TASCA M8 T01

Pendent: Fer una tramesa Pendent: Rebre una qualificació Descripció Exercicis d'algoritmes d'Agrupació.

PREPARACIÓ DEL DATASET I ANÀLISIS BÀSIC INICIAL

In [1]:
```
# Cridem llibreries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import warnings
```

In [2]:
```
# Importo el fitxer
dataset = pd.read_csv(r'C:\Users\Anna\DataScience\SPRINTS\SPRINT 8 Algoritmes aprenentatge

display(dataset)
```

	ï»¿status_id	status_type	status_published	num_reactions	num_comments	num_shares
0	246675545449582_1649696485147474	video	4/22/2018 6:00	529	512	262
1	246675545449582_1649426988507757	photo	4/21/2018 22:45	150	0	0
2	246675545449582_1648730588577397	video	4/21/2018 6:17	227	236	57
3	246675545449582_1648576705259452	photo	4/21/2018 2:29	111	0	0
4	246675545449582_1645700502213739	photo	4/18/2018 3:22	213	0	0
...	...	...	...	...	...	...
7045	1050855161656896_1061863470556065	photo	9/24/2016 2:58	89	0	0
7046	1050855161656896_1061334757275603	photo	9/23/2016 11:19	16	0	0
7047	1050855161656896_1060126464063099	photo	9/21/2016 23:03	2	0	0
7048	1050855161656896_1058663487542730	photo	9/20/2016 0:43	351	12	22
7049	1050855161656896_1050858841656528	photo	9/10/2016 10:30	17	0	0

7050 rows × 16 columns

In [3]:
```
dataset.describe()
```

Out[3]:

	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sad
count	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000
mean	230.117163	224.356028	40.022553	215.043121	12.728652	1.289362	0.696454	0.243688
std	462.625309	889.636820	131.599965	449.472357	39.972930	8.719650	3.957183	1.597150
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	17.000000	0.000000	0.000000	17.000000	0.000000	0.000000	0.000000	0.000000

	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sad
50%	59.500000	4.000000	0.000000	58.000000	0.000000	0.000000	0.000000	0.000000
75%	219.000000	23.000000	4.000000	184.750000	3.000000	0.000000	0.000000	0.000000
max	4710.000000	20990.000000	3424.000000	4710.000000	657.000000	278.000000	157.000000	51.000000

In [4]:

```
# Elimino les 4 últimes columnes, que no hi ha cap tipus de valor
dataset = dataset.drop(["Column1", "Column2", "Column3", "Column4"], axis=1)

dataset.describe()
```

Out[4]:

	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sad
count	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000	7050.000000
mean	230.117163	224.356028	40.022553	215.043121	12.728652	1.289362	0.696454	0.243688
std	462.625309	889.636820	131.599965	449.472357	39.972930	8.719650	3.957183	1.597150
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	17.000000	0.000000	0.000000	17.000000	0.000000	0.000000	0.000000	0.000000
50%	59.500000	4.000000	0.000000	58.000000	0.000000	0.000000	0.000000	0.000000
75%	219.000000	23.000000	4.000000	184.750000	3.000000	0.000000	0.000000	0.000000
max	4710.000000	20990.000000	3424.000000	4710.000000	657.000000	278.000000	157.000000	51.000000

In [5]:

```
# Divideixo la columna status_published en dos, el dia i l'hora, i li canvio el nom a les
publicacio = dataset.status_published.str.split(pat=" ",expand=True)
publicacio.columns = ["date_published", "time_published"]
dataset =pd.concat([dataset,publicacio], axis=1)
display(dataset)
```

	ï»¿status_id	status_type	status_published	num_reactions	num_comments	num_shares
0	246675545449582_1649696485147474	video	4/22/2018 6:00	529	512	262
1	246675545449582_1649426988507757	photo	4/21/2018 22:45	150	0	0
2	246675545449582_1648730588577397	video	4/21/2018 6:17	227	236	57
3	246675545449582_1648576705259452	photo	4/21/2018 2:29	111	0	0
4	246675545449582_1645700502213739	photo	4/18/2018 3:22	213	0	0
...	...	...	...	...	...	...
7045	1050855161656896_1061863470556065	photo	9/24/2016 2:58	89	0	0
7046	1050855161656896_1061334757275603	photo	9/23/2016 11:19	16	0	0
7047	1050855161656896_1060126464063099	photo	9/21/2016 23:03	2	0	0
7048	1050855161656896_1058663487542730	photo	9/20/2016 0:43	351	12	22
7049	1050855161656896_1050858841656528	photo	9/10/2016 10:30	17	0	0

7050 rows × 14 columns

In [6]:

```
dataset.columns
```

Out[6]:
```
Index(['ï»¿status_id', 'status_type', 'status_published', 'num_reactions',
       'num_comments', 'num_shares', 'num_likes', 'num_loves', 'num_wows',
       'num_hahas', 'num_sads', 'num_angrys', 'date_published',
       'time_published'],
      dtype='object')
```

In [7]:
```
# Modifico el nom de la primera columna per fer-lo més accessible
dataset.rename({"ï»¿status_id": "status_id"}, axis=1, inplace=True)

dataset.columns
```

Out[7]:
```
Index(['status_id', 'status_type', 'status_published', 'num_reactions',
       'num_comments', 'num_shares', 'num_likes', 'num_loves', 'num_wows',
       'num_hahas', 'num_sads', 'num_angrys', 'date_published',
       'time_published'],
      dtype='object')
```

In [8]:
```
# Reordeno les columnes colocant les que he creat abans a on han d'anar
dataset = dataset.reindex(columns=['status_id', 'status_type', 'status_published','date_pu
       'time_published', 'num_reactions',
       'num_comments', 'num_shares', 'num_likes', 'num_loves', 'num_wows',
       'num_hahas', 'num_sads', 'num_angrys'])
dataset.columns
```

Out[8]:
```
Index(['status_id', 'status_type', 'status_published', 'date_published',
       'time_published', 'num_reactions', 'num_comments', 'num_shares',
       'num_likes', 'num_loves', 'num_wows', 'num_hahas', 'num_sads',
       'num_angrys'],
      dtype='object')
```

