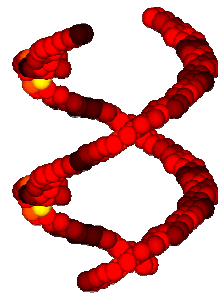


# A Barcode Shape Descriptor for Curve Point Cloud Data



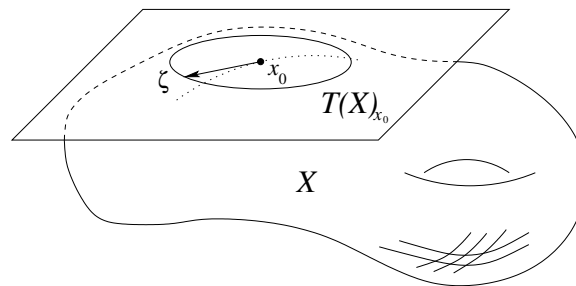
*Anne Collins*  
Centre College

Afra Zomorodian, Gunnar Carlsson, and Leonidas Guibas  
Departments of Mathematics and Computer Science  
Stanford University



# Plan

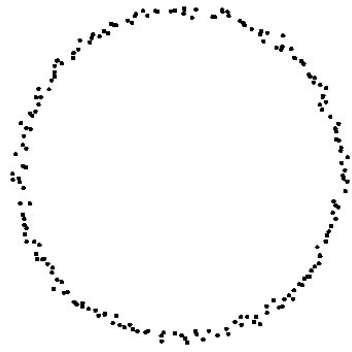
- Yesterday: *Theory*
  - Persistence Barcodes for Shapes by Afra Zomorodian



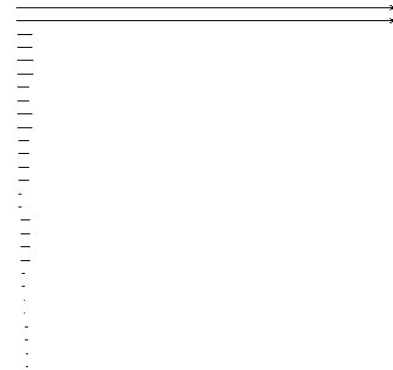
- Today: *Practice*
  - Point cloud data
  - Algorithms for construction
  - Detailed study



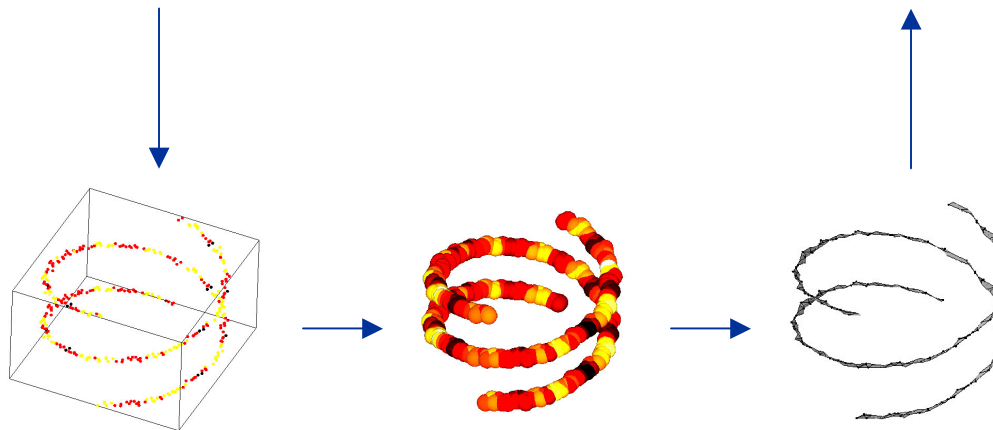
# Overview



Input: Shape

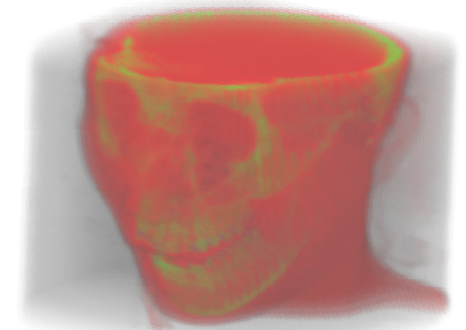
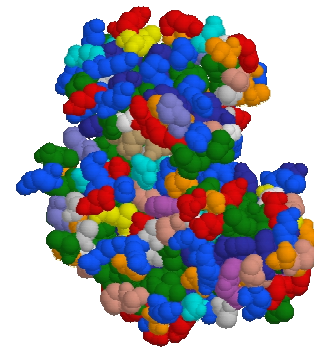
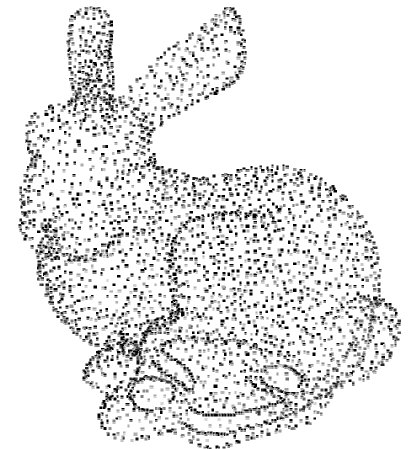
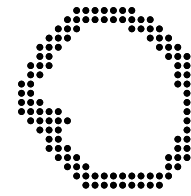


