Anem a practicar i a familiaritzar-nos amb algoritmes de clustering.

In [96]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from kneed import KneeLocator
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
%matplotlib inline
from sklearn.preprocessing import normalize
import scipy.cluster.hierarchy as shc
from sklearn.cluster import AgglomerativeClustering
```

In [97]:
```python
# Importación del data frame
raw_df = pd.read_csv('DelayedFlights.csv', encoding = 'utf-8', index_col = 0 )
```

In [98]:
```python
raw_df
```

Out[98]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCarrier	FlightNum	...	TaxiIn
0	2008	1	3	4	2003.0	1955	2211.0	2225	WN	335	...	4.0
1	2008	1	3	4	754.0	735	1002.0	1000	WN	3231	...	5.0
2	2008	1	3	4	628.0	620	804.0	750	WN	448	...	3.0
4	2008	1	3	4	1829.0	1755	1959.0	1925	WN	3920	...	3.0
5	2008	1	3	4	1940.0	1915	2121.0	2110	WN	378	...	4.0
...	...	...	...	...	...	...	...	...	...	...	...	...
7009710	2008	12	13	6	1250.0	1220	1617.0	1552	DL	1621	...	9.0
7009717	2008	12	13	6	657.0	600	904.0	749	DL	1631	...	15.0
7009718	2008	12	13	6	1007.0	847	1149.0	1010	DL	1631	...	8.0
7009726	2008	12	13	6	1251.0	1240	1446.0	1437	DL	1639	...	13.0
7009727	2008	12	13	6	1110.0	1103	1413.0	1418	DL	1641	...	8.0

1936758 rows × 29 columns

In [99]:
```python
# Se eliminan datos categóricos
df = raw_df.drop(columns=['UniqueCarrier', 'TailNum', 'Origin', 'Dest', 'CancellationCode'])
```

In [100…
```python
df
```

Out[100…

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTime	...	D
0	2008	1	3	4	2003.0	1955	2211.0	2225	335	128.0	...	
1	2008	1	3	4	754.0	735	1002.0	1000	3231	128.0	...	
2	2008	1	3	4	628.0	620	804.0	750	448	96.0	...	
4	2008	1	3	4	1829.0	1755	1959.0	1925	3920	90.0	...	
5	2008	1	3	4	1940.0	1915	2121.0	2110	378	101.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
7009710	2008	12	13	6	1250.0	1220	1617.0	1552	1621	147.0	...	
7009717	2008	12	13	6	657.0	600	904.0	749	1631	127.0	...	
7009718	2008	12	13	6	1007.0	847	1149.0	1010	1631	162.0	...	
7009726	2008	12	13	6	1251.0	1240	1446.0	1437	1639	115.0	...	
7009727	2008	12	13	6	1110.0	1103	1413.0	1418	1641	123.0	...	

1936758 rows × 24 columns

In [101…
```python
# Se eliminan las entradas NaN
df.dropna(inplace=True)
```

In [102…
```python
df
```

Out[102…

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTime	...	D
4	2008	1	3	4	1829.0	1755	1959.0	1925	3920	90.0	...	
6	2008	1	3	4	1937.0	1830	2037.0	1940	509	240.0	...	
11	2008	1	3	4	1644.0	1510	1845.0	1725	1333	121.0	...	
16	2008	1	3	4	1452.0	1425	1640.0	1625	675	228.0	...	
18	2008	1	3	4	1323.0	1255	1526.0	1510	4	123.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
7009705	2008	12	13	6	921.0	830	1112.0	1008	1616	111.0	...	
7009709	2008	12	13	6	1552.0	1520	1735.0	1718	1620	43.0	...	
7009710	2008	12	13	6	1250.0	1220	1617.0	1552	1621	147.0	...	
7009717	2008	12	13	6	657.0	600	904.0	749	1631	127.0	...	
7009718	2008	12	13	6	1007.0	847	1149.0	1010	1631	162.0	...	

1247488 rows × 24 columns

In [103…
```python
# Normalización de datos
data_scaled = normalize(df)
data_scaled = pd.DataFrame(data_scaled, columns=df.columns)
```

In [104…
```python
data_scaled
```

Out[104…

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	FlightNum	ActualElapsedTim
0	0.346115	0.000172	0.000517	0.000689	0.315261	0.302506	0.337669	0.331808	0.675683	0.01551
1	0.427918	0.000213	0.000639	0.000852	0.412788	0.389985	0.434099	0.413427	0.108471	0.05114
2	0.474320	0.000236	0.000709	0.000945	0.388337	0.356685	0.435817	0.407471	0.314875	0.02858
3	0.496899	0.000247	0.000742	0.000990	0.359312	0.352630	0.405834	0.402122	0.167035	0.05642
4	0.563119	0.000280	0.000841	0.001122	0.371019	0.351949	0.427948	0.423461	0.001122	0.03449
...	...	...	...	...	...	...	...	...	...	.
1247483	0.611886	0.003657	0.003961	0.001828	0.280651	0.252921	0.338853	0.307162	0.492434	0.03382
1247484	0.481822	0.002879	0.003119	0.001440	0.372405	0.364726	0.416316	0.412237	0.388721	0.01031
1247485	0.508123	0.003037	0.003290	0.001518	0.316312	0.308720	0.409181	0.392732	0.410193	0.03719
1247486	0.664125	0.003969	0.004300	0.001984	0.217296	0.198444	0.298988	0.247724	0.539436	0.04200
1247487	0.596697	0.003566	0.003863	0.001783	0.299240	0.251694	0.341437	0.300131	0.484668	0.04814

1247488 rows × 24 columns

In [105…
```python
# Limitación de muestras por motivos de rendimiento del equipo utilizado
df = data_scaled[ :10000]
```

In [106…
```python
df = df[['FlightNum', 'CRSArrTime']]
```

In [107…
```python
df
```

Out[107…

	FlightNum	CRSArrTime
0	0.675683	0.331808
1	0.108471	0.413427
2	0.314875	0.407471
3	0.167035	0.402122
4	0.001122	0.423461
...	...	...
9995	0.388244	0.410936
9996	0.347309	0.435082
9997	0.139540	0.450415
9998	0.512760	0.396537
9999	0.525204	0.367321

10000 rows × 2 columns

In [108…
```python
# Se crea un dendograma para encontrar el número optimo de clústers
# mediante aglomeración jerárquica
plt.figure(figsize=(8, 5))
plt.title("Dendrogram")
dend = shc.dendrogram(shc.linkage(df, method='ward'))
```

In [109…
```python
# Se marca en el gráfico la cantidad de clústers que se usara finalmente. Se cuenta las lineas verticales
# que atraviesan la zona delimitada
plt.figure(figsize=(8, 5))
plt.title("Dendrogram")
dend = shc.dendrogram(shc.linkage(df, method='ward'))
plt.axhline(y=12, color='r', linestyle='--')
plt.axhline(y=8, color='r', linestyle='--')
```

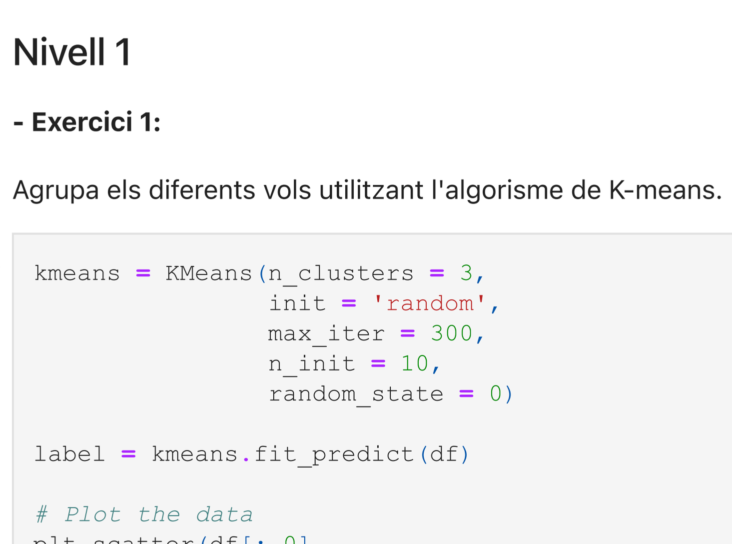
Out[109…
```
<matplotlib.lines.Line2D at 0x7ff79bed2af0>
```

In [110…
```python
df = np.array(df.loc[:,['FlightNum',
                        'CRSArrTime']])     \
                        .reshape(-1, 2)

# Una segunda opción para encontrar el punto de inflexión o "Elbow point" para determinar el número de clústers
wcss = []

for i in range(1, 11):
    model = KMeans(n_clusters = i,
                   init = 'k-means++',
                   max_iter = 300,
                   n_init = 1000,
                   random_state = 0)
    model.fit(df)
    wcss.append(model.inertia_)

# Plot del gráfico "Elbow Point"
plt.plot(range(1, 11), wcss)
plt.title('Elbow Point')
plt.xlabel('Clusters')
plt.ylabel('WCSS')
plt.show()
```



Nivell 1

- Exercici 1:

Agrupa els diferents vols utilitzant l'algorisme de K-means.

In [111…
```python
kmeans = KMeans(n_clusters = 3,
                init = 'random',
                max_iter = 300,
                n_init = 10,
                random_state = 0)

label = kmeans.fit_predict(df)

# Plot the data
plt.scatter(df[:,0],
            df[:,1])

# Plot the clusters
plt.scatter(df[labels==0, 0], df[labels==0, 1], s=50, marker='o', color='red')
plt.scatter(df[labels==1, 0], df[labels==1, 1], s=50, marker='o', color='blue')
plt.scatter(df[labels==2, 0], df[labels==2, 1], s=50, marker='o', color='green')
plt.scatter(kmeans.cluster_centers_[:, 0],
            kmeans.cluster_centers_[:, 1],
            s=100,                                # Set centroid size
            c='orange')                              # Set centroid color
plt.show()
```

In [112…
```python
#Predicción de los clústers.
print(label)
```

```
[0 2 1 ... 2 0 0]
```

In [113…
```python
#Unique labels
u_labels = np.unique(label)

# Grafica del resultado
u_labels
```

Out[113…
```
array([0, 1, 2], dtype=int32)
```

Nivell 2

- Exercici 2:

Agrupa els diferents vols utilitzant l'algorisme de clustering jeràrquic.

In [ ]:

Nivell 3

- Exercici 3:

Calcula el rendiment del clustering mitjançant un paràmetre com pot ser silhouette.