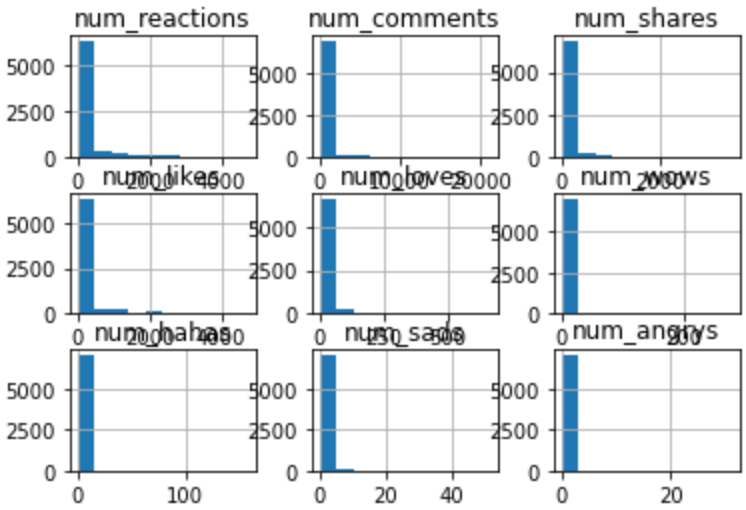
In [9]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7050 entries, 0 to 7049
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   status_id         7050 non-null   object
 1   status_type       7050 non-null   object
 2   status_published  7050 non-null   object
 3   date_published    7050 non-null   object
 4   time_published    7050 non-null   object
 5   num_reactions     7050 non-null   int64 
 6   num_comments      7050 non-null   int64 
 7   num_shares        7050 non-null   int64 
 8   num_likes         7050 non-null   int64 
 9   num_loves         7050 non-null   int64 
 10  num_wows          7050 non-null   int64 
 11  num_hahas         7050 non-null   int64 
 12  num_sads          7050 non-null   int64 
 13  num_angrys        7050 non-null   int64 
dtypes: int64(9), object(5)
memory usage: 771.2+ KB
```

Com a resume, tenim 14 columnes, 5 de categòriques de tipus object i 9 de numèriques de tipus int64. No tenim cap null al dataset, per tant les 7050 files són vàlides a per a treballar-les sense haver d'eliminar o convertir cap valor. Els noms de les columnes són fàcils per a entendre què són i per a treballar-los, per tant, el més bàsic de les dades ja ho tenim fet i les podem començar a treballar d'altres maneres.

In [10]:
```
# Fem un histograma dels valors numèrics per veure com es distribueixen d'una forma més vi
dataset.hist()
```

```
plt.rcParams['figure.figsize'] = [20, 20]
plt.show()
```



In [11]:
```
display(dataset)
```

	status_id	status_type	status_published	date_published	time_published	num_reacti
0	246675545449582_1649696485147474	video	4/22/2018 6:00	4/22/2018	6:00	
1	246675545449582_1649426988507757	photo	4/21/2018 22:45	4/21/2018	22:45	
2	246675545449582_1648730588577397	video	4/21/2018 6:17	4/21/2018	6:17	
3	246675545449582_1648576705259452	photo	4/21/2018 2:29	4/21/2018	2:29	
4	246675545449582_1645700502213739	photo	4/18/2018 3:22	4/18/2018	3:22	
...	...	...	...	...	...	
7045	1050855161656896_1061863470556065	photo	9/24/2016 2:58	9/24/2016	2:58	
7046	1050855161656896_1061334757275603	photo	9/23/2016 11:19	9/23/2016	11:19	
7047	1050855161656896_1060126464063099	photo	9/21/2016 23:03	9/21/2016	23:03	
7048	1050855161656896_1058663487542730	photo	9/20/2016 0:43	9/20/2016	0:43	
7049	1050855161656896_1050858841656528	photo	9/10/2016 10:30	9/10/2016	10:30	

7050 rows × 14 columns

Estandaritzo les dades amb standard scaler per reduir tots els valors en mitjana=0 i variança=1. És un procés bàsic per fer un PCA (Principal Component Analysis), sistema que permet fer anar més ràpid un algoritme de machine learning com per fer visualització de dades

In [12]:
```
# Importo la llibreria, separo les columnes en x i y i aplico l'standard scale
from sklearn.preprocessing import StandardScaler

X_features = ['num_reactions', 'num_comments', 'num_shares',
       'num_likes', 'num_loves', 'num_wows', 'num_hahas', 'num_sads',
       'num_angrys']

X = dataset[X_features]
y = dataset["status_type"]

X = StandardScaler().fit_transform(X)
```

In [13]:
```
# Aplico el PCA i passo de 8 components a 2
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
componentsPrincipals = pca.fit_transform(X)
datasetPrincipal = pd.DataFrame(data = componentsPrincipals, columns = ["Component Princip

