

# Report about

## TOPOLOGICAL DATA ANALYSIS

## Three persistence diagrams and comments

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#### Abstract

This report is intended to make a description of 3 different given datasets and perform persistence diagrams on all of them in order to determine the topological shape of each one.

#### 1 The dataset

The datasets we are going to study are just three bunches of points on the space. This points are represented on cartessian coordinates on a csv files by columns, X1, X2 and X3.

First, in order to have an idea of each of the datasets I have made it a simple R code that could bring some clues on its shape and could be useful to know in advanced to have an intuition about what their persistence diagrams should be like. (See the Appendix)

First, some summarys on the datasets have been done

```
> summary(data1)
                             x^2
         x1
          : -2.36374
   Min.
                       Min.
                              :-1.222399
                                            Min.
                                                   :-1.48675
   1st Qu.: -0.65768
                       1st Qu.: -0.451946
                                            1st Qu.: -0.50571
   Median : 0.05588
                       Median : -0.031955
                                            Median : -0.09062
   Mean
         : -0.01243
                       Mean : -0.003166
                                            Mean : -0.05599
                                            3rd Qu.: 0.39622
   3rd Qu.: 0.59328
                       3rd Qu.: 0.442404
         : 2.49243
                       Max.
                              : 1.242441
                                                   : 1.24336
  > summary(data2)
10
          : -4.6773
   Min.
                      Min.
                             : -3.45492
                                          Min.
                                                 :-1.466455
   1st Qu.: -2.0608
                      1st Qu.: -1.53789
                                          1st Qu.: -0.673516
12
13
   Median : 0.1211
                      Median : -0.01564
                                          Median: 0.037610
          : 0.1652
                      Mean
                            : -0.01442
                                          Mean : -0.007514
   Mean
   3rd Qu.: 2.3534
                      3rd Qu.: 1.46430
                                          3rd Qu.: 0.645450
15
                             : 3.41390
  Max.
          : 4.6326
                      Max.
                                          Max.
                                                 : 1.388798
  > summary(data3)
17
18
                                                 :-1.546380
          :-2.55408
                             :-1.23625
   Min.
                       Min.
                                           Min.
19
   1st Qu.: -0.86303
                       1 st Qu.: -0.62039
                                           1st Qu.: -0.096799
20
   Median : -0.07918
                       Median : -0.07707
                                           Median : 0.011875
   Mean
         : -0.04447
                       Mean
                             : -0.01162
                                           Mean
                                                 :-0.001196
22
   3rd Qu.: 0.78682
                       3rd Qu.: 0.64134
                                           3rd Qu.: 0.106685
   Max. : 2.35220
                       Max. : 1.17474
                                           Max. : 1.441551
```

This result give us an idea on where the datasets are located on the space. By looking some information we can have also a little intuition about the noise but we require another analysis to be able to detect it propperly and also have an intuition about the topological shape. For this we have plotted the pair diagrams and also the 3D plots as it can be seen on the following figures.

