



# 3D Segmentation using Topological Data Analysis

Presented By Pranav Bhasin



# Overview

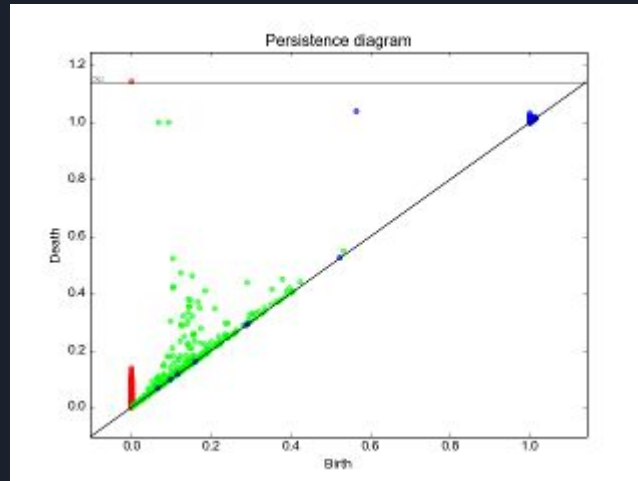
These days , the amount of sensory data has collected has increased, and its becoming increasingly hard to process this data for machine learning applications.

Today, I will present a Machine Learning application of Topological Data Analysis (TDA), a rapidly evolving field of data science which makes use of topology to improve this kind of data analysis.

# Understanding TDA

01

**TDA** is a mathematically grounded theory which aims at characterizing data using its topology, which is done by computing features of topological nature. The most common one is the **persistence diagram**, which takes the form of a set of points in the plane above the diagonal.