# Concateno les dues columnes noves amb la columna que he escollit com a target
datasetFinal = pd.concat([dataset["status_type"], datasetPrincipal], axis=1)
display(datasetFinal)
```

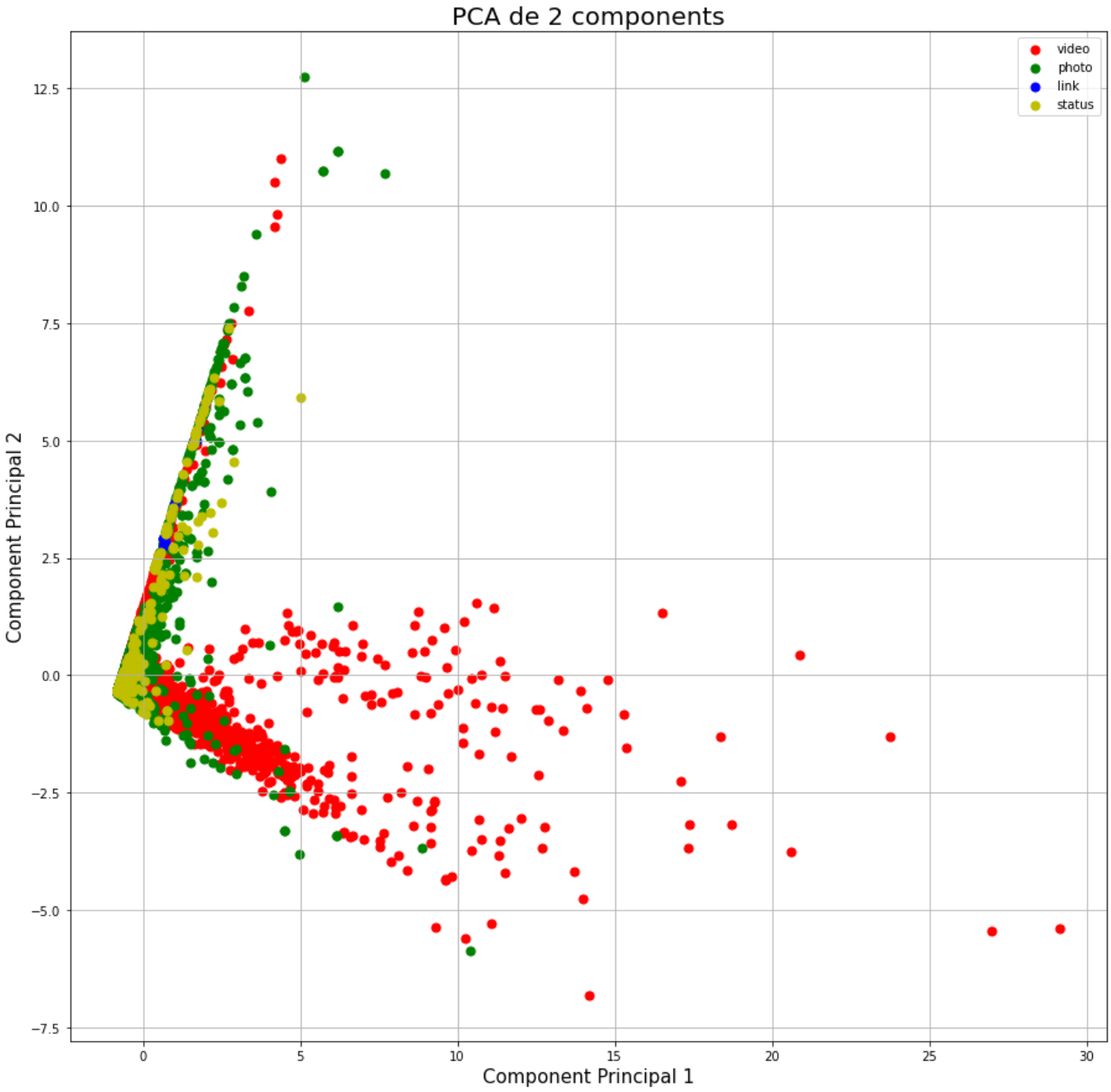
	status_type	Component Principal 1	Component Principal 2
0	video	2.255817	-0.122109
1	photo	-0.632921	0.047366
2	video	0.100804	-0.057427
3	photo	-0.682104	-0.061251
4	photo	-0.453211	0.170515
...	...	...	...
7045	photo	-0.709849	-0.122522
7046	photo	-0.710462	-0.371228
7047	photo	-0.808425	-0.370634
7048	photo	-0.277459	0.556486
7049	photo	-0.800648	-0.323046

7050 rows × 3 columns

In [14]:
```
datasetFinal.status_type.unique()
```

Out[14]:
```
array(['video', 'photo', 'link', 'status'], dtype=object)
```

In [15]:
```
# Faig la figura del PCA de 2 components (visualització de dades)

fig = plt.figure(figsize=(15,15))
ax = fig.add_subplot(1,1,1)

ax.set_xlabel("Component Principal 1", fontsize = 15)
ax.set_ylabel("Component Principal 2", fontsize = 15)
ax.set_title('PCA de 2 components', fontsize = 20)


posicions = ["video", "photo", "link", "status"]
colors = ["r", "g", "b", "y"]

for posicio, color in zip(posicions,colors):
    mantenir = datasetFinal["status_type"] == posicio
    ax.scatter(datasetFinal.loc[mantenir, "Component Principal 1"],
               datasetFinal.loc[mantenir, "Component Principal 2"],
               c = color,
               s = 50)

ax.legend(posicions)
ax.grid()
```



Preparem les dades per aplicar el PCA per fer més ràpids algoritmes de Machine Lerning

In [16]:
```
X_features = ['num_reactions', 'num_comments', 'num_shares',
       'num_likes', 'num_loves', 'num_wows', 'num_hahas', 'num_sads',
       'num_angrys']

X = dataset[X_features]
y_features = ['status_type'] #'status_id', 'status_type', 'date_published', 'time_publishe
# decideixo utilitzar status_type però em guardo les altres categòriques per si ho vull ca
y = dataset[y_features]
```

In [17]:
```
# Primer de tot dividim el dataset en train i test

from sklearn.model_selection import train_test_split

train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.30, random_state=0)
```

In [18]:
```
print(train_X.shape)
```

```
(4935, 9)
```

In [19]:
```
print(train_y.shape)
```

```
(4935, 1)
```

In [20]:
```
print(test_X.shape)
```

```
(2115, 9)
```

In [21]:
```
print(test_y.shape)
```

```
(2115, 1)
```

In [22]:
```
# Estandaritzem el dataset amb Standard Scaler, l'adaptem al train_X i l'apliquem al trai
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

scaler.fit(train_X)
train_X = scaler.transform(train_X)
test_X = scaler.transform(test_X)
```

Utilitzem el PCA per a fer més ràpids algoritmes de Machine Learning, els quals s'apliquen després del procés que farem ara (és a dir, al primer exercici, l'Exercici 1)

In [23]:
```
# Importem la llibreria, fem una instància del model i ho apliquem NOMÉS al training set
from sklearn.decomposition import PCA

pca = PCA(.95)

pca.fit(train_X)
```

Out[23]:
```
PCA(n_components=0.95)
```

In [24]:
```
pca.n_components_
```

Out[24]:
```
7
```

In [25]:
```
# Apliquem el mapeig/transformació al conjunt de train_X i al de test_X
train_X = pca.transform(train_X)
test_X = pca.transform(test_X)
```

In [26]:
```
# Importo el model que vull utilitzar (amb Sklearn tots els models de machine learning s'
from sklearn.linear_model import LogisticRegression

regLog = LogisticRegression(solver="lbfgs") #canviem el paràmetre solver perquè és molt le
regLog.fit(train_X, train_y)
```

```
C:\Users\Anna\anaconda3\lib\site-packages\sklearn\utils\validation.py:1111: DataConversion
Warning: A column-vector y was passed when a 1d array was expected. Please change the shap
e of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
C:\Users\Anna\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: Convergen
ceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[26]:

```
▾ LogisticRegression

LogisticRegression()
```

