jupyter 04_TP_AprendizajeNoSupervisado Last Checkpoint: hace unos segundos (autosaved)

# Practico Mentoria - Aprendizaje No Supervisado

El objectivo de este practico es realizar Clustering sobre el Dataset de las Caracteristicas de los jugadores.

De forma de juntar en los clusters a los jugadores con caracteristicas similares, y en particular de este practico analizar si estos clusters se corresponden con la posicion en la que juegan estos jugadores.

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## Importaciones

In [1]:
```
%load_ext autoreload
%autoreload 2

%matplotlib inline
```

In [2]:
```
#paquetería...

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy as sp
import warnings

from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

In [3]:
```
warnings.filterwarnings('ignore')

sns.set_style("whitegrid")
```

In [4]:
```
# Seteamos una semilla para Reproducibilidad
np.random.seed(1)
```

---

## Carga del Dateset

In [5]:
```
#daterio...

path = 'https://raw.githubusercontent.com/diplodatos2019mentoria/Aprendizaje_No_Supervisado/master/'

player_df = pd.read_csv(path + 'Datasets/football_player_full.csv', index_col = 'player_name')

print("Shape 'player_df' = {}".format(player_df.shape))

# Copy Dataframe
player2_df = player_df.copy(deep = False)
```

```
Shape 'player_df' = (9925, 36)
```

In [6]:
```
player2_df.sample(10)
```

Out[6]:

| player_name | overall_rating | potential | crossing | finishing | heading_accuracy | short_passing | volleys | dribbling | curve | free_kick_accuracy | ... | penalties | ma |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ariel Borysiuk | 66.12 | 74.38 | 56.92 | 49.79 | 49.38 | 67.25 | 58.88 | 64.08 | 45.79 | 52.38 | ... | 49.21 | |
| Sava Miladinovic Bento | 58.00 | 64.43 | 51.07 | 44.86 | 42.93 | 58.14 | 46.21 | 58.29 | 50.64 | 52.86 | ... | 49.50 | |
| Dusan Tadic | 78.16 | 81.88 | 81.52 | 68.36 | 56.64 | 78.60 | 69.84 | 81.36 | 79.72 | 73.08 | ... | 76.28 | |
| Samuel Souprayen | 64.24 | 71.76 | 58.29 | 20.76 | 57.19 | 56.90 | 22.10 | 55.71 | 61.67 | 31.67 | ... | 42.71 | |
| Daniele Croce | 67.68 | 67.68 | 63.32 | 51.58 | 44.74 | 72.16 | 53.89 | 66.16 | 54.95 | 58.74 | ... | 59.74 | |
| John Arne Riise | 76.32 | 77.64 | 84.00 | 60.82 | 67.05 | 78.32 | 75.05 | 69.41 | 74.05 | 77.55 | ... | 70.59 | |

In [7]:
```
player2_df.dtypes
```

Out[7]:
```
overall_rating        float64
potential             float64
crossing              float64
finishing             float64
heading_accuracy      float64
short_passing         float64
volleys               float64
```

```
dribbling            float64
curve                float64
free_kick_accuracy   float64
long_passing         float64
ball_control         float64
acceleration         float64
sprint_speed         float64
agility              float64
reactions            float64
balance              float64
shot_power           float64
jumping              float64
```

In [8]:
```
# NO

player2_position_list = player2_df.position.tolist()
```

In [9]:
```
player2_df = player2_df[[
    'overall_rating', 'potential', 'crossing', 'finishing', 'heading_accuracy',
    'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
    'long_passing', 'ball_control', 'acceleration', 'sprint_speed', 'agility',
    'reactions', 'balance', 'shot_power', 'jumping', 'stamina', 'strength',
    'long_shots', 'aggression', 'interceptions', 'positioning', 'vision',
    'penalties', 'marking', 'standing_tackle', 'sliding_tackle',
    'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes',
]]
```

In [10]:
```
player2_df.dtypes
```

Out[10]:
```
overall_rating       float64
potential            float64
crossing             float64
finishing            float64
heading_accuracy     float64
short_passing        float64
volleys              float64
dribbling            float64
curve                float64
free_kick_accuracy   float64
long_passing         float64
ball_control         float64
acceleration         float64
sprint_speed         float64
agility              float64
reactions            float64
balance              float64
shot_power           float64
jumping              float64
```

In [11]:
```
player2_df.sample(10)
```

Out[11]:

| player_name | overall_rating | potential | crossing | finishing | heading_accuracy | short_passing | volleys | dribbling | curve | free_kick_accuracy | ... | vision | penalt |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rolando Mandragora | 60.93 | 73.13 | 47.87 | 44.33 | 48.07 | 69.33 | 41.67 | 60.07 | 49.67 | 33.67 | ... | 65.07 | 31 |
| Daniel Pinillos | 59.71 | 66.14 | 59.57 | 32.14 | 48.14 | 48.29 | 33.14 | 52.29 | 57.57 | 39.14 | ... | 43.86 | 46 |
| Stopira | 60.25 | 65.00 | 56.00 | 28.00 | 32.00 | 49.00 | 32.00 | 44.00 | 47.00 | 42.00 | ... | 51.00 | 45 |
| Kakha Kaladze | 78.50 | 83.10 | 67.30 | 32.80 | 77.10 | 71.20 | 46.00 | 51.70 | 44.00 | 48.30 | ... | 61.00 | 64 |
| Sergi Darder | 69.43 | 75.61 | 48.91 | 39.13 | 35.65 | 77.17 | 36.04 | 63.83 | 61.87 | 54.26 | ... | 75.00 | 38 |
| Zeljko Brkic | 75.00 | 77.12 | 18.50 | 19.00 | 17.50 | 32.71 | 16.58 | 20.17 | 17.88 | 18.42 | ... | 27.33 | 31 |
| Stephen Elliott | 66.50 | 70.93 | 52.79 | 67.14 | 65.64 | 59.79 | 61.14 | 64.21 | 52.00 | 47.71 | ... | 64.93 | 63 |

> ### Aplicar Clustering sobre las features de los jugadores

Usar [K-Means](#) para el clustering.

Probar primero con 4 clusters, este numero se debe a cantidad de clases con respecto a la posicion de los jugadores:

- **GK**: Goalkeeper (Arquero)
- **DEF**: Defenser (Defensor)
- **MID**: Midfielder (Mediocampistas)
- **FW**: Forward (Delantero)

Luedo de hacer clustering, ver cuantos elementos tiene cada cluster.

In [12]:
```
# TODO

km_pred = KMeans(n_clusters = 4, random_state = 42).fit_predict(player2_df)
km_pred
```

Out[12]:
```
array([0, 3, 2, ..., 0, 3, 2])
```

In [13]:
```
#resultó algo así...
```

```
pd.concat([player_df['position'].reset_index(), pd.DataFrame(km_pred, columns = ['cluster'])], axis = 1).set_index('player_name'
```

Out[13]:

| player_name | position | cluster |
|---|---|---|
| Aaron Appindangoye | DEF | 0 |
| Aaron Cresswell | DEF | 3 |
| Aaron Doran | MID | 2 |
| Aaron Galindo | DEF | 0 |
| Aaron Hughes | DEF | 0 |
| Aaron Hunt | MID | 2 |
| Aaron Kuhl | MID | 0 |
| Aaron Lennon | MID | 2 |
| Aaron Lennox | GK | 1 |
| Aaron Meijers | MID | 3 |

In [14]:

```python
#side by side...
from IPython.display import display_html

def siamesas(*args):
    html_str = ''
    spaciador = '<table style="min-width: 30px !important;"><tr style="min-width: 30px !important; background:none !important;">
    for df in args:
        html_str += df.to_html() + spaciador

    display_html(html_str.replace('table', 'table style = "display:inline"'), raw = True)
```

In [15]:

```python
#clases originales...
#... y predichas.

siamesas(pd.DataFrame(player_df.position.value_counts()), pd.DataFrame(pd.DataFrame(km_pred, columns = ['cluster']).cluster.valu
```

| | position |
|---|---|
| DEF | 3664 |
| MID | 3473 |
| FW | 1919 |
| GK | 869 |

| | cluster |
|---|---|
| 2 | 3506 |
| 3 | 2877 |
| 0 | 2673 |
| 1 | 869 |

> ***Evaluar resultados***

Evaluar los resultados del clustering usando una medida como la Pureza.

**Hint 1**: Puede que en los clusters haya confusion entre las distintas posiciones dentro del campo de juego, esto no esta mal. Ya que hay que recordar que las posiciones estan simplicadas.

**Hint 2**: Un indicador de mala calidad es que haya clusters muy chiquitos y uno muy grande, lo cual indica que en el espacio no se distinguen bien grupos separados y hay que usar otro espacio.

In [16]:

```python
#purity...
from sklearn import metrics

contingency_matrix = metrics.cluster.contingency_matrix(player_df['position'].values, km_pred)
print(contingency_matrix)
print()
print('Purity: {}'.format(contingency_matrix.max(axis = 1).sum() / contingency_matrix.sum()))
```

```
[[2417    0    0 1247]
 [   3    0 1881   35]
 [   0  869    0    0]
 [ 253    0 1625 1595]]

Purity: 0.6843324937027708
```

In [17]:

```python
#normalized mutual information or NMI...
from sklearn.metrics.cluster import normalized_mutual_info_score

print('NMI: {}'.format(normalized_mutual_info_score(player_df['position'].values, km_pred)))
```

```
NMI: 0.5629166802850829
```

In [18]:

```python
#rand index score...
from sklearn.metrics.cluster import adjusted_rand_score

print('Rand index: {}'.format(adjusted_rand_score(player_df['position'].values, km_pred)))
```

```
Rand index: 0.4033761167152728
```

> ## Diferentes numero de clusters

Usar diferentes numero de clusters, especialmente numeros altos, para observar las subdivisiones de las clases, y que clases se confunden mas.

**Nota**: Las posiciones asignadas a los jugadores son simplificadas, esto quiere decir que al hacer mas de 4 clusters podemos llegar descubrir posiciones mas especificas dentro del campo de juego (por ejemplo: Defensor central, Lateral derecho/izquierdo, Mediocampista defensivo/ofensivo, etc.)

**Recordar**: Calcular la Pureza para analizar si tener una mayor cantidad de clusters da mejores resultados.

In [29]:
```
#purezas...

for bucle in range(2, 10):
    km_pred = KMeans(n_clusters = bucle, random_state = 42).fit_predict(player2_df)
    km_pred
    contingency_matrix = metrics.cluster.contingency_matrix(player_df['position'].values, km_pred)
    print('Purity para k={}: {}'.format(bucle, contingency_matrix.max(axis = 1).sum() / contingency_matrix.sum()))
```

```
Purity para k=2: 1.0
Purity para k=3: 0.8798992443324937
Purity para k=4: 0.6843324937027708
Purity para k=5: 0.5802518891687657
Purity para k=6: 0.4738539042821159
Purity para k=7: 0.469823677581864
Purity para k=8: 0.39476070528967255
Purity para k=9: 0.374911838790932
```

### Subconjunto de Features

Probar diferentes subconjunto de caracteristicas del dataset para analizar si los resultados mejoran.

Por ejemplo, probar con el siguiente subconjunto de caracteristicas:

- `gk_diving`
- `gk_handling`
- `gk_kicking`
- `gk_positioning`
- `standing_tackle`
- `sliding_tackle`
- `short_passing`
- `vision`
- `finishing`
- `volleys`

Tambien probar con otros subconjuntos.

**Recordar**: Calcular la Pureza

In [32]:
```
#subset...

player3_df = player2_df[['gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning', 'standing_tackle',
                         'sliding_tackle', 'short_passing', 'vision', 'finishing', 'volleys']]
player3_df.dtypes
```

Out[32]:
```
gk_diving          float64
gk_handling        float64
gk_kicking         float64
gk_positioning     float64
standing_tackle    float64
sliding_tackle     float64
short_passing      float64
vision             float64
finishing          float64
volleys            float64
dtype: object
```

In [33]:
```
#ejecutamos KMeans...

k = 4
km_pred = KMeans(n_clusters = k, random_state = 42).fit_predict(player3_df)

contingency_matrix = metrics.cluster.contingency_matrix(player_df['position'].values, km_pred)
print('Purity para k={}: {}'.format(k, contingency_matrix.max(axis = 1).sum() / contingency_matrix.sum()))
```

```
Purity para k=4: 0.7182871536523929
```

### Uso de Embedding

Aplicar el uso de embeddings, por ejemplo [PCA](), para comparar que sucede en ese espacio en comparacion con lo que sucede en el espacio original.

In [48]:
```
#embedding sobre data total...
from sklearn.preprocessing import StandardScaler

X = player2_df.values
y = player_df['position'].values

#estandarizamos X...
X = StandardScaler().fit_transform(X)

#PCA...
pca = PCA(n_components = 2)
PrincipalComponents = pca.fit_transform(X)

#display(pd.DataFrame(PrincipalComponents, columns = ['PC_1', 'PC_2']))

#Kmeans sobre PCA...
km_pred = KMeans(n_clusters = 4, random_state = 42).fit_predict(PrincipalComponents)
```

```
contingency_matrix = metrics.cluster.contingency_matrix(player_df['position'].values, km_pred)
print(contingency_matrix)
print()
print('Purity: {}'.format(contingency_matrix.max(axis = 1).sum() / contingency_matrix.sum()))
```

```
[[   5    0 2364 1295]
 [1844    0   32   43]
 [   0  869    0    0]
 [1833    0  280 1360]]

Purity: 0.6962216624685138
```

**mejora algunas décimas...**

In [49]:

```
#embedding sobre subset...

X = player3_df.values
y = player_df['position'].values

#estandarizamos X...
X = StandardScaler().fit_transform(X)

#PCA...
pca = PCA(n_components = 2)
PrincipalComponents = pca.fit_transform(X)

#display(pd.DataFrame(PrincipalComponents, columns = ['PC_1', 'PC_2']))

#Kmeans sobre PCA...
km_pred = KMeans(n_clusters = 4, random_state = 42).fit_predict(PrincipalComponents)

contingency_matrix = metrics.cluster.contingency_matrix(player_df['position'].values, km_pred)
print(contingency_matrix)
print()
print('Purity: {}'.format(contingency_matrix.max(axis = 1).sum() / contingency_matrix.sum()))
```

```
[[   0  814    0 2850]
 [1871   48    0    0]
 [   0    0  869    0]
 [1540 1780    0  153]]

Purity: 0.7425692695214106
```

**mejora unos puntos...**

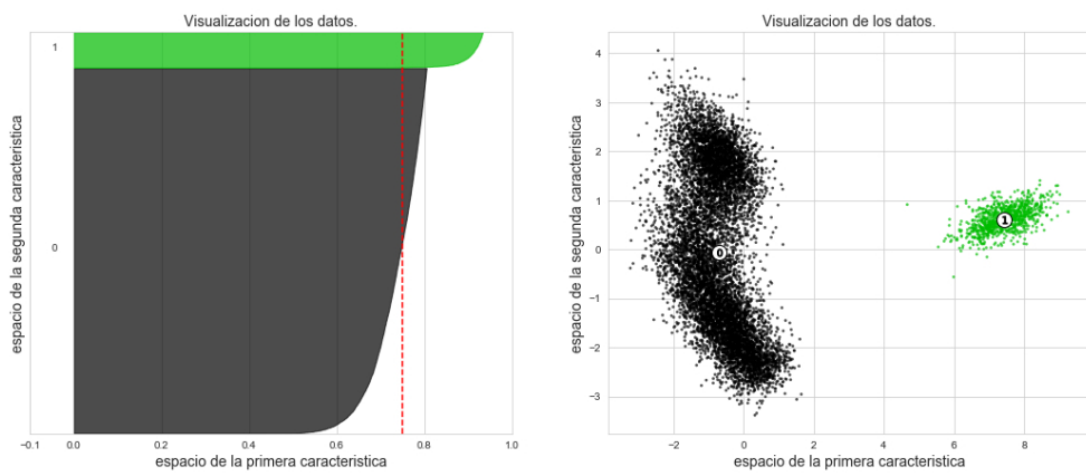
In [53]:

```
#aplicamos silhouette sobre el embedding del subset y observamos...
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.cm as cm

X = PrincipalComponents.copy()
range_n_clusters = 10
sse = {}
for n_clusters in range(2, range_n_clusters):
    # Create a subplot with 1 row and 2 columns
    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.set_size_inches(18, 7)

    # The 1st subplot is the silhouette plot
    # The silhouette coefficient can range from -1, 1 but in this example all
    # lie within [-0.1, 1]
    ax1.set_xlim([-0.1, 1])
    # The (n_clusters+1)*10 is for inserting blank space between silhouette
    # plots of individual clusters, to demarcate them clearly.
    ax1.set_ylim([0, len(X) + (n_clusters + 1) * 10])

    # Initialize the clusterer with n_clusters value and a random generator
    # seed of 10 for reproducibility.
    clusterer = KMeans(n_clusters = n_clusters, random_state = 42)
    cluster_labels = clusterer.fit_predict(X)
    sse[n_clusters] = clusterer.inertia_

    # The silhouette_score gives the average value for all the samples.
    # This gives a perspective into the density and separation of the formed
    # clusters
    silhouette_avg = silhouette_score(X, cluster_labels)
    print('Para n_clusters =', n_clusters, 'El silhouette_score promedio es :', silhouette_avg)

    # Compute the silhouette scores for each sample
    sample_silhouette_values = silhouette_samples(X, cluster_labels)

    y_lower = 10
    for i in range(n_clusters):
        # Aggregate the silhouette scores for samples belonging to
        # cluster i, and sort them
        ith_cluster_silhouette_values = \
            sample_silhouette_values[cluster_labels == i]

        ith_cluster_silhouette_values.sort()

        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = cm.nipy_spectral(float(i) / n_clusters)
        ax1.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
                          facecolor = color, edgecolor = color, alpha = 0.7)

        # Label the silhouette plots with their cluster numbers at the middle
        ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
```

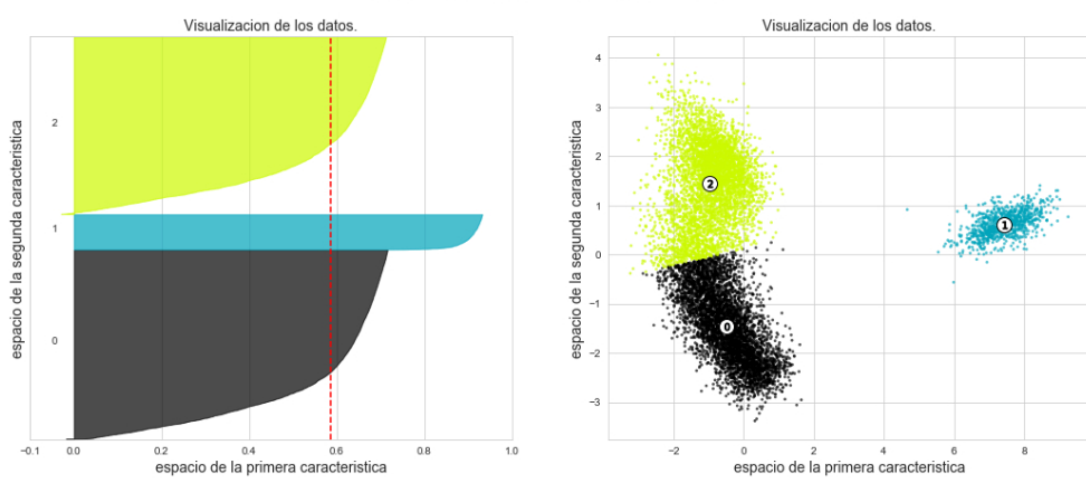
```
        # Compute the new y_lower for next plot
        y_lower = y_upper + 10  # 10 for the 0 samples

    ax1.set_title('Visualizacion de los datos.', fontsize = 14)
    ax1.set_xlabel('espacio de la primera caracteristica', fontsize = 14)
    ax1.set_ylabel('espacio de la segunda caracteristica', fontsize = 14)

    # The vertical line for average silhouette score of all the values
    ax1.axvline(x = silhouette_avg, color = 'red', linestyle = '--')

    ax1.set_yticks([])  # Clear the yaxis labels / ticks
    ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])


    # 2nd Plot showing the actual clusters formed
    colors = cm.nipy_spectral(cluster_labels.astype(float) / n_clusters)
    ax2.scatter(X[:, 0], X[:, 1], marker = '.', s = 30, lw  =0, alpha = 0.7,
                c = colors, edgecolor = 'k')

    # Labeling the clusters
    centers = clusterer.cluster_centers_
    # Draw white circles at cluster centers
    ax2.scatter(centers[:, 0], centers[:, 1], marker = 'o',
                c = 'white', alpha = 1, s = 200, edgecolor = 'k')

    for i, c in enumerate(centers):
        ax2.scatter(c[0], c[1], marker = '$%d$' % i, alpha = 1,
                    s = 50, edgecolor = 'k')

    ax2.set_title('Visualizacion de los datos.', fontsize = 14)
    ax2.set_xlabel('espacio de la primera caracteristica', fontsize = 14)
    ax2.set_ylabel('espacio de la segunda caracteristica', fontsize = 14)

    plt.suptitle(('Analisis de silueta para Kmedias '
                  'con n_clusters = %d' % n_clusters),
                 fontsize = 14, fontweight = 'bold')
    #plt.savefig("kmeans_%d" % n_clusters, dpi=300)

plt.show()
```

```
Para n_clusters = 2 El silhouette_score promedio es : 0.7496035117026993
Para n_clusters = 3 El silhouette_score promedio es : 0.5851505877728135
Para n_clusters = 4 El silhouette_score promedio es : 0.5174570129637843
Para n_clusters = 5 El silhouette_score promedio es : 0.4546350856569354
Para n_clusters = 6 El silhouette_score promedio es : 0.4253970573221955
Para n_clusters = 7 El silhouette_score promedio es : 0.3988955761606965
Para n_clusters = 8 El silhouette_score promedio es : 0.389450353886547
Para n_clusters = 9 El silhouette_score promedio es : 0.3914018774125045
```

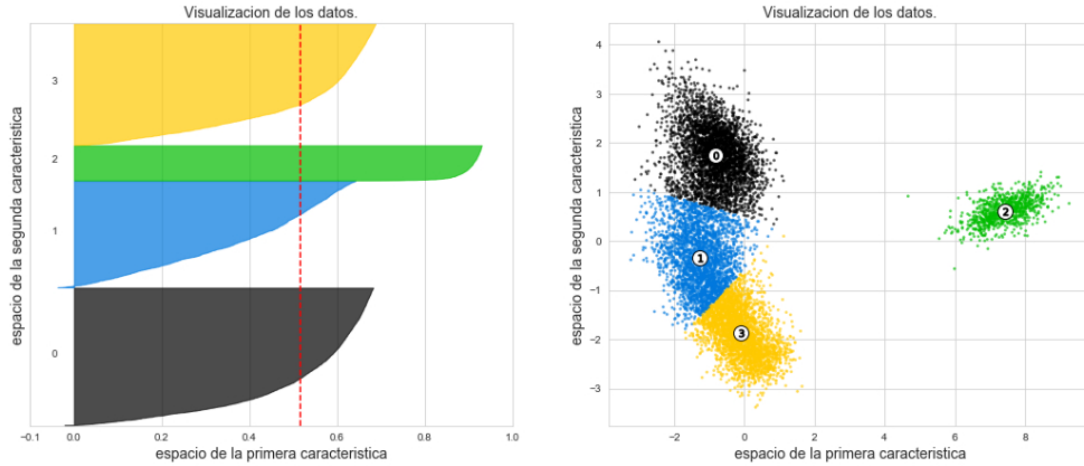
**Analisis de silueta para Kmedias con n_clusters = 2**



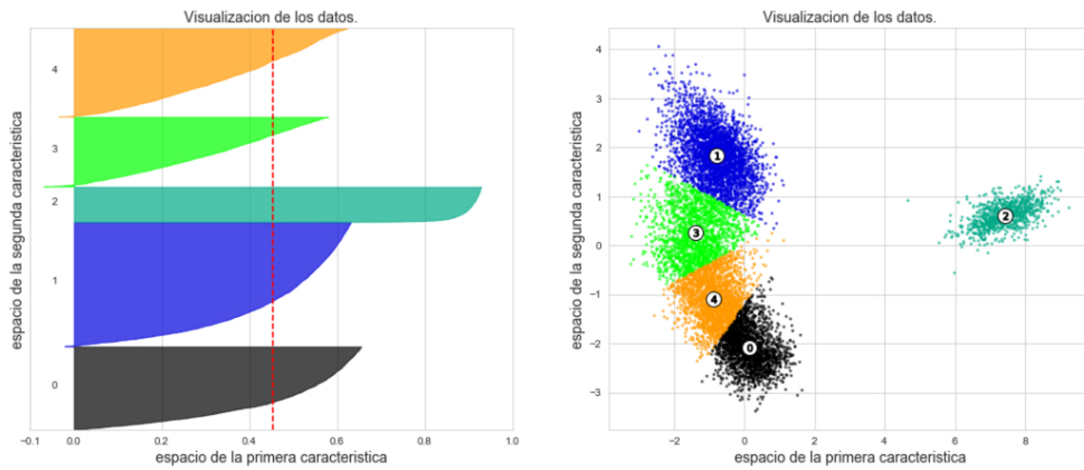

**Analisis de silueta para Kmedias con n_clusters = 3**



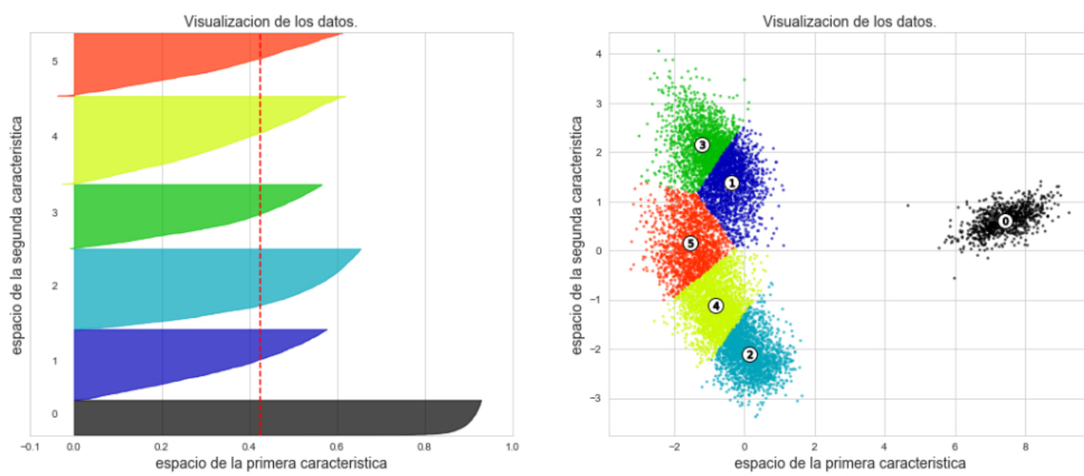

**Analisis de silueta para Kmedias con n_clusters = 4**



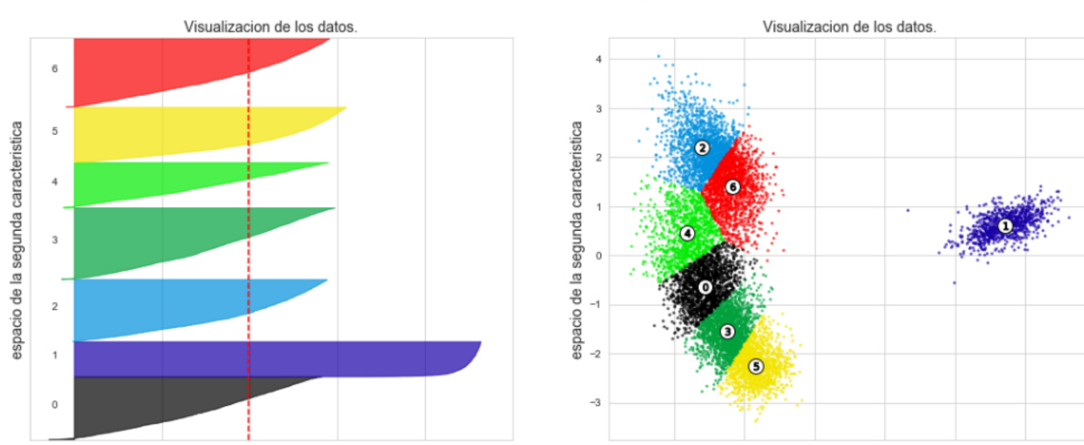