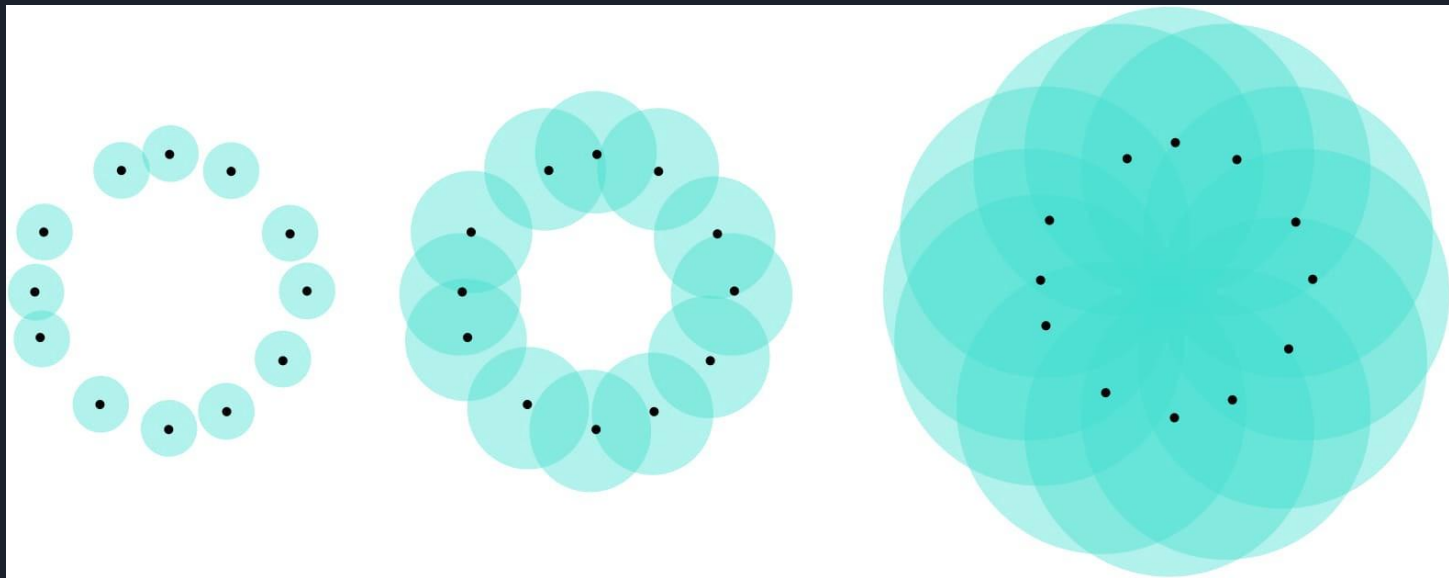




# Understanding TDA

- 01 **TDA** is a mathematically grounded theory which aims at characterizing data using its topology, which is done by computing features of topological nature. The most common one is the **persistence diagram**, which takes the form of a set of points in the plane above the diagonal.
- 02 Each of such point represents a **topological feature** (such as a connected component, a hole or a cavity) of the data. Moreover, the distance of the point to the diagonal act as an indicator of the importance of the corresponding feature, the usual interpretation being that points close to the diagonal are likely due to noise
- 03 The computation of such diagrams requires a filtration, that is, a sequence of growing spaces: each space in the sequence is included in the next one. For instance, given a point cloud, a possible filtration would be to compute unions of balls centered on the points with a sequence of increasing radii

# Understanding TDA

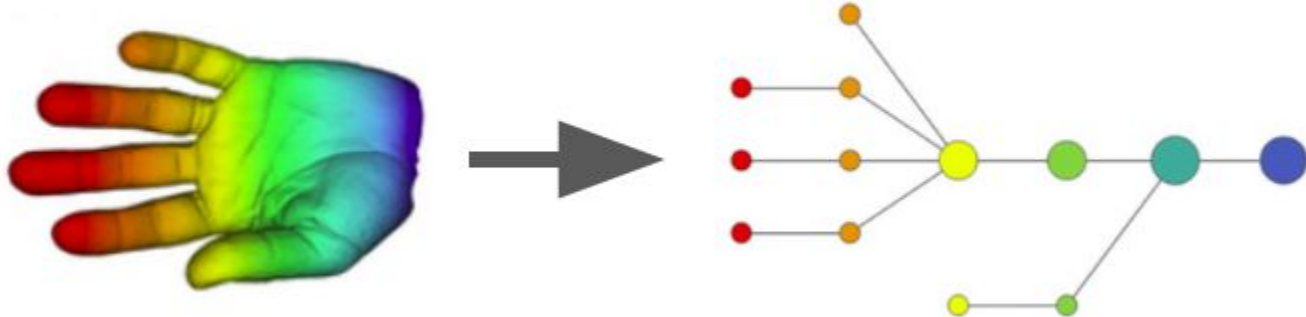


# Main Idea and Benefits: TDA

The idea is, for each space in the sequence, to record whether a topological feature is either created or destroyed in that space.