Output: Descriptor

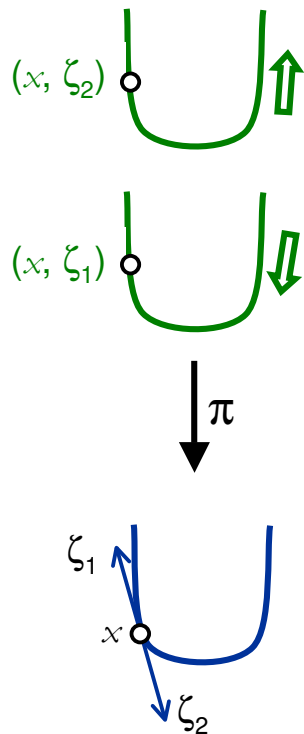


# Point Cloud Data

- Nearly all shape data
  - 2D: images
  - 3D: surface data, molecules
  - $n$ D: shape spaces
- Traditional approach: construct useful structure
  - Vision: OCR
  - Graphics: surface reconstruction
  - CAD: conversion to B-spline surfaces
- Recent approach: first class object
  - Shape representation
  - Rendering
  - Modeling



# Review of Tangent Complex

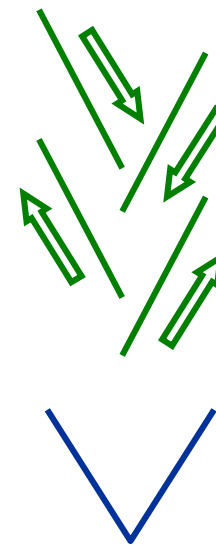


$T(X)$  has **two** components:  
 $\beta_0(T(X)) = 2$

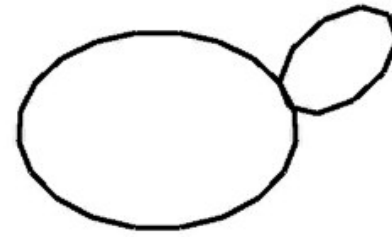
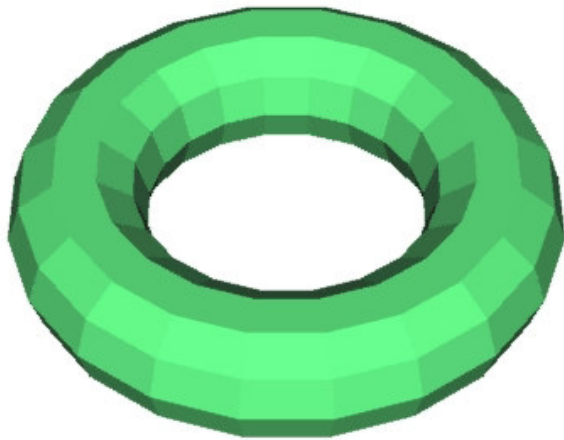
There are **two** points in its **fiber**  $\pi^{-1}(x)$


Every point  $x$  on a smooth curve  $X$  has **two** tangent directions.

A corner point has four tangent directions:  $\beta_0(T(X)) = 4$



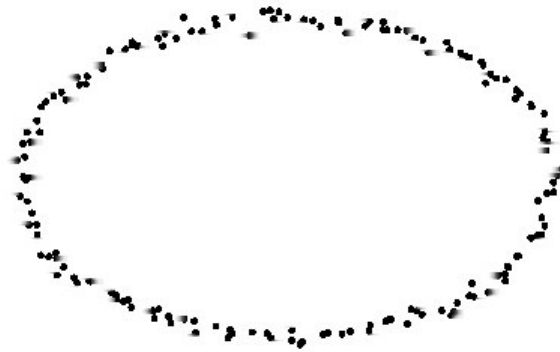
# Review of Persistence



- As the space evolves, topological attributes are **created** and **destroyed**, each having a **lifetime** of existence.   
Birth                      Death
- **Persistent Homology** gives us these lifetimes as a collection of intervals, a **persistence barcode**.



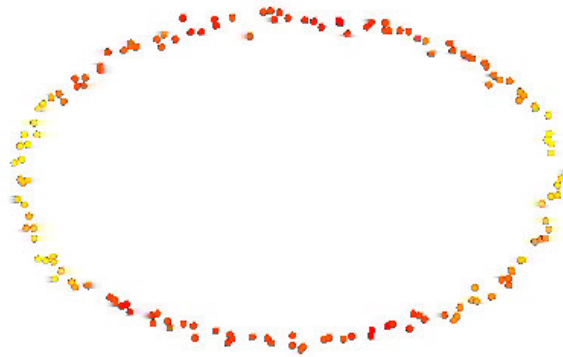
# Fibers



- PCD  $P \subset X$ , sampled from smooth closed 1-manifold
- We compute fibers  $\pi^{-1}(P)$  by Total Least Squares using k-nearest neighbors (What is k?)