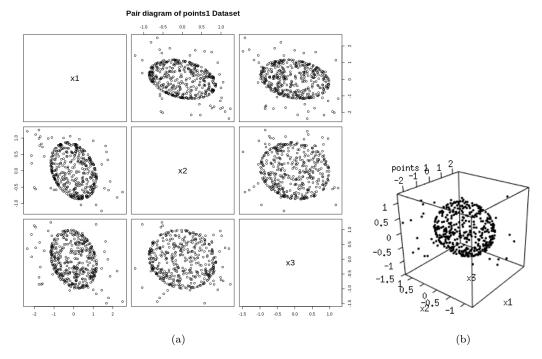


Figure 1: Pair diagram and 3D plot of the points1 dataset

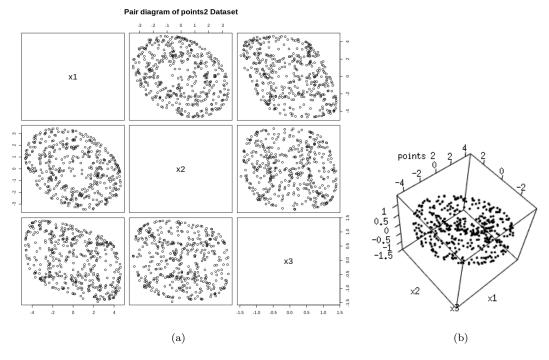


Figure 2: Pair diagram and 3D plot of the points2 dataset

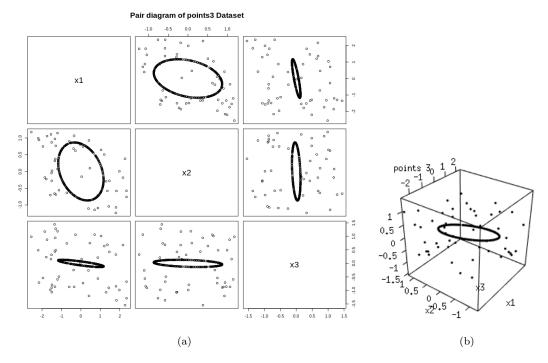


Figure 3: Pair diagram and 3D plot of the points3 dataset

On the figures 1, 2 and 3 we are able to visualize space like representation of the given datasets. Since our brain is kind of a pattern searching machine, we are already able to interpret these images and conclude that, the points1 dataset could be something similar of a noisy sphere\*. The points3 dataset could be something similar of a noisy circle. When it comes the turn of the points2 dataset, the decision is not so obvious since it is very noisy but one could see, however, that a very noisy torus shape can be seen with a bite of imagination.

By looking the borders of the distinguishable shapes that appear on the points1 and points2 datasets, we can also suspect that the shapes are *empty* or, in other words, the torus and the sphere would be 2-d shapes.

All the previous analysis has been very qualitative and poor since our brains could, sometimes, trick us, and we have not measured anything. To really study the topological shapes behind the datasets, we will perform on the next section the persistence diagram of each one.

## 2 Persistence diagrams

On this section we are going to perform persistence diagrams on each of the datasets that we have already described. We have intended two strategies, to plot the KDE diagrams and to plot the Vietoris-Rips diagram. Since the second strategy is more time consuming and also the results were not clear when it came to determine the topological shape, I have finally done the analysis by looking on the KDE diagrams.

<sup>\*</sup>In fact, depending on the axis representation, it would be more precise to call it ellipsoid. However, we are dealing with topological shapes so by sphere (or a shape x) we truly mean a shape topologically identical of a sphere (or x)

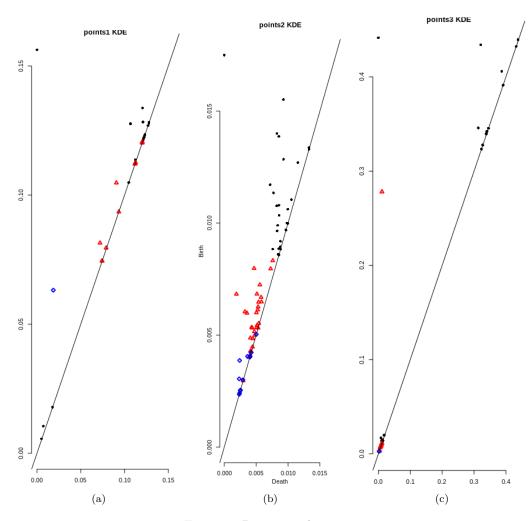


Figure 4: Persistent diagrams

On the figure 4 we can see all the KDE diagrams that have been ploted, one for each dataset. On the figure 4a, corresponing to the diagram for the points1 dataset, we can easily see a blue rhomboid that appears to be far from the diagonal respect from the other points. This fact, means that we have a shape with a 2 dimensional hole. This result confirms the suspicions that raised us the previous section, since we have postulated that it was a 2D sphere like shape. I have used a distance of 0.05 to determine which points are close enough to be neighbours.

On the figure 4c, corresponding to the diagram for the points3 dataset, we can easily see a red triangle that appears to be far from the diagonal respect from the other points. This fact means that we have a shape with a 1 dimensional hole. This result confirms the suspicions that raised us the previous section, since we have postulated that it was a circle like shape. I have used, again, a maximum distance of 0.05.

On the figure 4b, corresponding to the diagram for the points2 dataset, the results are not so obvious to interpret. This was also expected from the fact that it has been difficult to observe the shape even with our own eyes on the previous section. However we have postulated that it could be a very noisy torus. If that was the case we should obtain two 1 dimensional holes and one 2 dimensional hole (and the noise). We can see that two triangles appear to be slightly far form the diagonal respecting the other triangles, so that could prove the two one dimensional holes. The same happens with a blue rhomboid that seems



to be lightly far from the diagonal respect to the other rhomboids meaning one two dimensional hole could be there. However, even in this case, the noise is comparable with the points we expect to obtain so a further analysis must be performed in order to clean the data and determine whether we are, or not, in front of a 2d torus.

