No_supervisado

September 29, 2019

1 Introduccion

Todo ejercicio debe tener un análisis fundamentado en la teoría vista en la materia, dicho análisis sera parte del informe a entregar en pdf

- *Se recomienda hacer uso de las herramientas vistas en los demos de la materia.*
- **Usar lo hecho en el práctico Análisis Exploratorio y Curación de Datos**.

Objetivos: - Implementar modelos de clustering, variando el número de clusters. - Usar embeddings: PCA, correlación y t-distributed stochastic neighbor.

Implementar dos modelos de clustering con y sin embeddings uno de ellos k-means.

Realizar un análisis de lo obtenido. - Es muy recomendable integrar indicadores de mala calidad como por ejemplo "hay un cluster muy grande y el resto son muy chicos", lo cual indica que en el espacio no se distinguen bien grupos separados y hay que usar otro espacio - Evaluar con Silohuette y pureza con algunos datos etiquetados.

NOTA: Es de suma importancia usar el conocimiento del experto en este práctico.

2 Analisis de datos

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.cm as cm
        import seaborn as sns
        import pandas as pd

        %matplotlib inline
```

```
In [2]: plt.rcParams['figure.figsize'] = (10.0, 8.0)
```

```
In [3]: data = pd.read_csv("dataset/galaxias_1.csv")
        data.head()
```

```
Out[3]:                    objID          ra        dec  modelMag_u  modelMag_g  \
        0  1,23765119242489E+018  116.519097  39.886407    17.76235    16.72601
        1  1,23765149575578E+018  116.451900  41.421270    18.12179    16.26214
        2  1,23767370611537E+018  115.946713  41.918877    18.57293    17.42053
```

```
3   1,2376737066523E+018  116.051943  42.287231    21.37438    19.77335
4  1,23765127349266E+018  117.287392  43.434782    19.18845    17.99682

   modelMag_r  modelMag_i  modelMag_z  petroR90_r         z     Color  \
0    16.33972    16.06614    15.90478    8.393773  0.041521 -1.422625
1    15.39272    14.97515    14.65105    9.674847  0.040211 -2.729061
2    17.01788    16.75617    16.70899   11.277470  0.024386 -1.555044
3    19.55791    20.35405    18.88184    1.539542  0.039137 -1.816479
4    17.51119    17.26241    17.09056   12.471450  0.042591 -1.677259

   elliptical  spiral  uncertain
0           0       1          0
1           0       0          1
2           0       0          1
3           0       0          1
4           0       0          1
```

In [4]:
```
data.describe()
```

Out[4]:
```
                  ra           dec    modelMag_u    modelMag_g    modelMag_r  \
count   92102.000000  92102.000000  92102.000000  92102.000000  92102.000000
mean      181.086338     24.723737    184.319135    171.045909    160.125000
std        61.177151     18.853785   1737.511731   1612.598539   1525.504087
min         0.008745    -11.202394  -9999.000000  -9999.000000     11.524090
25%       150.287271      9.115292     17.733585     16.260870     15.572525
50%       183.219954     23.111344     18.453880     17.094630     16.506160
75%       222.722975     38.982500     19.047078     17.734885     17.227810
max       359.965567     70.133213  25756.000000  20542.000000  19138.000000

          modelMag_i    modelMag_z    petroR90_r             z         Color  \
count   92102.000000  92102.000000  92102.000000  92102.000000  92102.000000
mean      163.614406    139.806936     57.032318      0.036092     -3.462711
std      1530.181510   1402.492646    923.367743      0.008435     76.781199
min        11.220580  -9999.000000      0.842248      0.020001  -2902.000000
25%        15.210220     14.919152      6.120165      0.029082     -2.511168
50%        16.188085     15.947850      8.365595      0.036321     -1.995331
75%        16.947265     16.753538     11.368645      0.043620     -1.607067
max     23871.000000  20823.000000  78255.000000      0.050000  10015.860000

          elliptical        spiral     uncertain
count   92102.000000  92102.000000  92102.000000
mean        0.089651      0.326225      0.584124
std         0.285682      0.468833      0.492875
min         0.000000      0.000000      0.000000
25%         0.000000      0.000000      0.000000
50%         0.000000      0.000000      1.000000
75%         0.000000      1.000000      1.000000
max         1.000000      1.000000      1.000000
```

```
In [5]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 92102 entries, 0 to 92101
Data columns (total 14 columns):
objID          92102 non-null object
ra             92102 non-null float64
dec            92102 non-null float64
modelMag_u     92102 non-null float64
modelMag_g     92102 non-null float64
modelMag_r     92102 non-null float64
modelMag_i     92102 non-null float64
modelMag_z     92102 non-null float64
petroR90_r     92102 non-null float64
z              92102 non-null float64
Color          92102 non-null float64
elliptical     92102 non-null int64
spiral         92102 non-null int64
uncertain      92102 non-null int64
dtypes: float64(10), int64(3), object(1)
memory usage: 9.8+ MB
```

Seteo "objID" como index

```
In [6]: data.set_index("objID", inplace=True)
```

```
In [7]: data.head()
```

```
Out[7]:                                ra        dec  modelMag_u  modelMag_g  \
        objID
        1,23765119242489E+018  116.519097  39.886407    17.76235    16.72601
        1,23765149575578E+018  116.451900  41.421270    18.12179    16.26214
        1,23767370611537E+018  115.946713  41.918877    18.57293    17.42053
        1,2376737066523E+018   116.051943  42.287231    21.37438    19.77335
        1,23765127349266E+018  117.287392  43.434782    19.18845    17.99682

                               modelMag_r  modelMag_i  modelMag_z  petroR90_r  \
        objID
        1,23765119242489E+018    16.33972    16.06614    15.90478    8.393773
        1,23765149575578E+018    15.39272    14.97515    14.65105    9.674847
        1,23767370611537E+018    17.01788    16.75617    16.70899   11.277470
        1,2376737066523E+018     19.55791    20.35405    18.88184    1.539542
        1,23765127349266E+018    17.51119    17.26241    17.09056   12.471450

                                      z     Color  elliptical  spiral  uncertain
        objID
        1,23765119242489E+018  0.041521 -1.422625           0       1          0
        1,23765149575578E+018  0.040211 -2.729061           0       0          1
```

```
1,23767370611537E+018  0.024386 -1.555044          0       0           1
1,2376737066523E+018   0.039137 -1.816479          0       0           1
1,23765127349266E+018  0.042591 -1.677259          0       0           1
```

Veo que tipos de datos tengo

```
In [8]: data.dtypes

Out[8]: ra              float64
        dec             float64
        modelMag_u      float64
        modelMag_g      float64
        modelMag_r      float64
        modelMag_i      float64
        modelMag_z      float64
        petroR90_r      float64
        z               float64
        Color           float64
        elliptical        int64
        spiral            int64
        uncertain         int64
        dtype: object
```

2.1 Veo si tengo valores duplicados

```
In [9]: data[data.astype(str).duplicated()].shape

Out[9]: (61, 13)

In [10]: data[data.index.astype(str).duplicated()].shape[0] / data.shape[0]

Out[10]: 0.37372695489783064

In [11]: data[data.index.astype(str).duplicated()].shape[0]

Out[11]: 34421
```

Veo que hay muchos indices repetidos, pero no así tantas filas completas. Una explicación posible a esto es que las galaxias estan identificadas por el indice, pero hay observacion de una misma galaxia en diferentes momentos temporales, por lo que no esta mal tener indices repetidos.

Sin embargo, para nuestro estudio, no nos interesan los cambios o variaciones en una galaxia puntual, sino cada galaxia en particual. Por lo tanto vamos a eliminar los ObjID repetidos

2.1.1 Saco los duplicados

```
In [12]: data.shape

Out[12]: (92102, 13)

In [13]: #data_cl = data.loc[~(data.astype(str).duplicated(keep="first"))]
         data_cl = data.loc[~(data.index.astype(str).duplicated(keep="first"))].copy()
```

In [14]: data_cl.shape

Out[14]: (57681, 13)

In [15]: data_cl.head()