In [27]:

```
# Fem una predicció de dades noves utilitzant la informació que ens ha donat el model ante
# Predicció per una sola observació
regLog.predict(test_X[0].reshape(1,-1))
```

Out[27]:

```
array(['photo'], dtype=object)
```

In [28]:

```
# Predicció de més d'una observació al mateix moment
regLog.predict(test_X[0:100])
```

Out[28]:

```
array(['photo', 'video', 'photo', 'photo', 'photo', 'photo', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'video', 'photo', 'video', 'photo', 'photo', 'photo', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'video', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'video', 'video', 'photo', 'photo', 'video', 'video', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'photo', 'video',
       'video', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'video', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'photo', 'photo',
       'photo', 'photo', 'photo', 'photo', 'photo', 'video', 'photo',
       'video', 'photo', 'photo', 'video', 'video', 'photo', 'video',
       'photo', 'video', 'video', 'photo', 'photo', 'video', 'photo',
       'photo', 'photo'], dtype=object)
```

In [29]:

```
# Mesurem la precisió del rendiment del model (accuracy, o fracció de prediccions correcte
precisio = regLog.score(test_X, test_y)
print(precisio)
```

```
0.7612293144208038
```

Entenem doncs, que la precisió és el percentatge del resultat anterior

EXERCICI 1

Descarrega el dataset adjunt, de registres de publicacions a Facebook sobre Tailàndia, i classifica els diferents registres utilitzant l'algorisme de K-means.

In [30]:

```
# Importo llibreries necessàries
import matplotlib.pyplot as plt
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
from sklearn.decomposition import PCA
```

```
from sklearn.metrics import silhouette_score, adjusted_rand_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
```

In [31]:
```
display(dataset)
```

	status_id	status_type	status_published	date_published	time_published	num_reacti
0	246675545449582_1649696485147474	video	4/22/2018 6:00	4/22/2018	6:00	
1	246675545449582_1649426988507757	photo	4/21/2018 22:45	4/21/2018	22:45	
2	246675545449582_1648730588577397	video	4/21/2018 6:17	4/21/2018	6:17	
3	246675545449582_1648576705259452	photo	4/21/2018 2:29	4/21/2018	2:29	
4	246675545449582_1645700502213739	photo	4/18/2018 3:22	4/18/2018	3:22	
...	...	...	...	...	...	
7045	1050855161656896_1061863470556065	photo	9/24/2016 2:58	9/24/2016	2:58	
7046	1050855161656896_1061334757275603	photo	9/23/2016 11:19	9/23/2016	11:19	
7047	1050855161656896_1060126464063099	photo	9/21/2016 23:03	9/21/2016	23:03	
7048	1050855161656896_1058663487542730	photo	9/20/2016 0:43	9/20/2016	0:43	
7049	1050855161656896_1050858841656528	photo	9/10/2016 10:30	9/10/2016	10:30	

7050 rows × 14 columns

In [32]:
```
#Converteixo el dataset a array de numpy
features1 = dataset.to_numpy()

print(features1)
print(type(features1))
```

```
[['246675545449582_1649696485147474' 'video' '4/22/2018 6:00' ... 1 1 0]
 ['246675545449582_1649426988507757' 'photo' '4/21/2018 22:45' ... 0 0 0]
 ['246675545449582_1648730588577397' 'video' '4/21/2018 6:17' ... 1 0 0]
 ...
 ['1050855161656896_1060126464063099' 'photo' '9/21/2016 23:03' ... 0 0 0]
 ['1050855161656896_1058663487542730' 'photo' '9/20/2016 0:43' ... 0 0 0]
 ['1050855161656896_1050858841656528' 'photo' '9/10/2016 10:30' ... 0 0 0]]
<class 'numpy.ndarray'>
```

In [33]:
```
# Hem quedo només amb les columnes int de l'array anterior, amb les quals vull treballar
features = np.delete(features1, (0,1,2,3,4), axis=1)
print(features[:])
features.shape
```

```
[[529 512 262 ... 1 1 0]
 [150 0 0 ... 0 0 0]
 [227 236 57 ... 1 0 0]
 ...
 [2 0 0 ... 0 0 0]
 [351 12 22 ... 0 0 0]
 [17 0 0 ... 0 0 0]]
```

Out[33]:
```
(7050, 9)
```

In [34]:
```
#Canvio la forma de la matriu ja que sinó em donava error més endavant
```

```
features = np.reshape(features,(9,7050), order='F')
print(features)
print(features.shape)
```

```
[[529 170 221 ... 0 0 0]
 [150 210 152 ... 0 0 0]
 [227 222 234 ... 0 0 0]
 ...
 [503 332 102 ... 0 0 0]
 [295 135 37 ... 0 0 0]
 [203 150 75 ... 0 0 0]]
(9, 7050)
```

In [35]:
```
#Creo una array amb només els noms de cada columna i trec les primeres 5 perquè no són de
features_nom_etiqueta = np.genfromtxt (dataset, delimiter=',', usecols=(0,), skip_header=5
features_nom_etiqueta[:]
```

Out[35]:
```
array(['num_reactions', 'num_comments', 'num_shares', 'num_likes',
       'num_loves', 'num_wows', 'num_hahas', 'num_sads', 'num_angrys'],
      dtype='<U13')
```

In [36]:
```
#Converteixo els noms dels atributs en números per a poder utilitzar-los
label_encoder = LabelEncoder()

features_nom_encoder = label_encoder.fit_transform(features_nom_etiqueta)

features_nom_encoder[:]
print(features_nom_encoder)
print(features_nom_encoder.shape)
```

```
[5 1 7 3 4 8 2 6 0]
(9,)
```

In [37]:
```
# Guardem com a número de clusters el tamany del label_encoder per utilitzar-lo més endava
n_clusters = len(label_encoder.classes_)
print(n_clusters)
```

```
9
```

In [38]:
```
# Implementem el MinMaxScaler i el PCA al pipline per reduir la dimensionalitat, fer les c
preprocessor = Pipeline(
    [
        ("scaler", MinMaxScaler()),
        ("pca", PCA(n_components=2, random_state=42)),
    ]
)
```

In [39]:
```
# Creo un pipeline separat per dur a terme l'agrupament de k-means i invalido els argument
clusterer = Pipeline(
    [
        (
            "kmeans",
            KMeans(
                n_clusters=n_clusters,
                init="k-means++",
                n_init=50,
                max_iter=500,
                random_state=42,
            ),
        ),
```