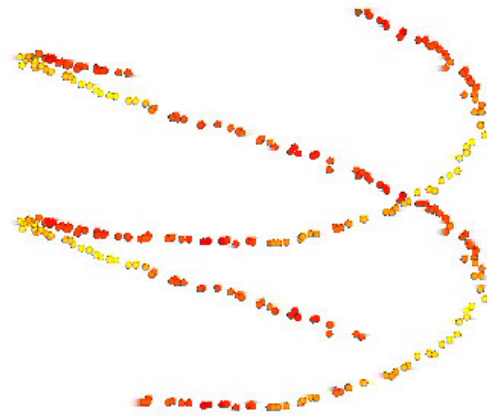
# Filtering by Curvature



- Construct tangent complex incrementally
- Transform points to coordinate frame provided by tangent computation
- Fit osculating parabola to estimate curvature



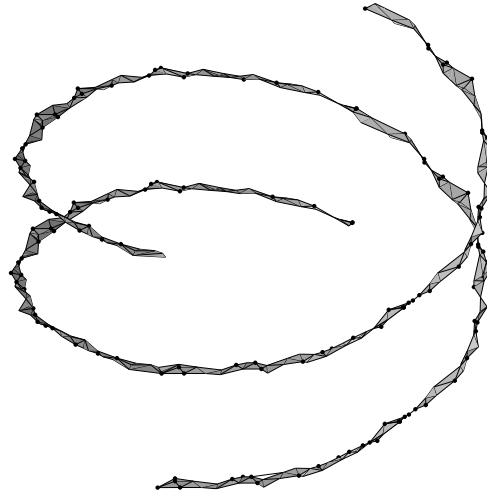
# Approximating $T(X)$



- $\mathbb{R}^n \times \mathbb{S}^{n-1}$  with  $ds^2 = dx^2 + \omega^2 d\zeta^2$
- $T(X) \approx \bigcup_{p \in \pi^{-1}(P)} B_\varepsilon(p)$



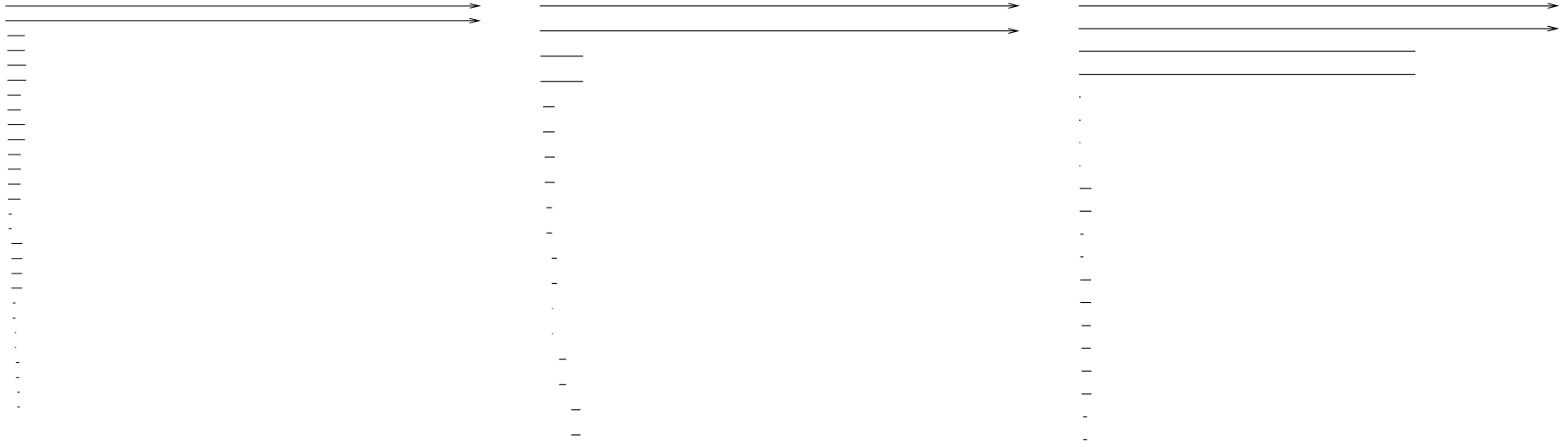
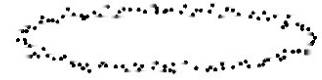
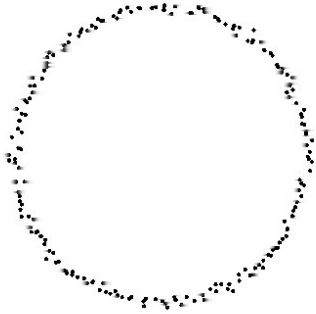
# Complex