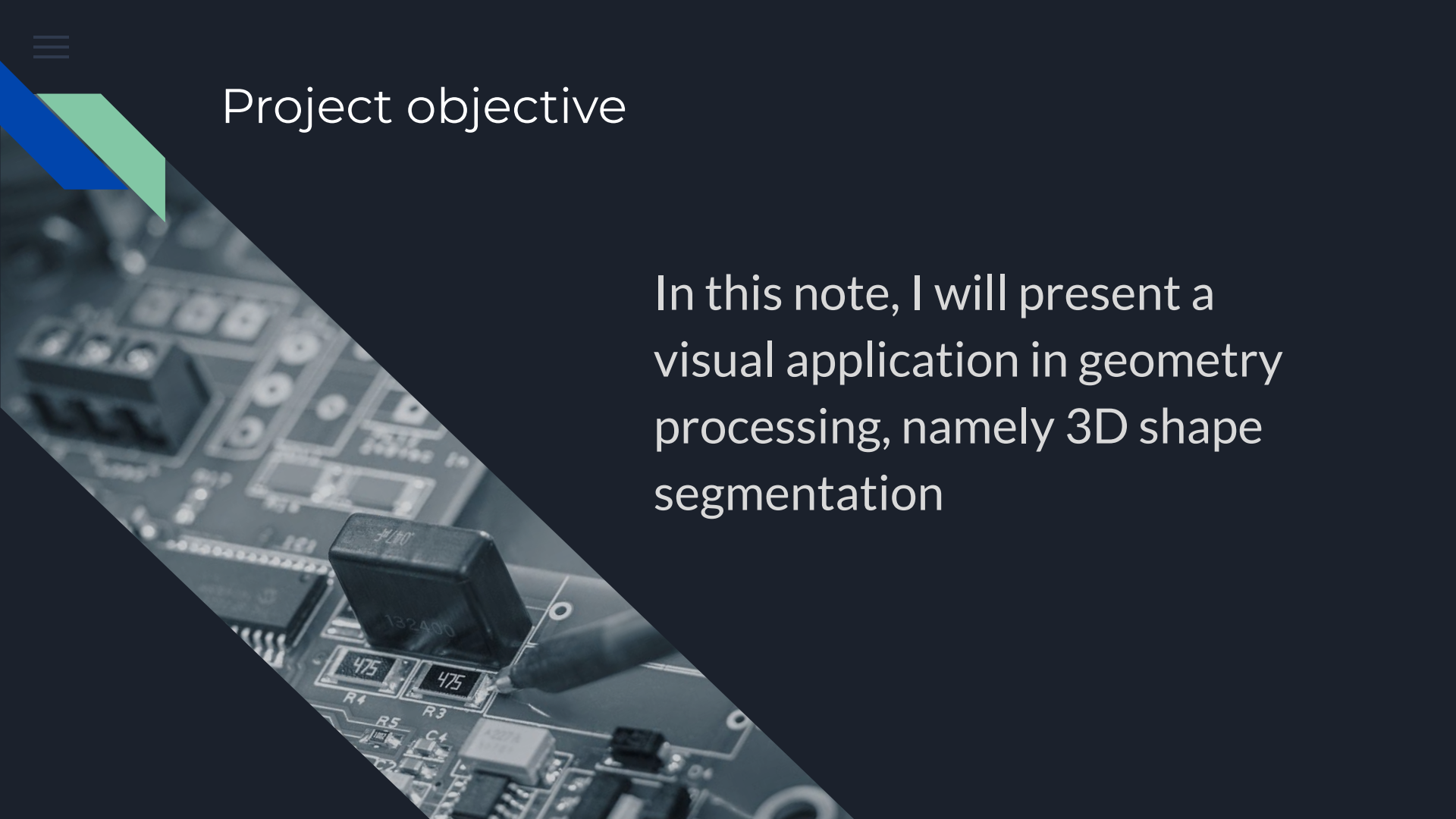
Three Benefits of this process are:

- Coordinate Invariance
- Deformation Invariance
- Compressed representation





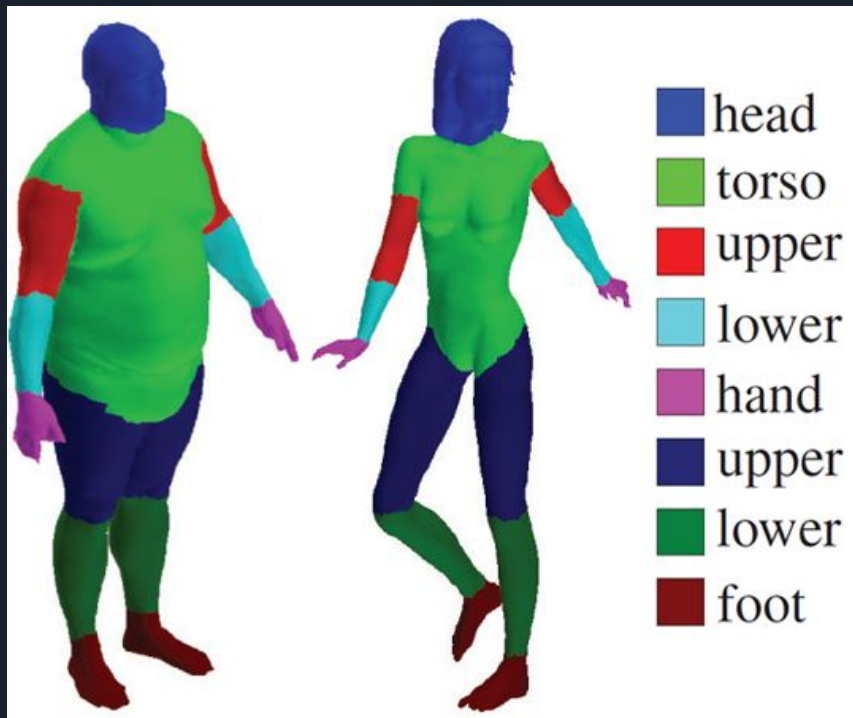
# Project objective



In this note, I will present a visual application in geometry processing, namely 3D shape segmentation

# 3D Segmentation

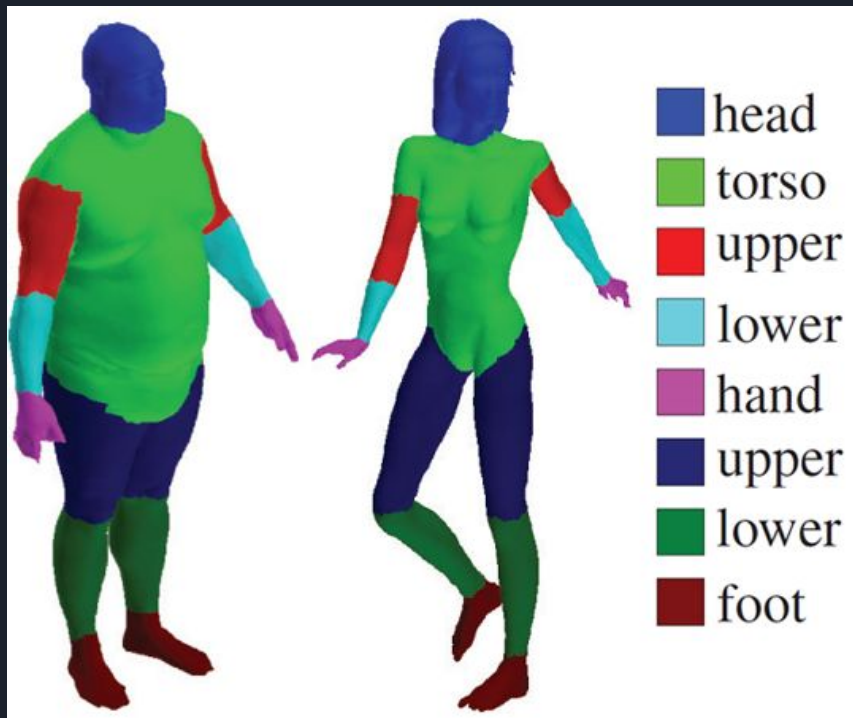
3D shapes are usually stored as a set of points, edges and triangles in a computer. The goal of segmentation is to provide labels for each point of each shape. For instance, if you are given a bunch of 3D shapes representing humans, the goal of segmentation is to successfully assign for each point the body part to which it belongs (“torso”, “arm”, “leg”...).





# 3D Segmentation

3D shapes are usually stored as a set of points, edges and triangles in a computer. The goal of segmentation is to provide labels for each point of each shape. For instance, if you are given a bunch of 3D shapes representing humans, the goal of segmentation is to successfully assign for each point the body part to which it belongs (“torso”, “arm”, “leg”...).





