INF391 - Reconocimiento de Patrones en Minería de Datos

Tarea 1: Técnicas de *Clustering*

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Introducción

En esta tarea se exploran distintas técnicas de reconocimiento de patrones basadas en *clustering* vistas en cátedra. Para ello, se cuenta con tres pequeños *datasets* con distintas características, que servirán para contrastar la aptitud que cada técnica posee para cada caso.

Luego de la experimentación, se responden las dos preguntas conceptuales planteadas en el enunciado.

Parte I

Primero, se prepara la ingesta de datos.

In [1]:
```
import os.path
import numpy as np

def ingest_dataset(txt_dir):
    dataset = list()
    if os.path.exists(txt_dir):
        with open(txt_dir, 'r') as f:
            for line in f.readlines():
                data_point = line.split()
                x_coord, y_coord = float(data_point[0]), float(data_point[1])
                dataset.append([x_coord, y_coord])
    return np.array(dataset)
```

Y se instancian los tres datasets.

In [2]:
```
smile = ingest_dataset('smile.txt')
mouse = ingest_dataset('mouse.txt')
spiral = ingest_dataset('spiral.txt')
```

(Hacer plot y breve análisis de cada dataset: hablar sobre cantidad de datos, presencia obvia de clusters, densidad de éstos, convexidad, etc.)

A continuación, se procede a aplicar las técnicas de *clustering*.

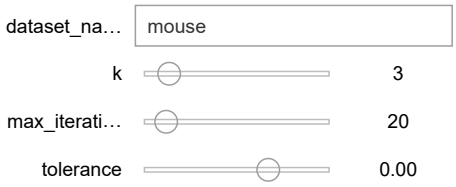
1. K-Means

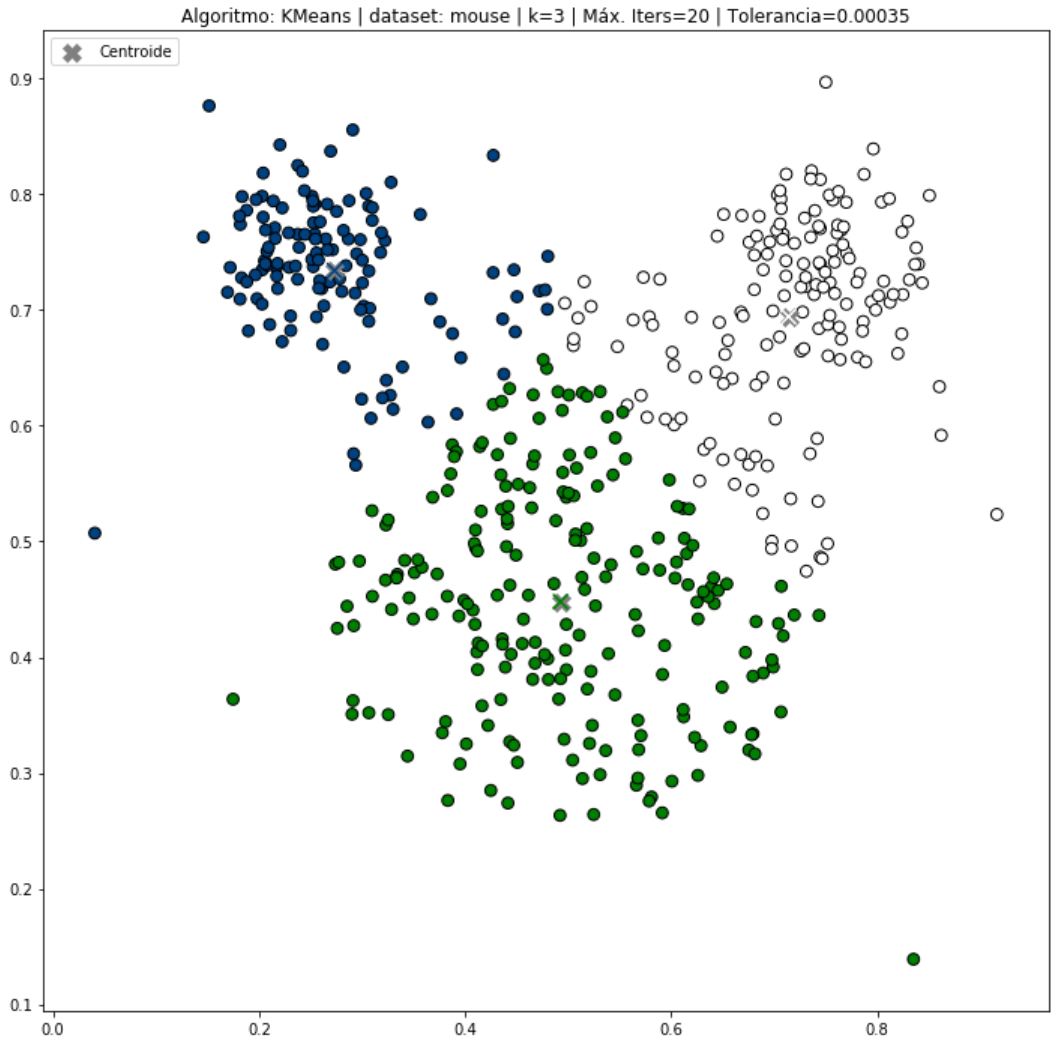
In [64]:

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from ipywidgets import interact
from ipywidgets import FloatSlider

def apply_kmeans(dataset, k, max_iterations=300, tolerance=1e-4):
    kmeans = KMeans(
        n_clusters=k,
        init='random',
        n_init=1,
        max_iter=max_iterations,
        tol=tolerance,
        random_state=0,
    )
    kmeans.fit(dataset)
    return kmeans.cluster_centers_, kmeans.labels_

@interact(
    dataset_name=['smile', 'mouse', 'spiral'],
    k=(2,10, 1),
    max_iterations=(10, 100, 10),
    tolerance=FloatSlider(min=5e-5, max=5e-4, step=5e-5, continuous_update=False),
)
def plot_kmeans(dataset_name, k, max_iterations, tolerance):
    if dataset_name == 'smile':
        dataset = smile
    elif dataset_name == 'mouse':
        dataset = mouse
    elif dataset_name == 'spiral':
        dataset = spiral
    centroids, labels = apply_kmeans(dataset, k, max_iterations, tolerance)
    plt.figure(figsize=(12,12))
    plt.scatter(dataset[:, 0], dataset[:, 1], marker='o', c=labels,
                edgecolors='k', s=60, cmap=plt.cm.ocean)
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='X', s=150,
                linewidths=.5, c='gray', cmap=plt.cm.ocean, label='Centroide')
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', s=100,
                linewidths=2, c=list(range(len(centroids))),
                cmap=plt.cm.ocean)
    plt.title('Algoritmo: KMeans | dataset: {} | k={} | Máx. Iters={} | Tolerancia={}'.format(dataset_nam
    plt.legend(loc='upper left')
```





Análisis K-Means

Bla...

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2. Agglomerative Hierarchical Clustering

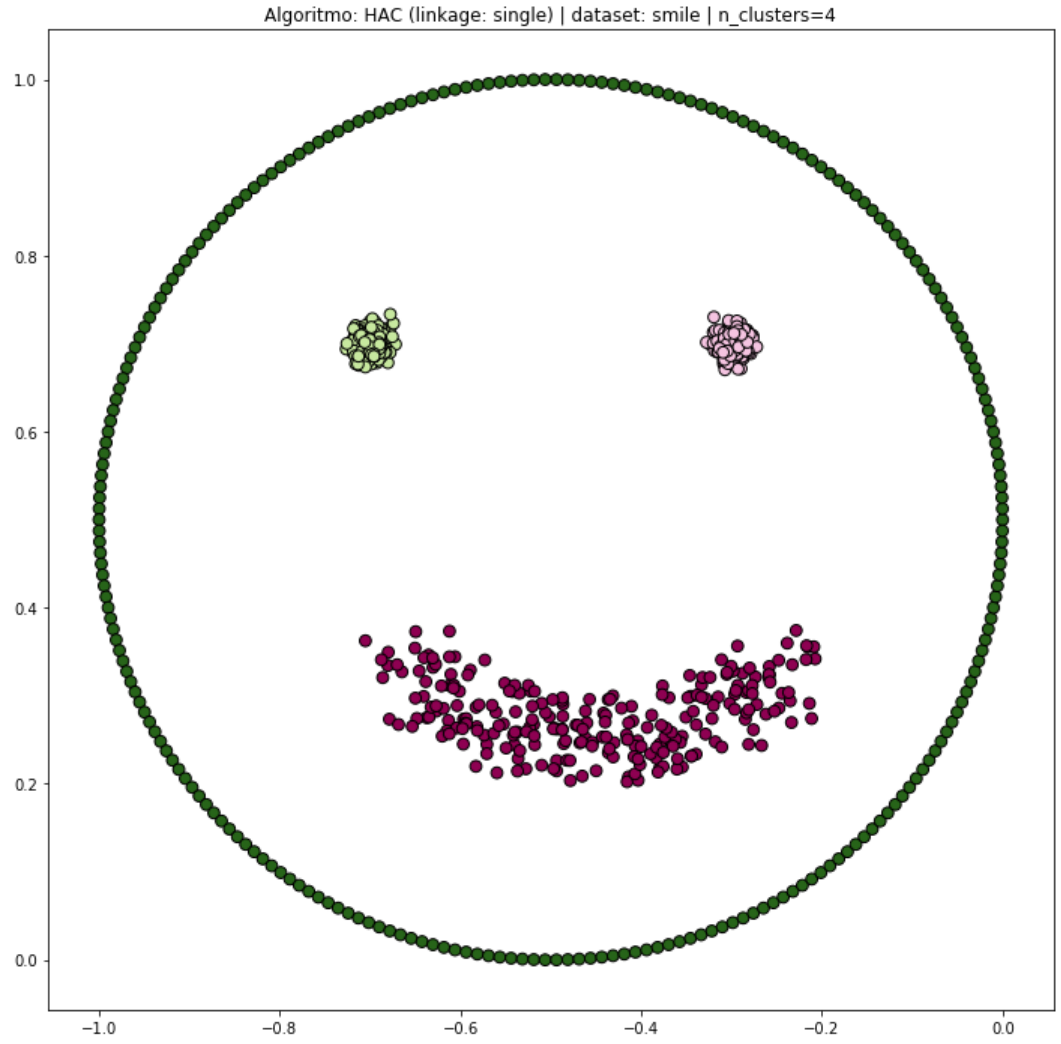
In [42]:

```
from sklearn.cluster import AgglomerativeClustering

def apply_hac(dataset, linkage, n_clusters):
    hac = AgglomerativeClustering(n_clusters=n_clusters, linkage=linkage)
    hac.fit(dataset)
    return hac.labels_

@interact(
    dataset_name=['smile', 'mouse', 'spiral'],
    linkage=['single', 'complete'],
    n_clusters=(2,10, 1),
)
def plot_hac(dataset_name, linkage, n_clusters):
    if dataset_name == 'smile':
        dataset = smile
    elif dataset_name == 'mouse':
        dataset = mouse
    elif dataset_name == 'spiral':
        dataset = spiral