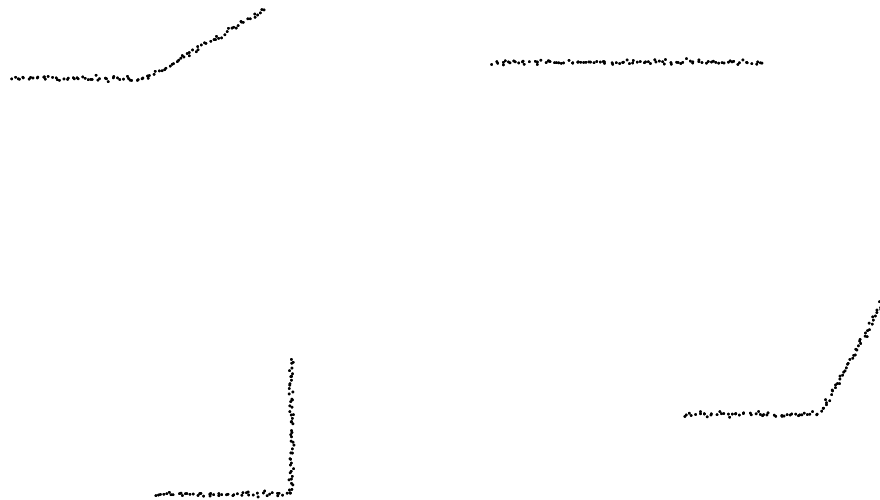
- Rips complex
- $R_\epsilon(M) = \{\text{conv } T \mid T \subseteq M, d(s, t) \leq \epsilon, s, t \in T\}$



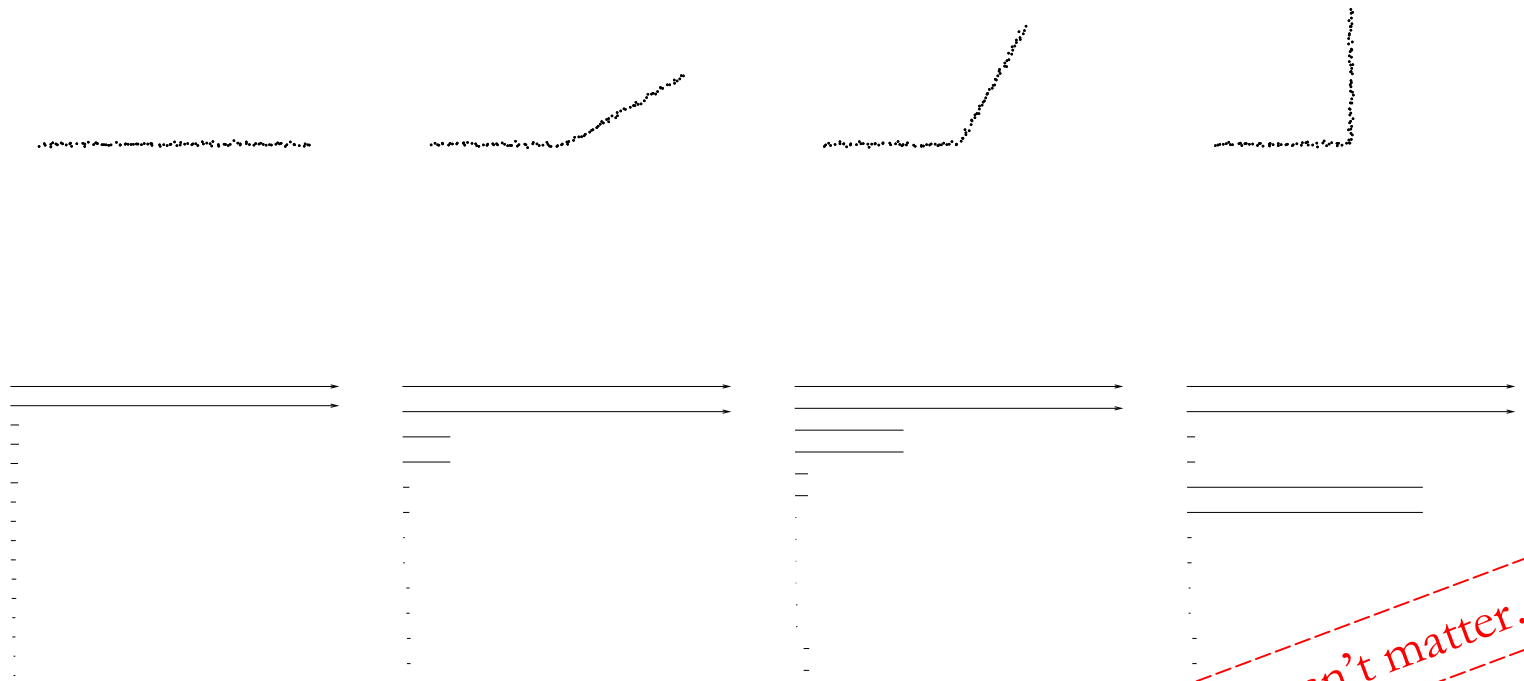
# Family of Ellipses



# Articulated Arm Family



# Parameterization



Order doesn't matter...