```
Out[15]:                             ra        dec  modelMag_u  modelMag_g  \
objID
1,23765119242489E+018  116.519097  39.886407    17.76235    16.72601
1,23765149575578E+018  116.451900  41.421270    18.12179    16.26214
1,23767370611537E+018  115.946713  41.918877    18.57293    17.42053
1,2376737066523E+018   116.051943  42.287231    21.37438    19.77335
1,23765127349266E+018  117.287392  43.434782    19.18845    17.99682

                       modelMag_r  modelMag_i  modelMag_z  petroR90_r  \
objID
1,23765119242489E+018    16.33972    16.06614    15.90478    8.393773
1,23765149575578E+018    15.39272    14.97515    14.65105    9.674847
1,23767370611537E+018    17.01788    16.75617    16.70899   11.277470
1,2376737066523E+018     19.55791    20.35405    18.88184    1.539542
1,23765127349266E+018    17.51119    17.26241    17.09056   12.471450

                              z     Color  elliptical  spiral  uncertain
objID
1,23765119242489E+018  0.041521 -1.422625           0       1          0
1,23765149575578E+018  0.040211 -2.729061           0       0          1
1,23767370611537E+018  0.024386 -1.555044           0       0          1
1,2376737066523E+018   0.039137 -1.816479           0       0          1
1,23765127349266E+018  0.042591 -1.677259           0       0          1
```

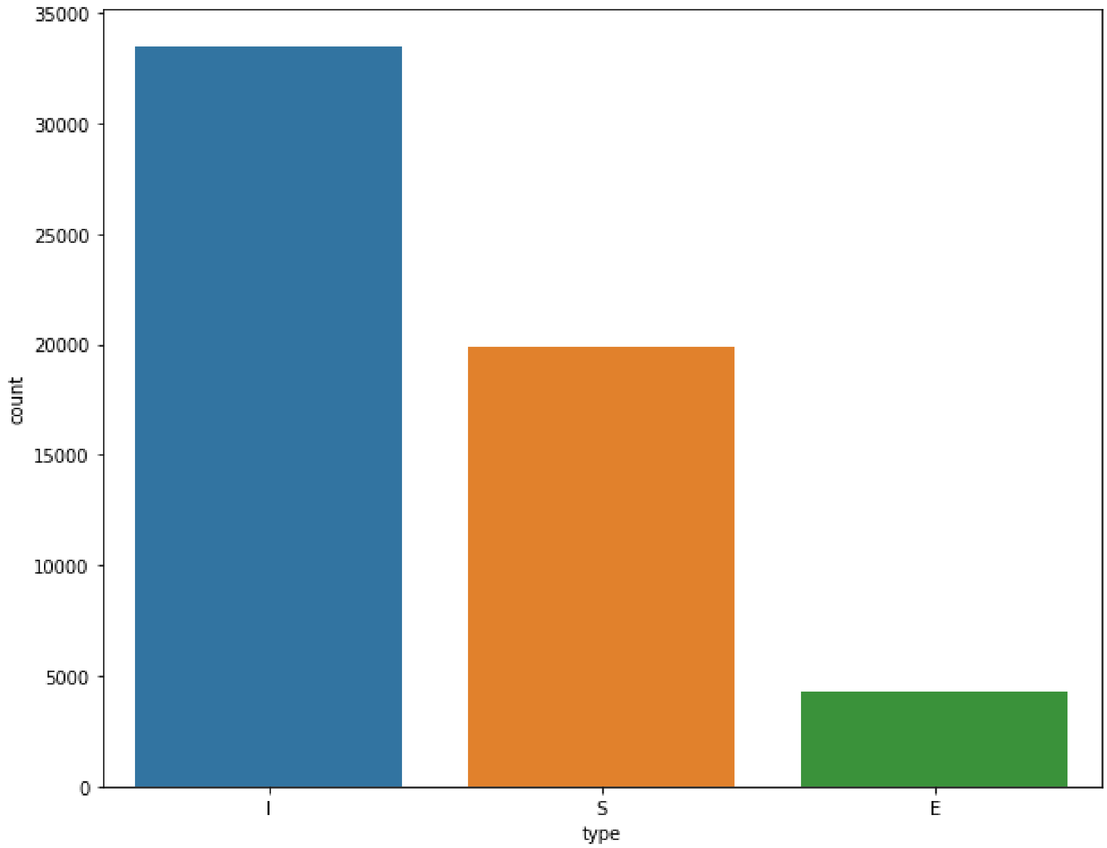
Hago un poco más de exploración en el data set

```
In [16]: def galaxy_morf(row):
             if row["elliptical"]:
                 return "E"
             elif row["spiral"]:
                 return "S"
             else:
                 return "I"
```

```
In [17]: data_cl["type"] = data_cl.apply(galaxy_morf, axis=1)
```

```
In [18]: sns.countplot(data_cl["type"], order=["I", "S", "E"])
```

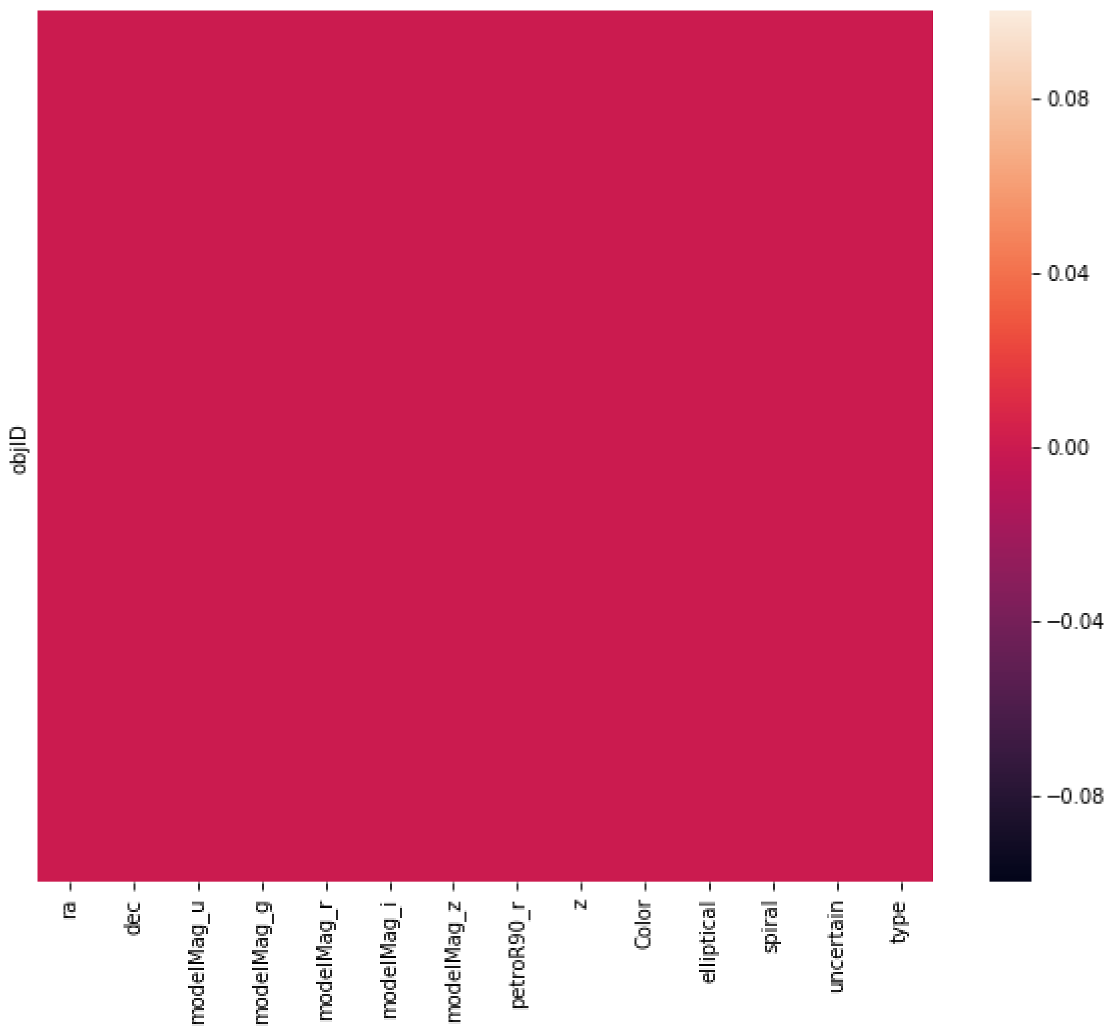
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f20a627fa20>



2.2 Veo valores faltantes

```
In [19]: sns.heatmap(data_cl.isna(), yticklabels=False)
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f20a431c080>
```



No tengo valores NaN. Pero puede que tenga valores que fisicamente no tienen sentido

2.3 Distribucion de datos

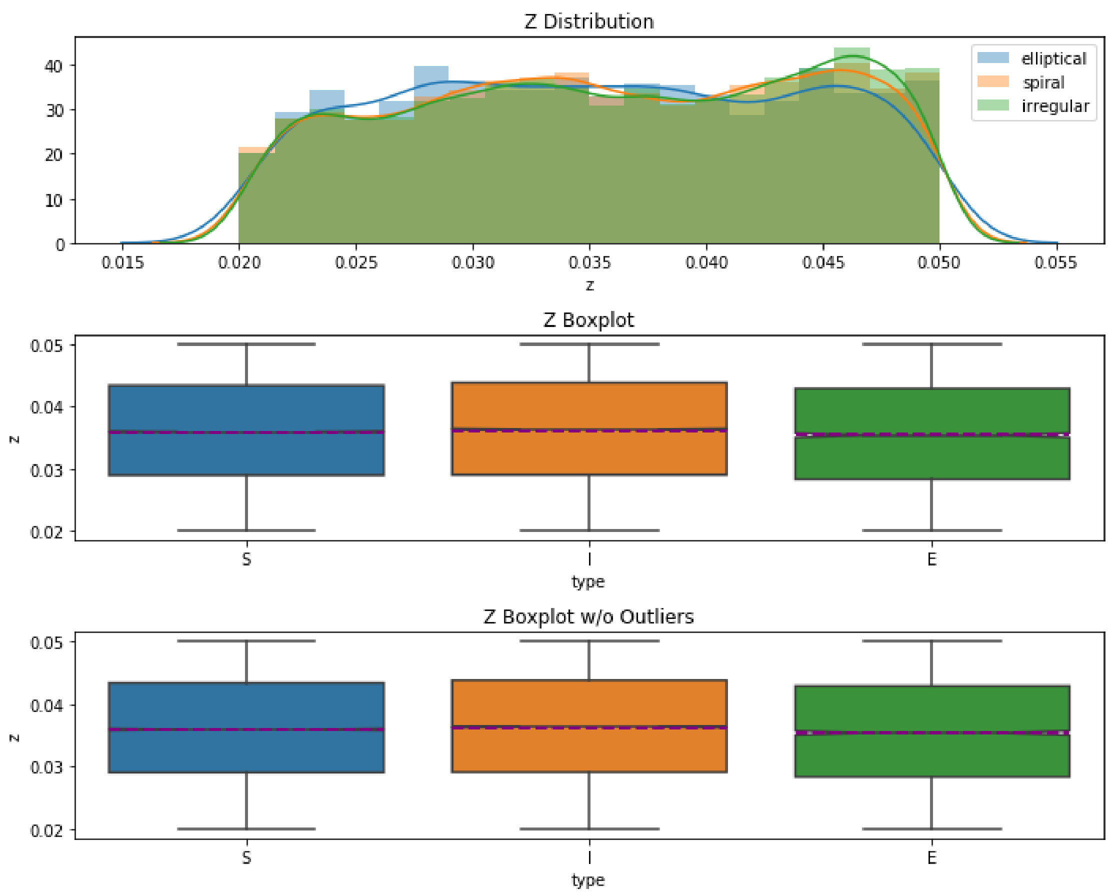
```
In [20]: box_params = {"notch": True,
                       "showmeans": True,
                       "meanline": True,
                       "meanprops": dict(linestyle='--', color='purple', linewidth=2)
                      }
```

```
In [21]: def distribution_per_type(df, col_name="", bins=20):
             plt.title(f"{col_name.capitalize()} Distribution")
             sns.distplot(df[df["elliptical"] == 1][col_name],label="elliptical", bins=bins)
             sns.distplot(df[df["spiral"] == 1][col_name],label="spiral", bins=bins)
             sns.distplot(df[df["uncertain"] == 1][col_name],label="irregular", bins=bins)
             plt.legend()
```

```
def exploratory_plots(df, col_name=""):
    plt.subplot(3, 1, 1)
    distribution_per_type(df, col_name)
    plt.subplot(3, 1, 2)
    plt.title(f"{col_name.capitalize()} Boxplot")
    sns.boxplot(x="type", y=col_name, data=df, **box_params)
    plt.subplot(3, 1, 3)
    plt.title(f"{col_name.capitalize()} Boxplot w/o Outliers")
    sns.boxplot(x="type", y=col_name, data=df, showfliers=False, **box_params)

    plt.tight_layout()
```

2.3.1 Z (red shift)