    labels = apply_hac(dataset, linkage, n_clusters)
    plt.figure(figsize=(12,12))
    plt.scatter(dataset[:, 0], dataset[:, 1], marker='o', c=labels,
                edgecolors='k', s=60, cmap=plt.cm.PiYG)
    plt.title('Algoritmo: HAC (linkage: {}) | dataset: {} | n_clusters={}'.format(linkage, dataset_name,
```

dataset_na… smile

linkage single

n_clusters 4



Análisis Agglomerative Hierarchical Clustering

Bla...

3. DBSCAN

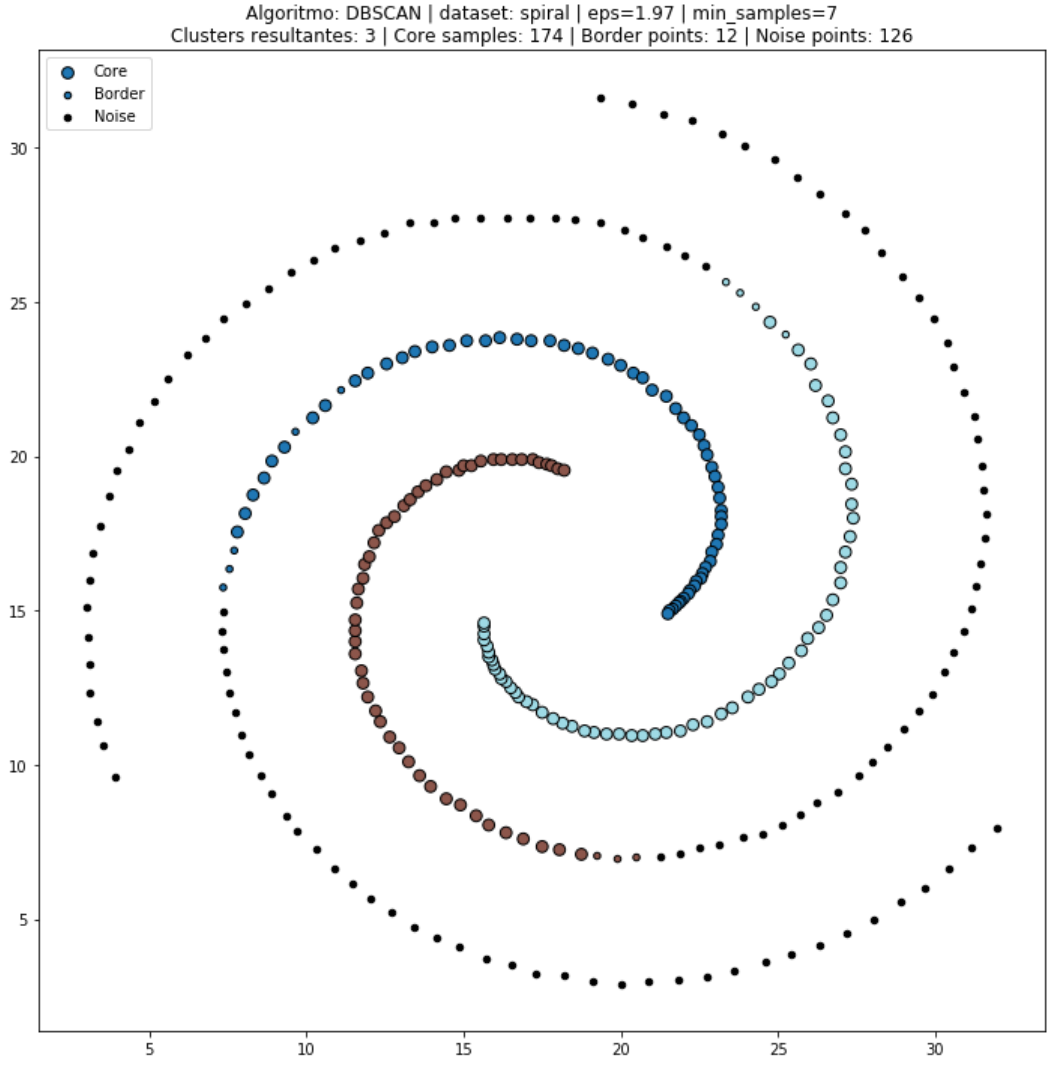
In [62]:

```
from sklearn.cluster import DBSCAN

def apply_dbscan(dataset, min_pts, eps):
    dbscan = DBSCAN(eps=eps, min_samples=min_pts)
    dbscan.fit(dataset)
    core_samples_mask = np.zeros_like(dbscan.labels_, dtype=bool)
    core_samples_mask[dbscan.core_sample_indices_] = True
    noise_points_mask = (dbscan.labels_ == -1)
    border_points_mask = np.zeros_like(dbscan.labels_, dtype=bool)
    border_points_mask[~core_samples_mask & ~noise_points_mask] = True