# Barcode Metric Algorithm

Three steps:  $D = D_1 + D_2 + D_3$

1. Count infinite intervals

$$D_1(B_1, B_2) = \begin{cases} 0 & \text{if equal,} \\ \infty & \text{otherwise} \end{cases}$$

2. Match infinite intervals (same number)

- Sort by birth times
- Match in order

$D_2(B_1, B_2) = \text{sum of paired length differences}$



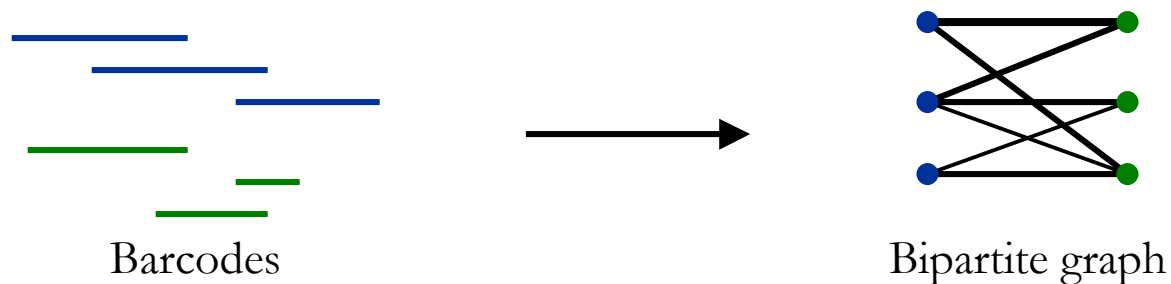
# Finite Interval Distance

## 3. Match finite intervals

- Matching  $M$  = pairing of intervals
- $D_M$  = dissimilarity between matched pairs  
+ lengths of unmatched intervals
- $D_3(B_1, B_2) = \min_M D_M(B_1, B_2)$

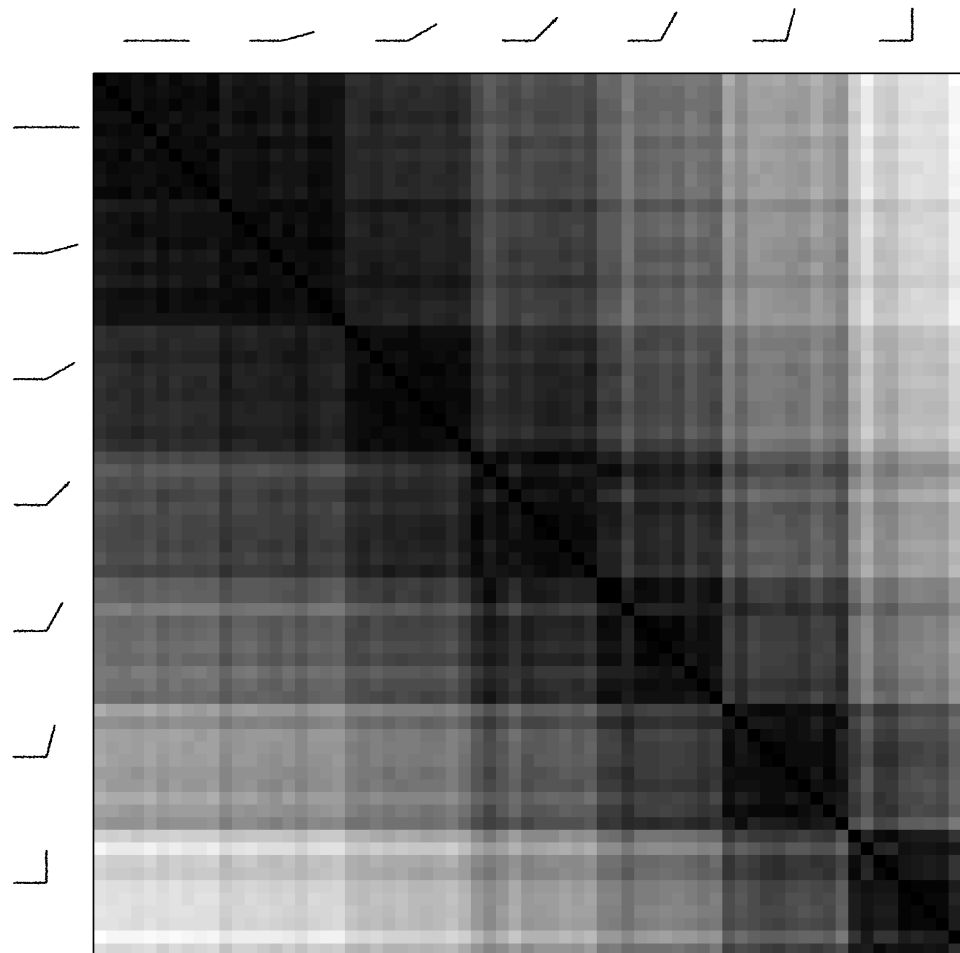
$$\delta(I, J) = |I \cup J - I \cap J|$$

