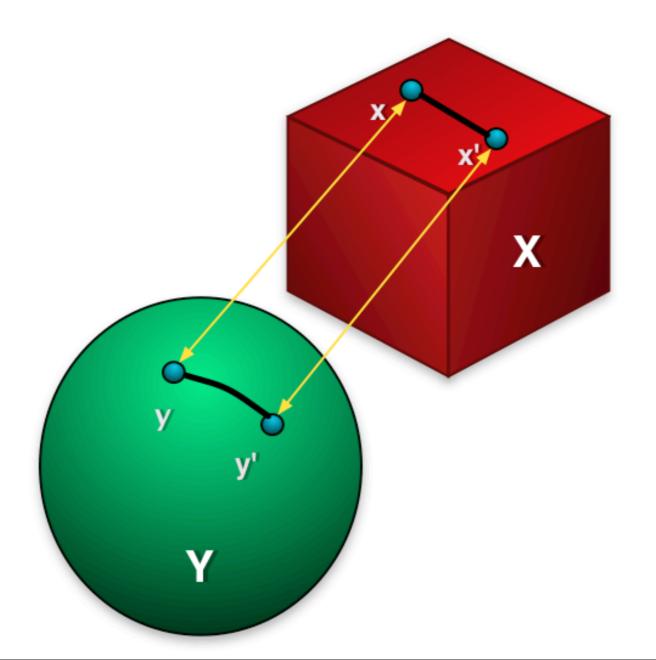


**Definition.** [BBI] For finite metric spaces  $(X, d_X)$  and  $(Y, d_Y)$ , define the Gromov-Hausdorff distance between them by

$$d_{\mathcal{GH}}(X,Y) = \frac{1}{2} \min_{C} \max_{\substack{(\boldsymbol{x},\boldsymbol{y}),(\boldsymbol{x}',\boldsymbol{y}') \in C}} |d_X(\boldsymbol{x},\boldsymbol{x}') - d_Y(\boldsymbol{y},\boldsymbol{y}')|$$

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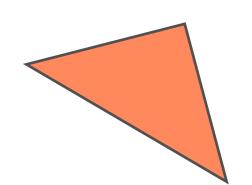


## **Construction of our signatures**

- Our signatures take the form of **persistence diagrams**: we capture certain topological and metric information from the shape.
- First example: construction based on **Rips filtrations**: Let  $(X, d_X)$  be a shape.
  - Let  $K_d(X)$  be the *d*-dimensional full simplicial complex on X.
  - To each  $\sigma = [x_0, x_1, \dots, x_k] \in K_d(X)$  assign its filtration time

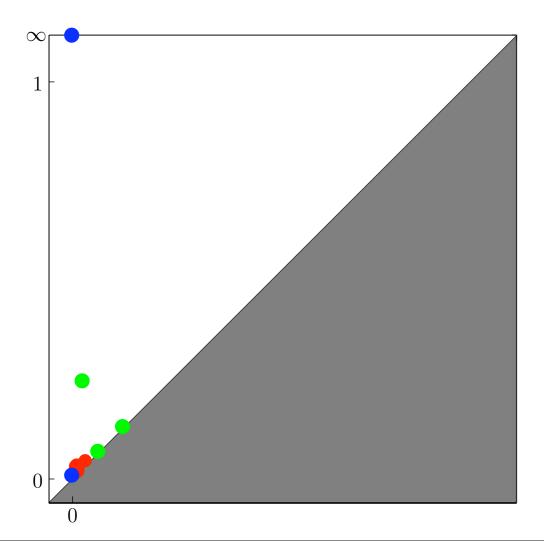
$$F(\sigma) := \frac{1}{2} \max_{i,j} d_X(x_i, x_j)$$

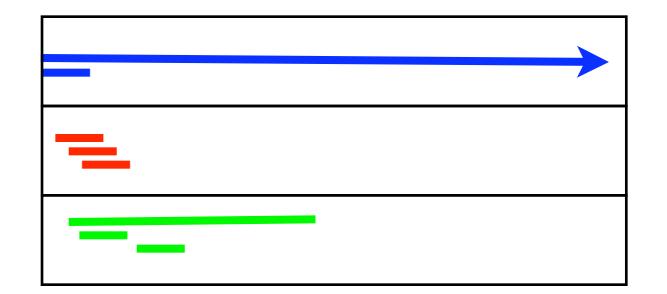
- This gives rise to a filtration  $(K_d(X), F)$ .