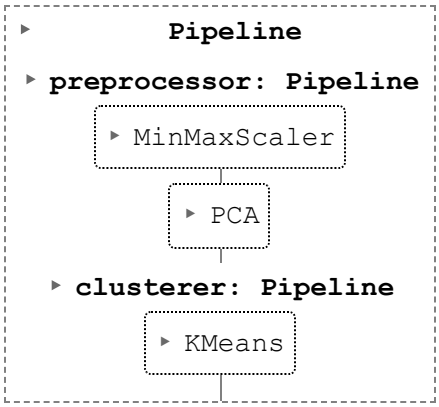
```
    ]
)
```

In [40]:
```
# Creo una pipline dins una altra pipline, és a dir una pipeline de clúster de k-means d'e

pipe = Pipeline(
    [
        ("preprocessor", preprocessor),
        ("clusterer", clusterer)
    ]
)
```

In [41]:
```
#Cridant .fit() amb dades com a argument realitza tots els passos de canalització de les c
pipe.fit(features)
```

```
C:\Users\Anna\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1332: UserWarning: KM
eans is known to have a memory leak on Windows with MKL, when there are less chunks than a
vailable threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

Out[41]:



In [42]:
```
#Evaluo el rendiment calculant el coeficient silhouette
preprocessed_data = pipe["preprocessor"].transform(features)
```

In [43]:
```
predicted_labels = pipe["clusterer"]["kmeans"].labels_
```

In [44]:
```
silhouette_score(preprocessed_data, predicted_labels, metric='euclidean')
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_4072/1031975282.py in <module>
----> 1 silhouette_score(preprocessed_data, predicted_labels, metric='euclidean')

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in silhouette_score
(X, labels, metric, sample_size, random_state, **kwds)
    115         else:
    116             X, labels = X[indices], labels[indices]
--> 117     return np.mean(silhouette_samples(X, labels, metric=metric, **kwds))
    118
    119

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in silhouette_sampl
es(X, labels, metric, **kwds)
    229     n_samples = len(labels)
    230     label_freqs = np.bincount(labels)
--> 231     check_number_of_labels(len(le.classes_), n_samples)
```

```
    232
    233     kwds["metric"] = metric

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in check_number_of_
labels(n_labels, n_samples)
     31     """
     32     if not 1 < n_labels < n_samples:
---> 33         raise ValueError(
     34             "Number of labels is %d. Valid values are 2 to n_samples - 1 (inclusiv
e)"
     35             % n_labels

ValueError: Number of labels is 9. Valid values are 2 to n_samples - 1 (inclusive)
```

Un coeficient de silhouette 0 indica que els clústers s'estan superposant significativament, i un coeficient desilhouette 1 indica que els clústers estan ben separats. En el nostre cas, està més a prop de l'1 que del 0

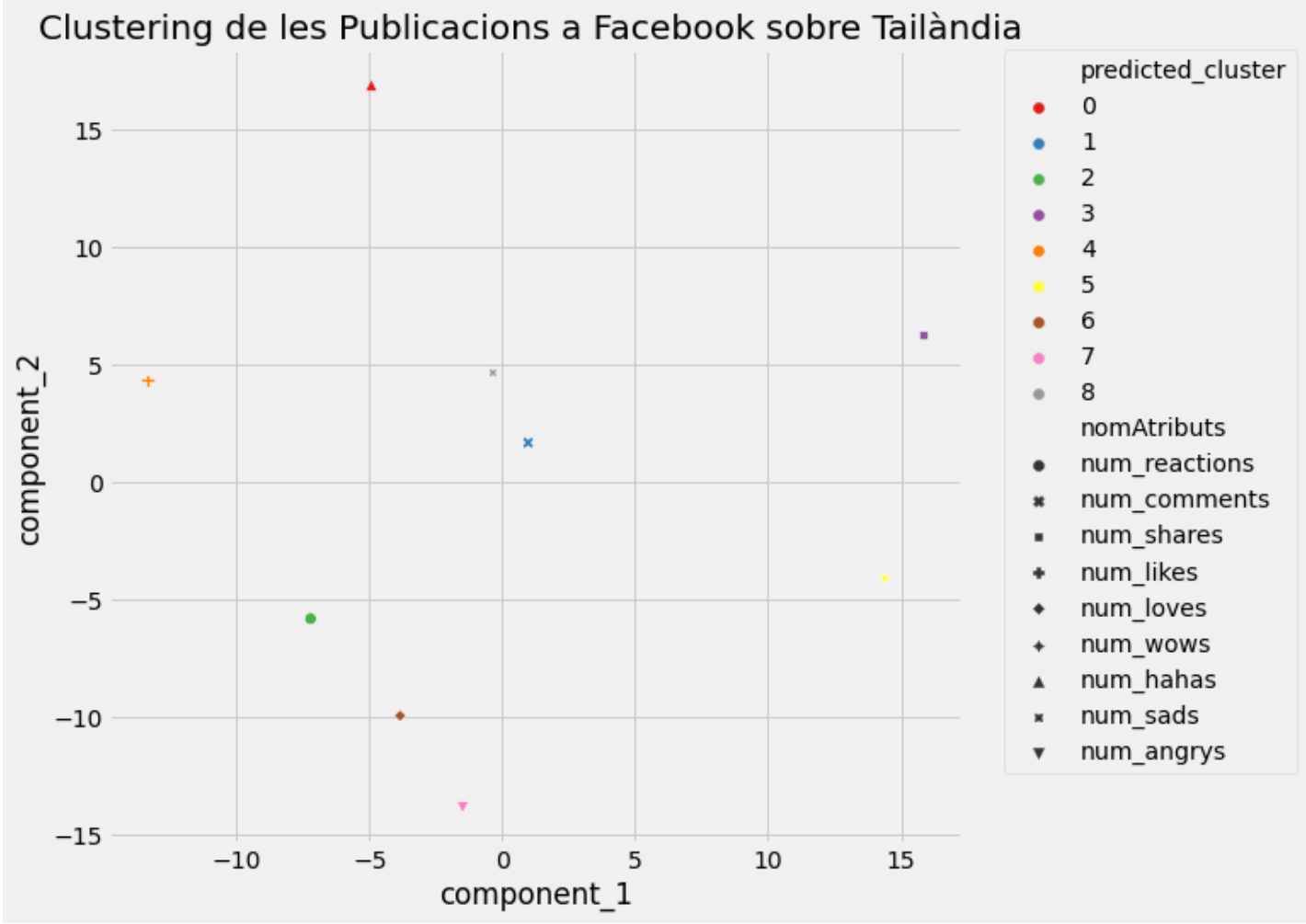
In [45]:

```
# Anem a fer el gràfic de tot això utilitzant DataFrame i seaborn
grafic = pd.DataFrame(
    pipe["preprocessor"].transform(features),
    columns=["component_1", "component_2"],
)

grafic["predicted_cluster"] = pipe["clusterer"]["kmeans"].labels_
grafic["nomAtributs"] = label_encoder.inverse_transform(features_nom_encoder)
```

In [46]:

```
plt.style.use("fivethirtyeight")
plt.figure(figsize=(8, 8))

scat = sns.scatterplot(
    "component_1",
    "component_2",
    s=50,
    data=grafic,
    hue="predicted_cluster",
    style="nomAtributs",
    palette="Set1",
)

scat.set_title("Clustering de les Publicacions a Facebook sobre Tailàndia ")
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.0)

plt.show()
```

```
C:\Users\Anna\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass t
he following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
```



In [ ]:

In [47]:

```
# Empty lists to hold evaluation metrics
silhouette_scores = []
ari_scores = []
for n in range(2, 11):
    # This set the number of components for pca,
    # but leaves other steps unchanged
    pipe["preprocessor"]["pca"].n_components = n
    pipe.fit(features)

    silhouette_coef = silhouette_score(
        pipe["preprocessor"].transform(features),
        pipe["clusterer"]["kmeans"].labels_,
    )
    ari = adjusted_rand_score(
        features_nom_encoder,
        pipe["clusterer"]["kmeans"].labels_,
    )

    # Add metrics to their lists
    silhouette_scores.append(silhouette_coef)
    ari_scores.append(ari)
```

```
C:\Users\Anna\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1332: UserWarning: KM
eans is known to have a memory leak on Windows with MKL, when there are less chunks than a
vailable threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
```

```
~\AppData\Local\Temp/ipykernel_4072/1932880641.py in <module>
      8     pipe.fit(features)
      9
---> 10     silhouette_coef = silhouette_score(
     11         pipe["preprocessor"].transform(features),
     12         pipe["clusterer"]["kmeans"].labels_,

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in silhouette_score
(X, labels, metric, sample_size, random_state, **kwds)
    115         else:
    116             X, labels = X[indices], labels[indices]
--> 117     return np.mean(silhouette_samples(X, labels, metric=metric, **kwds))
    118
    119

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in silhouette_sampl
es(X, labels, metric, **kwds)
    229     n_samples = len(labels)
    230     label_freqs = np.bincount(labels)
--> 231     check_number_of_labels(len(le.classes_), n_samples)
    232
    233     kwds["metric"] = metric

~\anaconda3\lib\site-packages\sklearn\metrics\cluster\_unsupervised.py in check_number_of_
labels(n_labels, n_samples)
     31     """
     32     if not 1 < n_labels < n_samples:
---> 33         raise ValueError(
     34             "Number of labels is %d. Valid values are 2 to n_samples - 1 (inclusiv
e)"
     35             % n_labels

ValueError: Number of labels is 9. Valid values are 2 to n_samples - 1 (inclusive)
```

In [ ]:

```
```

EXERCICI 2

Classifica els diferents registres utilitzant l'algorisme de clustering jeràrquic.

In [48]:

```
# Observem les dades que volem utilitzar per recordar el format
dataset.head()
```

Out[48]:

	status_id	status_type	status_published	date_published	time_published	num_reactions
0	246675545449582_1649696485147474	video	4/22/2018 6:00	4/22/2018	6:00	529
1	246675545449582_1649426988507757	photo	4/21/2018 22:45	4/21/2018	22:45	150
2	246675545449582_1648730588577397	video	4/21/2018 6:17	4/21/2018	6:17	227
3	246675545449582_1648576705259452	photo	4/21/2018 2:29	4/21/2018	2:29	111
4	246675545449582_1645700502213739	photo	4/18/2018 3:22	4/18/2018	3:22	213

In [49]:

```
dataset.columns
```

Out[49]:

```
Index(['status_id', 'status_type', 'status_published', 'date_published',
       'time_published', 'num_reactions', 'num_comments', 'num_shares',
       'num_likes', 'num_loves', 'num_wows', 'num_hahas', 'num_sads',
```