- Minimizing Dissimilarity = Maximizing Similarity



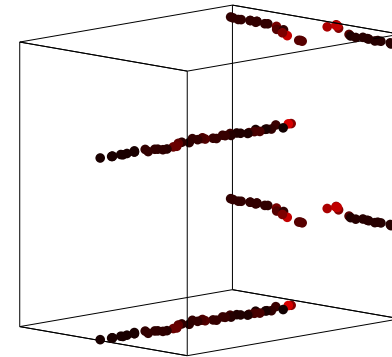
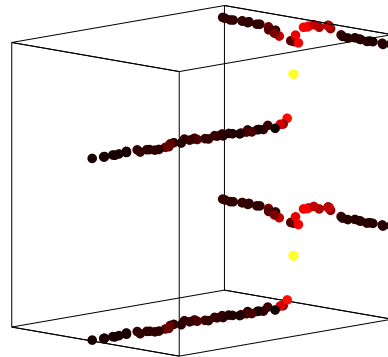
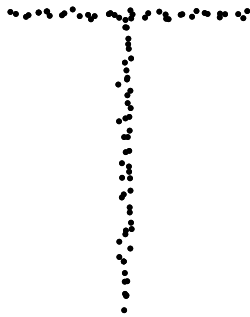
- Maximum Weighted Bipartite Matching (LEDA)

# Distance Matrix



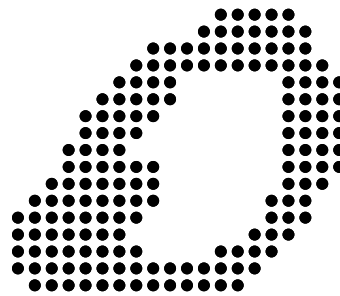
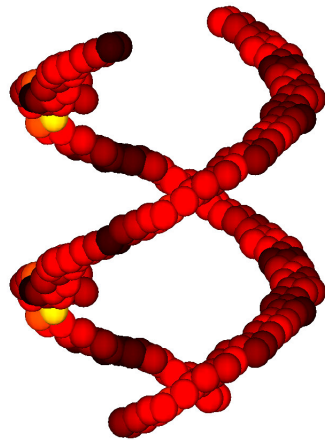
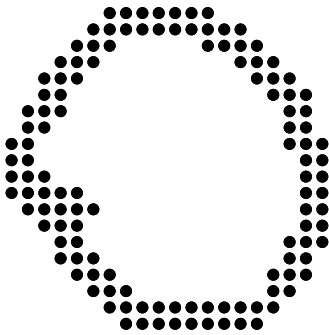
# Extensions

- Boundary points
  - Non-manifold points
  - Singularities
- } Remove points near singularities



# Noise

- Outliers introduce spurious components
- Thick curves affect tangent/curvature estimates
- MNIST database of handwritten digits

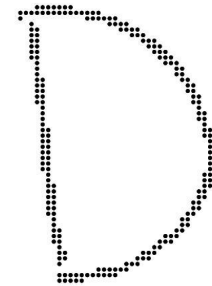
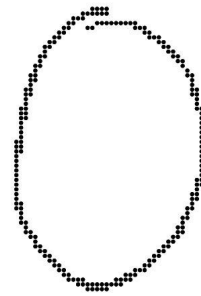
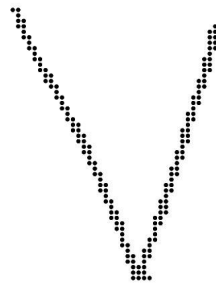
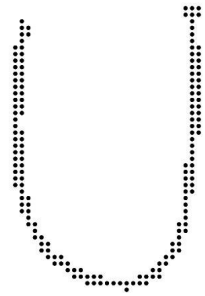


A A A A A A A A  
D D D D D D D D  
O O O O O O O O  
R R R R R R R R  
C C C C C C C C  
I I I I I I I I  
U U U U U U U U  
V V V V V V V V

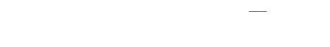
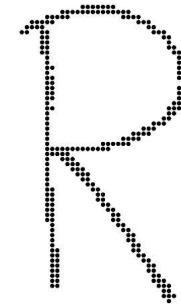
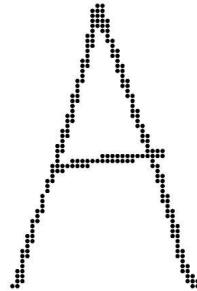
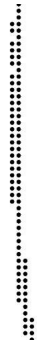
# Classification