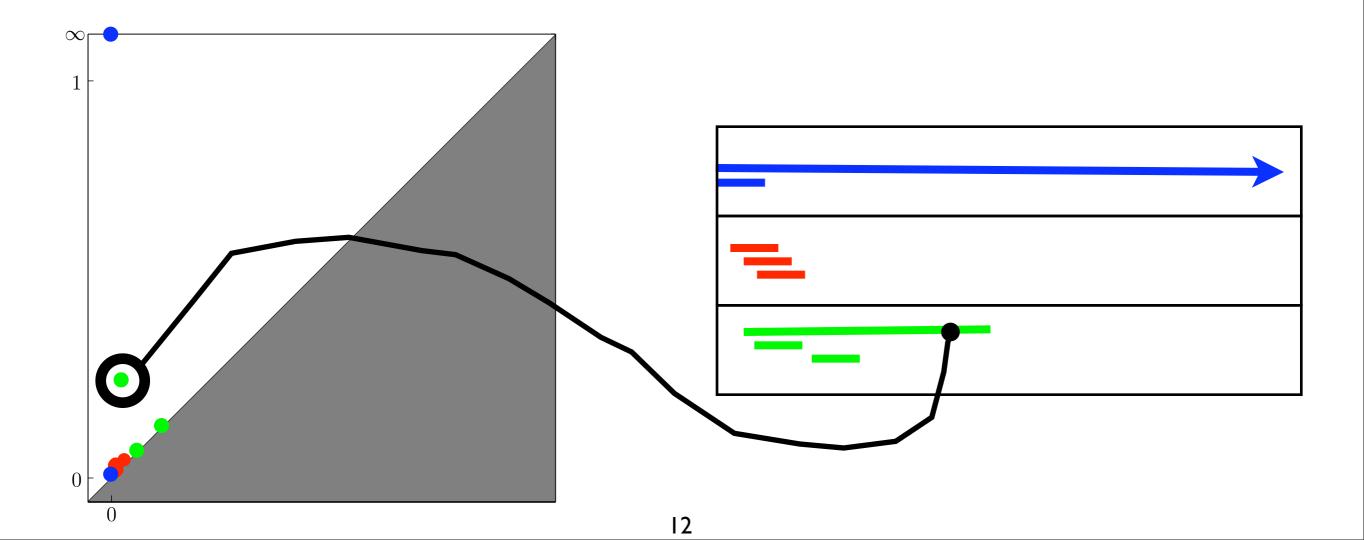
- Apply **persistence algorithm** [ELZ00] to summarize topological information in the filtration and obtain **persistence diagram**.

- Persistence diagrams are **colored multi-subsets** of the extended real plane.. can also be represented as **barcodes**.
- Let  $\mathcal{D}$  denote the collection of all persistence diagrams. Compare two different persistence diagrams with **bottleneck distance**  $\implies$  view  $(\mathcal{D}, d_B^{\infty})$  as a metric space.



