```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:95% !important; }</style>"))
```

```
# Conectamos con nuestro Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.
```

```
!mkdir EXABY
```

```
import numpy as np
import pandas as pd
import random
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import normalize
from datetime import datetime
from scipy.cluster.hierarchy import dendrogram, linkage
np.set_printoptions(precision=5, suppress=True)
from sklearn.cluster import AgglomerativeClustering
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors
from sklearn.mixture import GaussianMixture
from matplotlib.patches import Ellipse
from sklearn.preprocessing import StandardScaler

sns.set()
```

Analisis de las variables

```
data = pd.read_table('/content/drive/MyDrive/EXABY/full_df.csv', delimiter = ',')
```

```
data.drop(columns=data.columns[0], axis=1, inplace=True)
```

```
data.head(5)
```

	Genmodel_ID	Adv_ID	Reg_year	Bodytype	Runned_Miles	Gearbox	Fuel_type
0	10_1	10_1$$27	2000.0	Saloon	30000	Automatic	Petrol
1	10_1	10_1$$29	2000.0	Saloon	46000	Automatic	Petrol
2	10_1	10_1$$16	2000.0	Saloon	49700	Automatic	Petrol

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209520 entries, 0 to 209519
Data columns (total 26 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   Genmodel_ID             209520 non-null  object 
 1   Adv_ID                  209520 non-null  object 
 2   Reg_year                209520 non-null  float64
 3   Bodytype                209520 non-null  object 
 4   Runned_Miles            209520 non-null  object 
 5   Gearbox                 209520 non-null  object 
 6   Fuel_type               209520 non-null  object 
 7   Engine_power            209520 non-null  float64
 8   Wheelbase               209520 non-null  float64
 9   Height                  209520 non-null  float64
 10  Width                   209520 non-null  float64
 11  Length                  209520 non-null  float64
 12  Average_mpg             209520 non-null  float64
 13  Top_speed               209520 non-null  float64
 14  Seat_num                209520 non-null  float64
 15  Door_num                209520 non-null  float64
 16  Ad_Date                 209520 non-null  object 
 17  Ad_price_GBP            209520 non-null  float64
 18  Engine_size             209520 non-null  float64
 19  Entry_price_GBP         209520 non-null  float64
 20  Gas_emission            209520 non-null  float64
 21  Tot_devaluation         209520 non-null  float64
 22  Percentage_devaluation  209520 non-null  float64
 23  Age                     209520 non-null  float64
 24  Tot_Dev_PerYear         209520 non-null  float64
 25  Per_Dev_PerYear         209520 non-null  float64
dtypes: float64(19), object(7)
memory usage: 41.6+ MB
```

Reg_year

```
data.Reg_year.unique()
```

```
array([2000., 2002., 2003., 2016., 2017., 2004., 2005., 2008., 2009.,
       2010., 2011., 2012., 2013., 2014., 2015., 2019., 2006., 2007.,
       2001.])
```

```
data.Reg_year = data.Reg_year.astype(int)
```

Bodytype

```
data.Bodytype.unique()
```

```
array(['Saloon', 'SUV', 'Coupe', 'Convertible', 'Hatchback', 'Estate',
       'MPV', 'Combi Van', 'Panel Van', 'Minibus', 'Window Van',
       'Car Derived Van', 'Limousine'], dtype=object)
```

Gearbox

```
data.Gearbox.unique()
```

```
array(['Automatic', 'Semi-Automatic', 'Manual'], dtype=object)
```

Fuel_type

```
data.Fuel_type.unique()
```

```
array(['Petrol', 'Diesel', 'Other'], dtype=object)
```

```
data[data['Fuel_type'] == 'Other'].shape
```

```
(5063, 26)
```

Runned_Miles

```
data.Runned_Miles.unique()
```

```
array(['30000', '46000', '49700', ..., '91211', '91812', '96824'],
      dtype=object)
```

Runned_Miles no tiene valores decimales por lo tanto se convierte en una variable de tipo int

Es necesario cambiar el string "1 mile" a 1

```
data[data['Runned_Miles'] == '1 mile'].shape
```

```
(20, 26)
```

```
data.Runned_Miles = data.Runned_Miles.replace('1 mile', 1)
```

```
data.Runned_Miles = data.Runned_Miles.astype(int)
```

Ad_Date

```
data.Ad_Date.unique()
```

```
array(['2018-03-01', '2017-11-01', '2017-12-01', '2018-04-01',
       '2017-05-01', '2018-06-01', '2018-05-01', '2017-03-01',
       '2018-07-01', '2018-08-01', '2018-02-01', '2017-09-01',
       '2018-01-01', '2016-11-01', '2017-06-01', '2017-08-01',
       '2016-09-01', '2017-02-01', '2016-08-01', '2016-02-01',
       '2016-03-01', '2016-06-01', '2015-06-01', '2015-10-01',
       '2021-05-01', '2018-09-01', '2016-12-01', '2020-02-01',
       '2021-01-01', '2021-03-01', '2021-02-01', '2021-06-01',
       '2020-12-01', '2020-07-01', '2021-04-01', '2020-10-01',
       '2020-08-01', '2020-09-01', '2014-08-01', '2016-07-01',
       '2013-11-01', '2020-06-01', '2015-05-01', '2015-09-01',
       '2016-04-01', '2013-08-01', '2015-12-01', '2014-10-01',
       '2013-10-01', '2014-12-01', '2015-04-01', '2020-05-01',
       '2015-07-01'], dtype=object)
```

Engine_power

```
data.Engine_power.unique()
```

```
array([433.33333, 450.     , 400.     , ..., 141.71429, 135.77778,
       135.52941])
```

```
data.Engine_power = data.Engine_power.round(3)
```

Average_mpg

```
data.Average_mpg.unique()
```

```
array([13.22222, 13.22222, 13.     , ..., 74.02857, 47.7963 , 47.72549])
```

```
data.Average_mpg = data.Average_mpg.round(3)
```

Top_speed

```
data.Top_speed.unique()
```

```
array([168.33333, 179.     , 155.     , ..., 125.2    , 127.05556,
```

```
        127.11765])
```

```
data.Top_speed = data.Top_speed.round(3)
```

Ad_price_GBP

```
data.Ad_price_GBP.unique()
```

```
array([29934.12619, 21775.76519, 28889.91838, ...,  6018.38689,
        5361.73821,  7134.70169])
```

```
data.Ad_price_GBP = data.Ad_price_GBP.round(3)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209520 entries, 0 to 209519
Data columns (total 26 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   Genmodel_ID             209520 non-null  object 
 1   Adv_ID                  209520 non-null  object 
 2   Reg_year                209520 non-null  int64  
 3   Bodytype                209520 non-null  object 
 4   Runned_Miles            209520 non-null  int64  
 5   Gearbox                 209520 non-null  object 
 6   Fuel_type               209520 non-null  object 
 7   Engine_power            209520 non-null  float64
 8   Wheelbase               209520 non-null  float64
 9   Height                  209520 non-null  float64
 10  Width                   209520 non-null  float64
 11  Length                  209520 non-null  float64
 12  Average_mpg             209520 non-null  float64
 13  Top_speed               209520 non-null  float64
 14  Seat_num                209520 non-null  float64
 15  Door_num                209520 non-null  float64
 16  Ad_Date                 209520 non-null  object 
 17  Ad_price_GBP            209520 non-null  float64
 18  Engine_size             209520 non-null  float64
 19  Entry_price_GBP         209520 non-null  float64
 20  Gas_emission            209520 non-null  float64
 21  Tot_devaluation         209520 non-null  float64
 22  Percentage_devaluation  209520 non-null  float64
 23  Age                     209520 non-null  float64
 24  Tot_Dev_PerYear         209520 non-null  float64
 25  Per_Dev_PerYear         209520 non-null  float64
dtypes: float64(18), int64(2), object(6)
memory usage: 41.6+ MB
```

Clusterización

Incluimos las variables numericas que no sean el target o la variable objetivo para implemetar clusterizacion:

- PCA
- Metodo jerarquica
- k-means
- Dbscam

```
df = data.iloc[:, [2,4,7,8,9,10,11,12,13,14,15,17,18,19,20,23]]
```

```
scaler = StandardScaler()
```

```
df = pd.DataFrame(scaler.fit_transform(df.values), columns=df.columns, index=df.index)
```

```
df
```

	Reg_year	Runned_Miles	Engine_power	Wheelbase	Height	Width	Le
0	-2.841218	-0.561657	3.481406	1.340505	-0.105126	1.608635	2.54
1	-2.841218	-0.196791	3.481406	1.340505	-0.105126	1.608635	2.54
2	-2.841218	-0.112416	3.481406	1.340505	-0.105126	1.608635	2.54
3	-2.841218	-0.027037	3.481406	1.340505	-0.105126	1.608635	2.54
4	-2.841218	0.122467	3.481406	1.340505	-0.105126	1.608635	2.54
...	...	...	...	...	...	...	
209515	0.054426	0.847912	-0.419943	0.135576	-0.547336	-0.780856	0.43
209516	0.054426	0.897807	-0.419943	0.135576	-0.547336	-0.780856	0.43
209517	0.054426	0.920611	-0.419943	0.135576	-0.547336	-0.780856	0.43
209518	0.054426	0.962206	-0.419943	0.135576	-0.547336	-0.780856	0.43
209519	0.054426	1.032351	-0.419943	0.135576	-0.547336	-0.780856	0.43

209520 rows × 16 columns

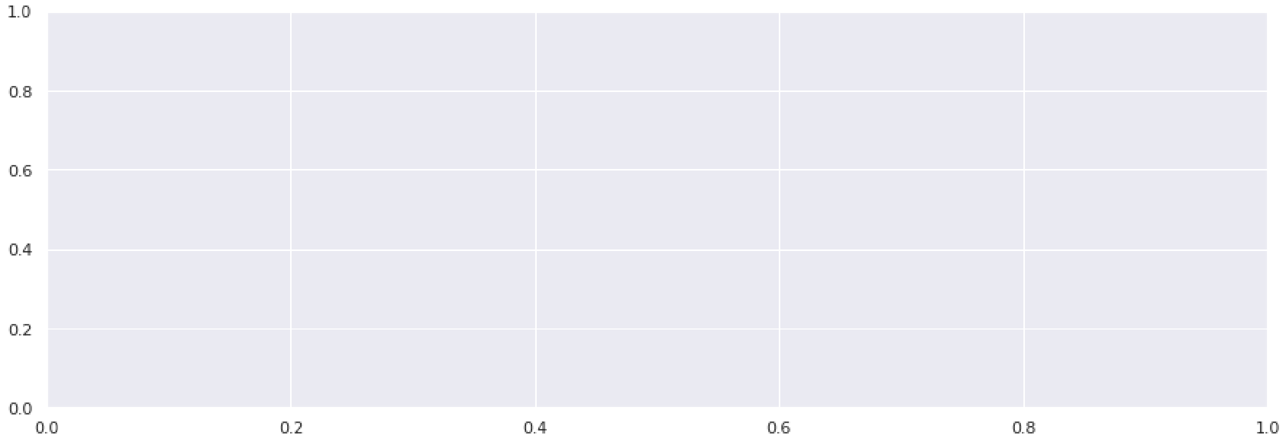
```
wcss =  []

for i in range(1,12):
  kmeans_pca =  KMeans(n_clusters= i, init = 'k-means++', random_state=50)
  kmeans_pca.fit(df)
  wcss.append(kmeans_pca.inertia_)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-37-c85cc5d797bd> in <module>
      7
      8 plt.figure(figsize=(15,5))
----> 9 plt.plot(range(1,24), wcss, marker = 'o', linestyle = '--')
     10 plt.title('K-means con PCA clusters')
     11 plt.ylabel('WCSS')
```

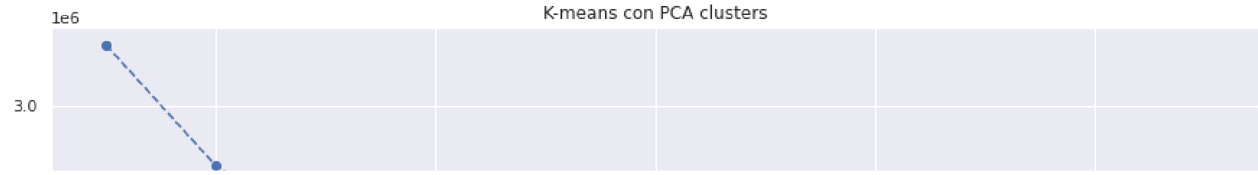
3 frames

```
/usr/local/lib/python3.7/dist-packages/matplotlib/axes/_base.py in _plot_args(self, tup, kwargs)
    340
    341         if x.shape[0] != y.shape[0]:
--> 342             raise ValueError(f"x and y must have same first dimension, but "
    343                              f"have shapes {x.shape} and {y.shape}")
    344         if x.ndim > 2 or y.ndim > 2:

ValueError: x and y must have same first dimension, but have shapes (23,) and (11,)
```

SEARCH STACK OVERFLOW




```
plt.figure(figsize=(15,5))
plt.plot(range(1,12), wcss, marker = 'o', linestyle = '--')
plt.title('K-means con PCA clusters')
plt.ylabel('WCSS')
plt.xlabel('Numero de clusters')
plt.show()
```



El grafico de WCSS evidencia que el codo se encuentra alrededor de 4-5 clusters


```
algoritmo =  KMeans(n_clusters= 5, init = 'k-means++',
                      max_iter= 300, n_init =10)
algoritmo.fit(df)
```

```
KMeans(n_clusters=5)
```

```
df
```

	Reg_year	Runned_Miles	Engine_power	Wheelbase	Height	Width	Le
0	-2.841218	-0.561657	3.481406	1.340505	-0.105126	1.608635	2.54
1	-2.841218	-0.196791	3.481406	1.340505	-0.105126	1.608635	2.54
2	-2.841218	-0.112416	3.481406	1.340505	-0.105126	1.608635	2.54
3	-2.841218	-0.027037	3.481406	1.340505	-0.105126	1.608635	2.54
4	-2.841218	0.122467	3.481406	1.340505	-0.105126	1.608635	2.54
...	...	...	...	...	...	...	
209515	0.054426	0.847912	-0.419943	0.135576	-0.547336	-0.780856	0.43
209516	0.054426	0.897807	-0.419943	0.135576	-0.547336	-0.780856	0.43
209517	0.054426	0.920611	-0.419943	0.135576	-0.547336	-0.780856	0.43
209518	0.054426	0.962206	-0.419943	0.135576	-0.547336	-0.780856	0.43
209519	0.054426	1.032351	-0.419943	0.135576	-0.547336	-0.780856	0.43

209520 rows × 16 columns

```
plt.figure(figsize=(15,5))
y_kmeans = algoritmo.predict(df)

ax = plt.figure(figsize=(20,10)).gca(projection='3d')

centers = algoritmo.cluster_centers_
ax.scatter(
    xs=centers[:, 0],
    ys=centers[:, 1],
    c = 'black',
    alpha = 1,
    s = 60,

)
```

```
ax.scatter(
    xs=df["Reg_year"],
    ys=df["Runned_Miles"],
    zs=df["Engine_size"],
    c = y_kmeans,
    cmap='winter',
    s = 10,
    alpha = 0.2
)
ax.set_xlabel('Reg_year')
ax.set_ylabel('Runned_Miles')
ax.set_zlabel('Engine_size')

#rotacion de ejes
ax.azim = 300
ax.elev = 10

#limit
#ax.axes.set_xlim3d(min(df["Reg_year"]),10)
ax.axes.set_ylim3d(min(df["Runned_Miles"]),3e6)
#ax.axes.set_zlim3d(min(df["Engine_size"]),10)

ax.zaxis.labelpad=50
ax.azim = 60
ax.elev = 50

plt.show()
```

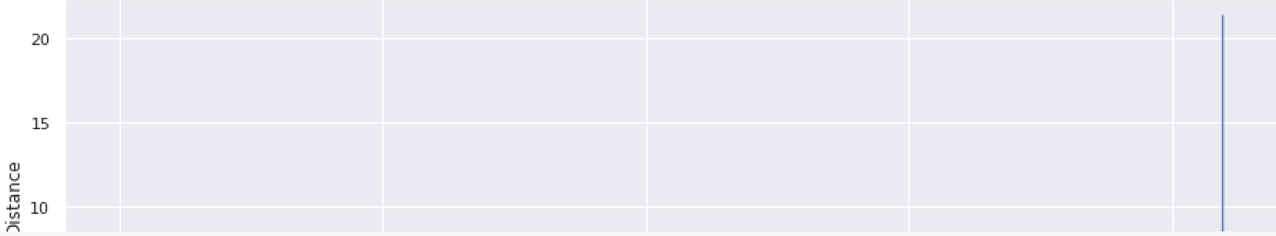
```
<Figure size 1080x360 with 0 Axes>
```

DBSCAN

El DBSCAN identifica regiones con alta densidad de observaciones seperas por regiones de baja densidad.
Para que una observación forme parte de un cluster, tiene que haber un mínimo de observaciones vecinas dentro de un radio de proximidad y de que los clusters están separados por regiones vacías o con pocas observaciones.

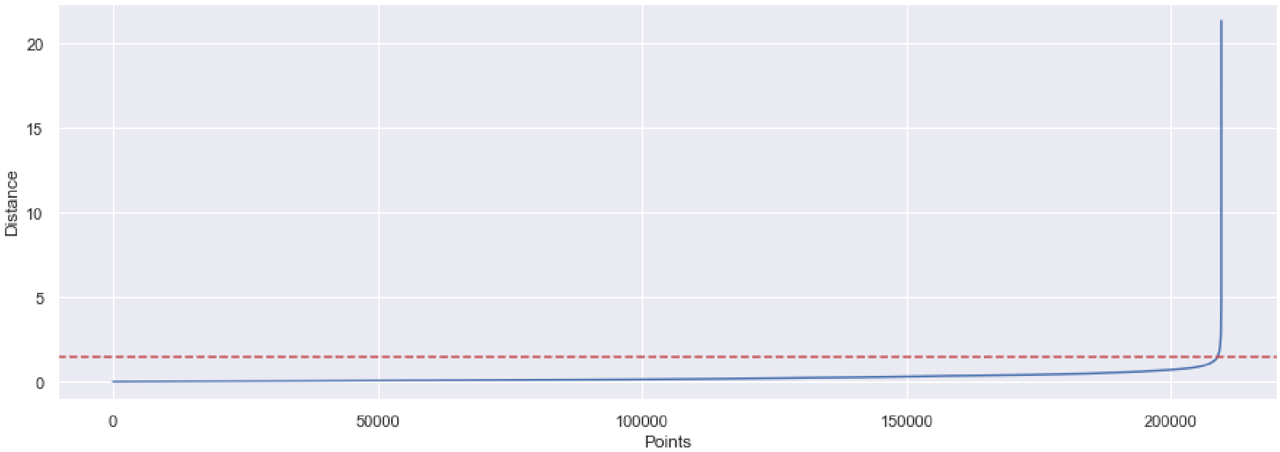
```
k = 2
data_nn = df.copy()

# Calculate NN
nearest_neighbors = NearestNeighbors(n_neighbors=k)
neighbors = nearest_neighbors.fit(data_nn)
distances, indices = neighbors.kneighbors(data_nn)
distances = np.sort(distances, axis=0)

# Get distances
distances = distances[:,1]

i = np.arange(len(distances))

plt.figure(figsize=(15,5))
sns.lineplot(
    x = i,
    y = distances
)

plt.axhline(y = 0.00008, color = 'r', linestyle='--')

plt.xlabel("Points")
plt.ylabel("Distance")
```

Text(0, 0.5, 'Distance')




```
plt.figure(figsize=(15,5))
sns.lineplot(
    x = i,
    y = distances
)

plt.axhline(y = 1.5, color = 'r', linestyle='--')

plt.xlabel("Points")
plt.ylabel("Distance")
```

Text(0, 0.5, 'Distance')



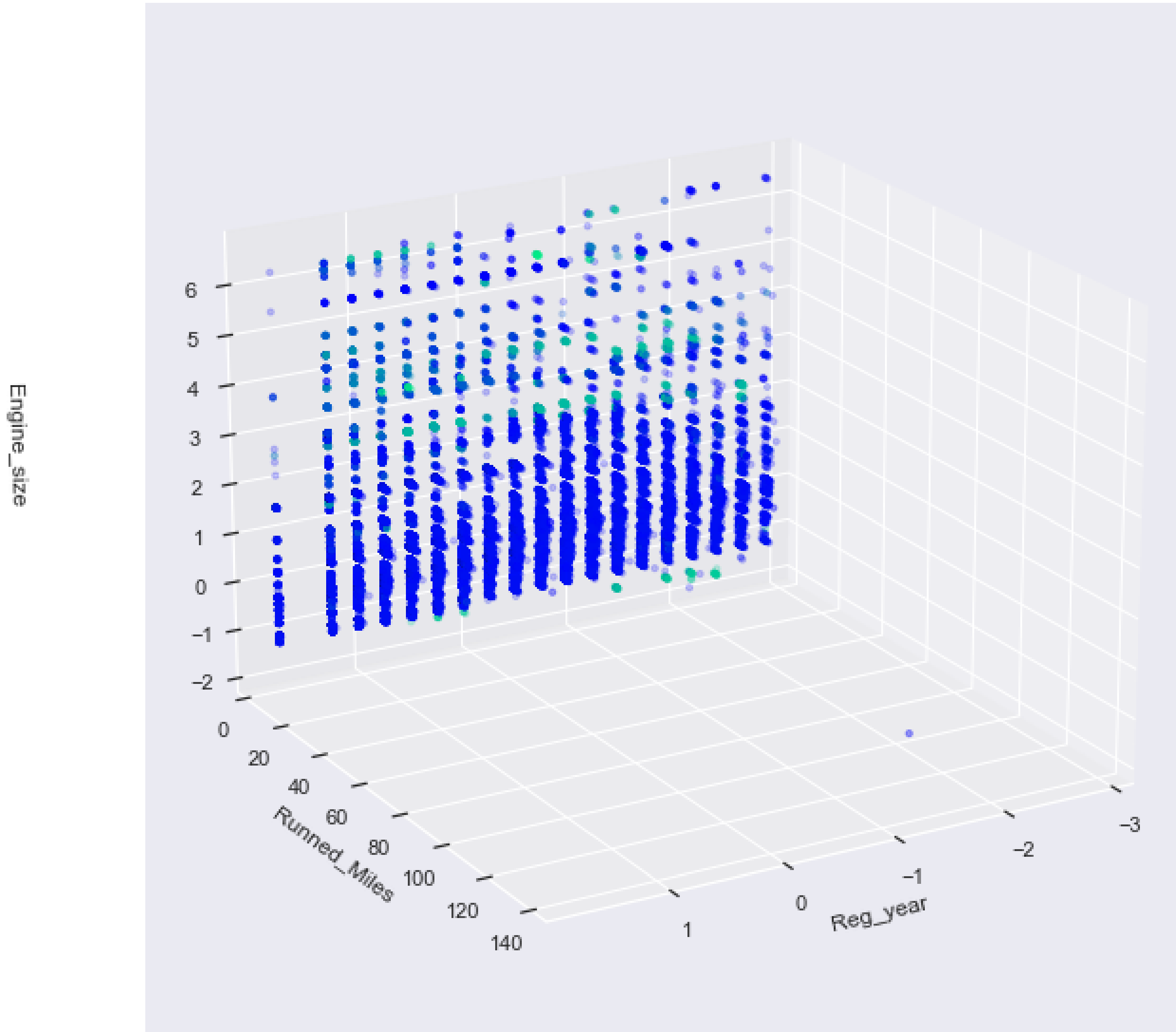
la mejor distancia se encuentre aproximadamente en 10,000.

```
db_1 = DBSCAN(eps=1.5, min_samples=8).fit(df)
```

```
labels = db_1.labels_

ax = plt.figure(figsize=(20,10)).gca(projection='3d')
ax.scatter(
    xs=df["Reg_year"],
    ys=df["Runned_Miles"],
    zs=df["Engine_size"],
    c = labels,
    cmap='winter',
    s = 10,
```

```
    alpha = 0.2
)
ax.set_xlabel('Reg_year')
ax.set_ylabel('Runned_Miles')
ax.set_zlabel('Engine_size')

#rotacion de ejes
ax.azim = 300
ax.elev = 10

#limit
#ax.axes.set_xlim3d(min(df["Reg_year"]),10)
ax.axes.set_ylim3d(min(df["Runned_Miles"]),max(df["Runned_Miles"]))
#ax.axes.set_zlim3d(min(df["Engine_size"]),10)

ax.zaxis.labelpad=50
ax.azim = 60
ax.elev = 20

plt.show()
```

```
C:\Users\pulzara\AppData\Local\Temp/ipykernel_13040/1570679377.py:3: MatplotlibDepre
  ax = plt.figure(figsize=(20,10)).gca(projection='3d')
```



PCA

El análisis de componentes principales (PCA), consiste en expresar un conjunto de variables en un conjunto de combinaciones lineales, de factores no correlacionados entre sí. Este método permite representar los datos originales en un espacio de dimensión inferior del espacio original, mientras se limite al máximo la perdida de información. La representación de los datos en espacios de baja dimensión (2 dimensiones) nos facilita considerablemente el análisis.

```
pca = PCA()
pca.fit(df)
```

```
PCA()
```

```
pca.explained_variance_ratio_.shape
```

```
(17,)
```

Varianza explicativa

```
plt.figure(figsize=(25,5))

plt.subplot(1,2,1)
plt.plot(range(1,18), pca.explained_variance_ratio_.cumsum(), marker = 'o', linestyle = ':
plt.title('Varianza explicativa por componentes')
plt.xlabel('Numero de componentes')
plt.ylabel('Variazan explicativa acumulada')

plt.subplot(1,2,2)
plt.bar(range(1,len(pca.explained_variance_ )+1),pca.explained_variance_ )
plt.ylabel('Explained variance')
plt.xlabel('Components')
```

```
Text(0.5, 0, 'Components')
```

El grafico de varianza explicativa describe cuanto de porcentaje de datos se pierden en funcion del numero de componentes.

Por debajo de 0.9 de varianza NO es aceptable la perdida de información. Entonces, en este caso decidimos elegir 3 componentes

EL grafico de varianza explicada vs componentes, evidencia la importancia de la cantidad de componentes

En este caso despues de la 5 componente ya no explica mucho el comportamiento de los datos

Entrenamos los datos con PCA con 3 componentes.

```
pca = PCA(n_components=10)
pca.fit(df)
```

```
PCA(n_components=10)
```

```
pca = pca.transform(df)
```

```
plt.figure(figsize=(25,5))

plt.subplot(1,2,1)
mglearn.discrete_scatter(pca[:,0], pca[:,1])
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')

plt.subplot(1,2,2)
mglearn.discrete_scatter(pca[:,1], pca[:,2])
plt.xlabel('PCA 2')
plt.ylabel('PCA 3')
```

```
Text(0, 0.5, 'PCA 3')
```

Se puede observar como es la distribucion de nuestras nuevas variables en 2D.

Creamos un dataframe de las nuevas variables con el fin de entrenar los modelos de clusterizacion

```
result=pd.DataFrame(pca, columns=['PCA%i' % i for i in range(10)], index=df.index)

result
```

	PCA0	PCA1	PCA2	PCA3	PCA4	PCA5	PCA6	
0	12.000701	2.849190	1.771252	-1.071790	-0.773086	-0.812983	-0.017271	-0.38
1	11.837100	3.020722	1.905551	0.398919	-1.159545	-0.699530	-0.011487	-0.36
2	9.891796	2.711089	1.626396	-0.040614	-0.498152	-0.510944	-0.210154	-0.34
3	11.896456	3.131805	1.959346	-1.687383	-0.275345	-0.591080	-0.004405	-0.26
4	11.892679	3.193726	1.995139	-1.668154	-0.229951	-0.546741	0.032984	-0.20
...	...	...	...	...	...	...	...	
209515	-1.285477	-0.280910	0.106661	0.204538	1.430375	0.396921	1.482705	0.32
209516	-1.157679	-0.025605	0.192718	1.201761	0.822769	0.269875	1.317547	0.13
209517	-1.303569	-0.237416	0.133707	0.216681	1.461597	0.425128	1.484599	0.34
209518	-1.338182	-0.167857	0.152089	1.506176	0.973771	0.403245	1.516018	0.34
209519	-1.330794	-0.150583	0.165419	1.294398	1.078975	0.428524	1.533367	0.38

209520 rows × 10 columns

```
df.shape
```

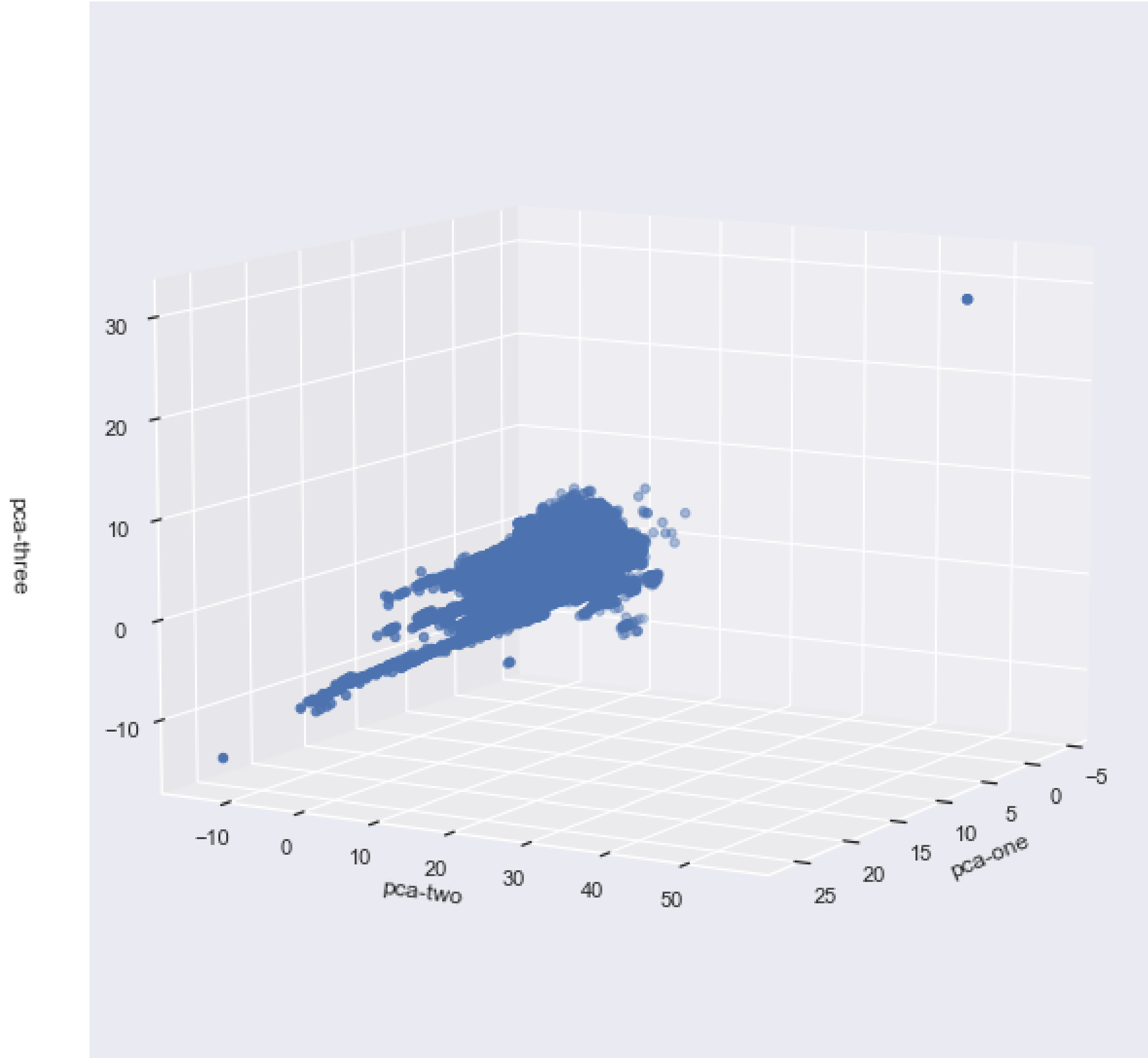
```
(209520, 17)
```

Tiene la misma cantidad de filas que el dataset original.

```
ax = plt.figure(figsize=(20,10)).gca(projection='3d')
ax.scatter(
    xs=result["PCA0"],
    ys=result["PCA1"],
    zs=result["PCA2"],
    cmap='tab10'
)
ax.set_xlabel('pca-one')
ax.set_ylabel('pca-two')
ax.set_zlabel('pca-three')
```

```
ax.zaxis.labelpad=20

ax.azim = 30
ax.elev = 10

plt.show()
```

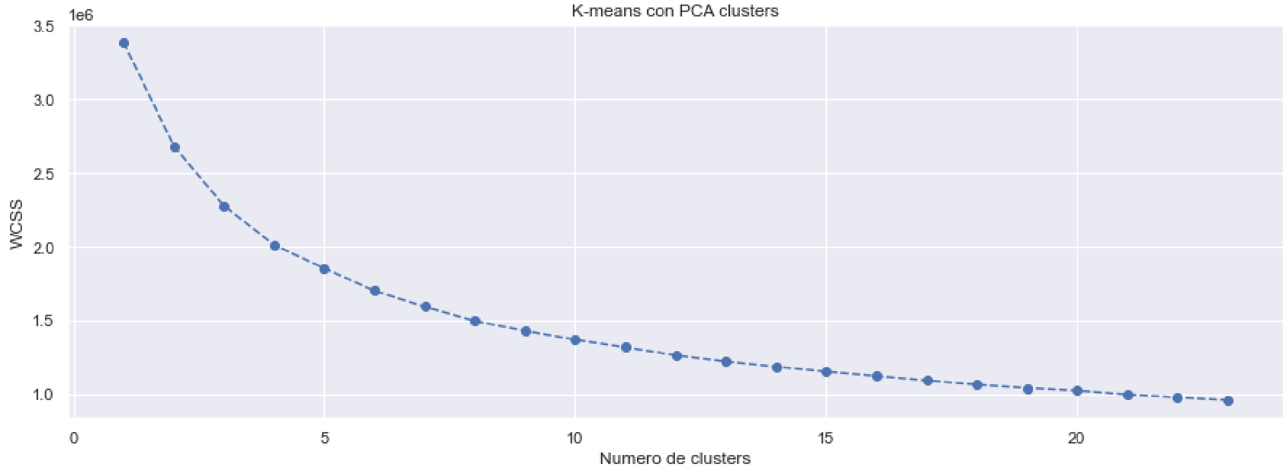
```
C:\Users\pulzara\AppData\Local\Temp/ipykernel_13040/1714263779.py:1: MatplotlibDepre
  ax = plt.figure(figsize=(20,10)).gca(projection='3d')
```



K-means - PCA

```
wcss =  []

for i in range(1,24):
  kmeans_pca =  KMeans(n_clusters= i, init = 'k-means++', random_state=50)
  kmeans_pca.fit(result)
  wcss.append(kmeans_pca.inertia_)

plt.figure(figsize=(15,5))
plt.plot(range(1,24), wcss, marker = 'o', linestyle = '--')
```

```
plt.title('K-means con PCA clusters')
plt.ylabel('WCSS')
plt.xlabel('Numero de clusters')
plt.show()
```



El grafico de WCSS evidencia que el codo se encuentra alrededor de 3-5 clusters.

Kmeans - PCA

```
 algoritmo =  KMeans(n_clusters= 5, init = 'k-means++',
                      max_iter= 300, n_init =10)
algoritmo.fit(result)
```

```
    KMeans(n_clusters=5)
```

```
plt.figure(figsize=(15,5))
y_kmeans = algoritmo.predict(result)

ax = plt.figure(figsize=(20,10)).gca(projection='3d')

centers = algoritmo.cluster_centers_
ax.scatter(
    xs=centers[:, 0],
    ys=centers[:, 1],
    c = 'black',
    alpha = 1,
    s = 60,

)



ax.scatter(
```

```
    xs=result["PCA0"],
    ys=result["PCA1"],
    zs=result["PCA2"],
    c = y_kmeans,
    cmap='winter',
    s = 10,
    alpha = 0.2
)
ax.set_xlabel('pca-one')
ax.set_ylabel('pca-two')
ax.set_zlabel('pca-three')

#rotacion de ejes
ax.azim = 300
ax.elev = 10

#limit
#ax.axes.set_xlim3d(min(result["PCA0"]),4e6)
#ax.axes.set_ylim3d(min(result["PCA1"]),max(result["PCA1"]))
#ax.axes.set_zlim3d(0,400000)

ax.zaxis.labelpad=10
ax.azim = 130
ax.elev = 50

plt.show()
```

```
C:\Users\pulzara\AppData\Local\Temp/ipykernel_13040/2585630893.py:4: MatplotlibDepre
  ax = plt.figure(figsize=(20,10)).gca(projection='3d')
<Figure size 1080x360 with 0 Axes>
```



```
centers = algoritmo.cluster_centers_
centers
```

```
array([[-0.95915, -1.10441, -0.18047,  0.01653, -0.00034,  0.01571,
        -0.0368 , -0.02316,  0.04265, -0.00834],
       [ 4.85971, -0.46924, -0.24959, -0.09635, -0.19076, -0.22575,
         0.03751,  0.07565,  0.12494, -0.10441],
       [-0.14683,  1.90714,  0.37083,  0.00684,  0.06585,  0.05244,
         0.04535,  0.01073, -0.11021,  0.04893]])
```

DBSCAN - PCA

K-vecinos

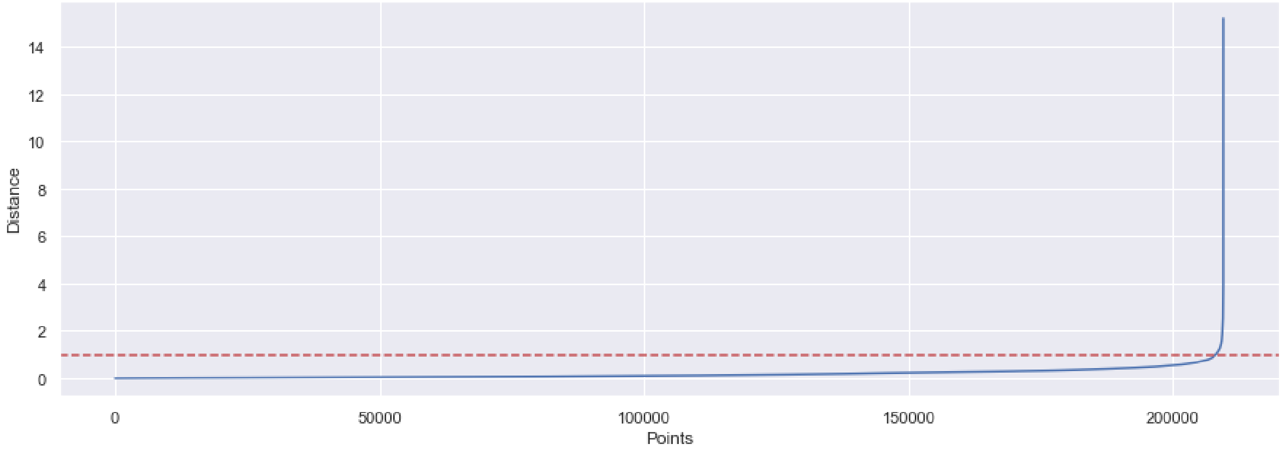
Para elegir el parámetro epsilon, es decir, la distancia máxima a la que debe haber otra observación para considerar que cúmple con el criterio de vecino cercano, debemos saber que tan de cerca o de lejos se encuentran las variables entre sí.

```
k = 2
data_nn = result.copy()

# Calculate NN
nearest_neighbors = NearestNeighbors(n_neighbors=k)
neighbors = nearest_neighbors.fit(data_nn)
distances, indices = neighbors.kneighbors(data_nn)
distances = np.sort(distances, axis=0)

# Get distances
distances = distances[:,1]

i = np.arange(len(distances))
```

```
plt.figure(figsize=(15,5))
sns.lineplot(
    x = i,
    y = distances
)

plt.axhline(y = 1, color = 'r', linestyle='--')
```

```
plt.xlabel("Points")
plt.ylabel("Distance")
```

```
Text(0, 0.5, 'Distance')
```

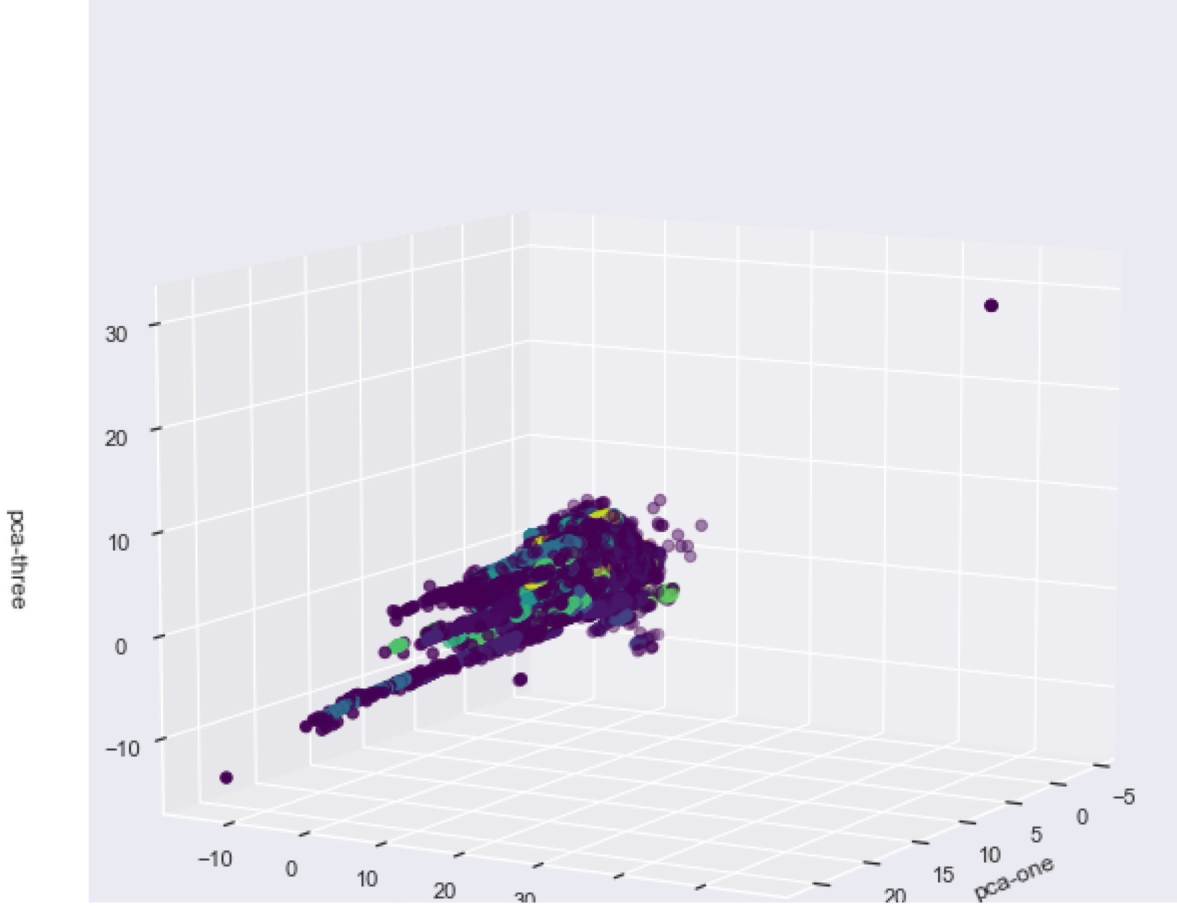


la mejor distancia se encuentre aproximadamente en 1.

```
db_1 = DBSCAN(eps=1, min_samples=8).fit(result)
labels = db_1.labels_
```

```
ax = plt.figure(figsize=(20,10)).gca(projection='3d')
ax.scatter(
    xs=result["PCA0"],
    ys=result["PCA1"],
    zs=result["PCA2"],
    c = labels,
    cmap='viridis',
    s = 30
)
ax.set_xlabel('pca-one')
ax.set_ylabel('pca-two')
ax.set_zlabel('pca-three')

ax.zaxis.labelpad=20
ax.azim = 30
ax.elev = 10

plt.show()
```

```
C:\Users\pulzara\AppData\Local\Temp/ipykernel_13040/3119286377.py:1: MatplotlibDepre
  ax = plt.figure(figsize=(20,10)).gca(projection='3d')
```



Conclusion

Se puede concluir que el modelo K-MEANS separa mejor el comportamiento de los datos que DBSCAN. Por otro lado, se selecciono el valor de n_clusters = 5, debido al grafico de WCSS donde la curvatura se encuentra alrededor de 3-5.

✓ 0 s completado a las 10:08