# Singularities



# Curvature

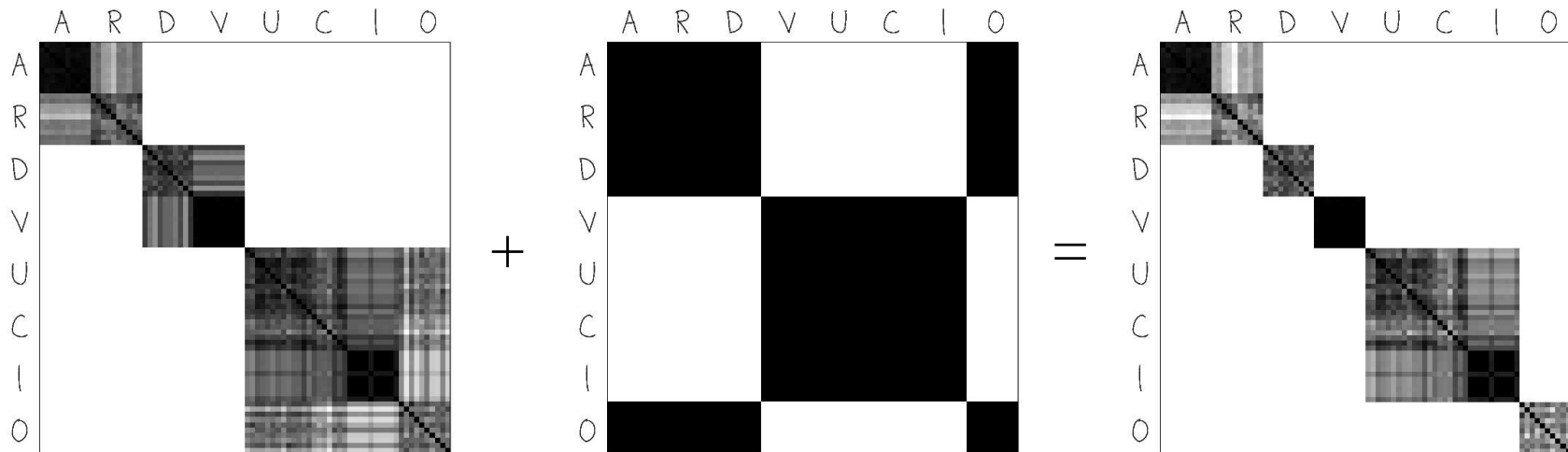


# Curvature Signature



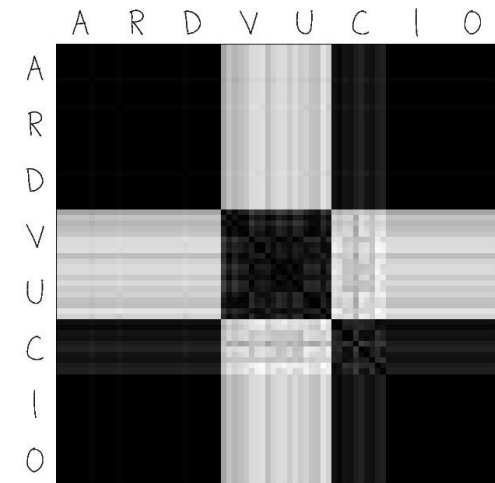
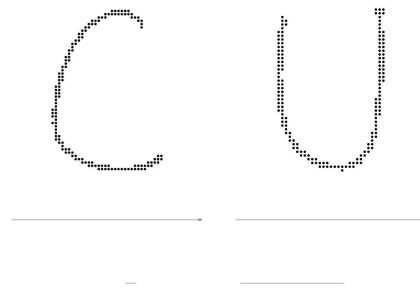
# Multiple Signatures

- Improve classification with additional information
  - New filtration
  - New derived space
  - New metric
- eg: include  $\beta_1$  of PCDs

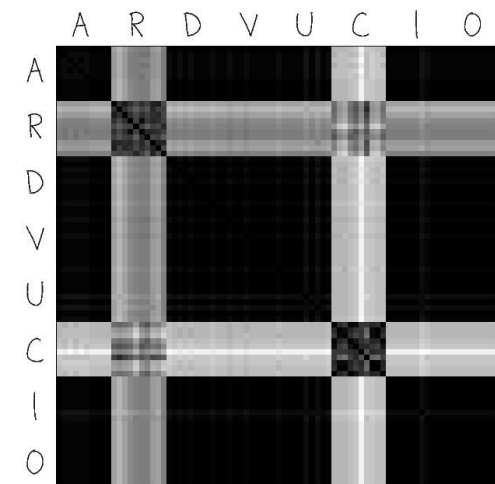
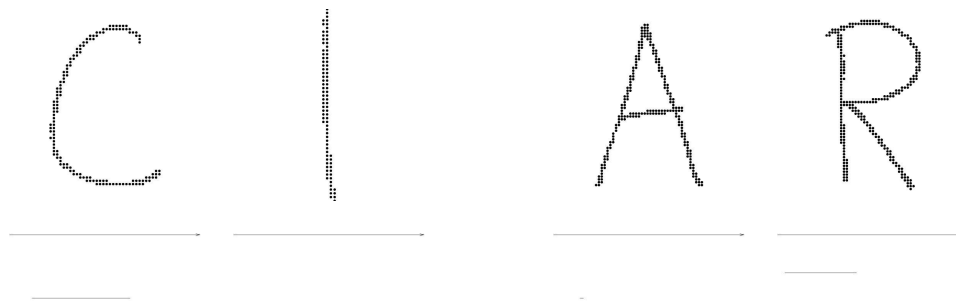