## 3 Results

points  $\rightarrow$  Sphere, points  $\rightarrow$  Very noisy torus (?), points  $\rightarrow$  Circle



### **Appendix**

### 3.1 Dataset basic analysis code

Here you can see the basic code that has been done on the first place in order to have an intuition of the datasets to be dealed with.

```
#Import dataset
   data1 = read.csv("/home/genis/Escritorio/tda/points1.csv")
   data2 = read.csv("/home/genis/Escritorio/tda/points2.csv")
data3 = read.csv("/home/genis/Escritorio/tda/points3.csv")
   # Summary
   summary (data1)
10 summary (data2)
   summary(data3)
11
14 # Visualize the dataset
15
pairs (data1, main = "Pair diagram of points1 Dataset", pch = 21)
   pairs (data2, main = "Pair diagram of points2 Dataset", pch = 21)
pairs (data3, main = "Pair diagram of points3 Dataset", pch = 21)
20 # 3D Plot
22 library (rgl)
plot3d(data1, xlab="x1", ylab="x2", zlab = "x3", main="points 1")
plot3d(data2, xlab="x1", ylab="x2", zlab = "x3", main="points 2")
plot3d(data3, xlab="x1", ylab="x2", zlab = "x3", main="points 3")
```

#### 3.2 Code to make the persistence diagrams of each of the datasets

Here you can see the code (that is, in fact, the continuation of the previous part) that let me plot the persistence diagrams.

```
1 # PERSISTENCE
 library("TDA")
 4 ##Points1
 6 Xlim <-c(-2.5,2.5)
   Ylim < c (-1.5, 1.5)
   Zlim \leftarrow c(-1.5, 1.5)
10 by <- 0.05
12 # Persitent homology on points1 with KDE function and VR
14 DiagKDE <- gridDiag(X=data1,
                                 \begin{aligned} & \text{FUN} = \text{kde}, \ \text{h=0.3}, \ \text{sublevel=FALSE}, \\ & \text{lim=} \ \text{cbind} \left( \text{Xlim}, \ \text{Ylim}, \ \text{Zlim} \right), \ \text{by=by}, \end{aligned} 
15
                                 library="Dionysus", printProgress = TRUE)
plot(x = DiagKDE[["diagram"]], main="points1 KDE")
#DiagVR <- ripsDiag(X=data1,
                                 maxdimension = 1, maxscale = 5, dist = 'euclidean',
20 #
# library="GUDHI", printProgress = FALSE)
22 #plot(x = DiagVR[["diagram"]], main="Vietoris-Rips Diagram")
24 #Points2
```



```
26 \text{ Xlim } \leftarrow c(-4.7, 4.7)
27 \text{ Ylim } \leftarrow c(-3.5, 3.5)
^{28} Zlim <-c(-1.5,1.5)
29
   by < -0.059
30
31
32 # Persitent homology on points2 with KDE function and VR
   DiagKDE <- gridDiag(X=data2,
34
35
                            FUN = kde, h=0.45, sublevel=FALSE,
                            lim= cbind(Xlim, Ylim, Zlim), by=by,
36
                             library="Dionysus", printProgress = TRUE)
37
   plot(x = DiagKDE[["diagram"]], main="points2 KDE")
39 #DiagVR <- ripsDiag(X=data2,
                            \begin{array}{lll} {\rm maxdimension} = 1, & {\rm maxscale} = 5, & {\rm dist} = {\rm 'euclidean'}, \\ {\rm library} = {\rm "GUDHI"}, {\rm printProgress} = {\rm FALSE}) \end{array}
40 #
41 #
42 #plot(x = DiagVR[["diagram"]], main="Vietoris-Rips Diagram")
43
44 #Points3
45
46 Xlim <-c(-2.6,2.4)
   Ylim < c (-1.25, 1.25)
47
   Zlim \leftarrow c(-1.6, 1.6)
48
49
50
   by < -0.05
51
_{\rm 52} # Persitent homology on points3 with KDE function and VR
53
54 DiagKDE <- gridDiag(X=data3,
                            FUN = kde, \ h\!=\!0.25, \ sublevel\!=\!\!FALSE,
                            lim= cbind(Xlim, Ylim, Zlim), by=by,
56
                             library="Dionysus", printProgress = TRUE)
57
plot(x = DiagKDE[["diagram"]], main="points3 KDE")
59 #DiagVR <- ripsDiag (X=data3,
60 #
                            maxdimension = 1, maxscale = 5, dist = 'euclidean',
# library="GUDHI", printProgress = FALSE)
#plot(x = DiagVR[["diagram"]], main="Vietoris-Rips Diagram")
```