

Clustering

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IPRODAM3D - Research group

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Programa



- 1. Kmenas
- 2. Mean Shift
- 3. DBSCAN

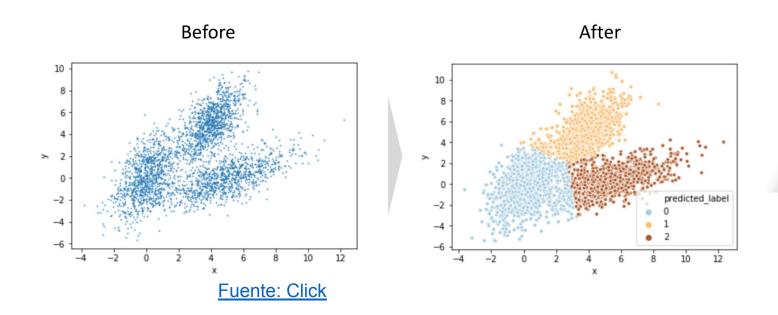
Nombre del curso

Nombre del docente



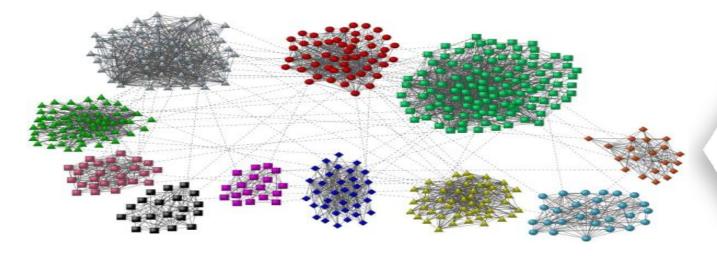
Clustering

• Técnica de *machine learning* que permite agrupar, de manera no supervisada un conjunto de datos de acuerdo a su estructura o características similares.



Clustering

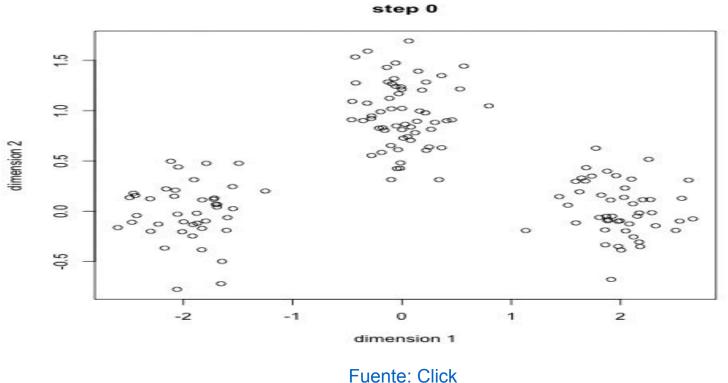
 El conjunto de datos que pertenecen a un mismo grupo deben tener características propiedades similares, y a la vez, características muy disímiles respecto a elementos de otros grupos





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K-Means





Algorithm: K-Means

Input —Dataset

—number of clusters

Output —K clusters

Step-1: —Initialize K centers of the cluster

Step-2: —Repeat

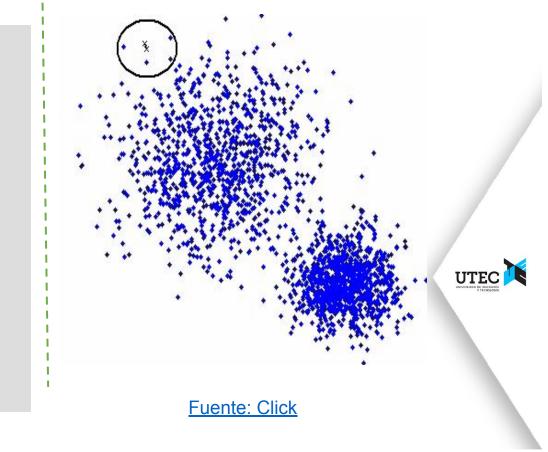
—Calculate the mean of all the objects belonging to that cluster

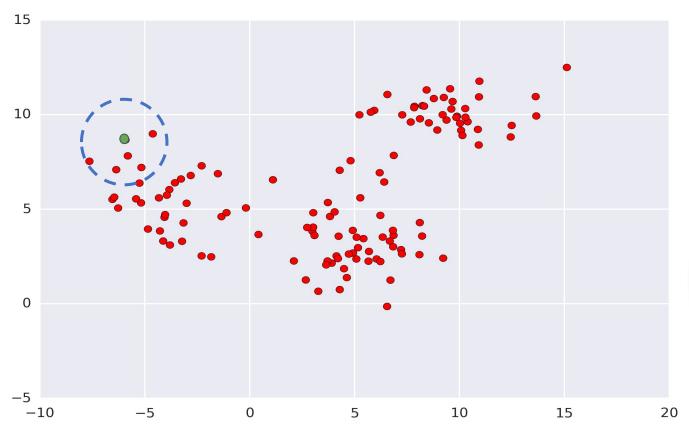
$$\mu_k = \frac{1}{N_k} \sum_{q=1}^{N_k} x_q$$

where μ_k is the mean of cluster k and N_k is the number of p belonging to that cluster

- —Assign objects to the closest cluster centroid
- —Update cluster centroids based on the assignment
- —Until centroids do not change