# Directional Filtrations

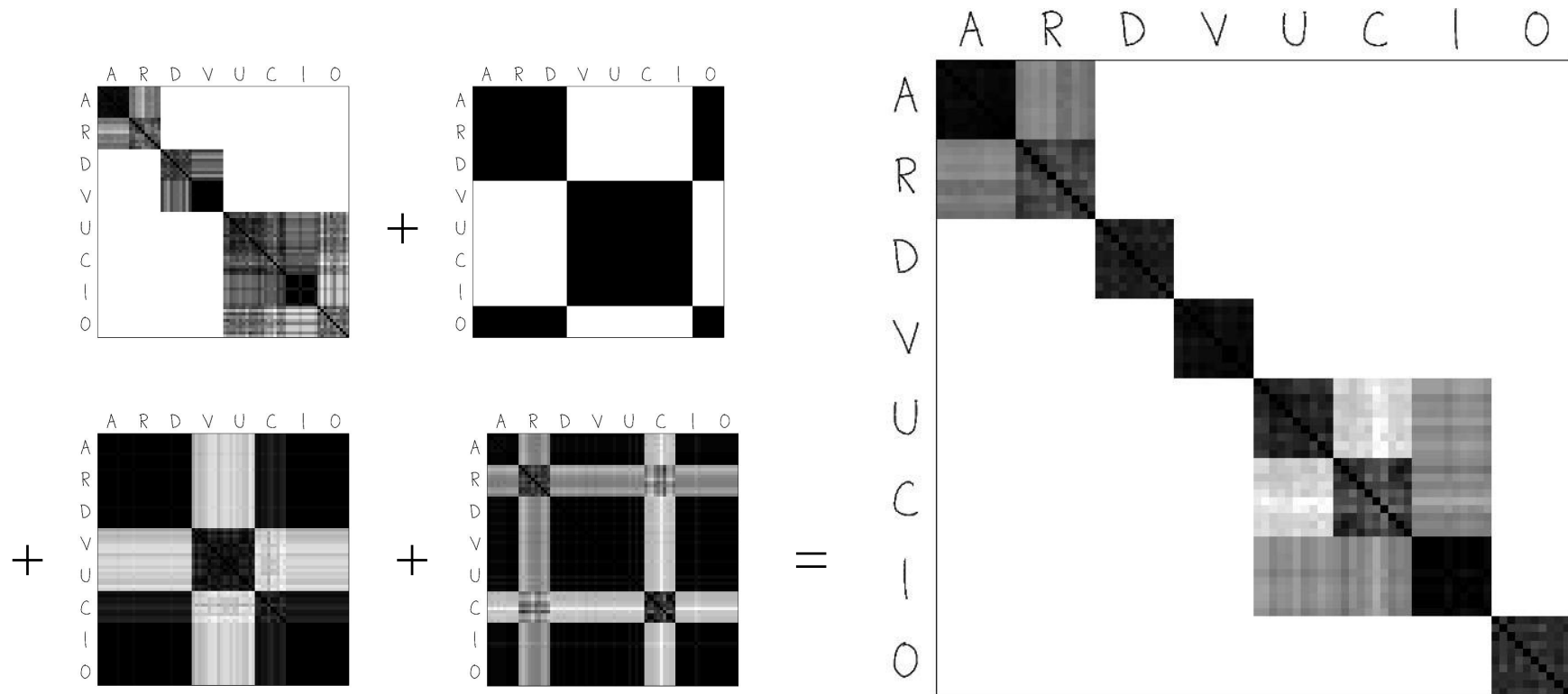
- Top-Down  $\beta_0$  of PCDs



- Right-Left  $\beta_1$  of PCDs



# Final Distance Matrix



# Conclusion

- Apply persistent homology to geometry-rich derived space to get a compact shape descriptor called barcode
- Compute tangent complexes for Curve Point Cloud Data
- Improve classification with multiple signatures
- Future Work:
  - Better handling of non-manifold points, outliers, curve thickness, etc.
  - Surface PCD
  - Complexes with lower intrinsic dimension
  - Learning Algorithms