# Problems Associated With 3D Segmentation

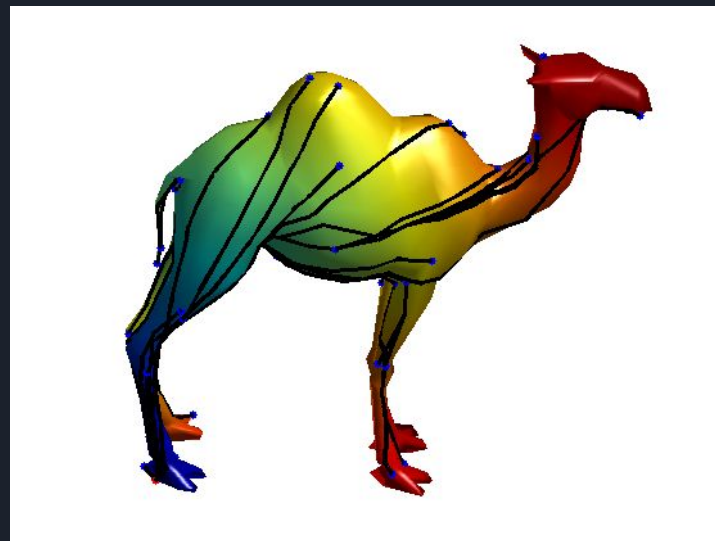
- The difficulty of this problem lies in the fact that you are only given point coordinates, which are poor features.
- Indeed, it is hopeless to characterize a point with its coordinates since they depend on the embedding, or pose, of the 3D shape.
- Think for instance of two human shapes, one of them having its right hand raised and not the other; the humans are identical, only their poses differ. Then, the right hand points of the two shapes will differ a lot, even though they share the same label.



## TDA to the rescue!

Thanks to their topological nature, persistence diagrams are intrinsic, meaning that they do not depend on the embedding, or pose, of the 3D shapes. Hence, they are good candidates for point features. To do this we thus need to define an intrinsic filtration.

This can be achieved with **geodesic distances**.



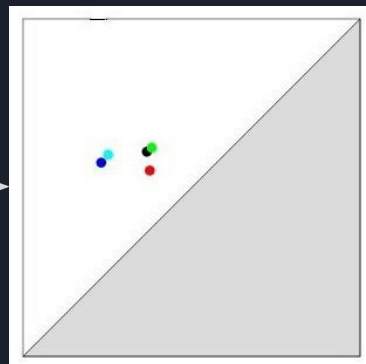
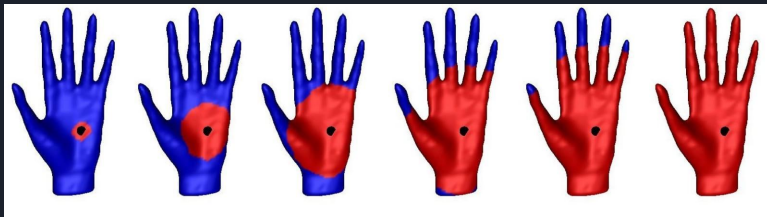


# Application to 3D Segmentation

Geodesic distances can then be used to define **geodesic balls**.

Again, by making  $r$  increase from 0 to infinity, we make the geodesic ball grow from the singleton  $\{x\}$  to the whole shape itself, which gives us an intrinsic filtration.

For example, take a look at the filtration displayed below on a 3D hand shape.





# Demo: Using Actual Data

Showcasing potential of this technique.

This demo utilizes a benchmark that is based on a set of polygonal models generously provided by Daniela Giorgi (IMATI-CNR)



# Motivation: MODE, Data Science & Topology

I'm a part of a start-up, MODE, that focuses on providing men a platform for fashion discovery.

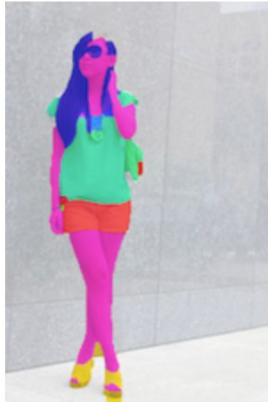
A part of the product focuses on segmenting people's outfits and understand trends. Equipped with this class's content, and through my interest in Data Science, I was motivated to explore TDA as means to solve this problem. Human Body segmentation was an interesting starting problem in the process that I attempted.



Superpixels



Pose estimation



Clothing parsing

- null
- shorts
- shoes
- purse
- top
- necklace
- hair
- skin



Pose re-estimation