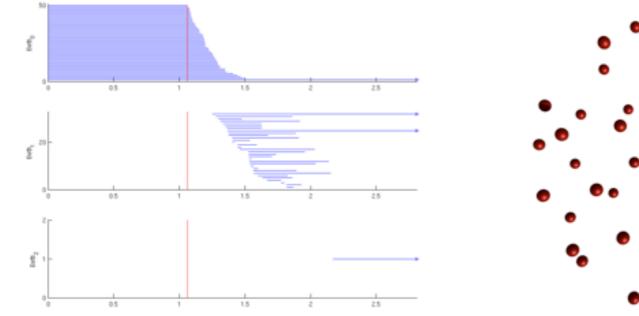


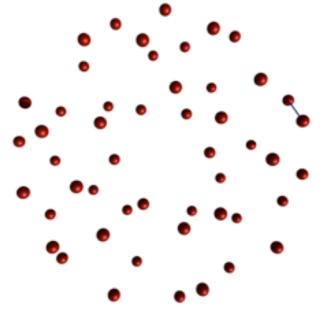
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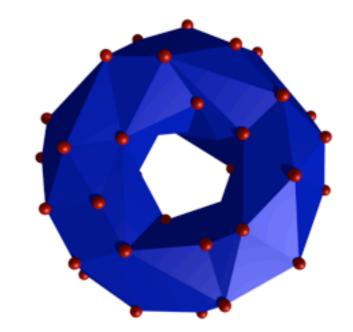


#### Example: Rips filtration on a torus

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#### Our signatures: more richness

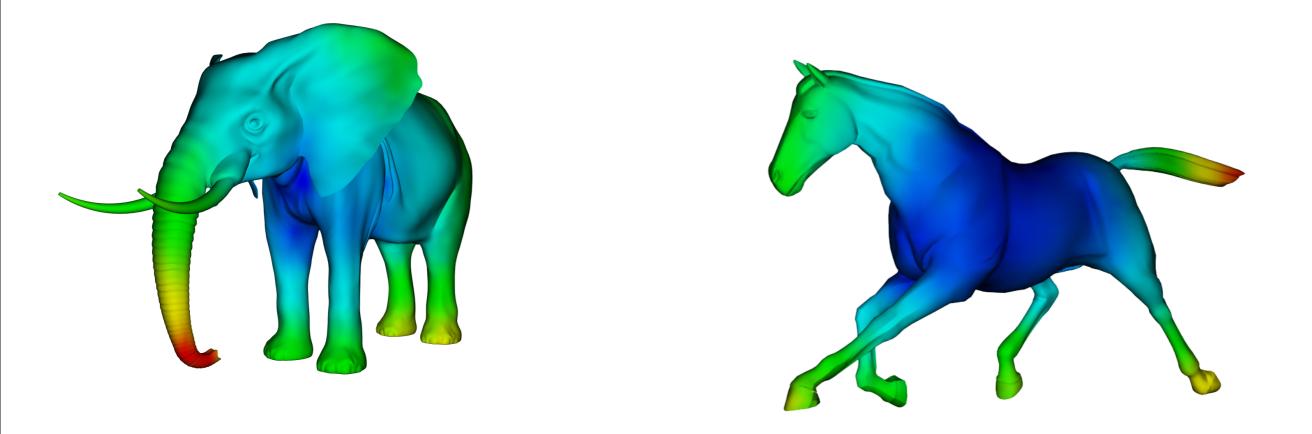
• Let's assume that in there is also a function defined on the shape:  $(X, d_X, f_X)$ . Then, we redefine the filtration values of  $\sigma = [x_0, x_1, \dots, x_k]$ 

$$F(\sigma) = \max\left(\frac{1}{2}\max_{i,j} d_X(x_i, x_j), \max_i f_X(x_i)\right)$$

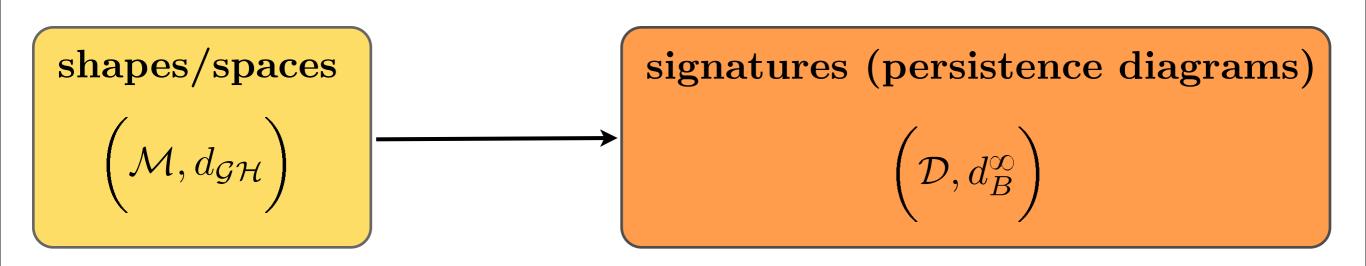
- Again, this gives rise to a filtration:  $(K_d(X), F) \implies$  use persistence algorithm to obtain a persistence diagram.
- This increases discrimination power!
- We denote by  $\mathcal{H}$  a family of maps that attach a function to a given finite metric space.
- Then, for each  $h \in \mathcal{H}$ , we denote by  $D_h(X)$  the persistence diagram arising from the filtration above. This constitutes our family projection onto  $\mathcal{D}$ .

**Example** (Eccentricity). To each finite metric space  $(X, d_X)$  one can assign the eccentricity function:

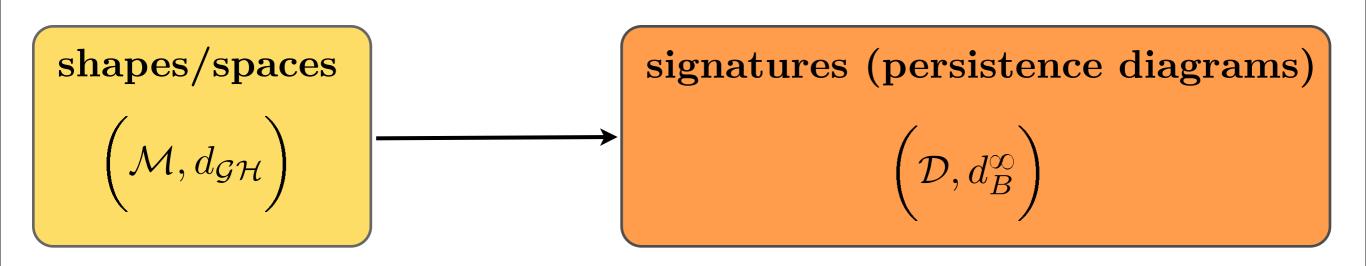
$$ecc_X(x) = \max_{x' \in X} d_X(x, x').$$



# $h \in \mathcal{H}$

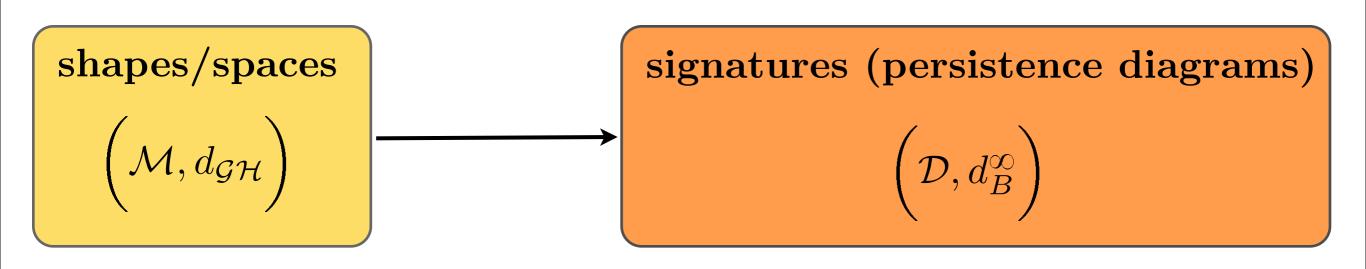


# $h \in \mathcal{H}$



X, Y

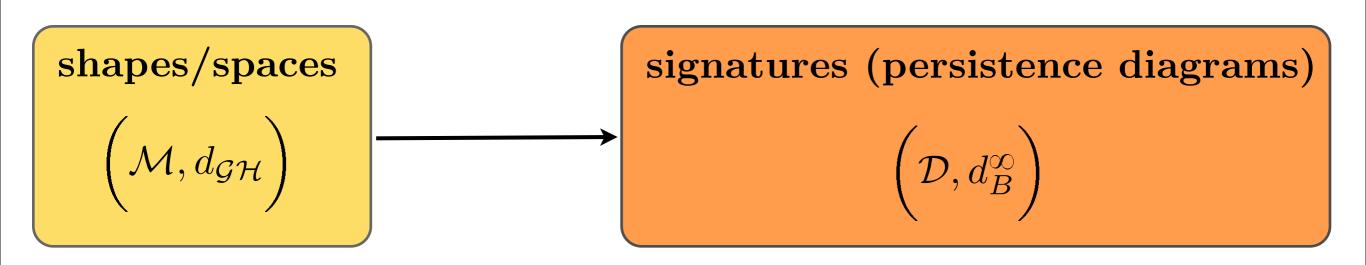
# $h \in \mathcal{H}$



X, Y

 $D_h(X), D_h(Y)$ 

# $h \in \mathcal{H}$

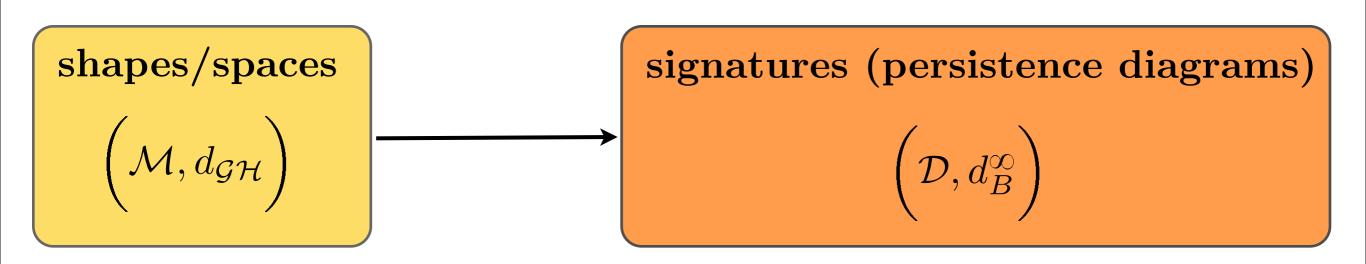


X, Y

 $D_h(X), D_h(Y)$ 

### $d_{\mathcal{GH}}(X,Y)$

# $h \in \mathcal{H}$

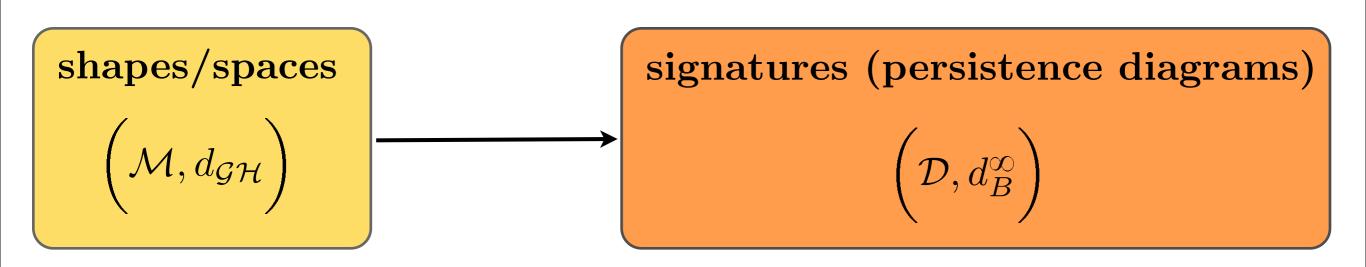


X, Y

 $D_h(X), D_h(Y)$ 



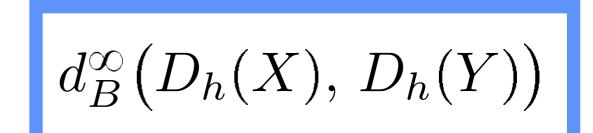
# $h \in \mathcal{H}$



X, Y

 $D_h(X), D_h(Y)$ 





 $d_{\mathcal{GH}}(X,Y) \ge C(h) \cdot d_B^{\infty}(D_h(X), D_h(Y)).$ 

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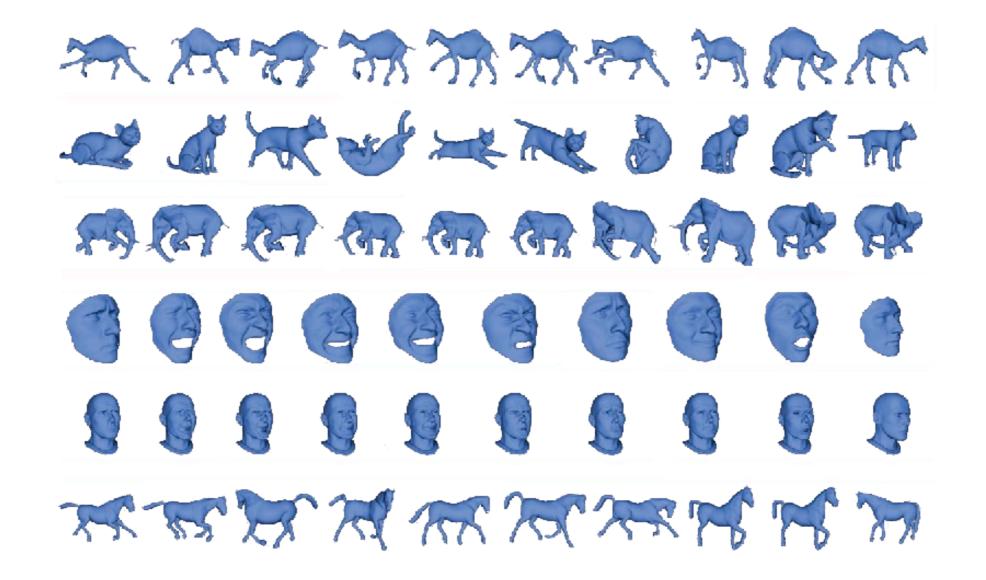
$$d_{\mathcal{GH}}(X,Y) \ge \sup_{h \in \mathcal{H}} C(h) \cdot d_B^{\infty}(D_h(X), D_h(Y)).$$

#### Remark.

- Proof relies on properties of the GH distance and new results on the stability of persistence diagrams [CCGG009].
- For a given h, the computation leads to a **BAP** which can be solved in polynomial time.
- There are adaptations one can do in practice to speed up, see paper.
- One can obtain more generality and discrimination power by working in the class of **mm-spaces**: shapes are represented as triples  $(X, d_X, \mu_X)$ where  $\mu_X$  are weights assigned to each point see [M07] and paper.
- Our results include stability of Rips persistence diagrams.