```
       'num_angrys'],
      dtype='object')
```

In [50]:
```
#Elimino les columnes que són de tipus objecte i em quedo només amb les de tipus int
dataset = dataset.drop(['status_id', 'status_type', 'status_published', 'date_published',
       'time_published'],axis=1)
dataset.head()
```

Out[50]:

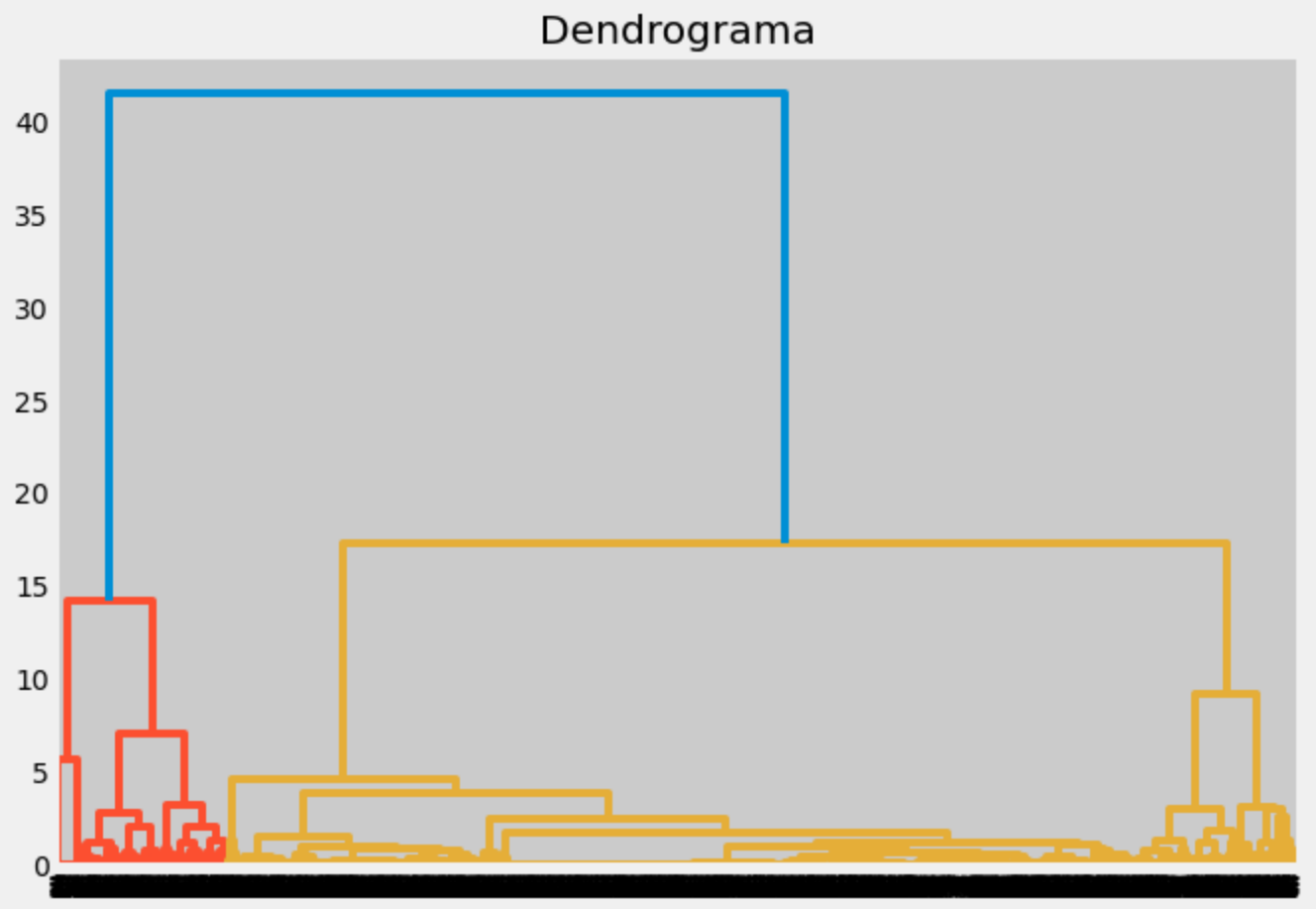
	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_ang
0	529	512	262	432	92	3	1	1	
1	150	0	0	150	0	0	0	0	
2	227	236	57	204	21	1	1	0	
3	111	0	0	111	0	0	0	0	
4	213	0	0	204	9	0	0	0	

In [51]:
```
#Normalitzem els valors del dataset
from sklearn.preprocessing import normalize
data_scaled = normalize(dataset)
data_scaled = pd.DataFrame(data_scaled, columns=dataset.columns)
data_scaled.head()
```

Out[51]:

	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_ang
0	0.589334	0.570395	0.291882	0.481271	0.102493	0.003342	0.001114	0.001114	
1	0.707107	0.000000	0.000000	0.707107	0.000000	0.000000	0.000000	0.000000	
2	0.581225	0.604269	0.145946	0.522334	0.053770	0.002560	0.002560	0.000000	
3	0.707107	0.000000	0.000000	0.707107	0.000000	0.000000	0.000000	0.000000	
4	0.721864	0.000000	0.000000	0.691363	0.030501	0.000000	0.000000	0.000000	

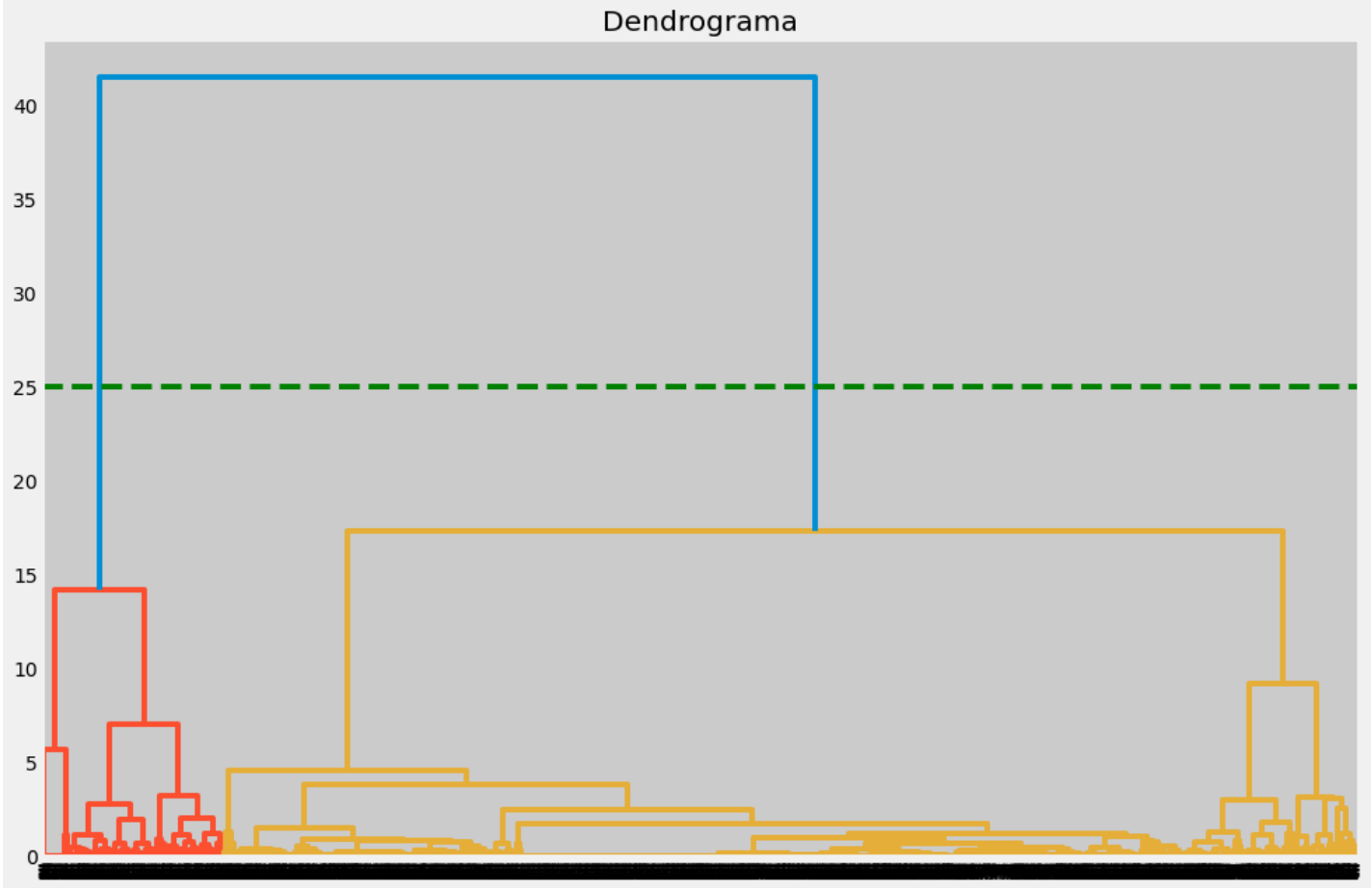
In [52]:
```
# Dibuixo el dendograma
import scipy.cluster.hierarchy as shc
plt.figure(figsize=(10, 7))
plt.title("Dendrograma")
