M8_T01

April 14, 2023

1 Sprint 8

1.1 Tasca M8 T01

1.2 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.

[1]:
```
import math
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score, adjusted_rand_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
import warnings
warnings.filterwarnings('ignore')

sns.set_theme(style='darkgrid', palette='deep')

df=pd.read_csv('Publicacions Facebook Thailandia.csv')
dfc=df.dropna(axis=1)
dfc['status_published']=pd.to_datetime(dfc['status_published']).dt.month
dfc.info()
df.info()
dfc.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7050 entries, 0 to 7049
Data columns (total 12 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   int64
 3   num_reactions     7050 non-null   int64
 4   num_comments      7050 non-null   int64
 5   num_shares        7050 non-null   int64
 6   num_likes         7050 non-null   int64
 7   num_loves         7050 non-null   int64
 8   num_wows          7050 non-null   int64
 9   num_hahas         7050 non-null   int64
 10  num_sads          7050 non-null   int64
 11  num_angrys        7050 non-null   int64
dtypes: int64(10), object(2)
memory usage: 661.1+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7050 entries, 0 to 7049
Data columns (total 16 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   num_reactions     7050 non-null   int64
 4   num_comments      7050 non-null   int64
 5   num_shares        7050 non-null   int64
 6   num_likes         7050 non-null   int64
 7   num_loves         7050 non-null   int64
 8   num_wows          7050 non-null   int64
 9   num_hahas         7050 non-null   int64
 10  num_sads          7050 non-null   int64
 11  num_angrys        7050 non-null   int64
 12  Column1           0 non-null      float64
 13  Column2           0 non-null      float64
 14  Column3           0 non-null      float64
 15  Column4           0 non-null      float64
dtypes: float64(4), int64(9), object(3)
memory usage: 881.4+ KB
```

[1]:

```
                            status_id status_type  status_published  \
0  246675545449582_1649696485147474       video                 4
1  246675545449582_1649426988507757       photo                 4
2  246675545449582_1648730588577397       video                 4
3  246675545449582_1648576705259452       photo                 4
4  246675545449582_1645700502213739       photo                 4

   num_reactions  num_comments  num_shares  num_likes  num_loves  num_wows  \
0            529           512         262        432         92         3
1            150             0           0        150          0         0
2            227           236          57        204         21         1
```

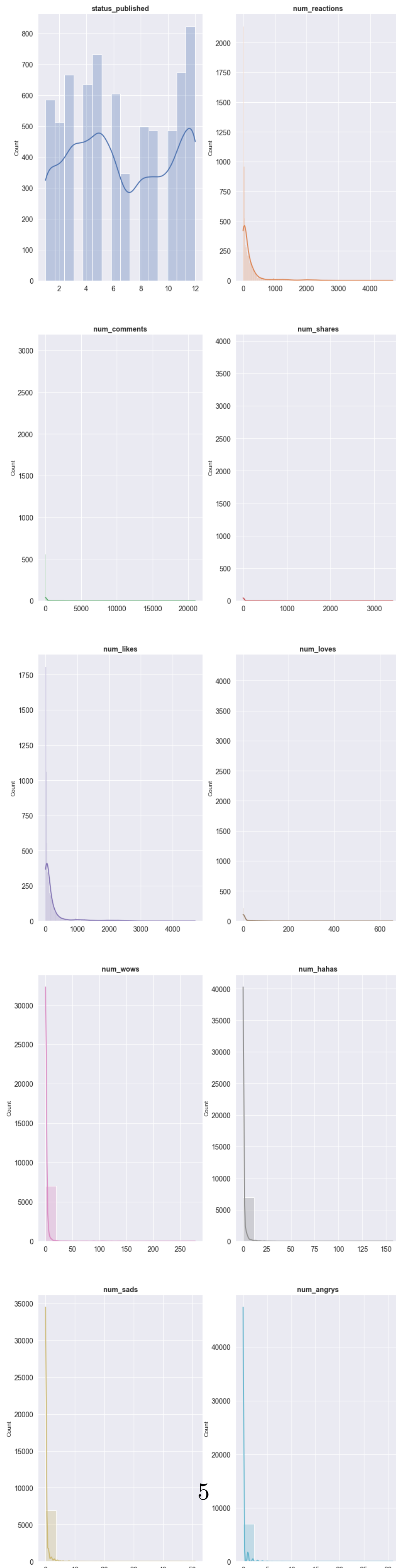
```
3            111            0            0         111            0            0
4            213            0            0         204            9            0

   num_hahas  num_sads  num_angrys
0          1         1           0
1          0         0           0
2          1         0           0
3          0         0           0
4          0         0           0
```

[2]:
```
dfc.select_dtypes(include=['float64', 'int']).describe().round(1)
```

[2]:
```
       status_published  num_reactions  num_comments  num_shares  num_likes  \
count            7050.0         7050.0        7050.0      7050.0     7050.0
mean                6.6          230.1         224.4        40.0      215.0
std                 3.6          462.6         889.6       131.6      449.5
min                 1.0            0.0           0.0         0.0        0.0
25%                 3.0           17.0           0.0         0.0       17.0
50%                 6.0           59.5           4.0         0.0       58.0
75%                10.0          219.0          23.0         4.0      184.8
max                12.0         4710.0       20990.0      3424.0     4710.0

       num_loves  num_wows  num_hahas  num_sads  num_angrys
count     7050.0    7050.0     7050.0    7050.0      7050.0
mean        12.7       1.3        0.7       0.2         0.1
std         40.0       8.7        4.0       1.6         0.7
min          0.0       0.0        0.0       0.0         0.0
25%          0.0       0.0        0.0       0.0         0.0
50%          0.0       0.0        0.0       0.0         0.0
75%          3.0       0.0        0.0       0.0         0.0
max        657.0     278.0      157.0      51.0        31.0
```

[3]:
```
# Distribution graph for each numerical variable

fig, axes = plt.subplots(ncols=2, nrows=5, figsize=(13, 15))
axes = axes.flat
columnas_numeric = dfc.select_dtypes(include=['float64', 'int']).columns

for i, column in enumerate(columnas_numeric):
    sns.histplot(
        data     = dfc,
        x        = column,
        stat     = "count",
        kde      = True,
        color    = (list(plt.rcParams['axes.prop_cycle'])*2)[i]["color"],
        line_kws= {'linewidth': 2},
        alpha    = 0.3,
```

```
        ax      = axes[i]
    )
    axes[i].set_title(column, fontsize = 14, fontweight = "bold")
    axes[i].tick_params(labelsize = 14)
    axes[i].set_xlabel("")

plt.subplots_adjust(top = 3)
```


status_published
num_reactions
num_comments
num_shares
num_likes
num_loves
num_wows
num_hahas
num_sads
num_angrys
Count

- Gràfiques amb la distribució de les variables númeriques del dataset on veiem que la majoria de publicacions no tenen molta interacció

[4]:
```python
# Correlation between numeric columns
# ==============================================================================
def tidy_corr_matrix(corr_mat):

    # Function to convert a pandas correlation matrix to tidy format

    corr_mat = corr_mat.stack().reset_index()
    corr_mat.columns = ['variable_1','variable_2','r']
    corr_mat = corr_mat.loc[corr_mat['variable_1'] != corr_mat['variable_2'], :]
    corr_mat['abs_r'] = np.abs(corr_mat['r'])
    corr_mat = corr_mat.sort_values('abs_r', ascending=False)

    return(corr_mat)



corr_matrix = dfc.select_dtypes(include=['float64', 'int']).
 ↪corr(method='pearson')
tidy_corr_matrix(corr_matrix).head(10)
```

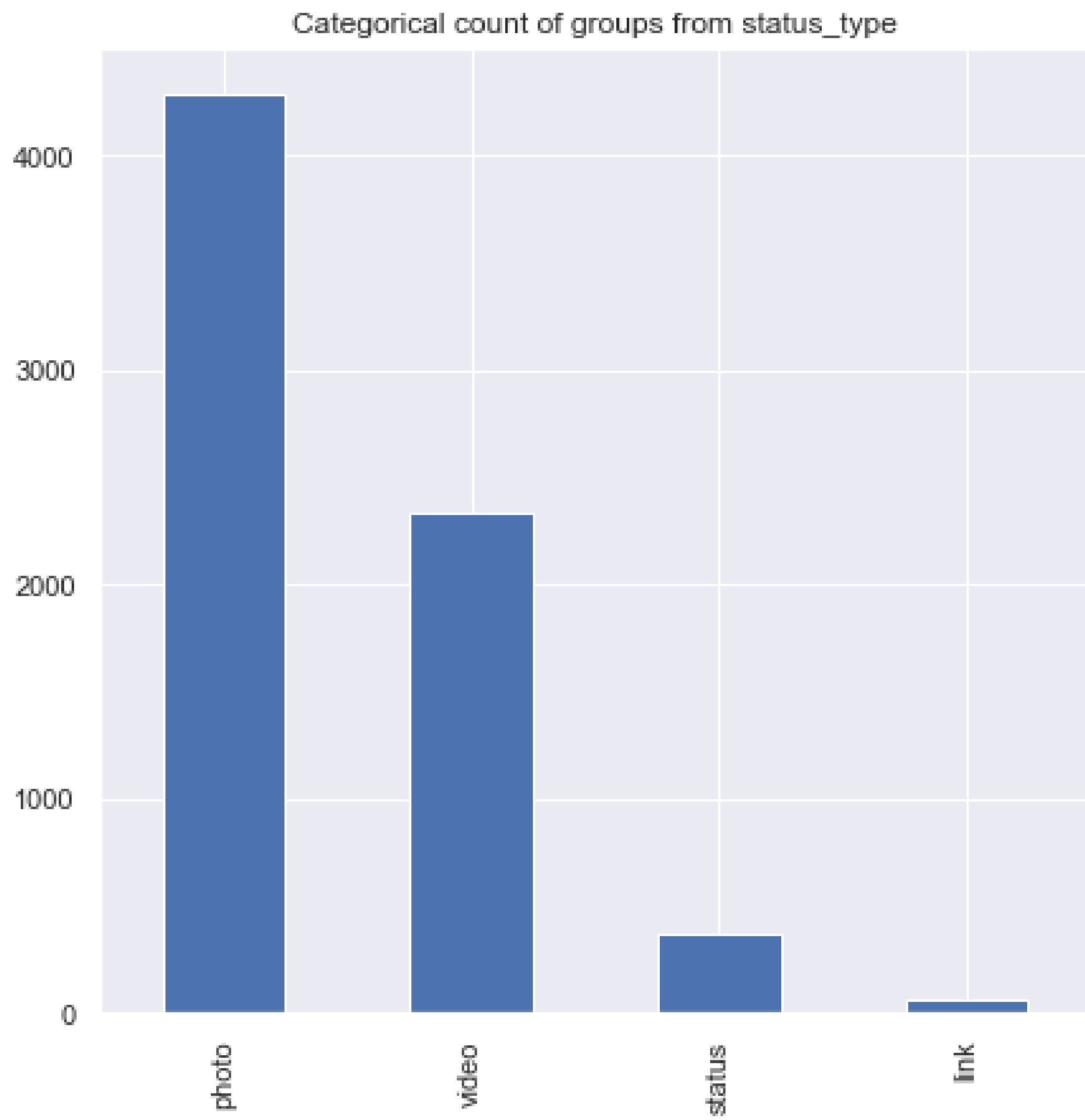
[4]:

	variable_1	variable_2	r	abs_r
41	num_likes	num_reactions	0.994923	0.994923
14	num_reactions	num_likes	0.994923	0.994923
35	num_shares	num_loves	0.820000	0.820000
53	num_loves	num_shares	0.820000	0.820000
23	num_comments	num_shares	0.640637	0.640637
32	num_shares	num_comments	0.640637	0.640637
52	num_loves	num_comments	0.521223	0.521223
25	num_comments	num_loves	0.521223	0.521223
56	num_loves	num_wows	0.508798	0.508798
65	num_wows	num_loves	0.508798	0.508798

- Correlacions que ens fan reforçar algunes creences entre relacions com el número de likes i de reaccions o el número de vegades compartit i número de *loves*.

[5]:
```python
# Qualitative variables (object type)
# ============================================================================
dfc.select_dtypes (include = ['object']).describe()

# Graph for status_type
# ==============================================================================
# Adjust number of subplots based on the number of columns
```

```
fig = plt.subplots(nrows=1, ncols=1, figsize=(7, 7))
columnas_object = dfc.select_dtypes(include=['object']).columns
columnas_object = columnas_object.drop('status_id')

for i, column in enumerate(columnas_object):
    dfc[column].value_counts().plot.bar()
    plt.title('Categorical count of groups from '+column)
```




```
[6]: # Adding dummy column
dfcd = pd.concat([dfc, pd.get_dummies(dfc['status_type'], prefix='type')],␣
 ↪axis=1)
dfML = dfcd.drop(['status_id','status_type'],axis=1)
```

```
scaler = MinMaxScaler()
#scaler = StandardScaler()
X_std0 = scaler.fit_transform(dfML)
X_std=pd.DataFrame(X_std0,columns=dfML.columns)
pd.DataFrame(X_std0).describe().round(1)
```

[6]:

```
            0       1       2       3       4       5       6       7       8  \
count  7050.0  7050.0  7050.0  7050.0  7050.0  7050.0  7050.0  7050.0  7050.0
mean      0.5     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
std       0.3     0.1     0.0     0.0     0.1     0.1     0.0     0.0     0.0
min       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
25%       0.2     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
50%       0.5     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
75%       0.8     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
max       1.0     1.0     1.0     1.0     1.0     1.0     1.0     1.0     1.0

            9      10      11      12      13
count  7050.0  7050.0  7050.0  7050.0  7050.0
mean      0.0     0.0     0.6     0.1     0.3
std       0.0     0.1     0.5     0.2     0.5
min       0.0     0.0     0.0     0.0     0.0
25%       0.0     0.0     0.0     0.0     0.0
50%       0.0     0.0     1.0     0.0     0.0
75%       0.0     0.0     1.0     0.0     1.0
max       1.0     1.0     1.0     1.0     1.0
```

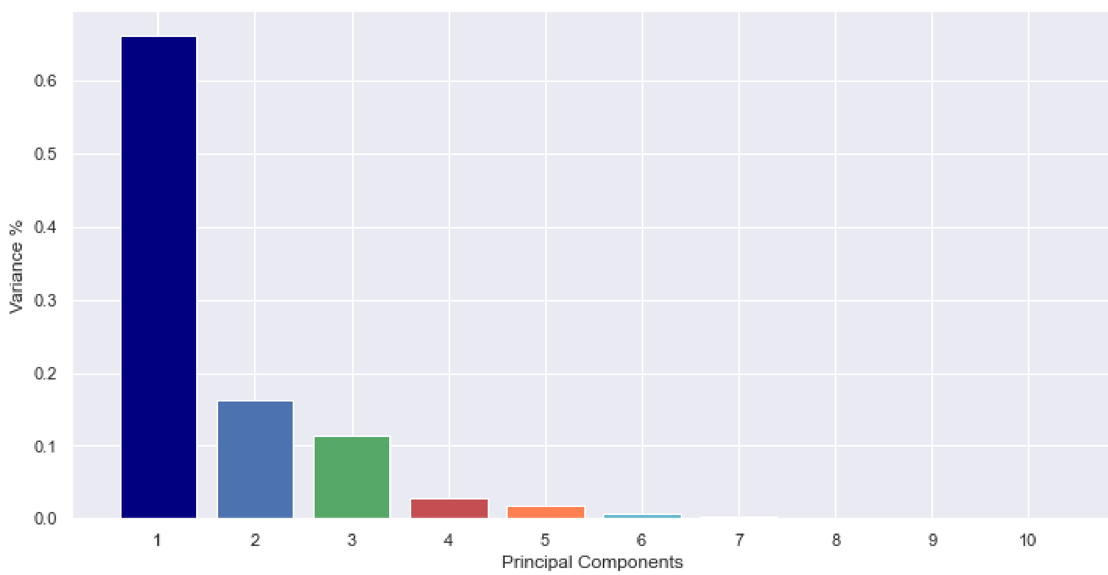
- És important marcar que les variables amb més *standard deviation* seràn les que possiblement més informació continguin i més pes tinguin al fer el PCA (Principal Component Analysis)

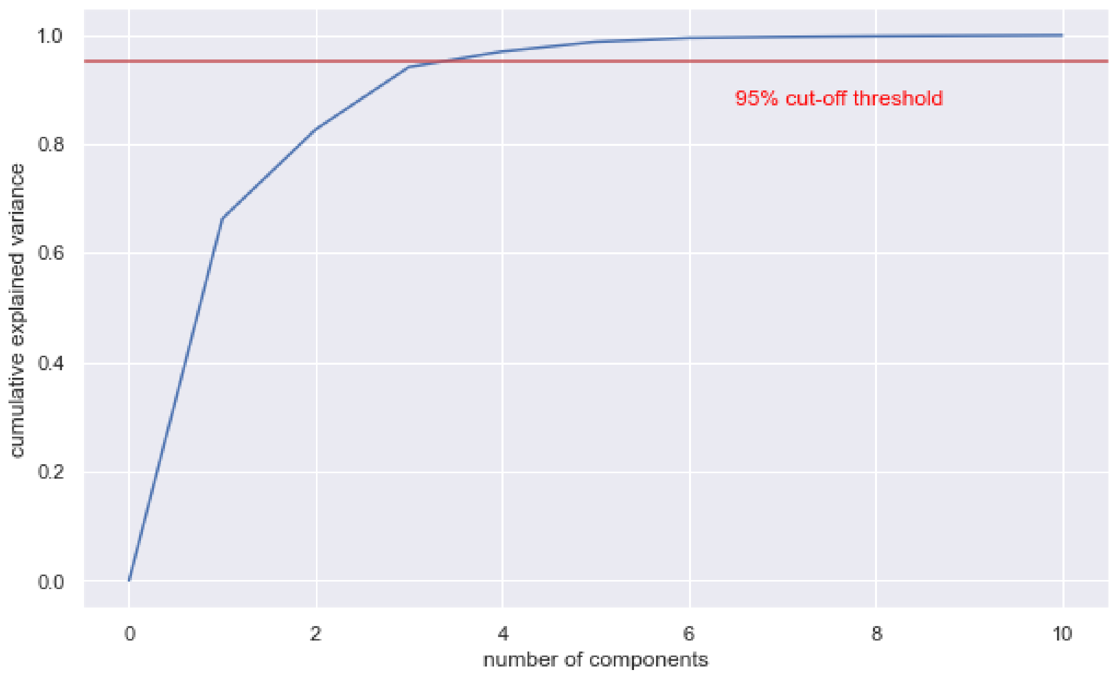
[7]:

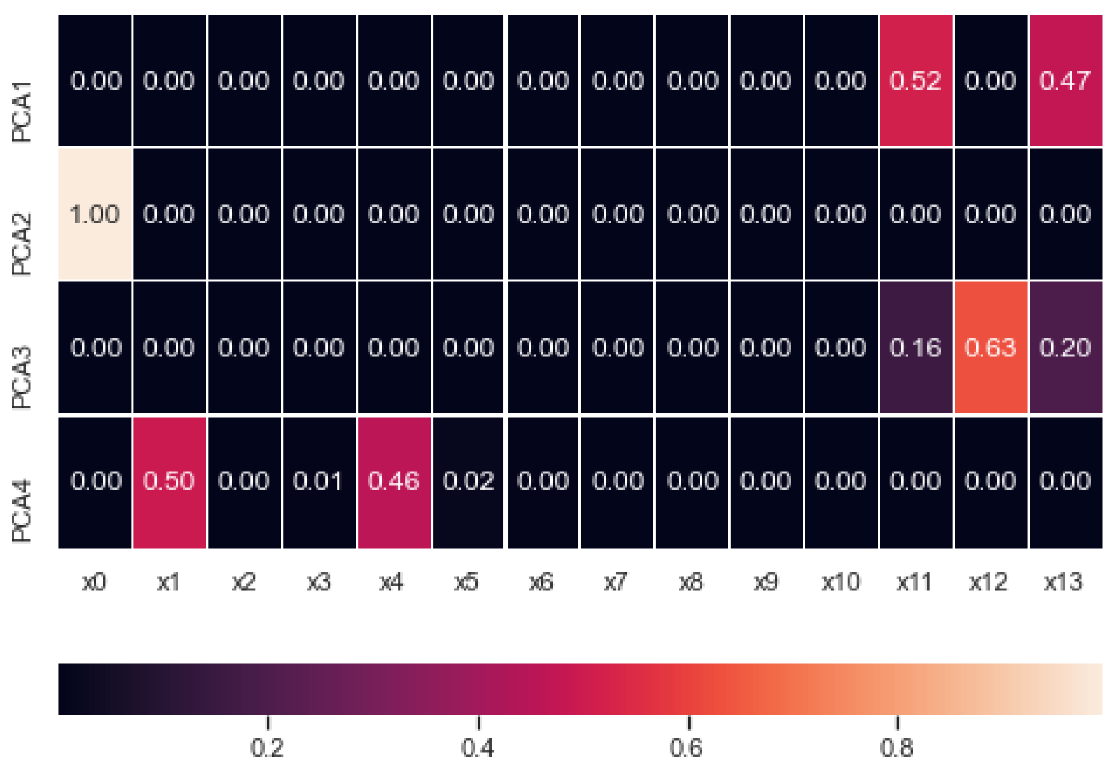
```
def pcan(N,X_std):
    sns.set(style="darkgrid")
    pca = PCA(n_components = 10)
    principalComponents = pca.fit_transform(X_std)
    print('PCA Explained Variance Ratio:',pca.explained_variance_ratio_.
 ↪round(3))
    PC = range(1, pca.n_components_+1)
    plt.figure(figsize=(12,6))
    plt.bar(PC, pca.explained_variance_ratio_,␣
 ↪color=('navy','b','g','r','coral','c','m','y','k','gray'))
    plt.xlabel('Principal Components')
    plt.ylabel('Variance %')
    plt.xticks(PC);

    #_ = sns.lineplot(x=PC, y=np.cumsum(pca.explained_variance_ratio_),␣
 ↪color='black', linestyle='-', linewidth=2, marker='o', markersize=8)
    plt.figure(figsize=(10,6))
```

```
    plt.plot(np.append([0],np.cumsum(pca.explained_variance_ratio_)))
    plt.xlabel('number of components')
    plt.ylabel('cumulative explained variance')
    plt.axhline(y=0.95, color='r', linestyle='-')
    plt.text(6.5, 0.87, '95% cut-off threshold', color = 'red', fontsize=12);
    col_name = ['x' + str(idx) for idx in range(0, X_std.shape[1])]
    plt.figure(figsize=(8,6))
    _ = sns.heatmap((pca.components_**2)[0:N,:],
                 yticklabels=["PCA"+str(x) for x in range(1,N+1)],
                 xticklabels=list(col_name),
                 annot=True,
                 fmt='.2f',
                 linewidths=0.05,
                 cbar_kws={"orientation": "horizontal"})

pcan(4,X_std)
```

```
PCA Explained Variance Ratio: [0.663 0.163 0.114 0.028 0.018 0.007 0.002 0.001
0.001 0.001]
```



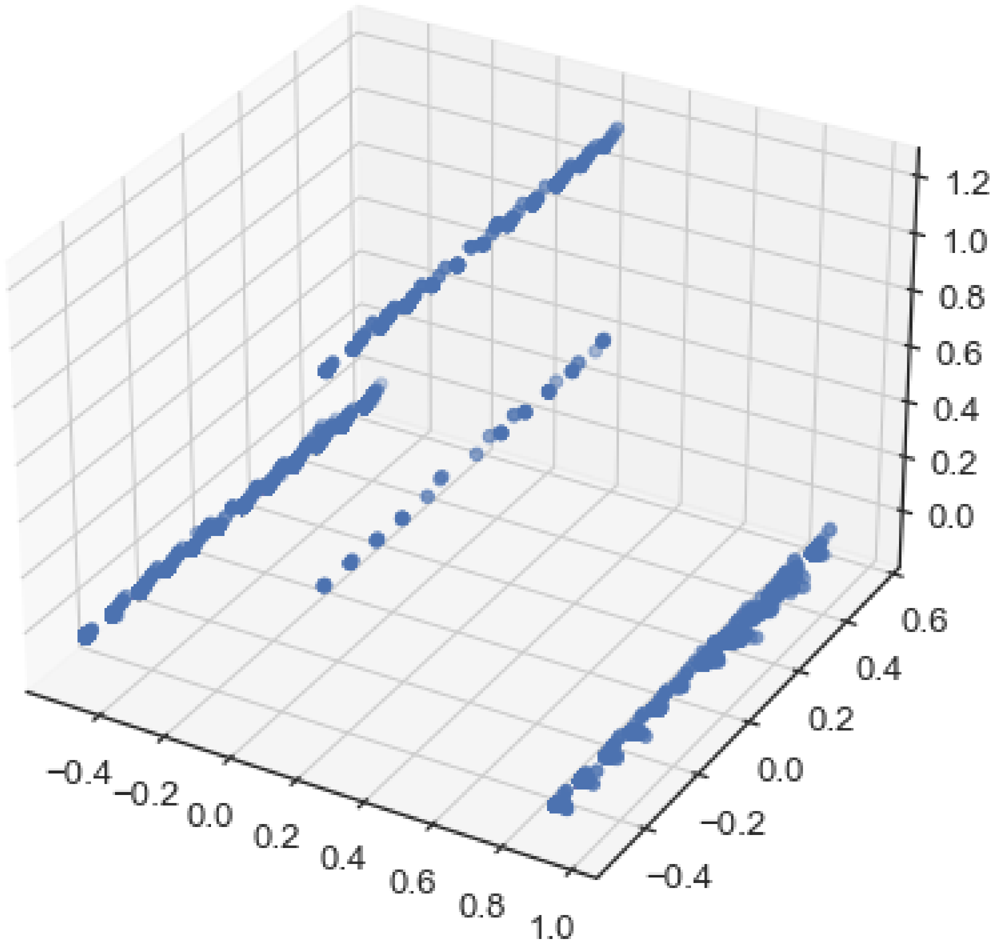




- Veiem quins són els PCA components amb més variança que poden aportar més informació, reduïnt així la dimensionalitat del dataset

[8]:
```
# Perform PCA (Choose n_components to keep)
pca = PCA(n_components=3)
pca_array = pca.fit_transform(X_std)

# Convert back to DataFrame for readability
df_pca = pd.DataFrame(data=pca_array)
df_pca.columns = ['PC' + str(col+1) for col in df_pca.columns.values]

display(df_pca.head())

# Plot Principal Component
_ = sns.set(style='ticks', font_scale=1.2)
fig, ax = plt.subplots(figsize=(10, 7))
seaborn_plot = plt.axes (projection='3d')
_ = seaborn_plot.scatter3D(df_pca.iloc[:,0],df_pca.iloc[:,1],df_pca.iloc[:,2])
```

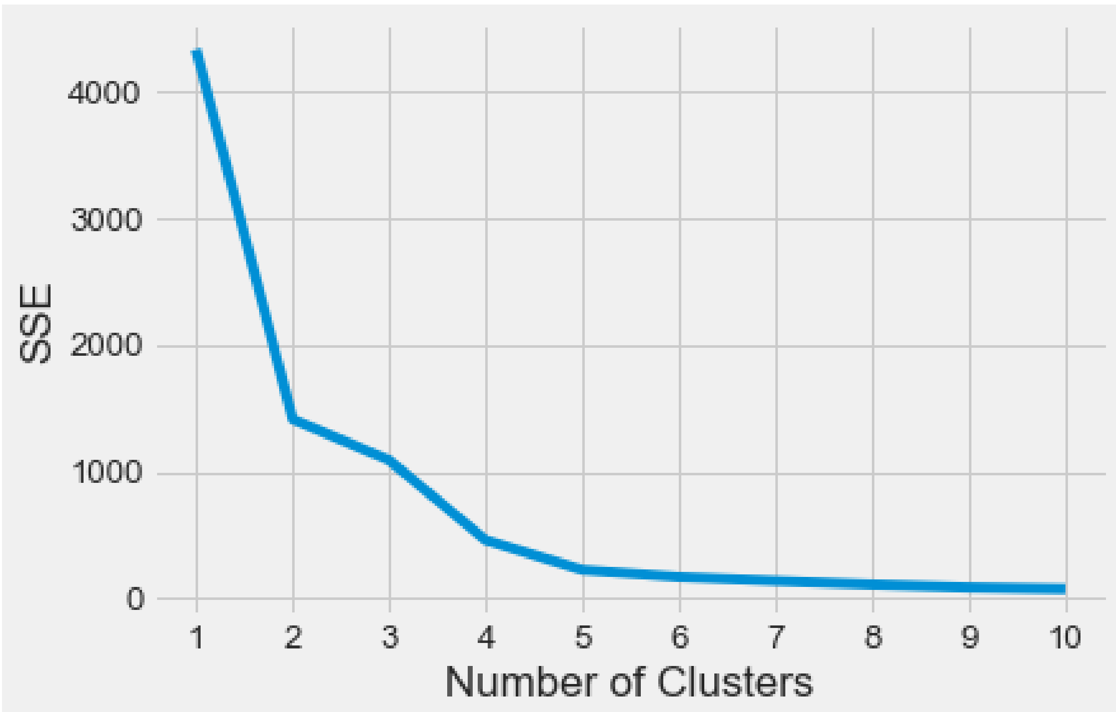
	PC1	PC2	PC3
0	0.907655	0.233909	-0.100575
1	-0.513215	0.235458	-0.050654
2	0.900265	0.227914	-0.102466
3	-0.513459	0.234788	-0.051455
4	-0.512346	0.236626	-0.049771



[9]:

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

# A list holds the SSE values for each k
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(df_pca)
    sse.append(kmeans.inertia_)
plt.style.use("fivethirtyeight")
plt.plot(range(1, 11), sse)
```

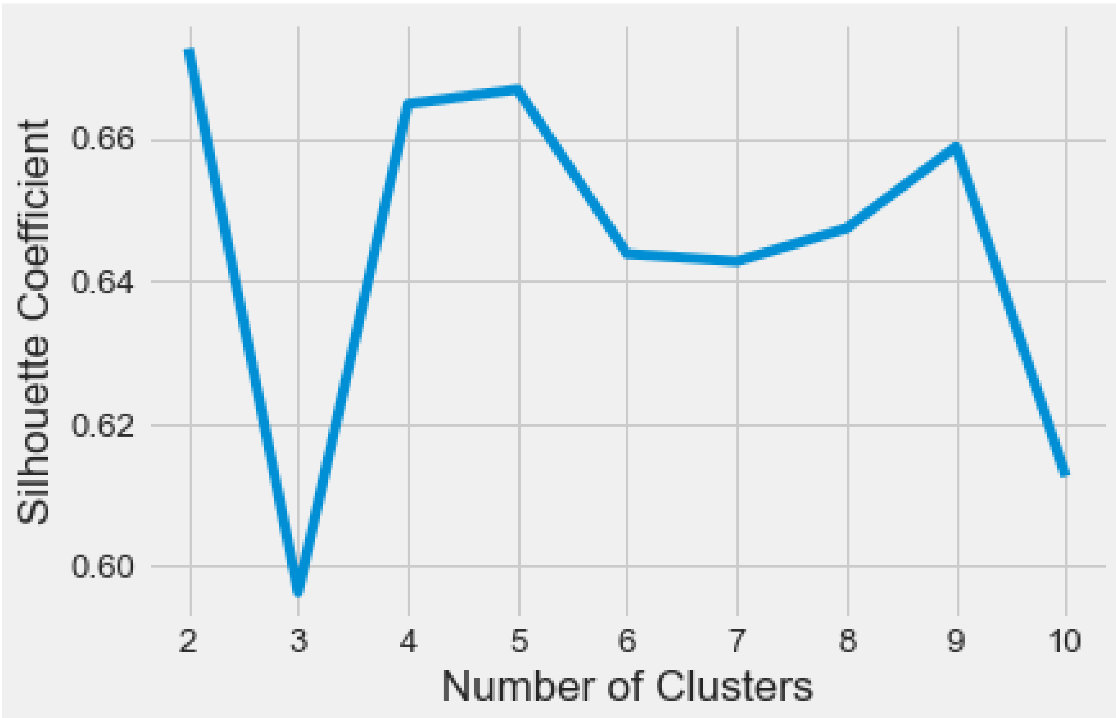
```
plt.xticks(range(1, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("SSE")
plt.show()

from kneed import KneeLocator
kl = KneeLocator(
    range(1, 11), sse, curve="convex", direction="decreasing"
)
print(r'Select %s clusters as best to execute Kmeans Model' %kl.elbow)
```




```
Select 4 clusters as best to execute Kmeans Model
```

[10]:
```
from sklearn.metrics import silhouette_score
silhouette_coefficients = []

# Notice you start at 2 clusters for silhouette coefficient
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(df_pca)
    score = silhouette_score(df_pca, kmeans.labels_)
    silhouette_coefficients.append(score)

plt.style.use("fivethirtyeight")
```

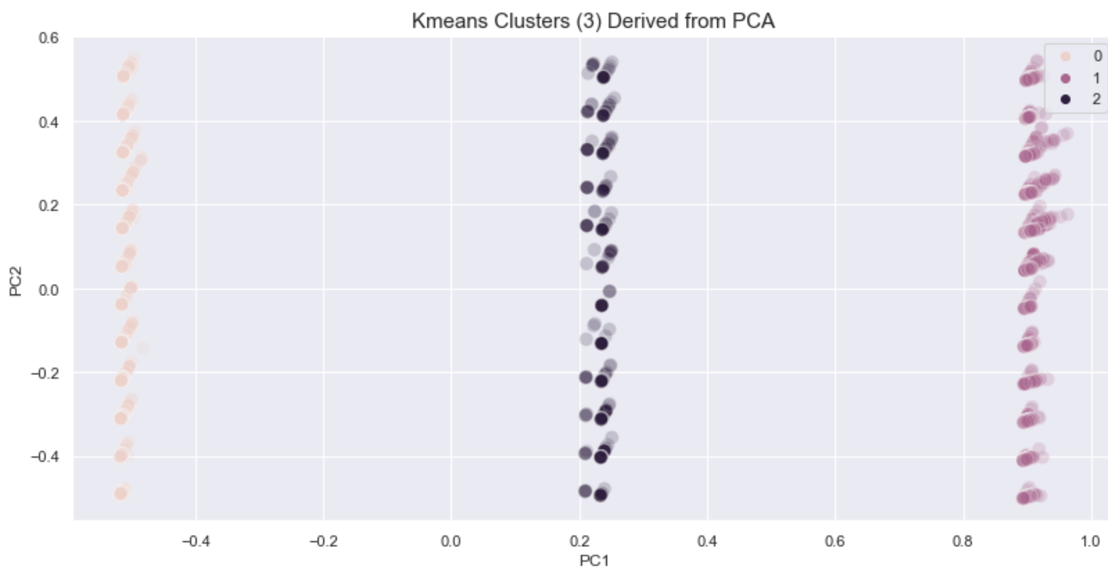
```
plt.plot(range(2, 11), silhouette_coefficients)
plt.xticks(range(2, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient")
plt.show()
```

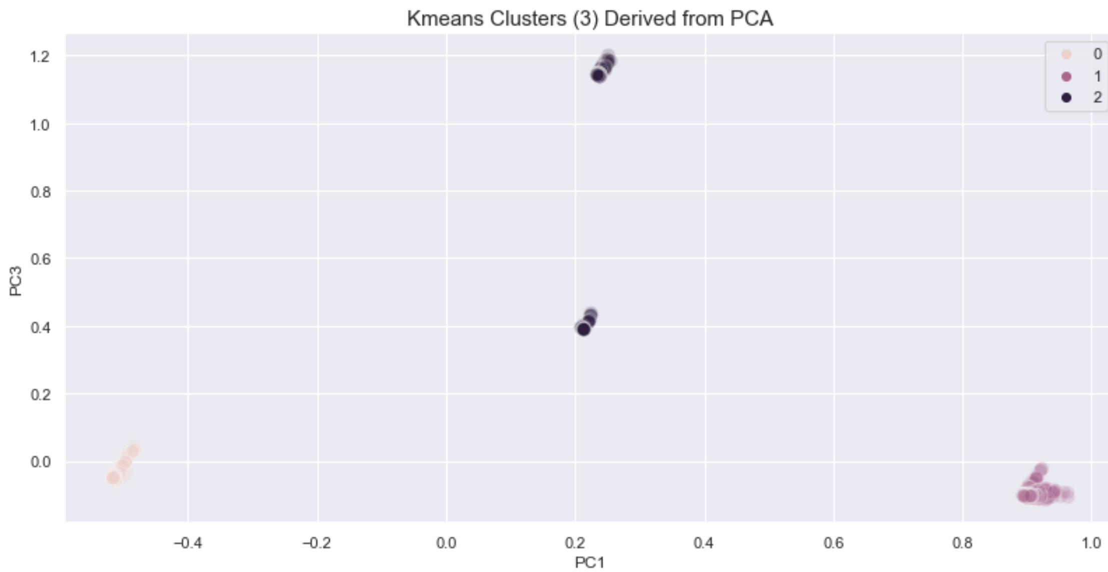


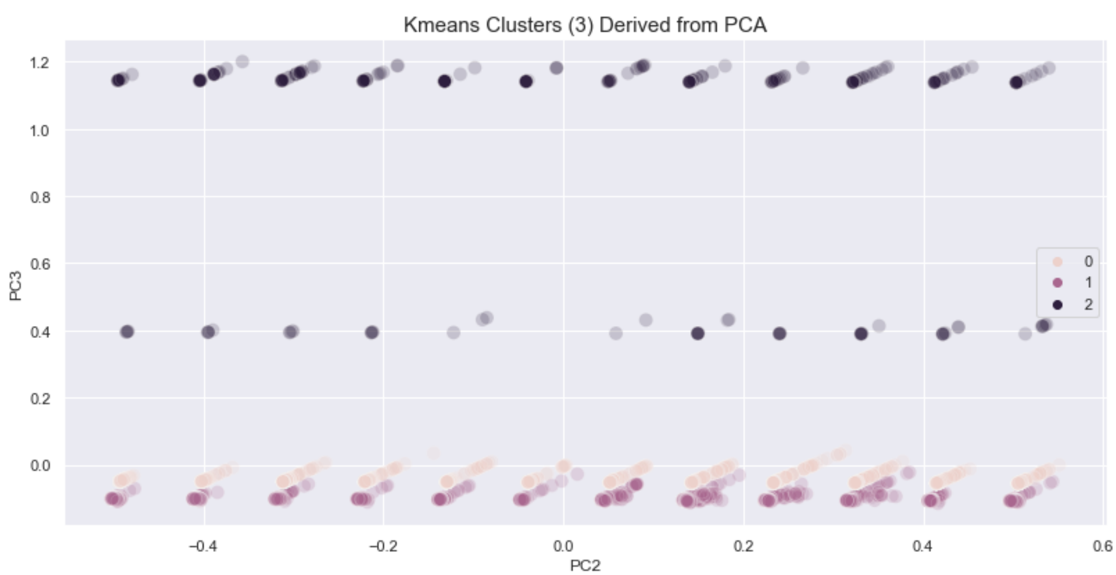
- Utilitzem els mètodes de elbow i de silhouette coefficients per veure quins són els millors valors de clusters que podríem determinar

[11]:
```
ks=3
sns.set(style="darkgrid")
k_means_pca = KMeans(init = "k-means++", n_clusters = ks, n_init = 12,␣
↪random_state= 42).fit(df_pca)
labels_pca = k_means_pca.labels_
#display(labels_pca)
clusters_pca = pd.concat([df_pca, pd.DataFrame({'pca_clusters':labels_pca})],␣
↪axis=1)

plt.figure(figsize=(12,6))

sns.scatterplot(clusters_pca.iloc[:,0], clusters_pca.iloc[:,1],
               hue = labels_pca, s=100,
               alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
               fontsize=15)
```

```
plt.figure(figsize=(12,6))
sns.scatterplot(clusters_pca.iloc[:,0], clusters_pca.iloc[:,2],
               hue = labels_pca, s=100,
               alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
               fontsize=15)
plt.figure(figsize=(12,6))
sns.scatterplot(clusters_pca.iloc[:,1], clusters_pca.iloc[:,2],
               hue = labels_pca, s=100,
               alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
               fontsize=15)
plt.legend()
plt.show()
```

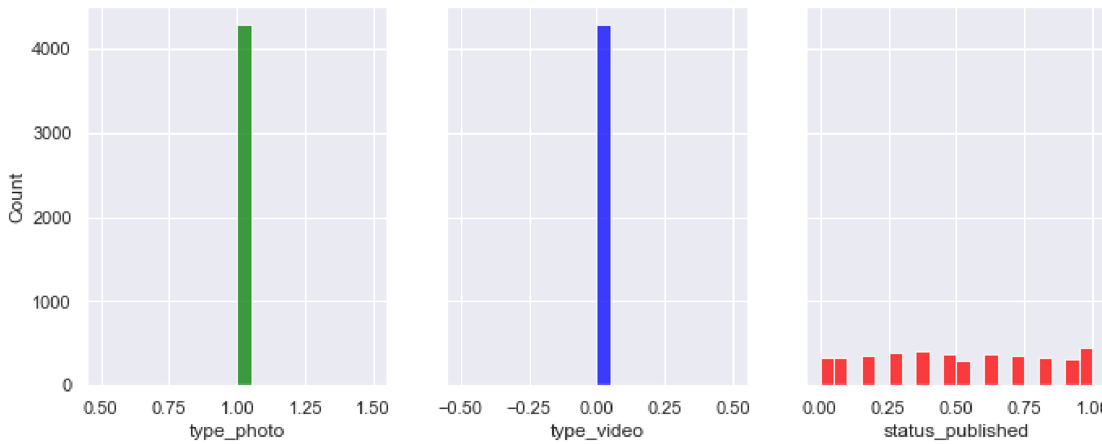


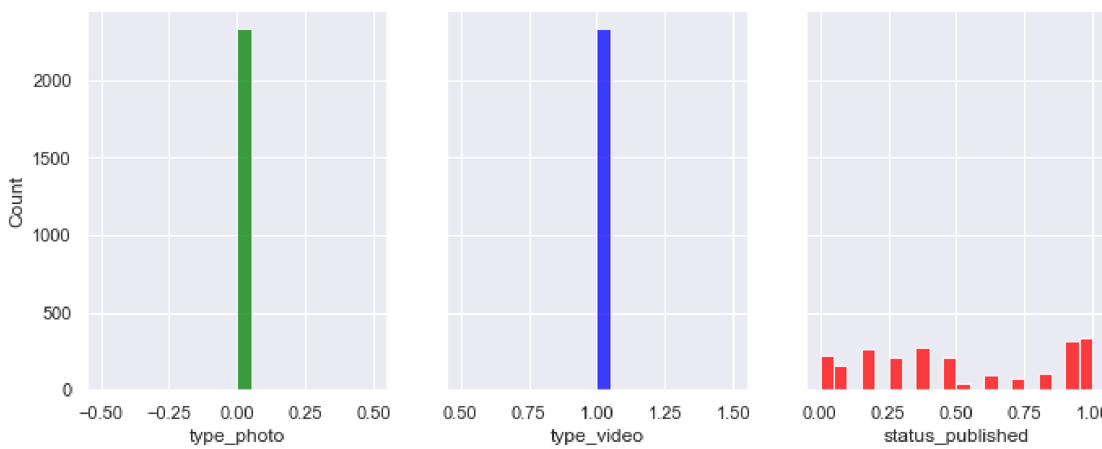


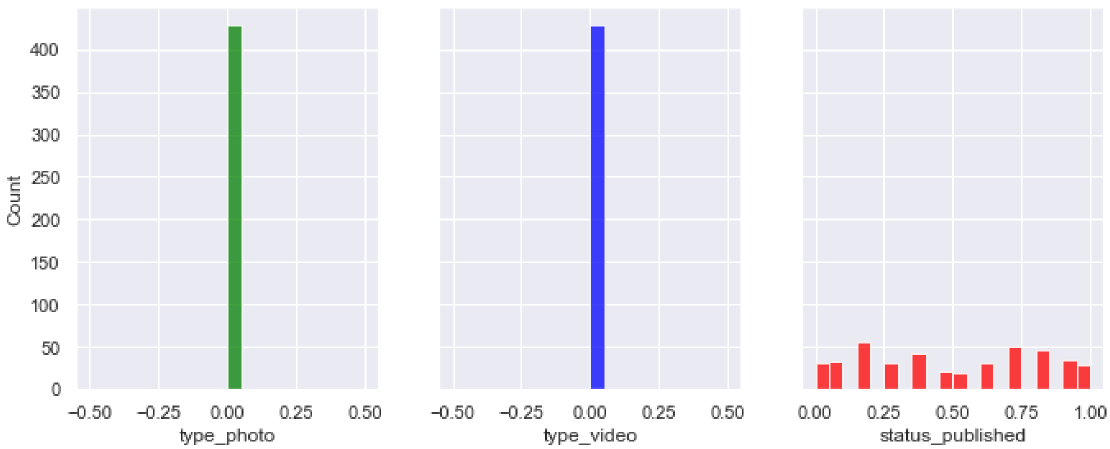


[12]:
```
def plotanalys(df):
    sns.set(style="darkgrid")
    fig, (ax1, ax2,ax3) = plt.subplots(nrows=1, ncols=3,␣
 ↪sharey=True,figsize=(10, 4))
    sns.histplot(data=df, x="type_photo",color="green", ax=ax1 , bins=20)
    sns.histplot(data=df, x="type_video",color="blue", ax=ax2, bins=20)
    sns.histplot(data=df, x="status_published",color="red", ax=ax3, bins=20)
```

[13]:
```
df_pca_kmeans=pd.concat([X_std.reset_index(drop=True), df_pca], axis=1)
df_pca_kmeans['Kmeans PCA'] = labels_pca
for ii in range(0,ks):
    df_cluster_ii = df_pca_kmeans.loc[df_pca_kmeans['Kmeans PCA'] == ii]

    plotanalys(df_cluster_ii)
```





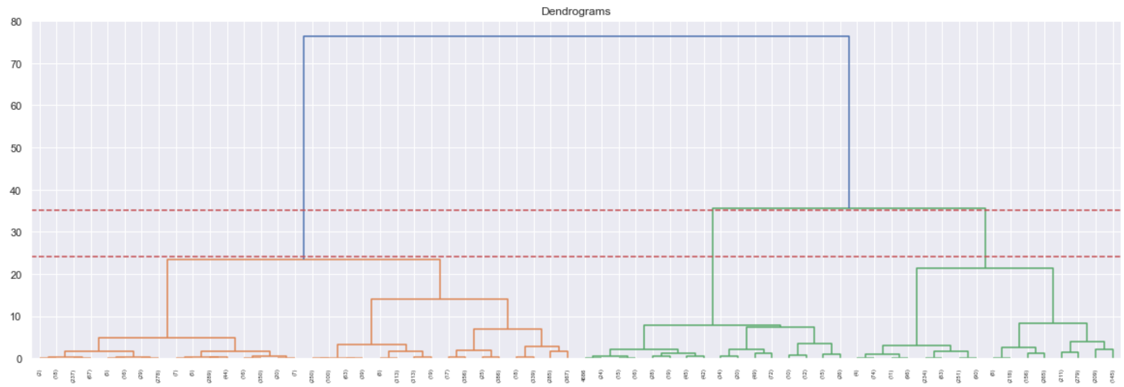


[14]:
```
ks=9
k_means_pca = KMeans(init = "k-means++", n_clusters = ks, n_init = 12, random_state= 42).fit(df_pca)
labels_pca = k_means_pca.labels_
#display(labels_pca)
clusters_pca = pd.concat([df_pca, pd.DataFrame({'Kmeans PCA':labels_pca})], axis=1)
df_pca_kmeans=pd.concat([X_std.reset_index(drop=True), df_pca], axis=1)
df_pca_kmeans['Kmeans PCA'] = labels_pca
```

1.3 Exercici 2

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

[15]:
```
import scipy.cluster.hierarchy as sch

plt.figure(figsize=(18, 6))
plt.title("Dendrograms");
dendrogram = sch.dendrogram(sch.linkage(df_pca, method='ward'),truncate_mode='level', p=5)
plt.axhline(y= 35, color='r', linestyle='--')
plt.axhline(y= 24, color='r', linestyle='--');
```



- Determinem visualment la regió on hi ha una separació més gran per determinar el nombre òptim de clusters que utilitzar a partir del dendrograma. Representa la divisió en clusters que es porta a terme en l'algorisme de clustering

[16]:
```
# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 3, affinity='euclidean',␣
↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
↪='rainbow')
plt.title("Agglomerative Hierarchical 3 Clusters - Scatter Plot", fontsize=18);

agc.fit(df_pca)
labels_hier = agc.labels_
labels_hier[:20]

clusters_all_pca3 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
↪labels_hier})], axis=1)
clusters_all_pca3.head()


# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 5, affinity='euclidean',␣
↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
↪='rainbow')
plt.title("Agglomerative Hierarchical 5 Clusters - Scatter Plot", fontsize=18);

agc.fit(df_pca)
labels_hier = agc.labels_
```

```python
labels_hier[:20]

clusters_all_pca5 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
 ↪labels_hier})], axis=1)
clusters_all_pca5.head()


# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 9, affinity='euclidean',␣
 ↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
 ↪='rainbow')
plt.title("Agglomerative Hierarchical 9 Clusters - Scatter Plot", fontsize=18);

agc.fit(df_pca)
labels_hier = agc.labels_
labels_hier[:20]

clusters_all_pca9 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
 ↪labels_hier})], axis=1)
clusters_all_pca9.head()
```

[16]:

```
   status_published  num_reactions  num_comments  num_shares  num_likes  \
0          0.272727       0.112314      0.024393    0.076519   0.091720
1          0.272727       0.031847      0.000000    0.000000   0.031847
2          0.272727       0.048195      0.011243    0.016647   0.043312
3          0.272727       0.023567      0.000000    0.000000   0.023567
4          0.272727       0.045223      0.000000    0.000000   0.043312

   num_loves  num_wows  num_hahas  num_sads  num_angrys  type_link  \
0   0.140030  0.010791   0.006369  0.019608         0.0        0.0
1   0.000000  0.000000   0.000000  0.000000         0.0        0.0
2   0.031963  0.003597   0.006369  0.000000         0.0        0.0
3   0.000000  0.000000   0.000000  0.000000         0.0        0.0
4   0.013699  0.000000   0.000000  0.000000         0.0        0.0

   type_photo  type_status  type_video       PC1       PC2       PC3  \
0         0.0          0.0         1.0  0.907655  0.233909 -0.100575
1         1.0          0.0         0.0 -0.513215  0.235458 -0.050654
2         0.0          0.0         1.0  0.900265  0.227914 -0.102466
3         1.0          0.0         0.0 -0.513459  0.234788 -0.051455
4         1.0          0.0         0.0 -0.512346  0.236626 -0.049771

   Kmeans PCA  PCA Clusters Hier
0           7                  2
```

1	3	1
2	7	2
3	3	1
4	3	1


Agglomerative Hierarchical 5 Clusters - Scatter Plot
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
1.0


```
[17]: # Scatter plot using the first 2 Principal Components to observe the Cluster␣
       ↪Distribution

      plt.figure(figsize=(20,12))

      plt.subplot(1,2,1)
      sns.scatterplot(x= 'PC1', y='PC2',
                      data= clusters_all_pca9,
                      hue = 'Kmeans PCA', palette='Set1', s= 80).set_title('Kmeans␣
       ↪Clusters (9) Derived from PCA',
                      fontsize= 22)
      plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
```

```
plt.subplot(1,2,2)
sns.scatterplot(x= 'PC1', y='PC2',
                data= clusters_all_pca9, s=80,
                hue= 'PCA Clusters Hier',palette='Set1').
 ↪set_title('Hierarchical Clustering (9) Derived from PCA',
                fontsize=22);
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0);
```

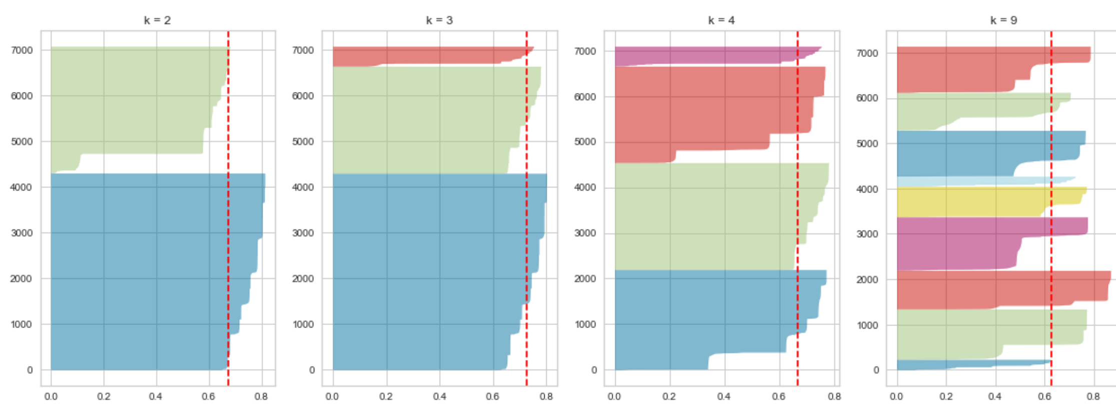
- Exemple comparatiu de Clustering utilitzant K-means i Hierarchical Clustering amb 9 clusters

1.4 Exercici 3

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

[18]:
```
# SilhouetteVisualizer
# ===============================================================================
from yellowbrick.cluster import SilhouetteVisualizer

fig,(ax1,ax2,ax3,ax4)=plt.subplots(figsize=(17,6),nrows=1,ncols=4)

#ax1
visualizer = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=2,␣
 ↪random_state=42), colors='yellowbrick',ax=ax1)
visualizer.fit(df_pca)       # Fit the data to the visualizer
ax1.set_title('k = 2')               # Title
```

```
sil1=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=2,␣
↪random_state=42).fit(df_pca).labels_)

#ax2
visualizer2 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=3,␣
↪random_state=42), colors='yellowbrick',ax=ax2)
visualizer2.fit(df_pca)      # Fit the data to the visualizer
ax2.set_title('k = 3')                # Title
sil2=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=3,␣
↪random_state=42).fit(df_pca).labels_)

#ax3
visualizer3 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=4,␣
↪random_state=42), colors='yellowbrick',ax=ax3)
visualizer3.fit(df_pca)       # Fit the data to the visualizer
ax3.set_title('k = 4');                # Title
sil3=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=4,␣
↪random_state=42).fit(df_pca).labels_)

#ax4
visualizer4 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=9,␣
↪random_state=42), colors='yellowbrick',ax=ax4)
visualizer4.fit(df_pca)       # Fit the data to the visualizer
ax4.set_title('k = 9');               # Title
sil4=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=9,␣
↪random_state=42).fit(df_pca).labels_)
```



[19]:
```
silhouette = pd.DataFrame({'Measure': ['2 Clusters' ,'3 Clusters', '4␣
↪Clusters', '9 Clusters'],
                            'Scores': [sil1,sil2,sil3,sil4]
                            })
silhouette
```

[19]:
```
       Measure    Scores
0  2 Clusters  0.672657
1  3 Clusters  0.727789
2  4 Clusters  0.664881
3  9 Clusters  0.626738
```

- El paràmetre silhouette ajuda a determinar com de similars són punts de un cluster amb els altres diferents clusters. Quanta més valoració del paràmetre silhouette, millor agrupació o més cohesió hi ha entre punts del mateix cluster.

2 Extra section

- Anem a fer aquest mateix anàlisis aplicant l'estandaritzat estàndard per veure com canvien els clusters

[20]:
```python
#scaler = MinMaxScaler()
scaler = StandardScaler()
X_std0 = scaler.fit_transform(dfML)
X_std=pd.DataFrame(X_std0,columns=dfML.columns)
pd.DataFrame(X_std0).describe().round(1)
```

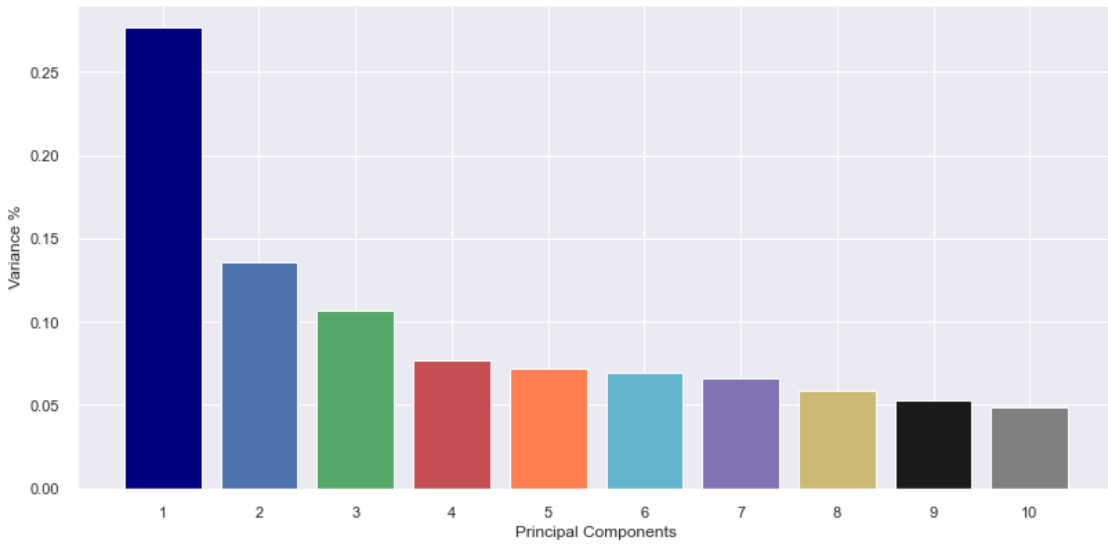
[20]:

	0	1	2	3	4	5	6	7	8
count	7050.0	7050.0	7050.0	7050.0	7050.0	7050.0	7050.0	7050.0	7050.0
mean	-0.0	0.0	0.0	-0.0	-0.0	0.0	-0.0	0.0	-0.0
std	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
min	-1.6	-0.5	-0.3	-0.3	-0.5	-0.3	-0.1	-0.2	-0.2
25%	-1.0	-0.5	-0.3	-0.3	-0.4	-0.3	-0.1	-0.2	-0.2
50%	-0.2	-0.4	-0.2	-0.3	-0.3	-0.3	-0.1	-0.2	-0.2
75%	1.0	-0.0	-0.2	-0.3	-0.1	-0.2	-0.1	-0.2	-0.2
max	1.5	9.7	23.3	25.7	10.0	16.1	31.7	39.5	31.8

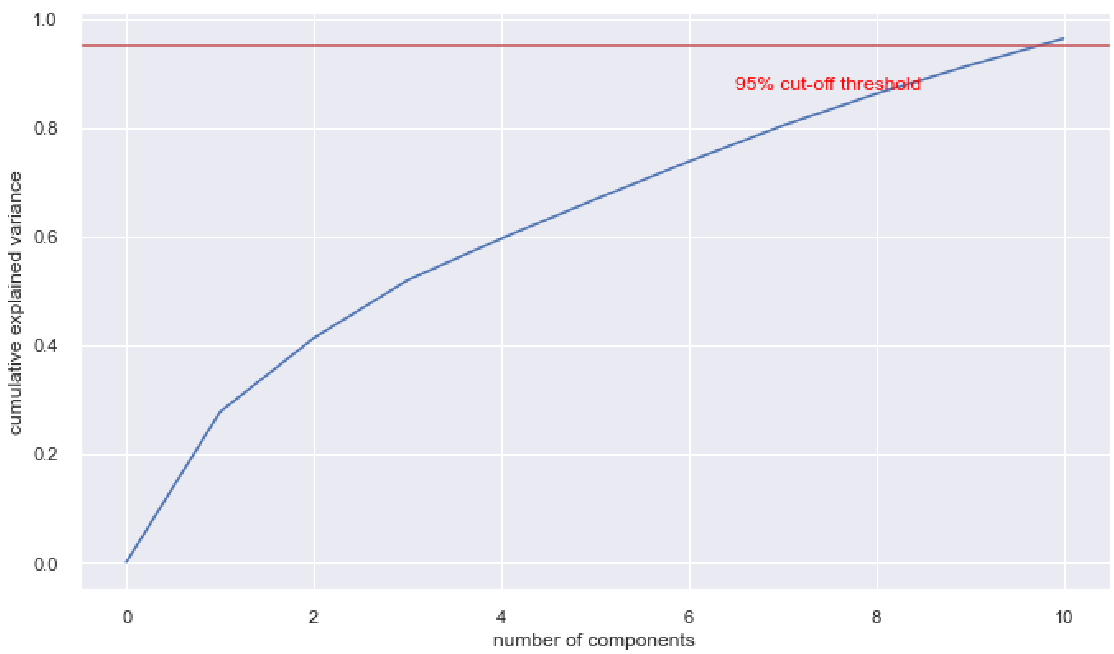
	9	10	11	12	13
count	7050.0	7050.0	7050.0	7050.0	7050.0
mean	-0.0	-0.0	0.0	0.0	-0.0
std	1.0	1.0	1.0	1.0	1.0
min	-0.2	-0.1	-1.2	-0.2	-0.7
25%	-0.2	-0.1	-1.2	-0.2	-0.7
50%	-0.2	-0.1	0.8	-0.2	-0.7
75%	-0.2	-0.1	0.8	-0.2	1.4
max	42.5	10.5	0.8	4.3	1.4

[21]:
```python
pcan(4,X_std)
```

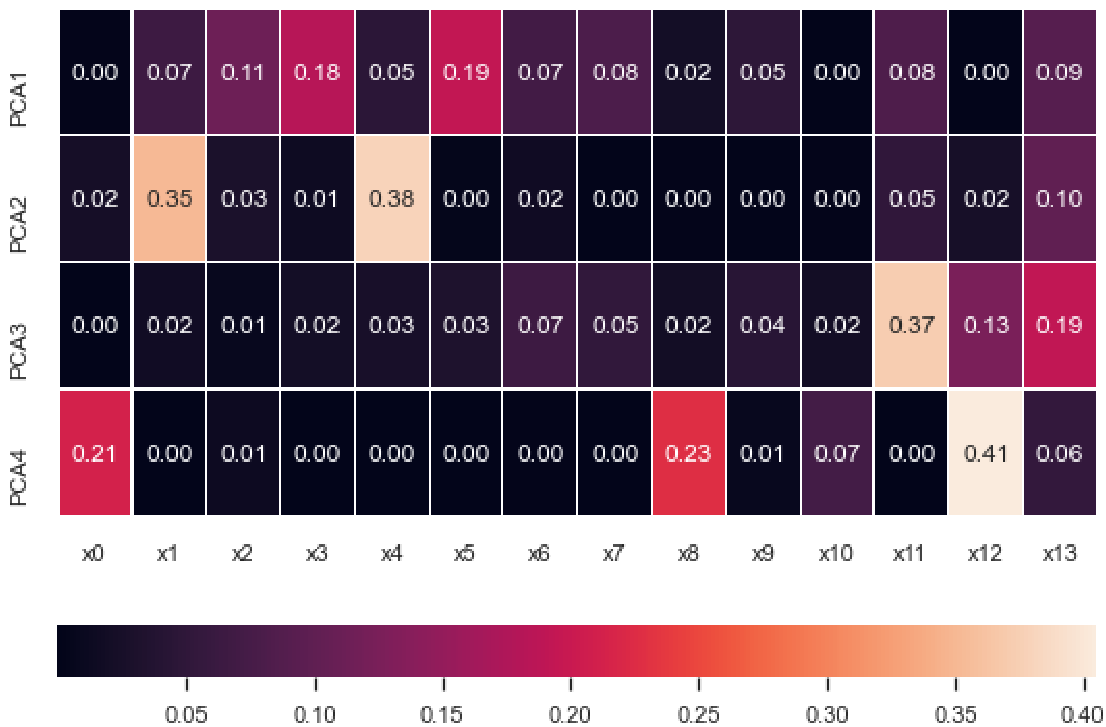
```
PCA Explained Variance Ratio: [0.276 0.136 0.106 0.077 0.072 0.07  0.066 0.059
0.053 0.049]
```



0.25
0.20
0.15
0.10
0.05
0.00
Variance %
1
2
3
4
5
6
7
8
9
10
Principal Components

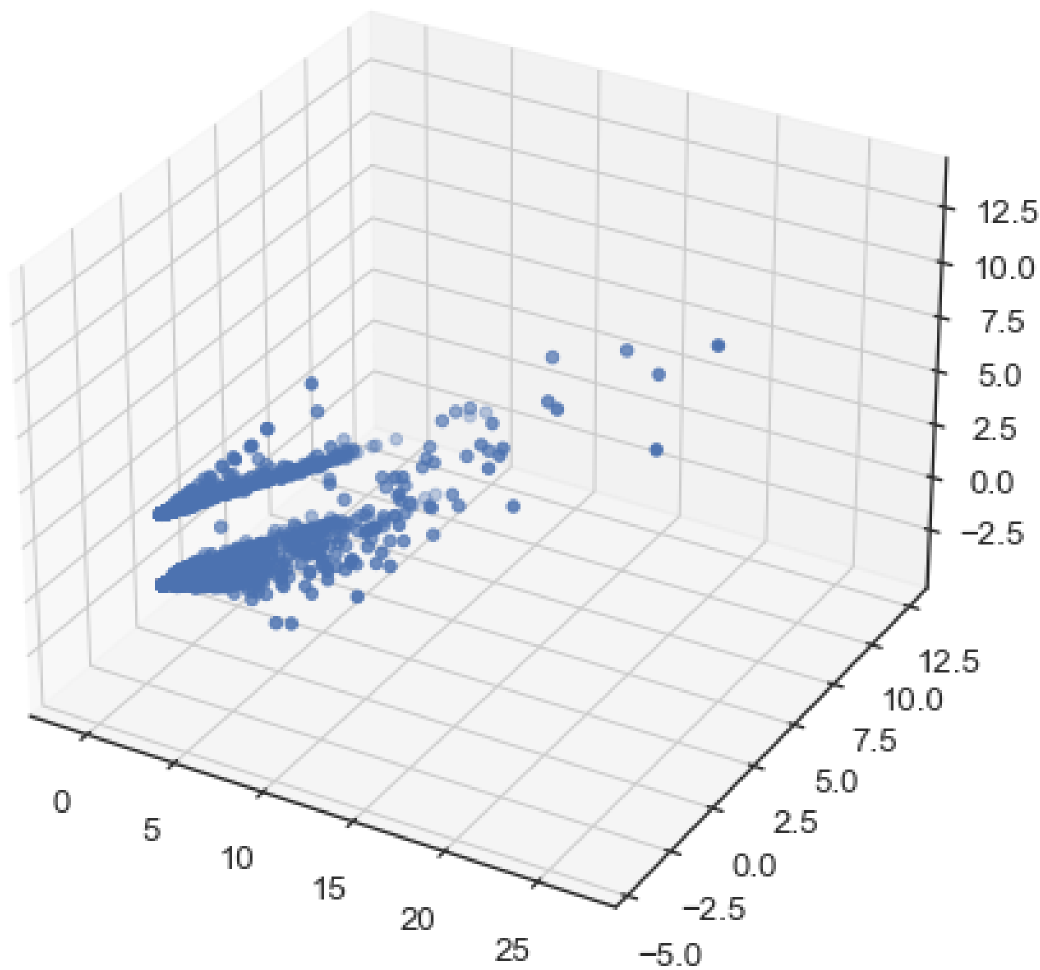


1.0
0.8
0.6
0.4
0.2
0.0
cumulative explained variance
95% cut-off threshold
0
2
4
6
8
10
number of components



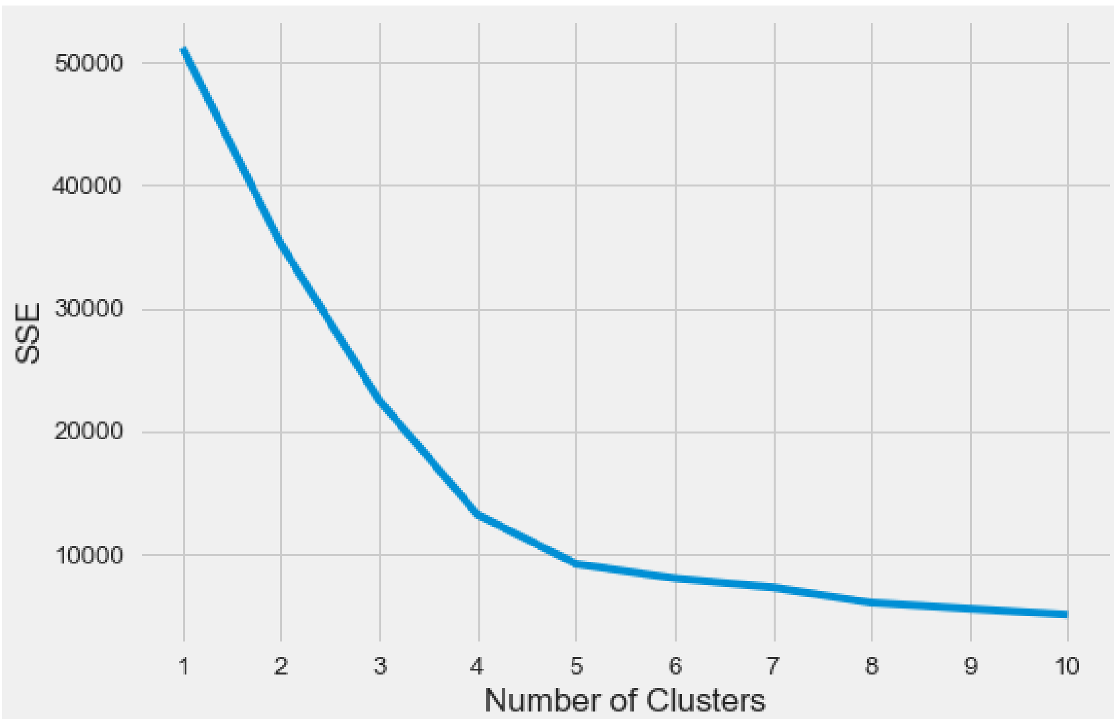
[22]:
```
# Perform PCA (Choose n_components to keep)
pca = PCA(n_components=3)
pca_array = pca.fit_transform(X_std)

# Convert back to DataFrame for readability
df_pca = pd.DataFrame(data=pca_array)
df_pca.columns = ['PC' + str(col+1) for col in df_pca.columns.values]

display(df_pca.head())

# Plot Principal Component
_ = sns.set(style='ticks', font_scale=1.2)
fig, ax = plt.subplots(figsize=(10, 7))
seaborn_plot = plt.axes (projection='3d')
_ = seaborn_plot.scatter3D(df_pca.iloc[:,0],df_pca.iloc[:,1],df_pca.iloc[:,2])
```

	PC1	PC2	PC3
0	2.900869	-0.366195	-0.713281
1	-0.991235	0.381651	0.677323
2	0.918009	-0.706606	-1.274291
3	-1.031437	0.278177	0.702570
4	-0.831252	0.521203	0.680444



[23]:
```
kmeans_kwargs = {
    "init": "random",
    "n_init": 10,
    "max_iter": 300,
    "random_state": 42,
}

# A list holds the SSE values for each k
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(df_pca)
    sse.append(kmeans.inertia_)
plt.style.use("fivethirtyeight")
```

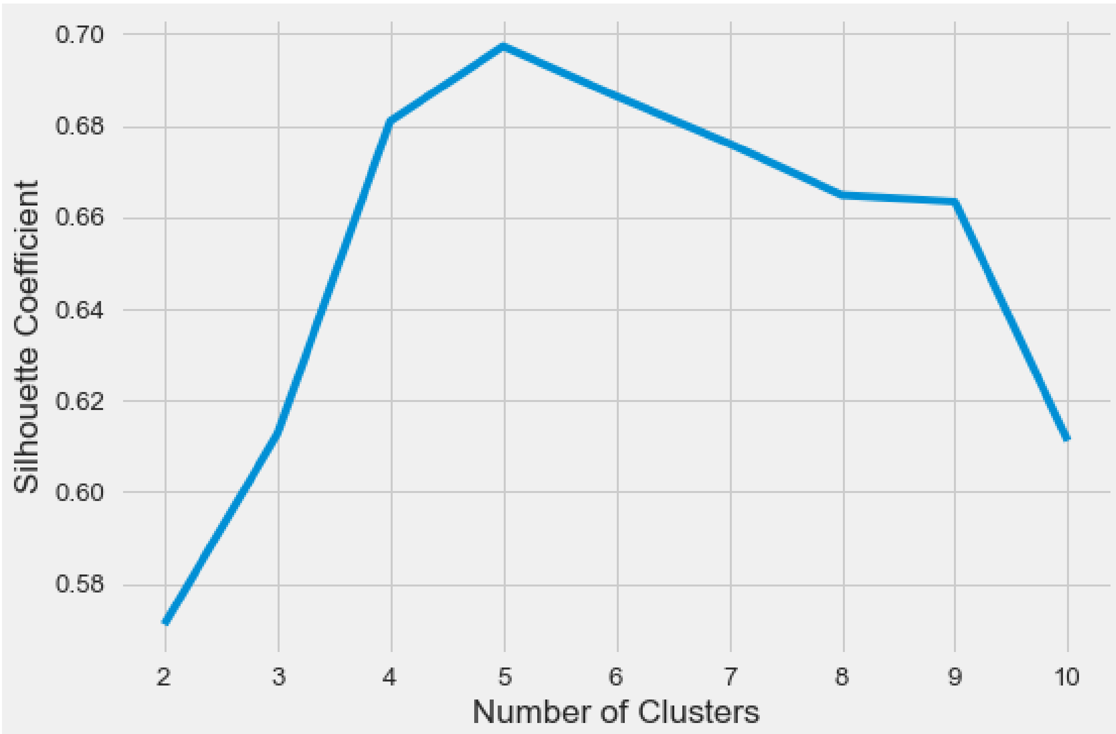
```
plt.plot(range(1, 11), sse)
plt.xticks(range(1, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("SSE")
plt.show()

kl = KneeLocator(
    range(1, 11), sse, curve="convex", direction="decreasing"
)
print(r'Select %s clusters as best to execute Kmeans Model' %kl.elbow)
```




```
Select 4 clusters as best to execute Kmeans Model
```

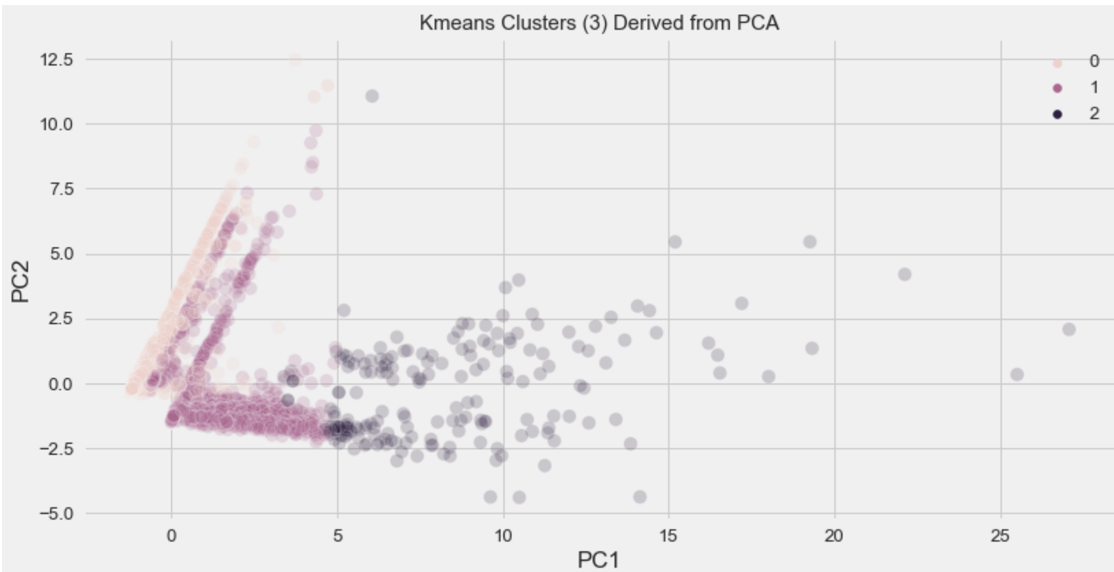
[24]:
```
silhouette_coefficients = []

# Notice you start at 2 clusters for silhouette coefficient
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(df_pca)
    score = silhouette_score(df_pca, kmeans.labels_)
    silhouette_coefficients.append(score)

plt.style.use("fivethirtyeight")
plt.plot(range(2, 11), silhouette_coefficients)
```

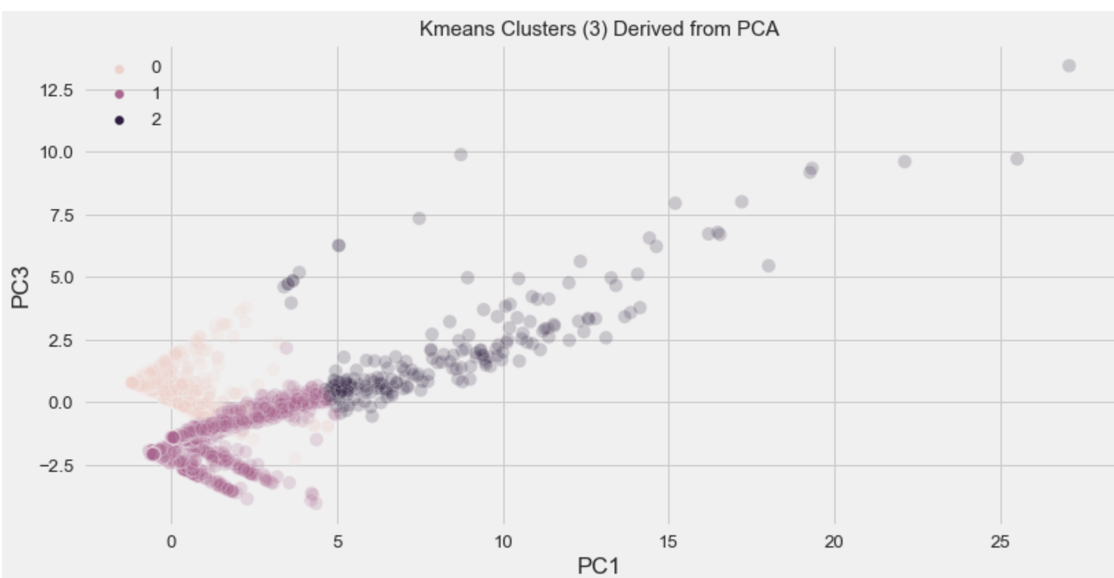
```
plt.xticks(range(2, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient")
plt.show()
```

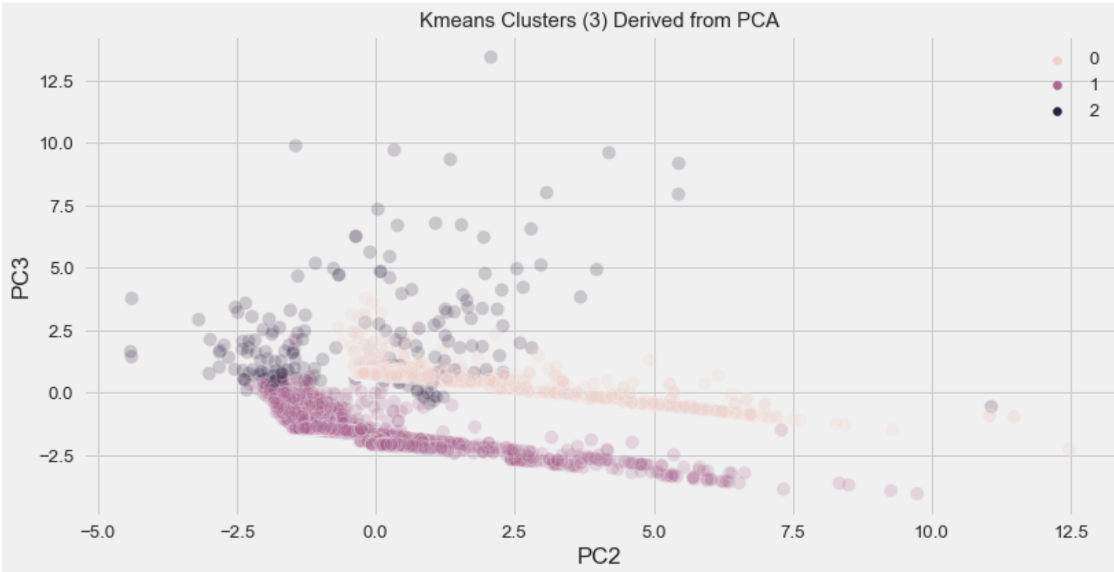


[25]:
```
ks=3
k_means_pca = KMeans(init = "k-means++", n_clusters = ks, n_init = 12,␣
 ↪random_state= 42).fit(df_pca)
labels_pca = k_means_pca.labels_
#display(labels_pca)
clusters_pca = pd.concat([df_pca, pd.DataFrame({'pca_clusters':labels_pca})],␣
 ↪axis=1)

plt.figure(figsize=(12,6))

sns.scatterplot(clusters_pca.iloc[:,0], clusters_pca.iloc[:,1],
               hue = labels_pca, s=100,
               alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
               fontsize=15)
plt.figure(figsize=(12,6))
sns.scatterplot(clusters_pca.iloc[:,0], clusters_pca.iloc[:,2],
               hue = labels_pca, s=100,
               alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
```

```
                fontsize=15)
plt.figure(figsize=(12,6))
sns.scatterplot(clusters_pca.iloc[:,1], clusters_pca.iloc[:,2],
                hue = labels_pca, s=100,
                alpha=0.2).set_title('Kmeans Clusters (%s) Derived from PCA' %ks,
                fontsize=15)
plt.legend()
plt.show()
```

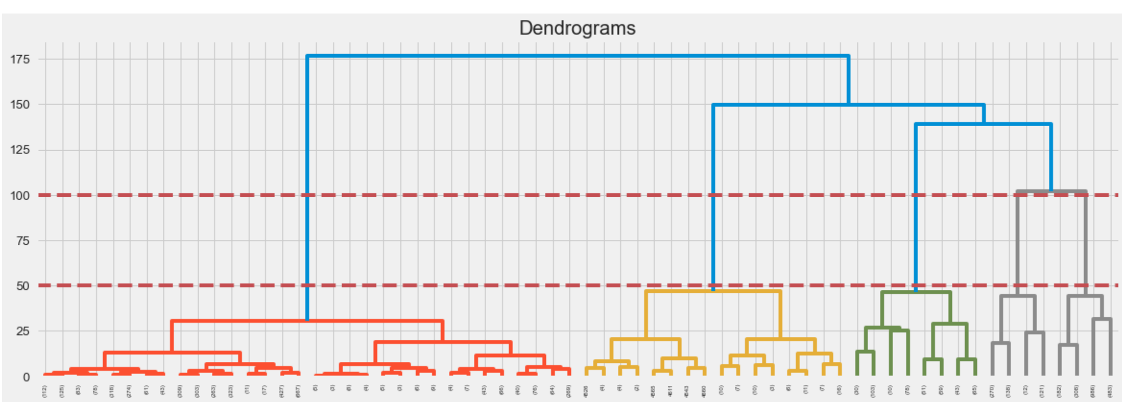






[26]:
```python
ks=9
k_means_pca = KMeans(init = "k-means++", n_clusters = ks, n_init = 12, random_state= 42).fit(df_pca)
labels_pca = k_means_pca.labels_
#display(labels_pca)
clusters_pca = pd.concat([df_pca, pd.DataFrame({'Kmeans PCA':labels_pca})], axis=1)
df_pca_kmeans=pd.concat([X_std.reset_index(drop=True), df_pca], axis=1)
df_pca_kmeans['Kmeans PCA'] = labels_pca
```

[27]:
```python
plt.figure(figsize=(18, 6))
plt.title("Dendrograms");
dendrogram = sch.dendrogram(sch.linkage(df_pca, method='ward'),truncate_mode='level', p=5)
plt.axhline(y= 100, color='r', linestyle='--')
plt.axhline(y= 50, color='r', linestyle='--');
```

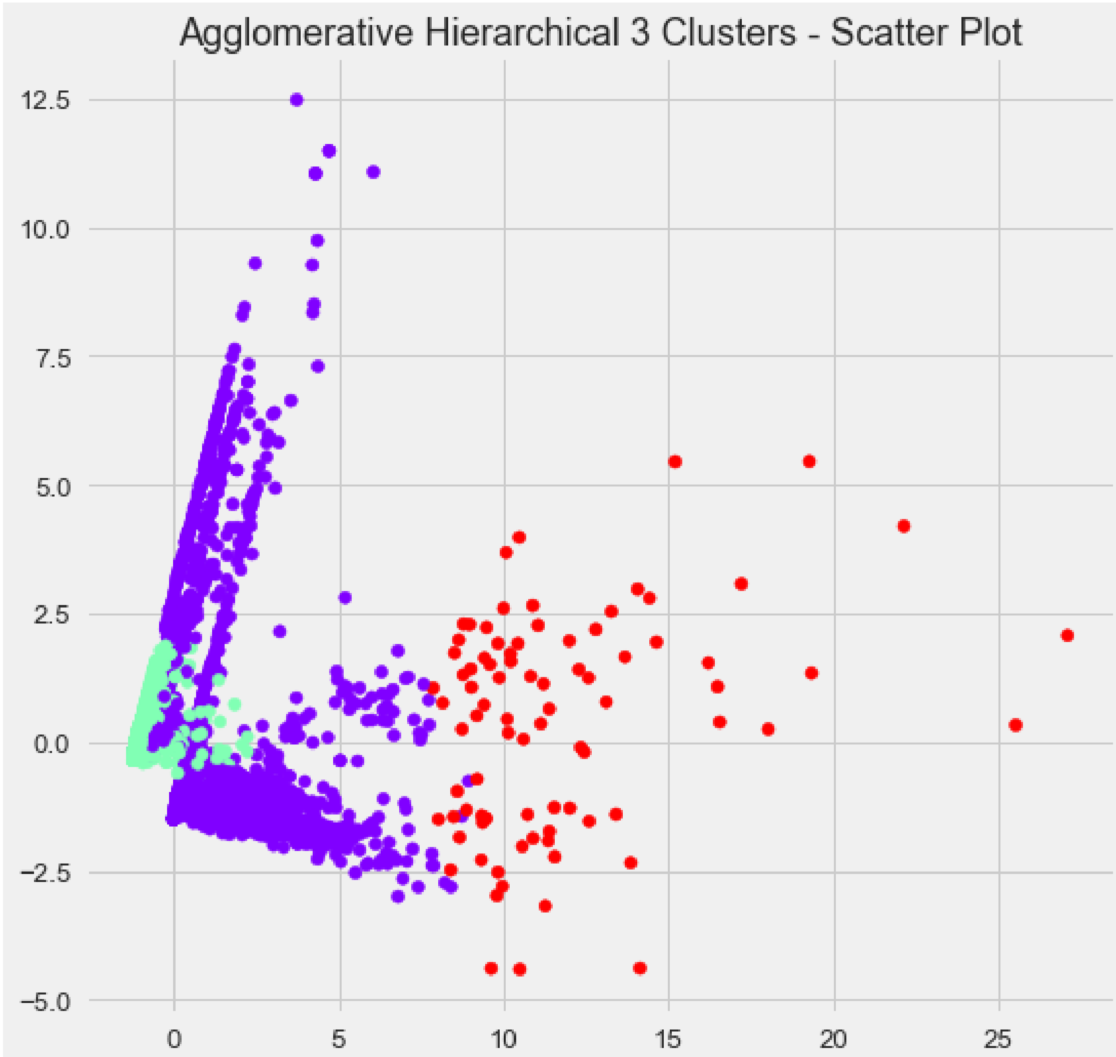


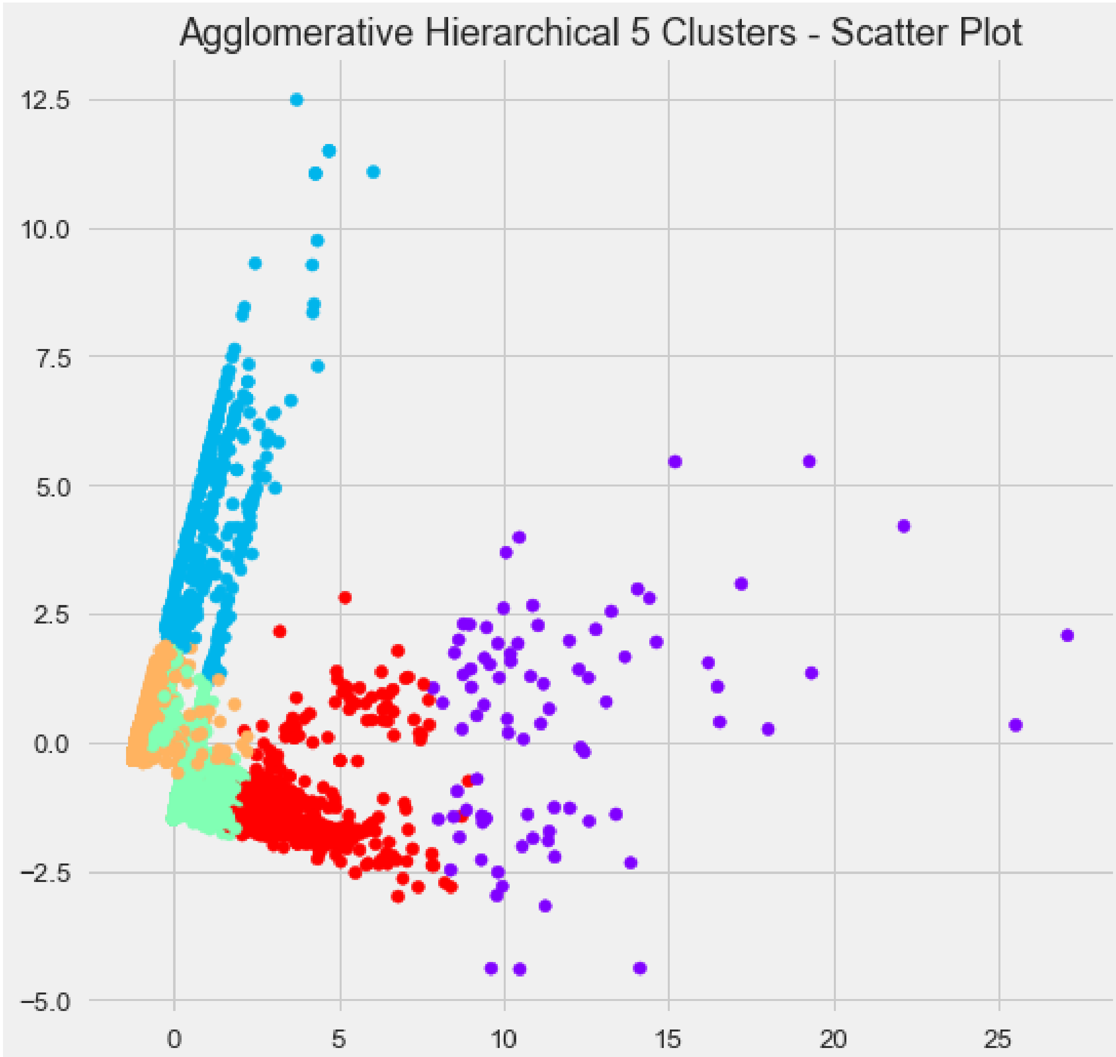
[28]:
```
# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 3, affinity='euclidean',␣
↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
↪='rainbow')
plt.title("Agglomerative Hierarchical 3 Clusters - Scatter Plot", fontsize=18);

agc.fit(df_pca)
labels_hier = agc.labels_
labels_hier[:20]

clusters_all_pca3 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
↪labels_hier})], axis=1)
clusters_all_pca3.head()


# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 5, affinity='euclidean',␣
↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
↪='rainbow')
plt.title("Agglomerative Hierarchical 5 Clusters - Scatter Plot", fontsize=18);

agc.fit(df_pca)
labels_hier = agc.labels_
labels_hier[:20]

clusters_all_pca5 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
↪labels_hier})], axis=1)
clusters_all_pca5.head()


# Create the clusters using Agglomerative hierarchical clustering

agc = AgglomerativeClustering(n_clusters= 9, affinity='euclidean',␣
↪linkage='ward')
plt.figure(figsize =(8, 8))
plt.scatter(df_pca['PC1'], df_pca['PC2'], c = agc.fit_predict(df_pca), cmap␣
↪='rainbow')
plt.title("Agglomerative Hierarchical 9 Clusters - Scatter Plot", fontsize=18);
```

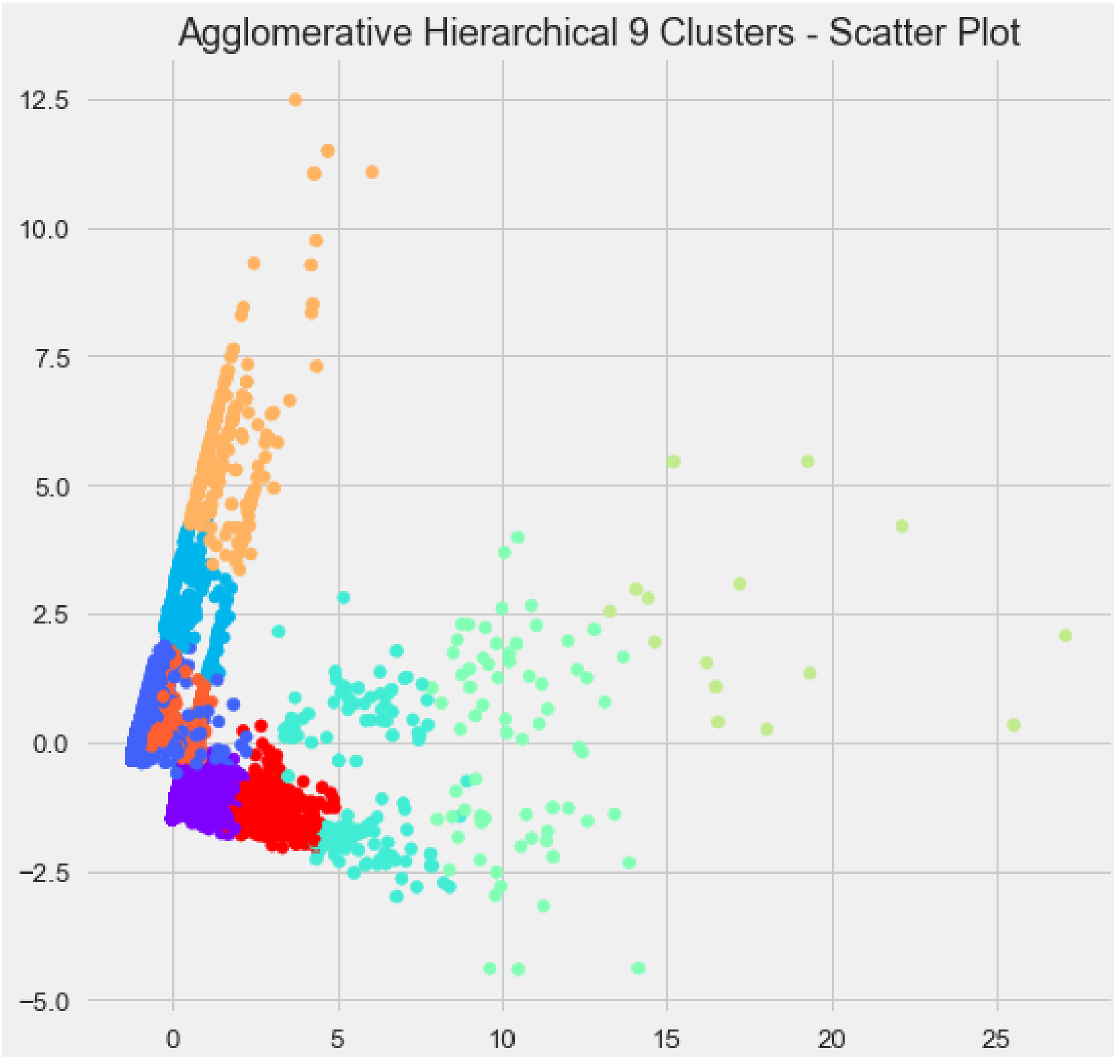
```python
agc.fit(df_pca)
labels_hier = agc.labels_
labels_hier[:20]

clusters_all_pca9 = pd.concat([df_pca_kmeans, pd.DataFrame({'PCA Clusters Hier':
 ↪labels_hier})], axis=1)
clusters_all_pca9.head()
```

[28]:

```
   status_published  num_reactions  num_comments  num_shares  num_likes  \
0         -0.718661       0.646104      0.323350    1.686879   0.482727
1         -0.718661      -0.173192     -0.252206   -0.304144  -0.144720
2         -0.718661      -0.006738      0.013089    0.129017  -0.024571
3         -0.718661      -0.257499     -0.252206   -0.304144  -0.231495
4         -0.718661      -0.037003     -0.252206   -0.304144  -0.024571

   num_loves  num_wows  num_hahas  num_sads  num_angrys  type_link  \
0   1.983266  0.196196   0.076713  0.473570   -0.155748  -0.094957
1  -0.318454 -0.147879  -0.176010 -0.152587   -0.155748  -0.094957
2   0.206938 -0.033187   0.076713 -0.152587   -0.155748  -0.094957
3  -0.318454 -0.147879  -0.176010 -0.152587   -0.155748  -0.094957
4  -0.093286 -0.147879  -0.176010 -0.152587   -0.155748  -0.094957

   type_photo  type_status  type_video       PC1       PC2       PC3  \
0   -1.245993    -0.233666    1.421466  2.900869 -0.366195 -0.713281
1    0.802573    -0.233666   -0.703499 -0.991235  0.381651  0.677323
2   -1.245993    -0.233666    1.421466  0.918009 -0.706606 -1.274291
3    0.802573    -0.233666   -0.703499 -1.031437  0.278177  0.702570
4    0.802573    -0.233666   -0.703499 -0.831252  0.521203  0.680444

   Kmeans PCA  PCA Clusters Hier
0           2                  8
1           0                  1
2           4                  0
3           0                  1
4           0                  1
```

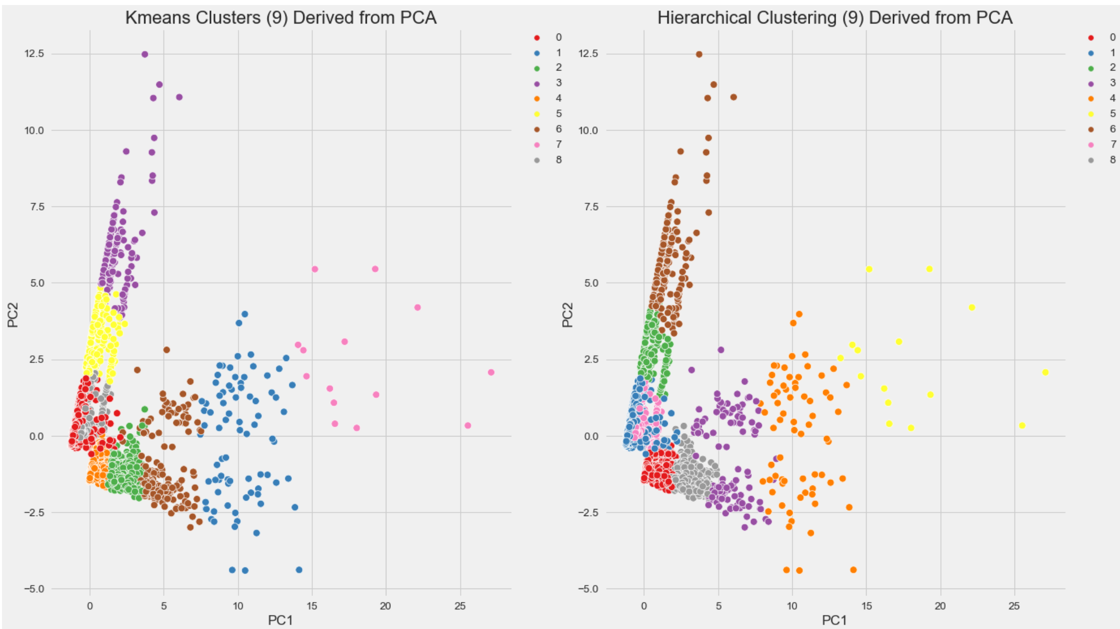

Agglomerative Hierarchical 3 Clusters - Scatter Plot
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
0
5
10
15
20
25


Agglomerative Hierarchical 5 Clusters - Scatter Plot
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
0
5
10
15
20
25



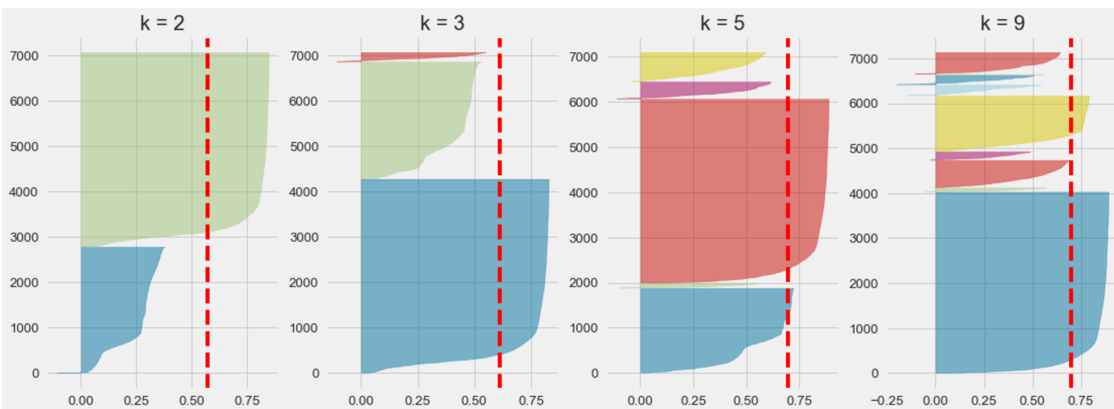
[29]:
```
# Scatter plot using the first 2 Principal Components to observe the Cluster␣
↪Distribution

plt.figure(figsize=(20,12))

plt.subplot(1,2,1)
sns.scatterplot(x= 'PC1', y='PC2',
                data= clusters_all_pca9,
                hue = 'Kmeans PCA', palette='Set1', s= 80).set_title('Kmeans␣
↪Clusters (9) Derived from PCA',
                fontsize= 22)
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
```

```
plt.subplot(1,2,2)
sns.scatterplot(x= 'PC1', y='PC2',
                data= clusters_all_pca9, s=80,
                hue= 'PCA Clusters Hier',palette='Set1').
↪set_title('Hierarchical Clustering (9) Derived from PCA',
                fontsize=22);
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0);
```



[30]:
```
# SilhouetteVisualizer
# ==============================================================================

fig,(ax1,ax2,ax3,ax4)=plt.subplots(figsize=(17,6),nrows=1,ncols=4)

#ax1
visualizer = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=2,␣
↪random_state=42), colors='yellowbrick',ax=ax1)
visualizer.fit(df_pca)       # Fit the data to the visualizer
ax1.set_title('k = 2')                # Title
sil1=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=2,␣
↪random_state=42).fit(df_pca).labels_)

#ax2
visualizer2 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=3,␣
↪random_state=42), colors='yellowbrick',ax=ax2)
visualizer2.fit(df_pca)      # Fit the data to the visualizer
```

```
ax2.set_title('k = 3')                    # Title
sil2=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=3,␣
↪random_state=42).fit(df_pca).labels_)

#ax3
visualizer3 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=5,␣
↪random_state=42), colors='yellowbrick',ax=ax3)
visualizer3.fit(df_pca)       # Fit the data to the visualizer
ax3.set_title('k = 5');                    # Title
sil3=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=5,␣
↪random_state=42).fit(df_pca).labels_)

#ax4
visualizer4 = SilhouetteVisualizer(KMeans(init = "k-means++",n_clusters=9,␣
↪random_state=42), colors='yellowbrick',ax=ax4)
visualizer4.fit(df_pca)       # Fit the data to the visualizer
ax4.set_title('k = 9');                   # Title
sil4=silhouette_score(df_pca, KMeans(init = "k-means++",n_clusters=9,␣
↪random_state=42).fit(df_pca).labels_)
```



[32]:
```
silhouette = pd.DataFrame({'Measure': ['2 Clusters' ,'3 Clusters', '5␣
↪Clusters', '9 Clusters'],
                           'Scores': [sil1,sil2,sil3,sil4]
                           })
silhouette
```

[32]:

	Measure	Scores
0	2 Clusters	0.571075
1	3 Clusters	0.612628
2	5 Clusters	0.697317
3	9 Clusters	0.697545

- Podem veure resultats en les agrupacions totalment diferents ja que les variances s'han dividit més equitativament entre les diferents variables/features. Això ha generat que els components del PCA que s'han creat siguin diferents als anteriors proporcionant una reducció de dimensionalitat diferent i obtenint per així dir-ho, diferents punts projectats entre el mètode amb estandarització estandard i MinMax.