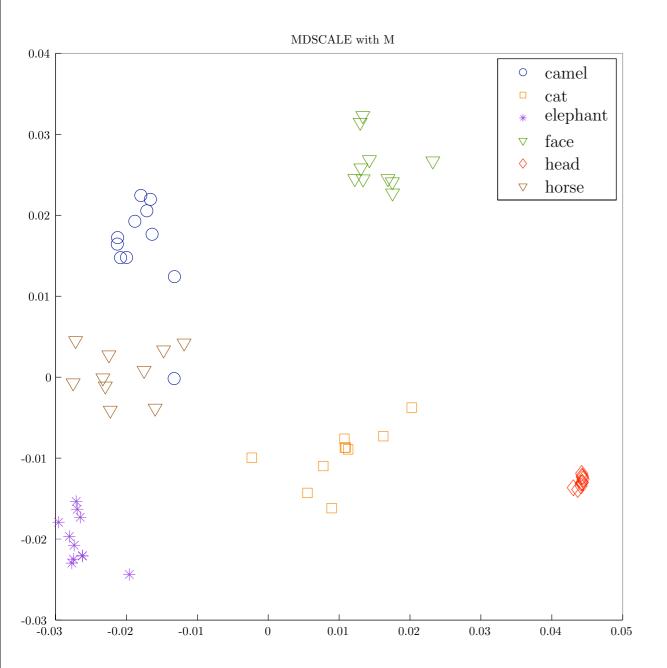
#### Some experiments

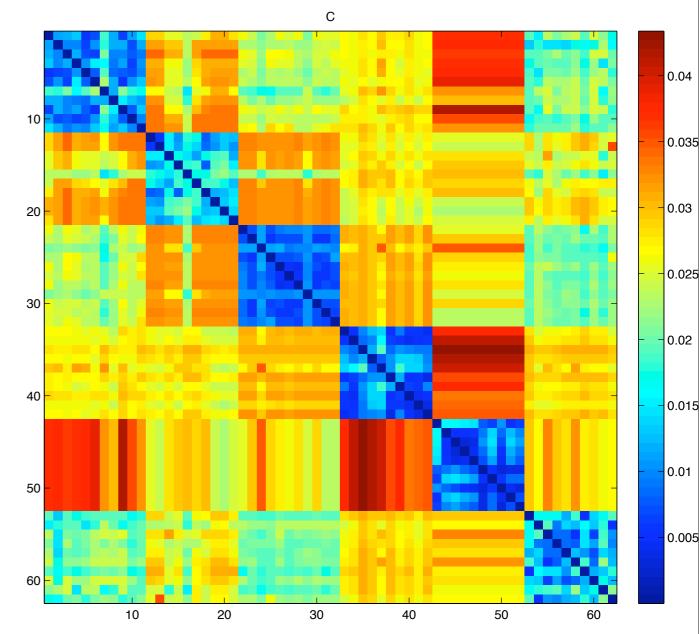
• Sumner database: 62 shapes total, 6 classes. Used graph estimate of the geodesic distance. Number of vertices ranged from 7K to 30K.



#### Some experiments

- Summer database: 62 shapes total, 6 classes. Used graph estimate of the geodesic distance. Number of vertices ranged from 7K to 30K.
- Subsampled shapes and retained subsets of 300 points (farthest point sampling). Normalized distance matrices.
- Used the mm-space representation of shapes: weights were based on Voronoi regions.
- Used several functions  $\pm \lambda \cdot h$  for  $\lambda$  in a finite subset of scales.
- Obtained 4% (or 2%) classification error in a 1-nn classification problem.





### Discussion

- Summary of our proposal:
  - Use the metric (or mm-space) representation of shapes.
  - Formulate the shape matching problem using the Gromov-Hausdorff distance.
  - Compute our signatures for shapes.
  - Solve the BAP lower bounds: computationally easy! By our theorem, the computed quantities give lower bounds for the GH distance.
- Implications and Future directions:
  - We do not need a mesh– general: can be applied to any dataset.
  - We obtain stability of Rips persistence diagrams.
  - Richness of the family  $\mathcal{H}$ ? how close can I get to the GH distance?
  - Local signatures: more discrimination.
  - Extension to partial shape matching: which (local) signatures are useful for this?

### Acknowledgements

- ONR through grant N00014-09-1-0783
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- INRIA-Stanford associated TGDA team.

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#### http://math.stanford.edu/~memoli

Let  $X_1, X_2 \subset Z$  be two different samples of the same shape Z, and Y another shape then

 $\left| d_{\mathcal{GH}}(X_1, Y) - d_{\mathcal{GH}}(X_2, Y) \right| \leq d_{\mathcal{GH}}(X_1, X_2) \leq r_1 + r_2$