dend = shc.dendrogram(shc.linkage(data_scaled, method='ward'))
```



L'eix X conté les mostres i l'eix Y representa la distància entre aquestes mostres. La línia vertical amb distància màxima és la línia blava i, per tant, podem decidir un llindar i tallar el dendrograma (sobre 25 per exemple)

In [53]:
```
plt.figure(figsize=(15, 10))
plt.title("Dendrograma")
dend = shc.dendrogram(shc.linkage(data_scaled, method='ward'))
plt.axhline(y=25, color='g', linestyle='--')
```

Out[53]:
```
<matplotlib.lines.Line2D at 0x248661f0cd0>
```



Tenim dos clústers ja que la línia talla el dendrograma en dos punts. Ara apliquem l'agrupació jeràrquica per a 2 clústers

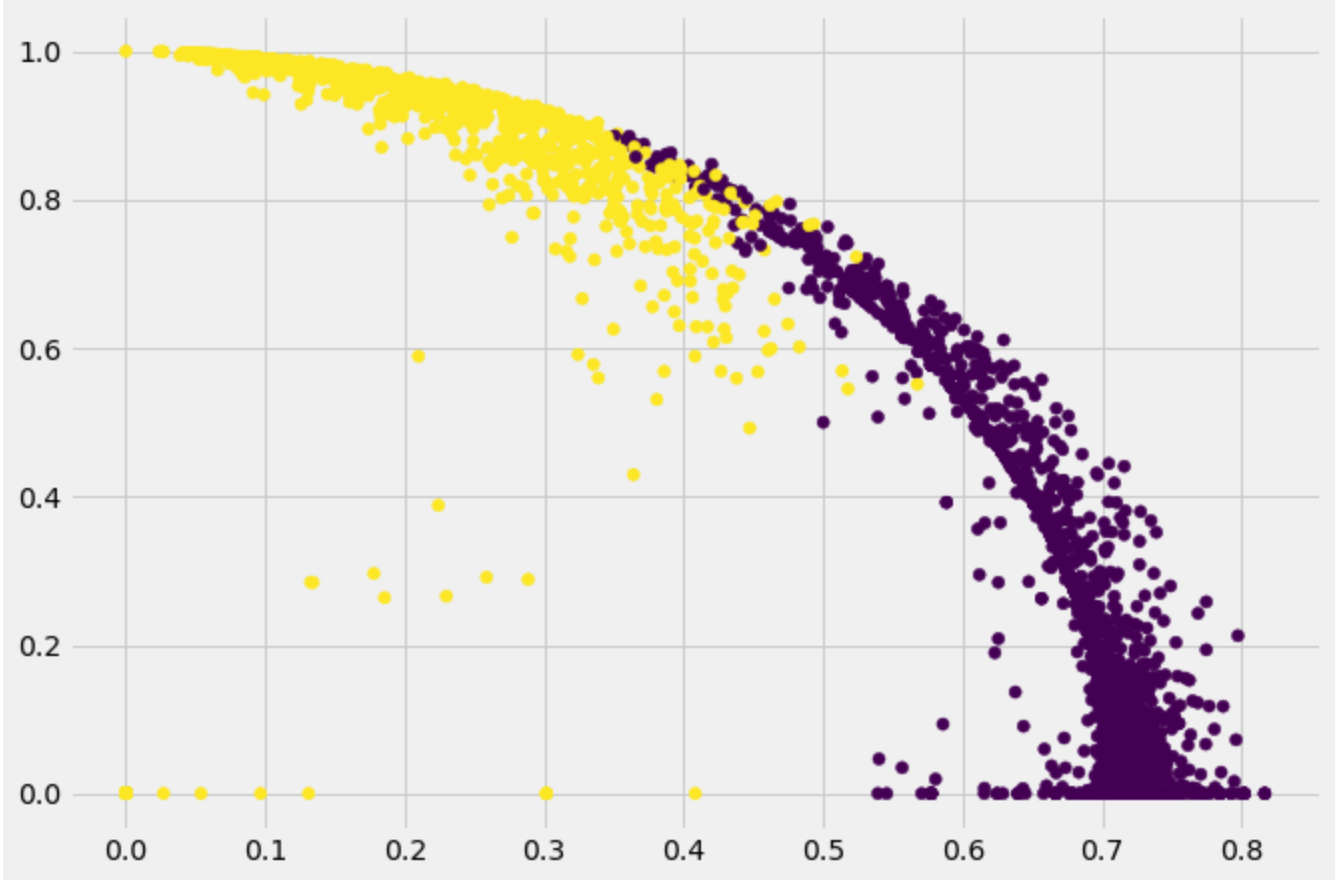
In [54]:
```
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters=2, affinity='euclidean', linkage='ward')
cluster.fit_predict(data_scaled)
```

Out[54]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

Podem veure els valors de 0 i 1 a la sortida ja que hem definit 2 clústers. 0 representa els punts que pertanyen al primer clúster i 1 representa els punts del segon clúster. Visualitzem ara els dos grups:

In [60]:
```
plt.figure(figsize=(10, 7))
plt.scatter(data_scaled["num_reactions"], data_scaled["num_comments"], c=cluster.labels_)
```

Out[60]:
```
<matplotlib.collections.PathCollection at 0x248647df0d0>
```



EXERCICI 3

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

In [ ]: