

```
In [ ]: Sprint 11. Aprenentatge No Supervisat - Agrupació
```

```
In [ ]: #Nivell 1
```

```
In [ ]: #Exercici 1  
#Classifica els diferents vols utilitzant l'algorisme de K-means.
```

```
In [1]: #Llibreries import  
import numpy as np  
import matplotlib.pyplot as plt  
import pandas as pd
```

```
In [41]: #Llibreries from  
from kneed import KneeLocator  
from sklearn.datasets import make_blobs  
from sklearn.cluster import KMeans  
from sklearn.metrics import silhouette_score  
from sklearn.preprocessing import StandardScaler
```

```
In [3]: #Accedim a les dades del fitxer DelayedFlights  
df_vols=pd.read_csv('Python/DelayedFlights.csv', engine="python", error_bad_lines=False, warn_bad_lines=False, sep=',',  
)
```

```
In [6]: # Netegem el dataset d'atributs innecessaris.  
df_vols.drop(['Year', 'Month', 'DayofMonth', 'DayOfWeek', 'TailNum', 'Cancelled', 'CancellationCode', 'Diverted', 'UniqueCarrier', 'Origin', 'Dest'], axis=1, inplace=True)
```

```
In [7]: # Suprimim valors no numerics.  
df_vols=df_vols.dropna()
```

```
In [8]: # Utilitzarem només una petita part de les instàncies del dataframe.  
df_vols=df_vols.head(10)
```

In [9]: df_vols

Out[9]:

	Unnamed: 0	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Dis
3	4	1829.0	1755	1959.0	1925	3920	90.0	90.0	77.0	34.0	34.0	
5	6	1937.0	1830	2037.0	1940	509	240.0	250.0	230.0	57.0	67.0	
7	11	1644.0	1510	1845.0	1725	1333	121.0	135.0	107.0	80.0	94.0	
9	16	1452.0	1425	1640.0	1625	675	228.0	240.0	213.0	15.0	27.0	
11	18	1323.0	1255	1526.0	1510	4	123.0	135.0	110.0	16.0	28.0	
12	19	1416.0	1325	1512.0	1435	54	56.0	70.0	49.0	37.0	51.0	
13	21	1657.0	1625	1754.0	1735	623	57.0	70.0	47.0	19.0	32.0	
17	26	1422.0	1255	1657.0	1610	188	155.0	195.0	143.0	47.0	87.0	
19	30	2107.0	1945	2334.0	2230	362	147.0	165.0	134.0	64.0	82.0	
23	37	1812.0	1650	1927.0	1815	422	135.0	145.0	118.0	72.0	82.0	

In [99]: `#features`

```
Out[99]: array([[ 9.77075874e+00,  3.27621022e+00],
 [-9.71349666e+00,  1.12745180e+01],
 [-6.91330582e+00, -9.34755911e+00],
 [-1.08618591e+01, -1.07506350e+01],
 [-8.50038027e+00, -4.54370383e+00],
 [-4.82456978e+00, -5.20159136e+00],
 [-3.03819028e+00,  9.84354132e+00],
 [-8.17498253e+00, -6.24197227e+00],
 [ 3.91207254e+00,  9.45363489e+00],
 [-4.64425636e+00, -5.14863028e+00],
 [ 2.09082004e+00,  1.80947495e+00],
 [ 5.26539366e+00,  5.56781226e+00],
 [ 7.61826975e+00,  4.87112533e+00],
 [ 3.30512908e+00,  2.19832357e+00],
 [-9.29263277e-01,  2.48591905e+00],
 [-9.15936347e+00, -8.42060745e+00],
 [-2.70722546e+00,  1.17740016e+01],
 [-9.14073328e+00, -6.20996976e+00],
 [ 6.52709436e+00, -2.46179896e+00],
 [-2.51808095e+00, -1.02841022e+01],
 [ 1.04758084e+01,  4.81244915e+00],
 [ 3.33377923e+00,  1.76514294e-01],
 [-5.99215115e+00, -9.15499469e+00],
 [-2.32349506e+00,  5.09622862e+00],
 [-5.00425652e+00, -7.73334317e+00],
 [-4.37073312e+00,  1.06963959e+01],
 [-5.67442996e+00,  1.00474557e+01],
 [-7.29703620e+00, -5.26223728e+00],
 [-1.93482274e+00,  3.62519329e+00],
 [ 1.23826438e+00, -1.65808600e+00],
 [ 4.61611430e-01,  6.41525984e-01],
 [ 1.10051899e+01, -3.16180960e+00],
 [-1.15907471e+01, -3.15696056e+00],
 [-9.14974448e+00, -7.76392066e+00],
 [-1.51535971e+00,  1.32438867e+01],
 [-2.23515637e+00,  7.62972808e+00],
 [-5.74406569e+00, -8.43035211e+00],
 [-8.95340615e-01,  1.50380391e+01],
 [-6.20596912e+00, -8.27420333e+00],
 [-2.25685549e+00,  3.54847161e+00],
 [ 1.33906372e+00,  1.05329129e+00],
```

[-4.73255503e+00, 7.63445426e+00],
[-9.57877598e+00, -5.60932504e+00],
[9.12900992e+00, -1.95971911e+00],
[-9.12973407e+00, -1.12604459e+00],
[6.36046404e+00, -3.84013596e-01],
[2.19371415e+00, -2.70308600e-01],
[-6.68767146e+00, -7.93972198e+00],
[8.51288074e-01, -6.05849176e-01],
[8.15820063e-03, 9.91835168e+00],
[-8.57669125e-01, -9.10292988e+00],
[-4.00625012e+00, 9.31932325e+00],
[-3.63616686e+00, -8.17034264e+00],
[-3.33859769e-01, 6.51347063e+00],
[-6.57513310e+00, 7.03471456e+00],
[-4.16389081e+00, 1.41080511e+01],
[-1.01378541e+00, -1.22483510e+01],
[3.94531642e+00, -1.45823407e+00],
[-4.43984363e+00, 8.11321523e+00],
[1.36379422e+00, 3.77869211e+00],
[-4.26596164e+00, -8.46659465e+00],
[-5.03761427e+00, 1.32766057e+01],
[-4.40572753e+00, -6.03503591e+00],
[-6.93192176e+00, -9.63706535e+00],
[-4.48074544e+00, -6.37591908e+00],
[-6.33221303e+00, -8.53070601e+00],
[-5.43053284e+00, 1.03166653e+01],
[-2.47199115e-01, 5.65696609e+00],
[-4.19804792e+00, -7.28451739e+00],
[-4.78414528e-01, 9.48554890e+00],
[-1.61796671e+00, 7.95530986e+00],
[-6.26337287e+00, -6.84548049e+00],
[-5.00626383e+00, 5.13045095e+00],
[2.81996606e+00, 4.31736135e+00],
[1.34848673e+00, 5.15919571e+00],
[6.05622582e+00, 3.38608105e+00],
[1.69492447e+00, 3.29996883e+00],
[-3.80025218e+00, 1.05063262e+01],
[6.05625997e+00, 1.25681813e+01],
[-3.82692678e+00, 8.50372394e+00],
[-2.54631499e+00, 6.10558107e+00],
[5.22863663e+00, -1.45261196e+00],
[-4.27360635e+00, -8.43896330e-01],

[-5.98816972e+00, -7.23800299e+00],
[-6.61288829e+00, -5.24342777e+00],
[-5.37510939e+00, -7.43613939e+00],
[-6.86520702e+00, -6.75091296e+00],
[-2.26981819e+00, 8.19201591e+00],
[4.79995281e+00, -1.16999864e+00],
[-7.47825050e+00, -3.85847325e+00],
[4.76520140e+00, 1.81268728e-01],
[-6.40146716e+00, 7.85751149e+00],
[-6.77352206e+00, 9.20283431e+00],
[-2.60465499e+00, 5.80042152e+00],
[4.67563404e+00, 5.97038840e+00],
[-8.85534880e+00, -7.46708926e+00],
[-4.81704581e+00, 8.16395209e+00],
[5.32873417e+00, 2.92590226e+00],
[5.86038226e+00, 4.10341333e+00],
[-3.58749504e+00, 4.98962002e+00],
[-3.28956047e+00, -6.82234903e+00],
[-8.11730724e+00, -5.16727228e+00],
[-3.45166254e+00, 6.80802364e+00],
[-7.45196338e+00, -8.23586216e+00],
[-1.69486686e+00, 9.73218813e+00],
[4.02535618e+00, 3.93667104e+00],
[-5.45142428e+00, -2.66507758e+00],
[3.77288841e+00, 4.06033504e+00],
[7.83857915e+00, 2.00131060e+00],
[-1.12643033e+01, -8.52839091e+00],
[5.35455652e+00, 4.12318258e+00],
[6.02859385e+00, 4.35399647e+00],
[-1.56424733e+00, 4.16592570e+00],
[-4.98173121e+00, -7.98346589e+00],
[-3.96603818e+00, 1.04257716e+01],
[-1.27203404e+01, -8.32593590e+00],
[-2.88898227e+00, -4.24211482e+00],
[-7.25272166e+00, 7.46799542e+00],
[-3.77595424e+00, 1.19213723e+01],
[-2.82723040e+00, 8.18625097e+00],
[-9.58375433e-01, -8.99031539e+00],
[9.49487800e+00, 3.08686939e+00],
[-5.23317252e+00, 7.45696737e+00],
[-6.67116466e+00, -8.74230430e+00],
[-5.93979826e+00, -1.72063979e+00],