Mean-Shift







Mean-Shift

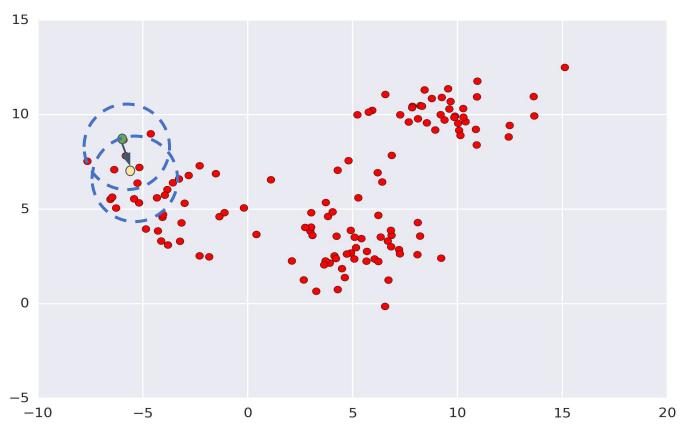
Smoothing kernel

$$f(x) = \sum_{m} K(x - x_m) = \sum_{m} k(\frac{x - x_m}{h})$$

Gaussian Kernel

$$k(x) = (2\pi)^{-d/2} exp(-\frac{1}{2}||x||^2)$$



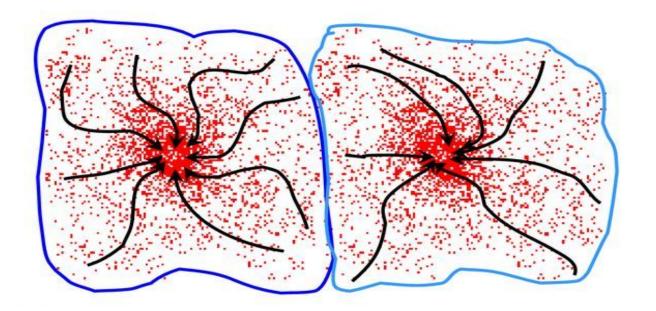




- Calculamos el mean shift vector
- Movemos el kernel windows

$$\hat{x} = \frac{\sum_{m} x_{m} exp(-\frac{1}{2} || \frac{x - x_{m}}{h} ||^{2})}{\sum_{m} exp(-\frac{1}{2} || \frac{x - x_{m}}{h} ||^{2})} - x$$



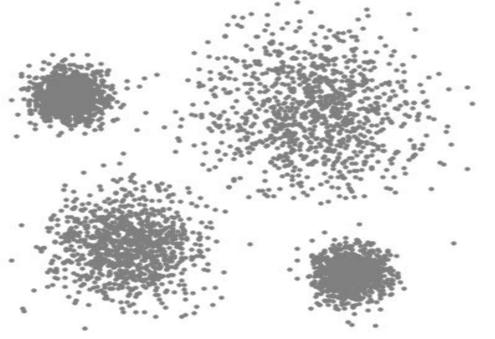




- 1. Elegir un kernel y un radio
- 2. Por cada punto p:
 - a. Centrar una ventana en el punto p
 - b. Computar la media de los datos en la ventana de búsqueda
 - c. Centrar la ventana en la nueva localización
 - d. Repetir (b,c) hasta que converga
- Asignar el cluster el centroide a todos los nodos que le dieron orígen.



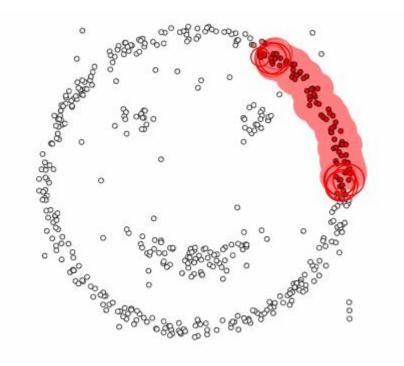
Mean-Shift





Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

epsilon = 1.00 minPoints = 4



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ALGORITHM 1: Pseudocode of Original Sequential DBSCAN Algorithm

```
Input: DB: Database
   Input: \varepsilon: Radius
   Input: minPts: Density threshold
   Input: dist: Distance function
   Data: label: Point labels, initially undefined
1 foreach point p in database DB do
                                                                                // Iterate over every point
        if label(p) \neq undefined then continue
                                                                                // Skip processed points
       Neighbors N \leftarrow \text{RangeQuery}(DB, dist, p, \varepsilon)
                                                                               // Find initial neighbors
       if |N| < minPts then
                                                                               // Non-core points are noise
            label(p) \leftarrow Noise
            continue
6
        c \leftarrow \text{next cluster label}
                                                                               // Start a new cluster
        label(p) \leftarrow c
8
        Seed set S \leftarrow N \setminus \{p\}
                                                                               // Expand neighborhood
        foreach q in S do
10
            if label(q) = Noise then label(q) \leftarrow c
11
            if label(q) \neq undefined then continue
12
            Neighbors N \leftarrow \text{RangeQuery}(DB, dist, q, \varepsilon)
13
            label(q) \leftarrow c
14
            if |N| < minPts then continue
                                                                               // Core-point check
15
            S \leftarrow S \cup N
16
```



Gracias

Inserta texto adicional aquí