**Analisis de silueta para Kmedias con n_clusters = 5**



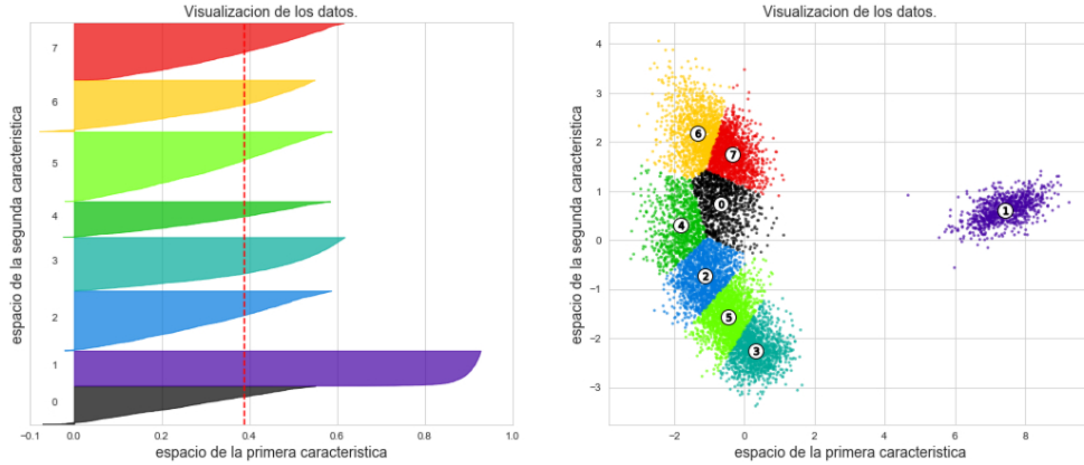

**Analisis de silueta para Kmedias con n_clusters = 6**



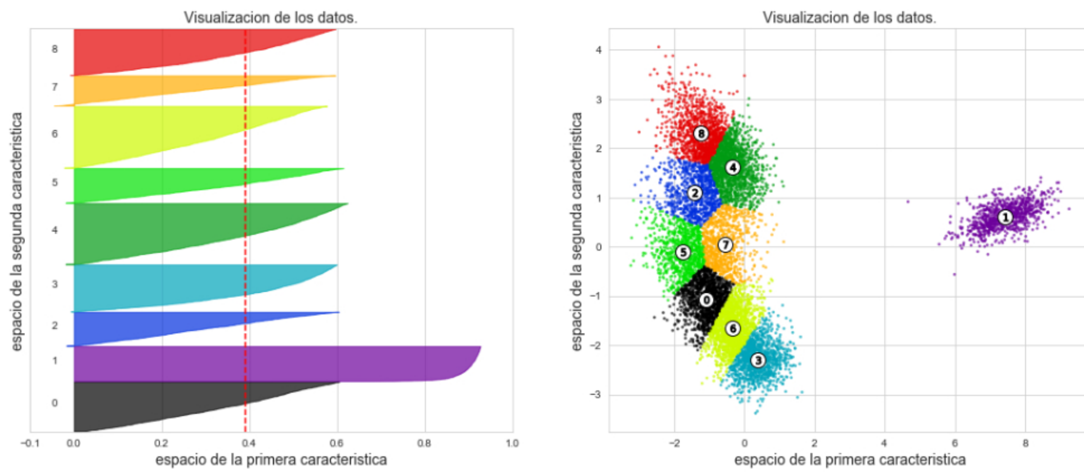

**Analisis de silueta para Kmedias con n_clusters = 7**




**Analisis de silueta para Kmedias con n_clusters = 8**




**Analisis de silueta para Kmedias con n_clusters = 9**

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**Comunicación de Resultados**

Se pide que toda esta información no quede plasmada solamente en un Jupyter Notebook, sino que se diagrame una comunicación en formato textual o interactivo (Google Docs, PDF o Markdown por ejemplo).

La comunicación debe estar apuntada a un público técnico pero sin conocimiento del tema particular, como por ejemplo, sus compañeros de clase.

```
In [ ]:
```