[3.41196272e+00, 4.32826637e+00],
[-1.59822319e+00, 1.16970352e+01],
[-2.72025275e-01, 5.62940926e+00],
[2.20927089e+00, 2.39591373e+00],
[3.26051064e-01, 1.15753065e+01],
[7.26338369e+00, 3.76449563e+00],
[-6.93710657e+00, -6.55745929e+00],
[1.52133649e+00, 8.39340130e+00],
[-6.81222421e+00, -5.51061429e+00],
[-9.18886226e+00, -8.52843937e+00],
[7.28916319e+00, 3.10831723e+00],
[4.81664889e+00, -9.90628455e-01],
[1.05357251e+01, 3.71644700e+00],
[-2.24223436e+00, 1.16780599e+01],
[8.12388450e+00, 2.70786535e-02],
[-7.78581847e+00, 8.94137297e+00],
[-5.29448320e+00, 9.87846629e+00],
[-1.05102685e+01, -1.84359799e+00],
[2.19299941e-01, 2.48091279e+00],
[4.42784914e+00, 2.91133761e+00],
[-6.16170926e+00, 9.55565453e+00],
[2.76981085e+00, 2.61186735e+00],
[-4.52106323e+00, -7.31994055e+00],
[-6.56745449e+00, -5.05925024e+00],
[3.42975650e+00, 2.33270627e+00],
[-5.55161880e+00, 5.72471791e+00],
[-6.93053832e+00, -7.67392085e+00],
[6.90054428e+00, 7.18935039e+00],
[-7.19461177e+00, -3.47611474e+00],
[2.51460950e+00, 1.32191852e+00],
[-3.69482229e+00, -4.70303718e+00],
[-9.64617499e+00, -1.02191283e+01],
[-1.80093405e+00, 8.80955986e+00],
[5.94128230e+00, 1.77289017e+00],
[7.82601668e+00, -2.83706692e-01],
[-2.74751611e-01, 1.27439462e+01],
[3.96506152e+00, -9.96047680e-02],
[5.62379408e+00, 3.51532713e+00],
[-7.17871760e+00, -5.77540236e+00],
[-3.11329531e+00, 9.99634570e+00],
[6.20982774e+00, 5.09597519e+00],
[5.44582814e+00, 8.70328437e-03],

```
[ -4.66314418e+00,  8.12861696e+00],  
[ -6.10689955e+00, -8.59253327e+00],  
[  5.40077853e+00,  4.24792362e+00],  
[ -3.36604873e+00, -8.50693091e+00],  
[ -2.49513562e+00,  8.36917151e+00],  
[  2.67279364e+00,  3.84206349e+00],  
[ -5.89783460e+00, -8.78561098e+00],  
[  6.33565117e-01,  1.10821020e+01],  
[  8.60338038e+00, -1.97545123e+00],  
[ -2.34356455e+00,  1.57882019e+01],  
[ -4.16095402e+00,  8.21212832e+00],  
[ -2.95273333e+00,  1.01254260e+01],  
[  1.17244796e+00,  4.49729004e+00],  
[ -3.78359628e+00,  7.73352931e+00],  
[  2.46044681e+00,  1.65764447e+00],  
[ -6.61101792e+00, -9.00588650e+00],  
[ -5.16329769e+00, -5.15215944e+00],  
[ -4.60973223e+00, -4.64295809e+00],  
[  1.55501100e+00,  7.58904303e+00],  
[  6.07521814e+00,  2.78987754e+00],  
[  5.11612638e+00,  3.03279248e+00],  
[  2.31119611e+00, -2.19266018e+00],  
[ -2.60771923e+00,  1.33170562e+01],  
[ -1.51469855e+00,  7.24020680e+00],  
[  2.63137060e+00,  2.56843081e+00],  
[ -9.35026754e+00, -5.52733187e+00],  
[ -8.96724201e+00, -6.46652668e+00],  
[ -1.84380138e+00,  3.75276546e+00],  
[ -6.02463139e+00, -2.82288000e+00],  
[  2.67781361e+00,  9.49437511e+00],  
[  1.83363762e+00,  1.11247316e+01],  
[  3.34206621e+00,  4.96778383e+00],  
[  1.95950424e+00,  4.13765234e+00]])
```



```
In [98]: #true_labels
```

```
Out[98]: array([1, 0, 2, 2, 2, 2, 0, 2, 1, 2, 1, 1, 1, 1, 1, 2, 0, 2, 1, 2, 1, 1,
                2, 0, 2, 0, 0, 2, 0, 1, 1, 1, 2, 2, 0, 0, 2, 0, 2, 0, 1, 0, 2, 1,
                2, 1, 1, 2, 1, 0, 2, 0, 2, 0, 0, 0, 2, 1, 0, 1, 2, 0, 2, 2, 2, 2,
                0, 0, 2, 0, 0, 2, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 2, 2, 2, 2, 0,
                1, 2, 1, 0, 0, 0, 1, 2, 0, 1, 1, 0, 2, 2, 0, 2, 0, 1, 2, 1, 1, 2,
                1, 1, 0, 2, 0, 2, 2, 0, 0, 0, 2, 1, 0, 2, 2, 1, 0, 0, 1, 0, 1, 2,
                0, 2, 2, 1, 1, 1, 0, 1, 0, 0, 2, 1, 1, 0, 1, 2, 2, 1, 0, 2, 1, 2,
                1, 2, 2, 0, 1, 1, 0, 1, 1, 2, 0, 1, 1, 0, 2, 1, 2, 0, 1, 2, 0, 1,
                0, 0, 0, 1, 0, 1, 2, 2, 2, 0, 1, 1, 1, 0, 0, 1, 2, 2, 0, 2, 0, 0,
                1, 1])
```

```
In [105]: scaler = StandardScaler()
scaled_df_vols = scaler.fit_transform(df_vols)
```

In [106]: scaled_df_vols

```
Out[106]: array([[ -1.50613218,  0.68949749,  0.85513662,  0.57728312,  0.76486616,
    2.83419411, -0.76502995, -0.97524604, -0.78676507, -0.44913737,
   -0.95481654, -0.76660618, -1.125      ,  1.2579418 , -0.64061319,
    0.          ,  0.          ,  0.          , -0.13150595],
  [ -1.3026008 ,  1.12986253,  1.17987205,  0.89914219,  0.83235435,
   -0.27330705,  1.77378626,  1.64726432,  1.84151126,  0.5736507 ,
    0.3365337 ,  1.67311062, -1.125      , -0.31448545,  0.09151617,
    0.          ,  0.          ,  0.          ,  0.50481316],
  [ -0.79377236, -0.06483152, -0.20566577,  0.10687372, -0.13497638,
    0.47737631, -0.24034127, -0.237665   , -0.27141677,  1.59643877,
    1.39309299, -0.05691161,  0.75        ,  0.20965697, -0.09151617,
    0.          ,  0.          ,  0.          ,  1.56534502],
  [ -0.28494393, -0.8477027 , -0.57369925, -0.73903794, -0.58489765,
   -0.12207715,  1.57068097,  1.48335743,  1.54948056, -1.29404925,
   -1.22873932,  1.44183635,  1.375      ,  0.20965697, -0.54909702,
    0.          ,  0.          ,  0.          , -0.97993143],
  [ -0.08141255, -1.37369428, -1.30976622, -1.20944734, -1.10230711,
   -0.73337392, -0.20649039, -0.237665   , -0.21988194, -1.24958021,
   -1.1896075 , -0.03423766, -0.5        ,  0.73379939, -0.82364553,
    0.          ,  0.          ,  0.          , -0.81024634],
  [  0.02035314, -0.99449105, -1.00667982, -1.26721692, -1.43974807,
   -0.68782274, -1.34049496, -1.30305984, -1.26775682, -0.31573023,
   -0.28957551, -1.43548765, -1.75        , -1.36277029,  0.27454851,
    0.          ,  0.          ,  0.          , -0.42845487],
  [  0.22388451, -0.01182462,  0.29226188, -0.26862853, -0.08998425,
   -0.16945037, -1.32356952, -1.30305984, -1.30211337, -1.11617307,
   -1.03308019, -1.43548765,  0.125      , -1.36277029, -0.18303234,
    0.          ,  0.          ,  0.          , -0.97993143],
  [  0.73271295, -0.97002633, -1.30976622, -0.66888916, -0.65238584,
   -0.56574559,  0.33512374,  0.74577639,  0.34700119,  0.12896023,
    1.11917021,  0.54394801,  0.75        , -0.83862787,  2.83700127,
    0.          ,  0.          ,  0.          , -1.19203781],
  [  1.1397757 ,  1.82302972,  1.6777997 ,  2.12468248,  2.13712604,
   -0.4072275 ,  0.19972021,  0.25405569,  0.1923967 ,  0.88493402,
    0.92351108,  0.26959324,  0.75        , -0.31448545, -0.36606468,
    0.          ,  0.          ,  0.          ,  1.01386845],
  [  1.85213551,  0.62018077,  0.40050703,  0.44523838,  0.26995276,
   -0.35256609, -0.00338509, -0.0737581 , -0.08245573,  1.2406864 ,
    0.92351108, -0.19975748,  0.75        ,  1.78208422, -0.54909702,
    0.          ,  0.          ,  0.          ,  1.4380812 ]])
```

```
In [107]: kmeans = KMeans(init="random", n_clusters=3, n_init=10, max_iter=300, random_state=42)
```

```
In [108]: kmeans.fit(scaled_df_vols)
```

```
Out[108]: KMeans(init='random', n_clusters=3, random_state=42)
```

```
In [109]: print("Valor SSE més baix:", kmeans.inertia_)
```

```
Valor SSE més baix: 83.95196805310437
```

```
In [110]: kmeans.cluster_centers_
```

```
Out[110]: array([[ -0.33582677, -0.42262812, -0.29226188, -0.54200242, -0.46679332,
                   0.31088677, -0.90889621, -0.95475768, -0.8941293 , -0.78265522,
                   -0.86676993, -0.91795478, -0.8125      , -0.18344985, -0.34318564,
                   0.          , 0.          , 0.          , -0.58753465],
                 [ -0.28494393, -0.22928883, -0.23453114, -0.16959497, -0.13497638,
                   -0.3203766 ,  1.22653032,  1.29213271,  1.24599767, -0.19714611,
                   0.07565486,  1.21963166,  0.33333333, -0.31448545,  0.79314014,
                   0.          , 0.          , 0.          , -0.55571869],
                 [  0.73271295,  0.79279299,  0.62421365,  0.89226486,  0.75736747,
                   -0.0941391 , -0.01466872, -0.01912247, -0.05382527,  1.2406864 ,
                   1.08003838,  0.00430805,  0.75          ,  0.55908525, -0.33555929,
                   0.          , 0.          , 0.          ,  1.33909822]])
```

```
In [111]: print("Iteracions: ", kmeans.n_iter_) #Nombre d'iteracions necessaries per la convergencia.
```

```
Iteracions:  2
```

```
In [112]: kmeans.labels_
```

```
Out[112]: array([0, 1, 2, 1, 0, 0, 0, 1, 2, 2])
```

```
In [113]: kmeans_kwargs = {"init": "random", "n_init": 10, "max_iter": 300, "random_state": 42, }
```

```
In [114]: sse = []
          for k in range(1, 11):
              kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
              kmeans.fit(scaled_df_vols)
              sse.append(kmeans.inertia_)
```

C:\Users\Xavier\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:1039: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
warnings.warn(

In [125]: scaled_df_vols

```
Out[125]: array([[ -1.50613218,  0.68949749,  0.85513662,  0.57728312,  0.76486616,
    2.83419411, -0.76502995, -0.97524604, -0.78676507, -0.44913737,
   -0.95481654, -0.76660618, -1.125      ,  1.2579418 , -0.64061319,
    0.          ,  0.          ,  0.          , -0.13150595],
  [ -1.3026008 ,  1.12986253,  1.17987205,  0.89914219,  0.83235435,
   -0.27330705,  1.77378626,  1.64726432,  1.84151126,  0.5736507 ,
    0.3365337 ,  1.67311062, -1.125      , -0.31448545,  0.09151617,
    0.          ,  0.          ,  0.          ,  0.50481316],
  [ -0.79377236, -0.06483152, -0.20566577,  0.10687372, -0.13497638,
    0.47737631, -0.24034127, -0.237665   , -0.27141677,  1.59643877,
    1.39309299, -0.05691161,  0.75        ,  0.20965697, -0.09151617,
    0.          ,  0.          ,  0.          ,  1.56534502],
  [ -0.28494393, -0.8477027 , -0.57369925, -0.73903794, -0.58489765,
   -0.12207715,  1.57068097,  1.48335743,  1.54948056, -1.29404925,
   -1.22873932,  1.44183635,  1.375      ,  0.20965697, -0.54909702,
    0.          ,  0.          ,  0.          , -0.97993143],
  [ -0.08141255, -1.37369428, -1.30976622, -1.20944734, -1.10230711,
   -0.73337392, -0.20649039, -0.237665   , -0.21988194, -1.24958021,
   -1.1896075 , -0.03423766, -0.5        ,  0.73379939, -0.82364553,
    0.          ,  0.          ,  0.          , -0.81024634],
  [  0.02035314, -0.99449105, -1.00667982, -1.26721692, -1.43974807,
   -0.68782274, -1.34049496, -1.30305984, -1.26775682, -0.31573023,
   -0.28957551, -1.43548765, -1.75        , -1.36277029,  0.27454851,
    0.          ,  0.          ,  0.          , -0.42845487],
  [  0.22388451, -0.01182462,  0.29226188, -0.26862853, -0.08998425,
   -0.16945037, -1.32356952, -1.30305984, -1.30211337, -1.11617307,
   -1.03308019, -1.43548765,  0.125      , -1.36277029, -0.18303234,
    0.          ,  0.          ,  0.          , -0.97993143],
  [  0.73271295, -0.97002633, -1.30976622, -0.66888916, -0.65238584,
   -0.56574559,  0.33512374,  0.74577639,  0.34700119,  0.12896023,
    1.11917021,  0.54394801,  0.75        , -0.83862787,  2.83700127,
    0.          ,  0.          ,  0.          , -1.19203781],
  [  1.1397757 ,  1.82302972,  1.6777997 ,  2.12468248,  2.13712604,
   -0.4072275 ,  0.19972021,  0.25405569,  0.1923967 ,  0.88493402,
    0.92351108,  0.26959324,  0.75        , -0.31448545, -0.36606468,
    0.          ,  0.          ,  0.          ,  1.01386845],
  [  1.85213551,  0.62018077,  0.40050703,  0.44523838,  0.26995276,
   -0.35256609, -0.00338509, -0.0737581 , -0.08245573,  1.2406864 ,
    0.92351108, -0.19975748,  0.75        ,  1.78208422, -0.54909702,
    0.          ,  0.          ,  0.          ,  1.4380812 ]])
```

```
In [129]: x=scaled_df_vols[0]
y=scaled_df_vols[1]
kl = KneeLocator(x,y, S=1.0, curve="concave", direction="increasing")
```

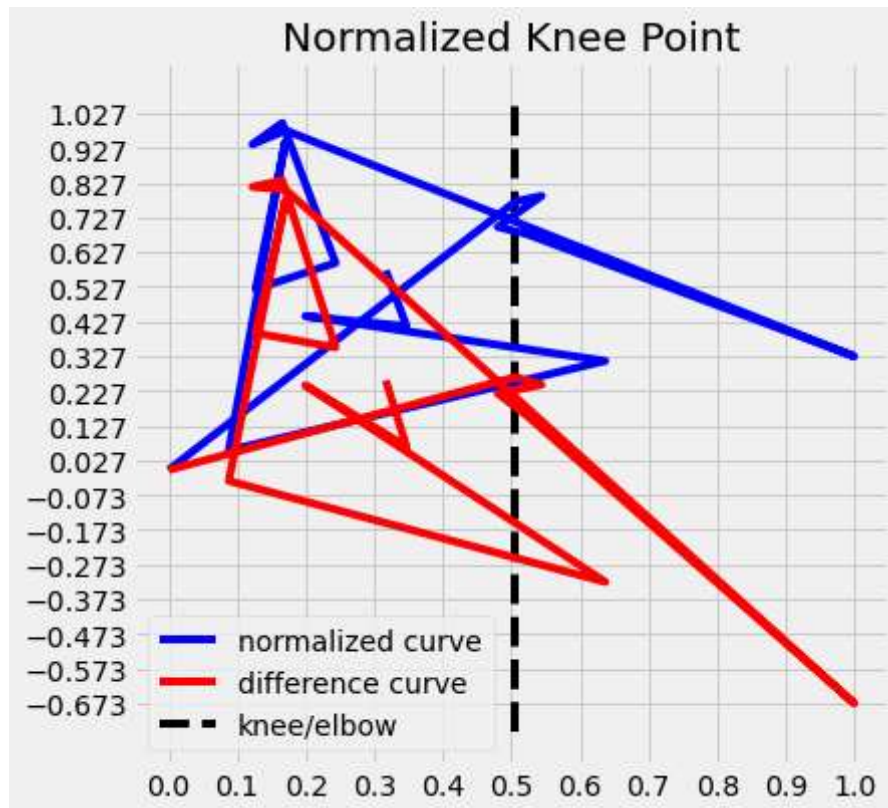
```
In [134]: print("Valor knee:", round(kl.knee, 3))
```

Valor knee: 0.689

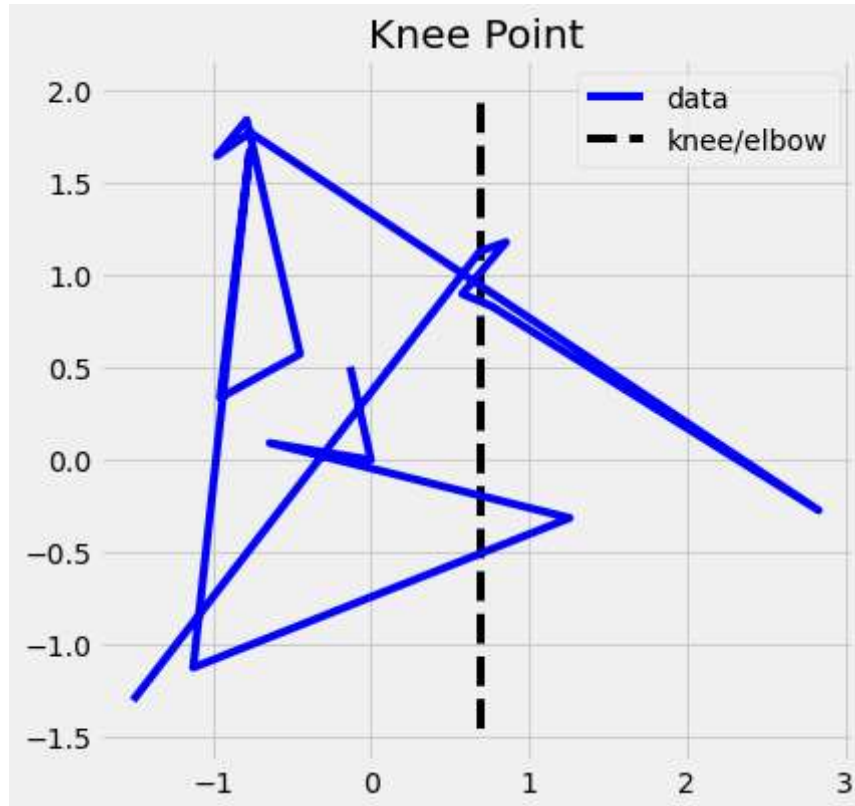
```
In [135]: print("Valor elbow:", round(kl.elbow, 3))
```

Valor elbow: 0.689

```
In [132]: kl.plot_knee_normalized()
```




```
In [133]: kl.plot_knee()
```



```
In [ ]: #Nivell 2
```

```
In [ ]: #Exercici 2  
#Classifica els diferents vols utilitzant l'algorisme de clustering jeràrquic.
```

```
In [ ]: #Agglomerative Hierarchical clustering
```

```
In [31]: df_vols #dataframe de 10 instàncies de les dades dels vols.
```

Out[31]:

	Unnamed: 0	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Dis
3	4	1829.0	1755	1959.0	1925	3920	90.0	90.0	77.0	34.0	34.0	
5	6	1937.0	1830	2037.0	1940	509	240.0	250.0	230.0	57.0	67.0	
7	11	1644.0	1510	1845.0	1725	1333	121.0	135.0	107.0	80.0	94.0	
9	16	1452.0	1425	1640.0	1625	675	228.0	240.0	213.0	15.0	27.0	
11	18	1323.0	1255	1526.0	1510	4	123.0	135.0	110.0	16.0	28.0	
12	19	1416.0	1325	1512.0	1435	54	56.0	70.0	49.0	37.0	51.0	
13	21	1657.0	1625	1754.0	1735	623	57.0	70.0	47.0	19.0	32.0	
17	26	1422.0	1255	1657.0	1610	188	155.0	195.0	143.0	47.0	87.0	
19	30	2107.0	1945	2334.0	2230	362	147.0	165.0	134.0	64.0	82.0	
23	37	1812.0	1650	1927.0	1815	422	135.0	145.0	118.0	72.0	82.0	

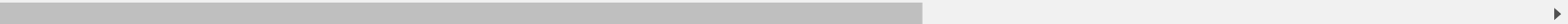
```
In [38]: #Llibreries import
import scipy.cluster.hierarchy as shc #Hierachical clustering
```

```
In [ ]: #Llibreries from
from sklearn.preprocessing import normalize
from sklearn.cluster import AgglomerativeClustering #Agglomerative Hierachical clustering
```

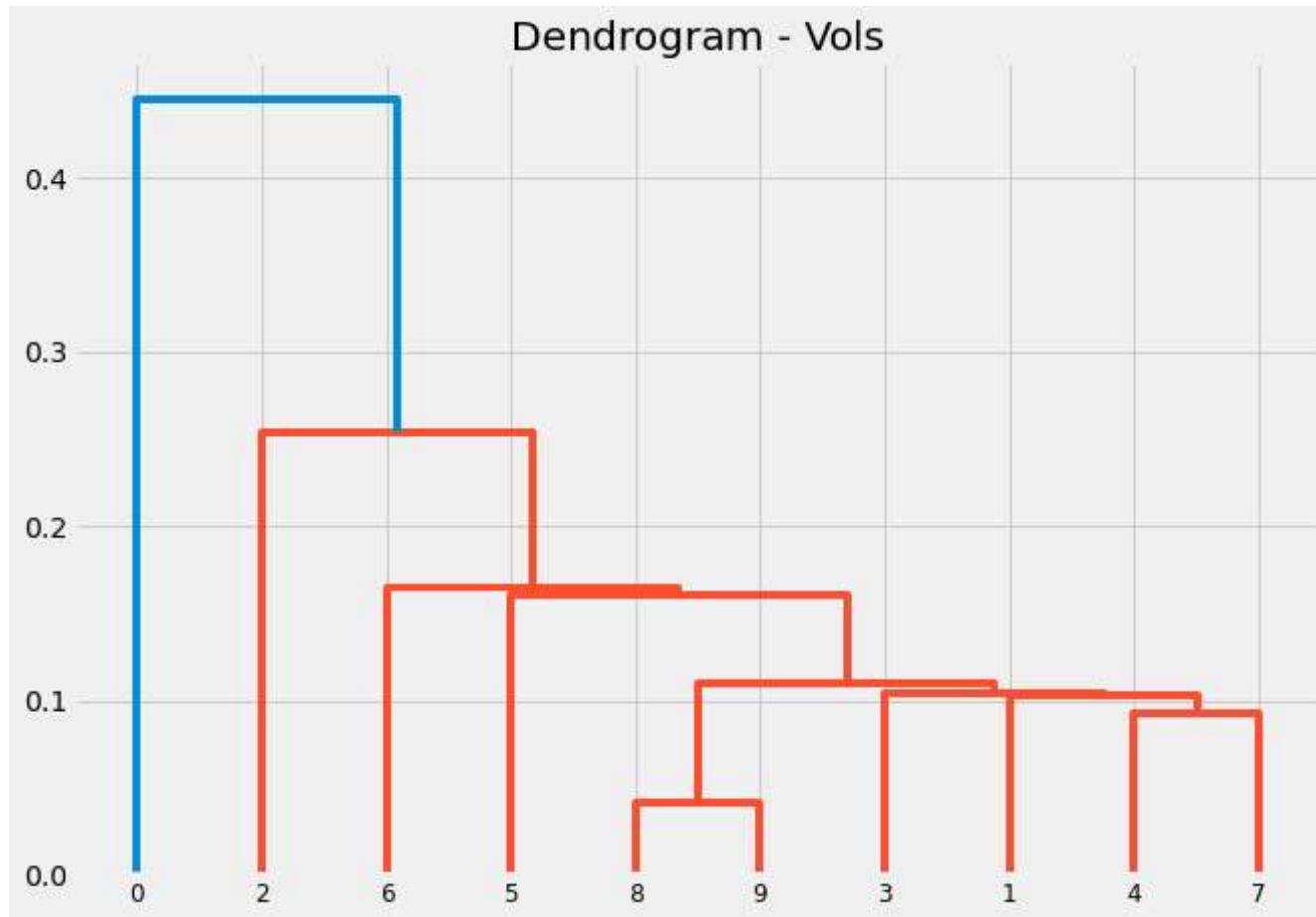
```
In [34]: #Normalització dels vols
df_vols_scaled = normalize(df_vols)
df_vols_scaled = pd.DataFrame(df_vols_scaled, columns=df_vols.columns)
df_vols_scaled.head()
```

Out[34]:

	Unnamed: 0	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Dis
0	0.000735	0.336031	0.322435	0.359915	0.353668	0.720197	0.016535	0.016535	0.014147	0.006247	0.006247	0.0
1	0.001415	0.456716	0.431487	0.480294	0.457423	0.120015	0.056588	0.058946	0.054231	0.013440	0.015798	0.3
2	0.002951	0.441114	0.405160	0.495046	0.462848	0.357667	0.032466	0.036223	0.028710	0.021465	0.025222	0.2
3	0.004562	0.414041	0.406342	0.467650	0.463373	0.192478	0.065015	0.068437	0.060737	0.004277	0.007699	0.4
4	0.006108	0.448963	0.425887	0.517852	0.512422	0.001357	0.041740	0.045813	0.037329	0.005430	0.009502	0.2



```
In [54]: plt.figure(figsize=(10, 7))
plt.title("Dendrogram - Vols") #Generem un dendrograma dels vols
vols = shc.dendrogram(shc.linkage(df_vols_scaled, method='single'))
```



```
In [51]: cluster = AgglomerativeClustering(n_clusters=2, affinity='euclidean', linkage='ward')
cluster.fit_predict(df_vols_scaled)
```

```
Out[51]: array([1, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

```
In [ ]: #Nivell 3
```

```
In [ ]: #Exercici 3  
#Calcula el rendiment del clustering mitjançant un paràmetre com pot ser silhouette.  
#El parametre silhouette té un interval [-1,1]
```

```
In [55]: #Llibreries import  
import pandas as pd  
import numpy as np  
import seaborn as sns
```

```
In [56]: #Llibreries from  
from sklearn.cluster import KMeans  
from sklearn.metrics import silhouette_score  
%matplotlib inline
```

```
In [66]: X= df_vols_scaled['ArrDelay']  
Y= df_vols_scaled['Distance']  
Z= np.concatenate((X,Y))  
Z=pd.DataFrame(Z)
```

```
In [68]: KMean= KMeans(n_clusters=2)  
KMean.fit(Z)  
label=KMean.predict(Z)
```

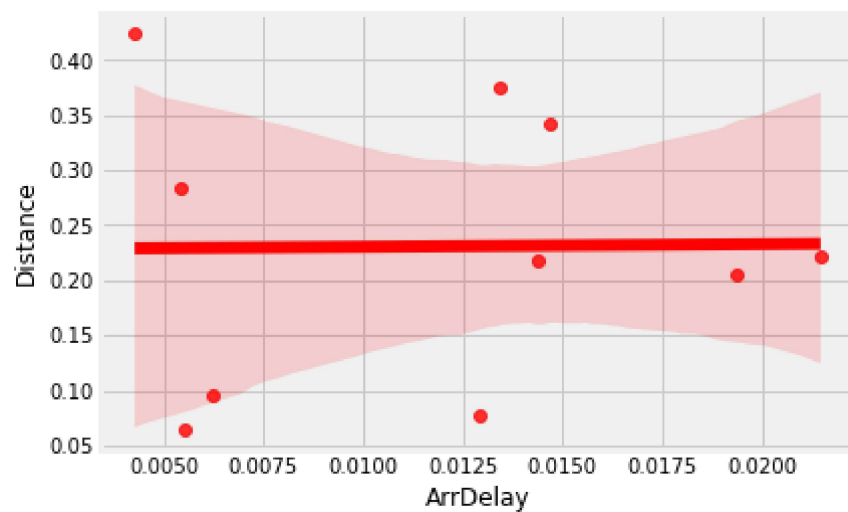
```
In [69]: print(f'Silhouette Score(n=2): {silhouette_score(Z, label)}')
```

Silhouette Score(n=2): 0.7766823273238923

```
In [ ]: #El gran de separació dels clusters és més gran si el parametre silhouette s'apropa a 1.  
#En el cas de l'exercici els clusters es troben més separats que junts.
```

```
In [88]: sns.regplot(x=X, y=Y, scatter=True, color="r")
```

```
Out[88]: <matplotlib.axes._subplots.AxesSubplot at 0x2a2a123a4f0>
```



```
In [ ]:
```