    # Number of clusters in labels, ignoring noise if present.
    n_clusters_ = len(set(dbscan.labels_)) - (1 if -1 in dbscan.labels_ \
                                              else 0)
    n_noise_ = list(dbscan.labels_).count(-1)
    return dbscan.labels_, n_clusters_, n_noise_, core_samples_mask, \
        border_points_mask, noise_points_mask

@interact(
    dataset_name=['smile', 'mouse', 'spiral'],
    min_pts=(1,50, 1),
    eps=(0.01, 5.0, 0.01),
)
def plot_dbscan(dataset_name, min_pts, eps):
    if dataset_name == 'smile':
        dataset = smile
    elif dataset_name == 'mouse':
        dataset = mouse
    elif dataset_name == 'spiral':
        dataset = spiral
    labels, n_clusters, n_noise, core_samples_mask, border_points_mask,\
    noise_points_mask = apply_dbscan(dataset, min_pts, eps)
    core_points = dataset[core_samples_mask]
    border_points = dataset[border_points_mask]
    noise_points = dataset[noise_points_mask]
    n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
    plt.figure(figsize=(12,12))
    # Plot core samples
    plt.scatter(core_points[:, 0], core_points[:, 1], marker='o',
                c=labels[core_samples_mask], edgecolors='k', s=60,
                cmap=plt.cm.tab20, label='Core')
    # Plot border points
    plt.scatter(border_points[:, 0], border_points[:, 1], marker='o',
                c=labels[border_points_mask], edgecolors='k', s=20,
                cmap=plt.cm.tab20, label='Border')
    # Plot noise points
    plt.scatter(noise_points[:, 0], noise_points[:, 1], marker='o',
                c='black', edgecolors='k', s=20,
                cmap=plt.cm.tab20, label='Noise')
    plt.title('Algoritmo: DBSCAN | dataset: {} | eps={} | min_samples={}\n\
Clusters resultantes: {} | Core samples: {} | Border points: {} | Noise points: {}'
              .format(dataset_name, eps, min_pts, n_clusters,
                      len(core_points), len(border_points),
                      len(noise_points)))
    plt.legend(loc='upper left')

```

dataset_na… spiral

min_pts 7

eps 1.97



Análisis DBSCAN

Bla...

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4. Mean-shift

In [67]:

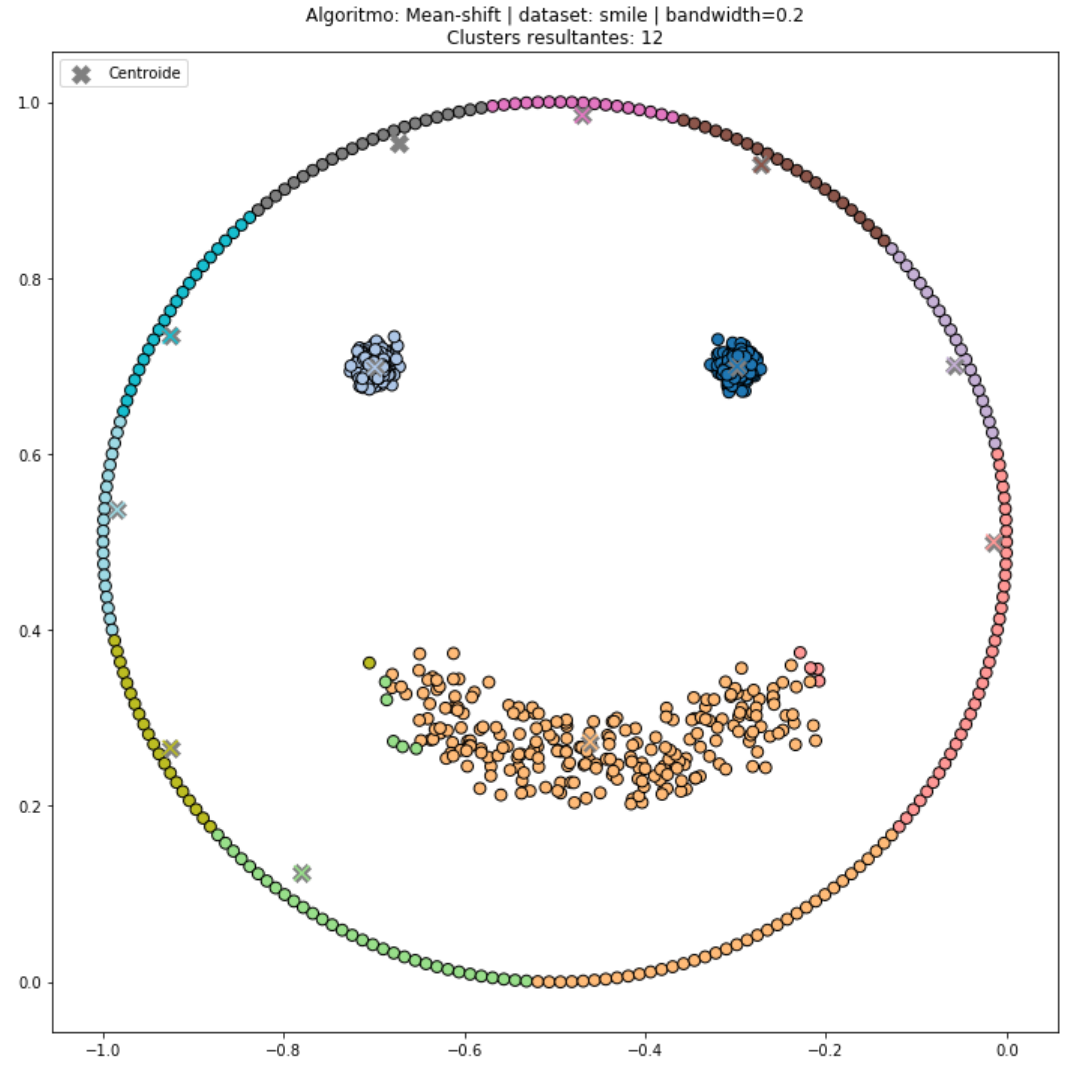
```
from sklearn.cluster import MeanShift

def apply_meanshift(dataset, bandwidth):
    meanshift = MeanShift(bandwidth=bandwidth)
    meanshift.fit(dataset)
    return meanshift.cluster_centers_, meanshift.labels_

@interact(
    dataset_name=['smile', 'mouse', 'spiral'],
    bandwidth=(0.1, 10, 0.1),
)
def plot_kmeans(dataset_name, bandwidth):
    if dataset_name == 'smile':
        dataset = smile
    elif dataset_name == 'mouse':
        dataset = mouse
    elif dataset_name == 'spiral':
        dataset = spiral
    centroids, labels = apply_meanshift(dataset, bandwidth=bandwidth)
    plt.figure(figsize=(12,12))
    plt.scatter(dataset[:, 0], dataset[:, 1], marker='o', c=labels,
                edgecolors='k', s=60, cmap=plt.cm.tab20)
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='X', s=150,
                linewidths=.5, c='gray', cmap=plt.cm.tab20, label='Centroide')
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', s=100,
                linewidths=2, c=list(range(len(centroids))),
                cmap=plt.cm.tab20)
    plt.title('Algoritmo: Mean-shift | dataset: {} | bandwidth={}\nClusters resultantes: {}'.format(datas
    plt.legend(loc='upper left')
```

dataset_na... smile

bandwidth 0.20



Análisis Mean-shift

Bla...

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5. Spectral clustering

In [ ]:

```
from sklearn.cluster import SpectralClustering

def generate_affinity_matrix(dataset, method):
    # METHOD -> PARAMETERS
    # epsilon-ball -> epsilon
    # k-nearest -> k
    # fully connected -> (no parameters)
    # RBF kernel -> delta (kernel width)

def apply_spectral(dataset, n_clusters, random_state=0, n_init=1,):
    return
```