```
In [22]: exploratory_plots(data_cl, "z")
```

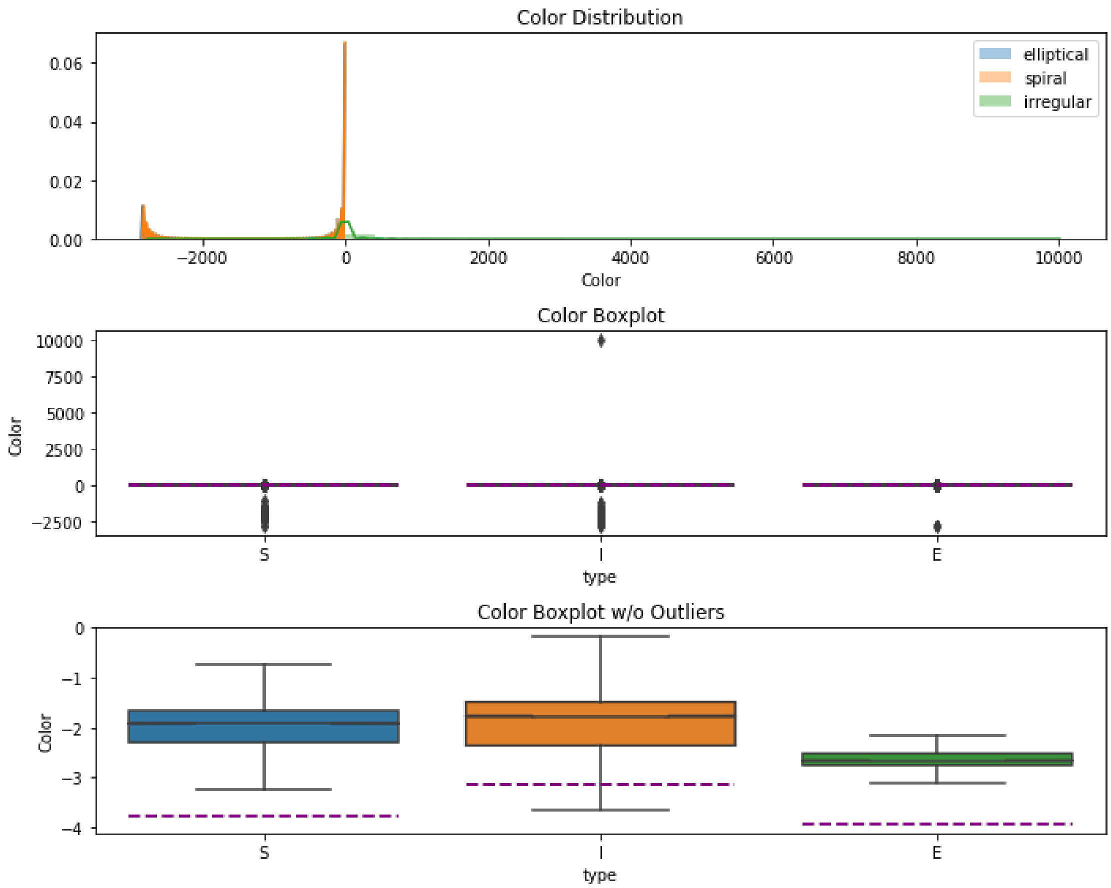


La columna "z", tiene una ditribcuion uniforme y no parece tener outliers

---

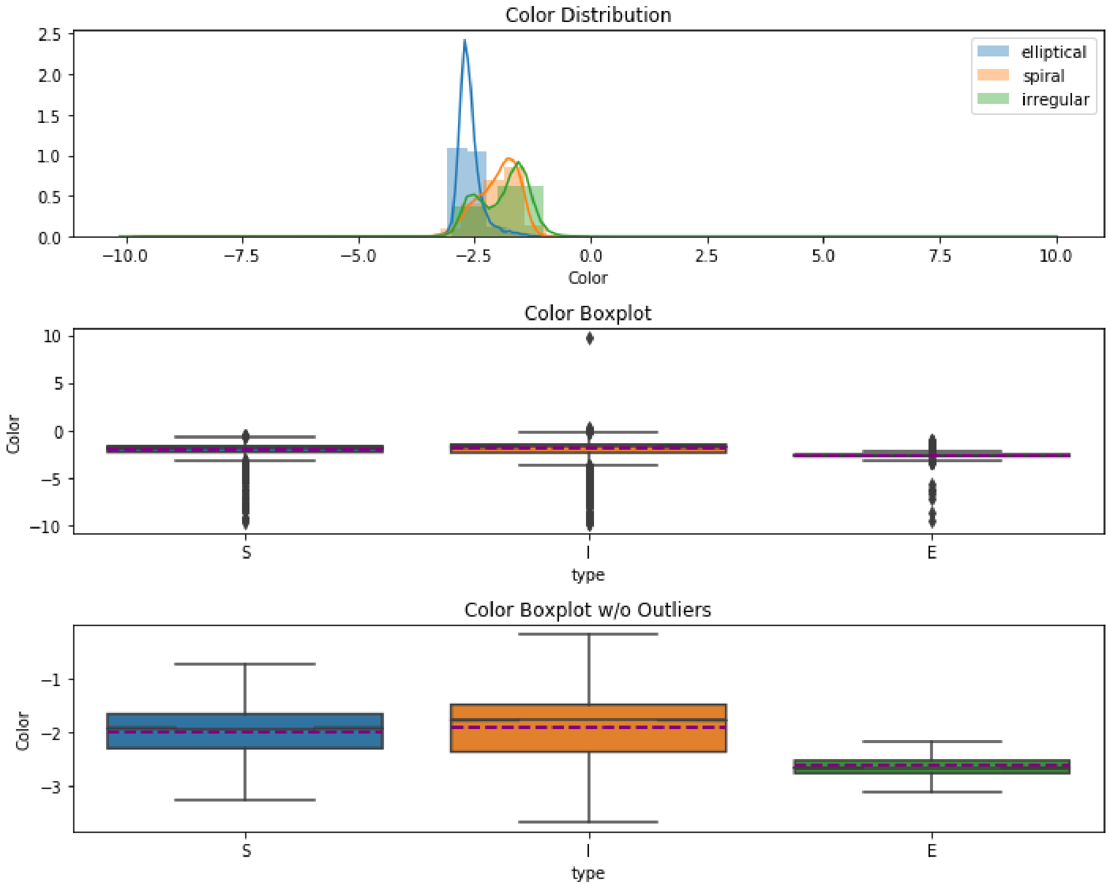
2.3.2 Color

```
In [23]: exploratory_plots(data_cl, "Color")
```



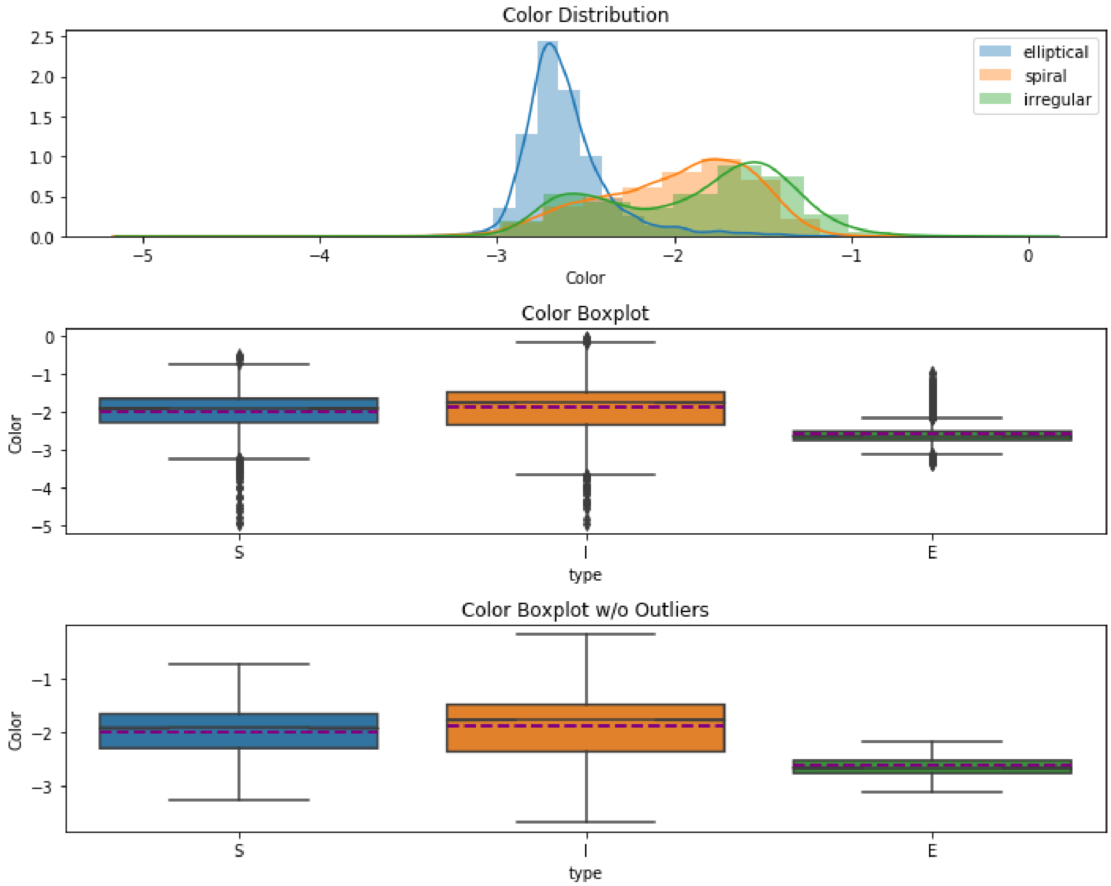
Vemos que hay valores muy extremos, mientras que gran parte de la distribucion esta en valores alrededor de 0

```
In [24]: mask_color = (data_cl["Color"] < 10) & (data_cl["Color"]>-10)
         exploratory_plots(data_cl[mask_color], "Color")
```

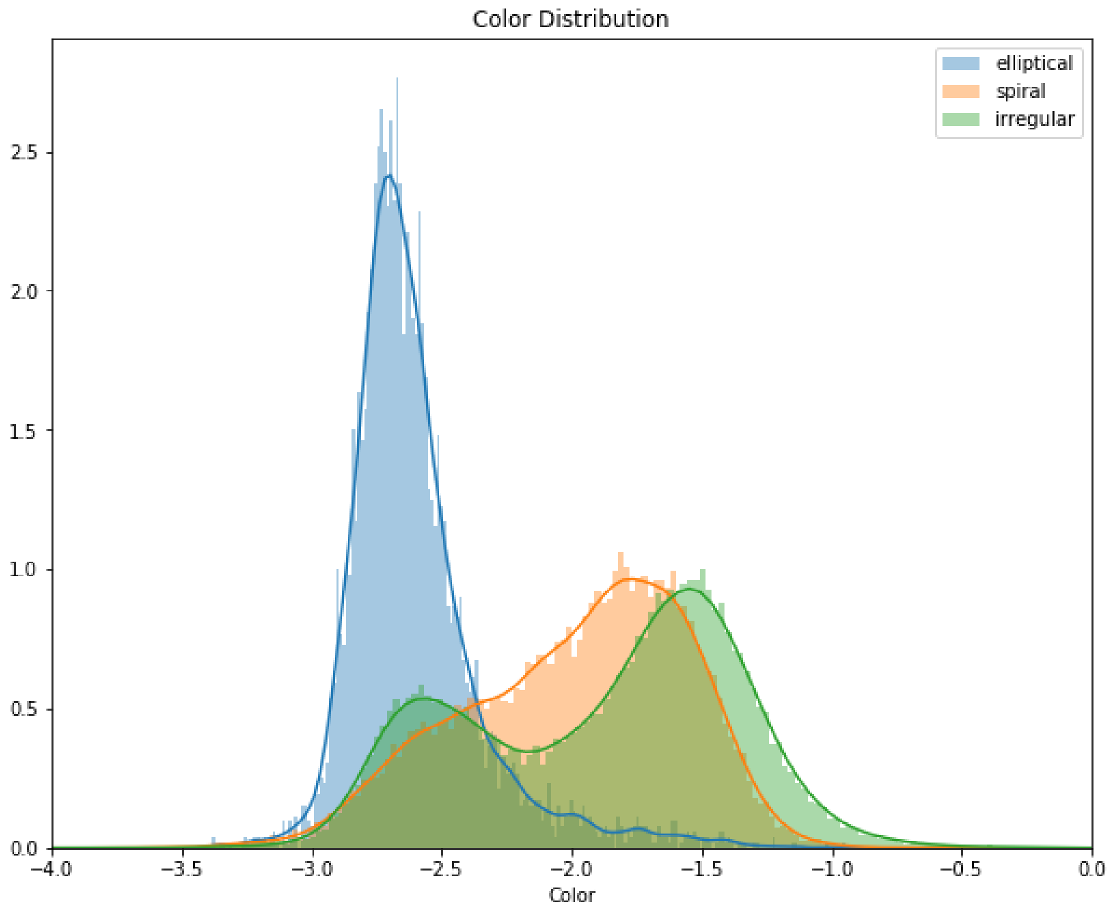


Podemos decir que los datos de color que tienen sentido deben estar entre 0 y -5

```
In [25]: mask_color = (data_cl["Color"] < 0) & (data_cl["Color"]>-5)
         data_cl_color = data_cl[mask_color]

In [26]: print(data_cl.shape)
         print(data_cl_color.shape)

(57681, 14)
(57506, 14)


In [27]: exploratory_plots(data_cl_color, "Color")
```

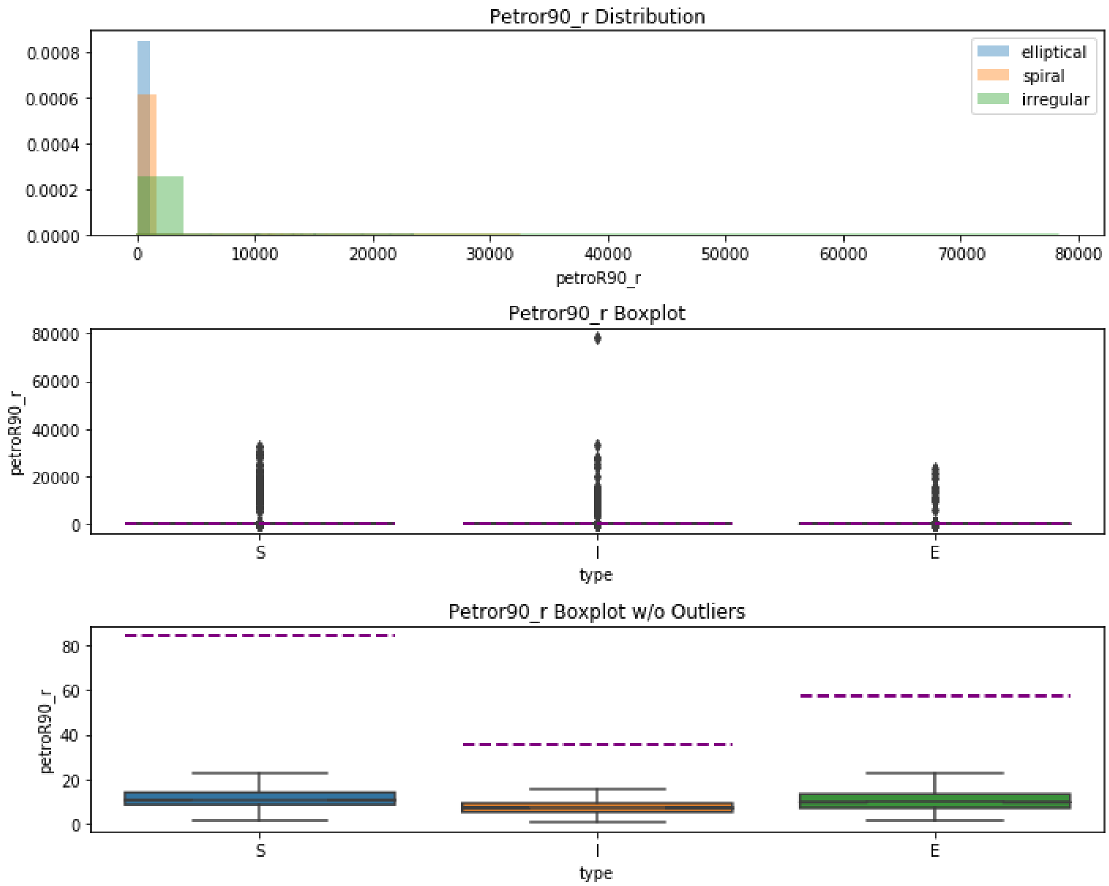



```
In [28]: distribution_per_type(data_cl_color, col_name="Color", bins=200)
         _ = plt.xlim([-4, 0])
```

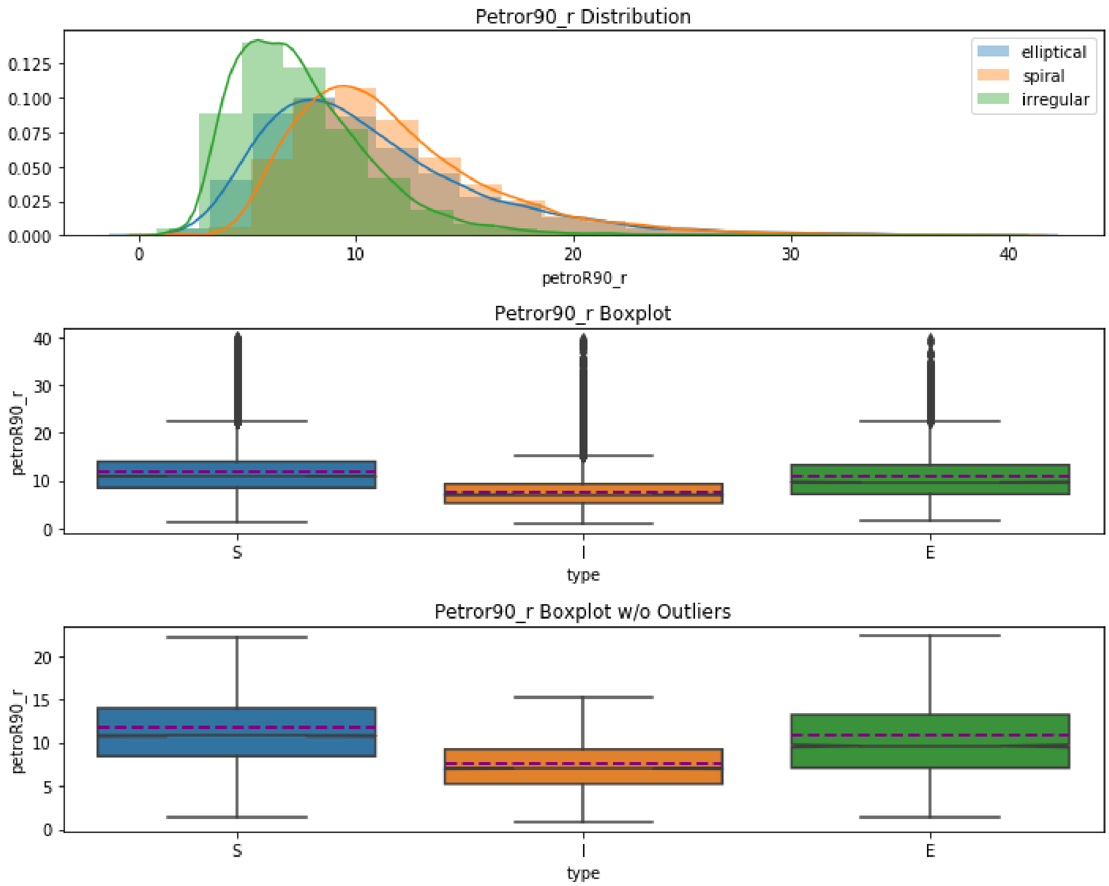


2.3.3 petroR90_r

```
In [29]: exploratory_plots(data_cl, "petroR90_r")
```



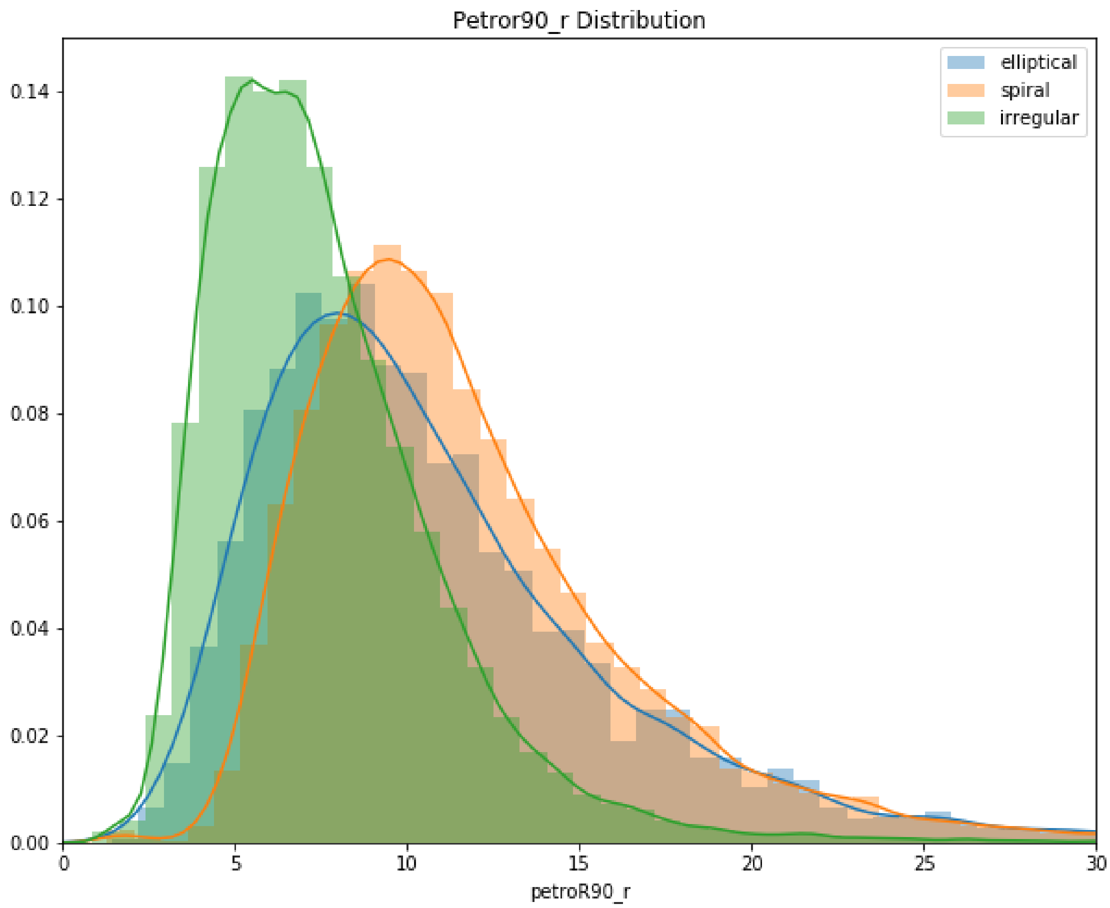
In [30]:
```
mask_petro = data_cl["petroR90_r"]<40
data_cl_petro = data_cl[mask_petro]
exploratory_plots(data_cl_petro, "petroR90_r")
```



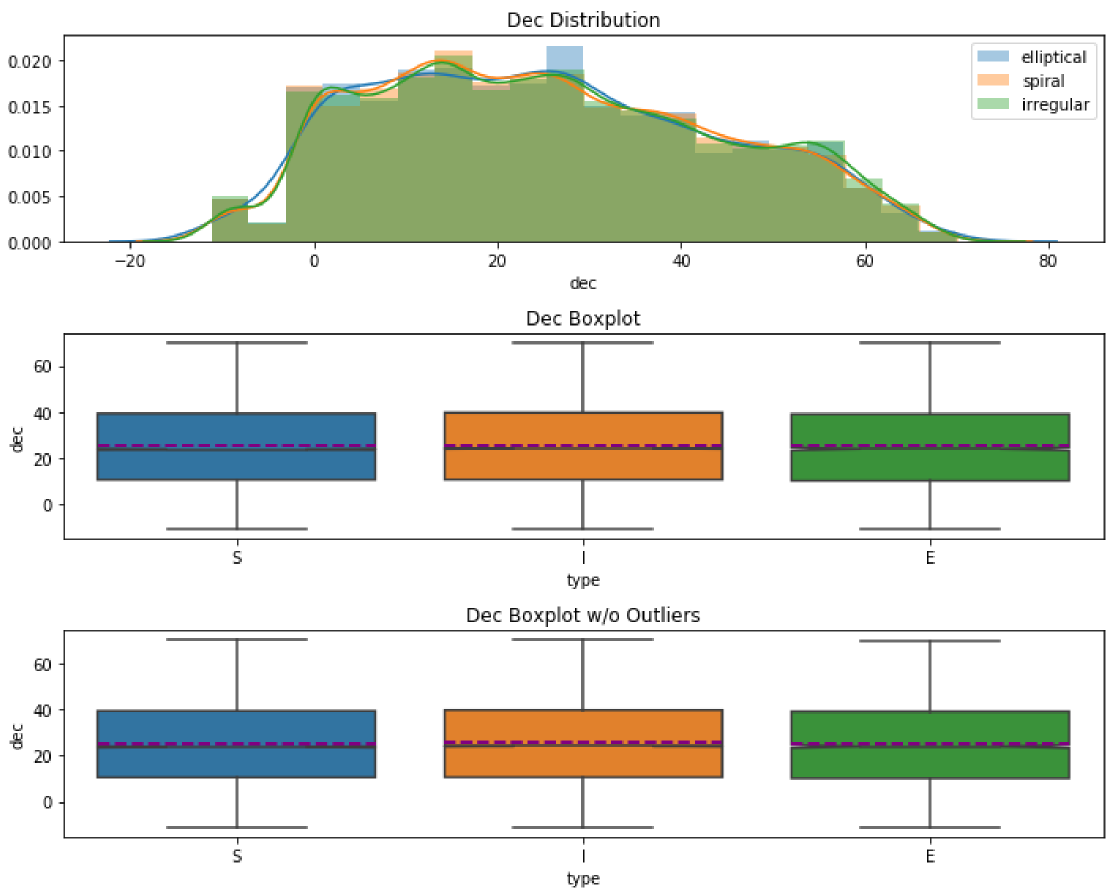

```
In [31]: data_cl_petro = data_cl[data_cl["petroR90_r"]<40]

In [32]: print(data_cl.shape)
         print(data_cl_petro.shape)
```

```
(57681, 14)
(57428, 14)
```

```
In [33]: distribution_per_type(data_cl_petro, col_name="petroR90_r", bins=50)
         _ = plt.xlim([0, 30])
```

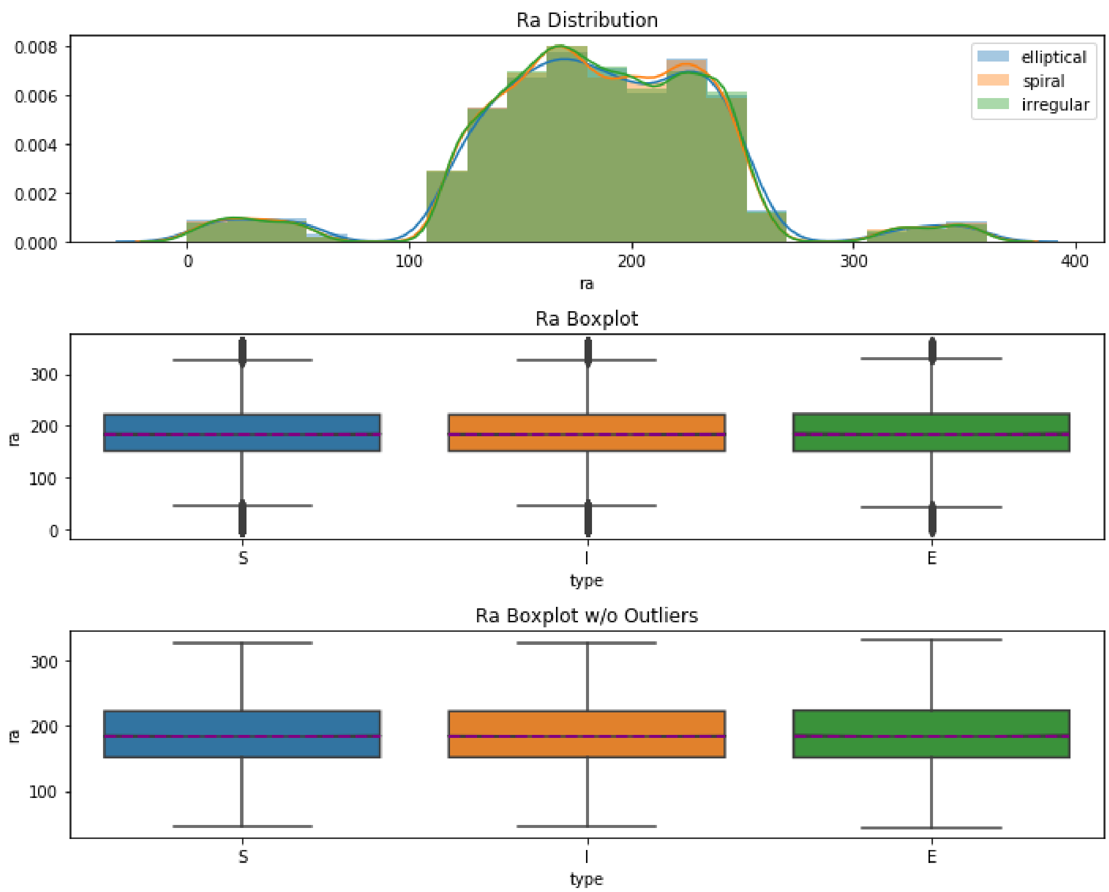



```
In [34]: exploratory_plots(data_cl, "dec")
```



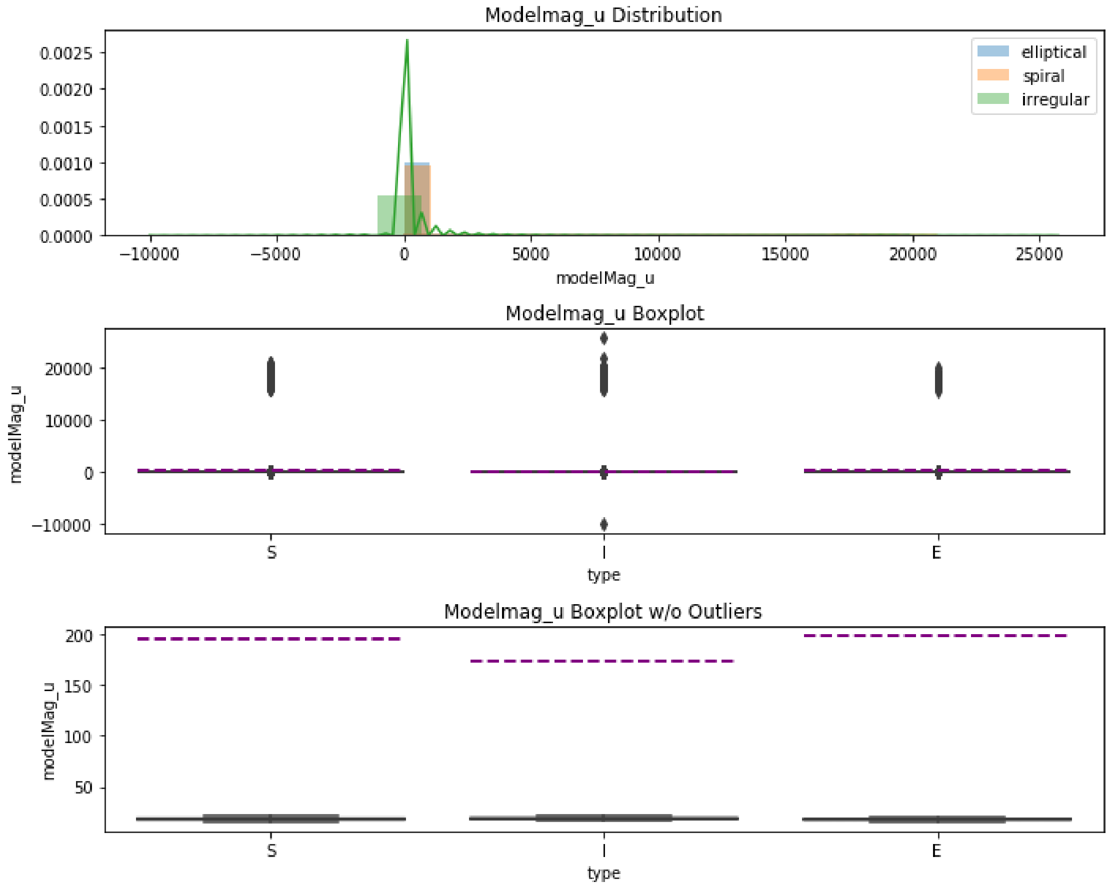
2.3.4 Ra

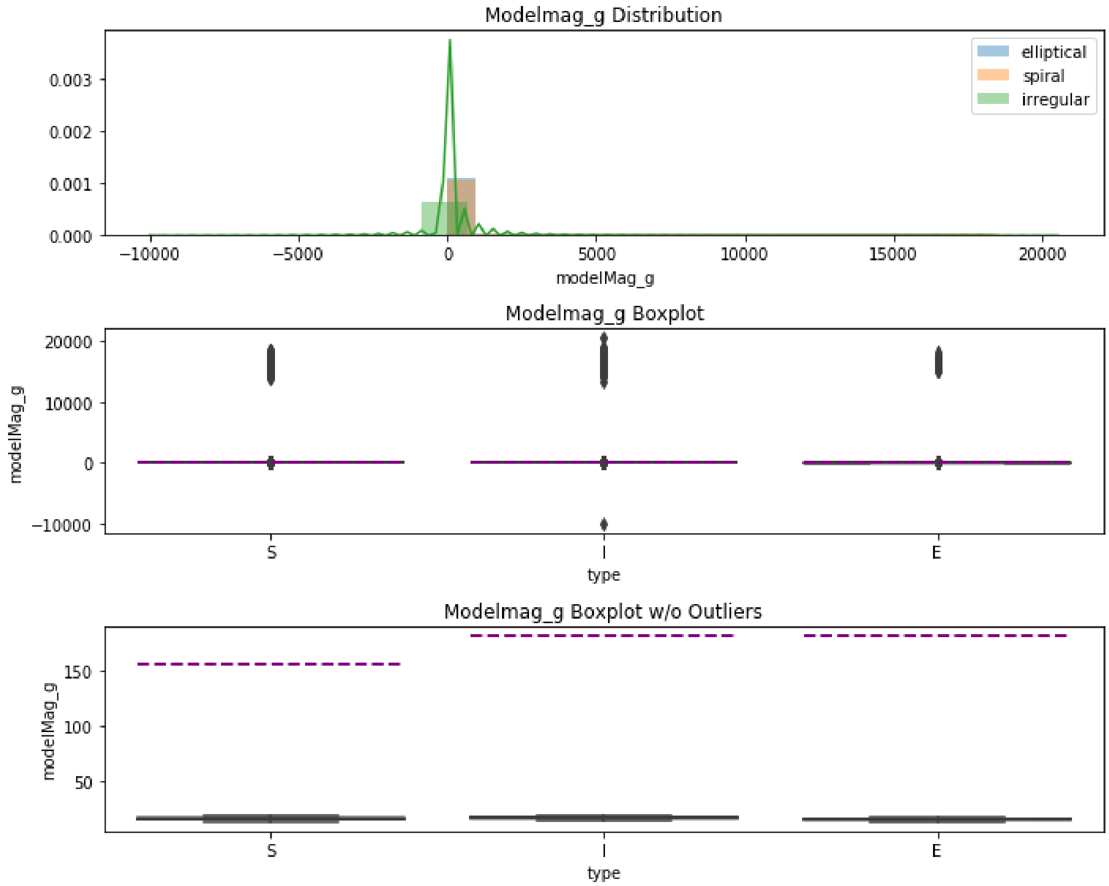
```
In [35]: exploratory_plots(data_cl, "ra")
```

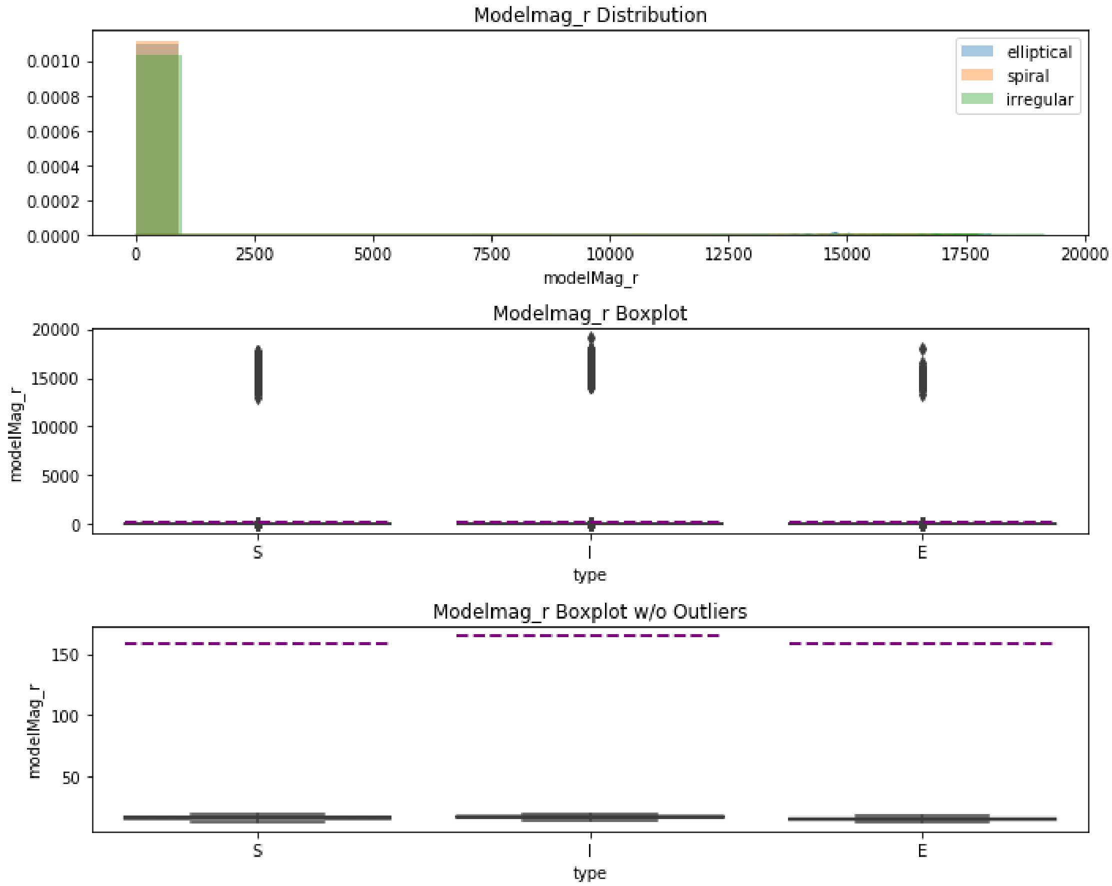


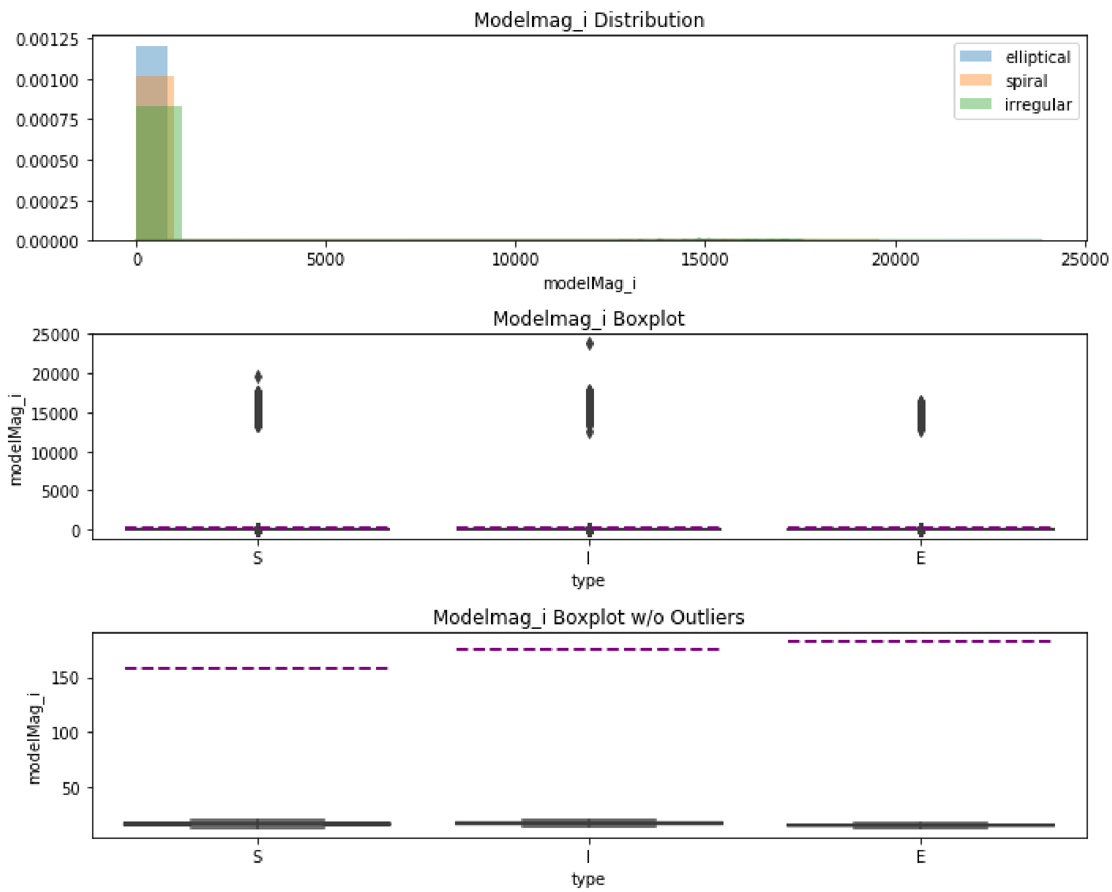
2.3.5 Mag Distributions

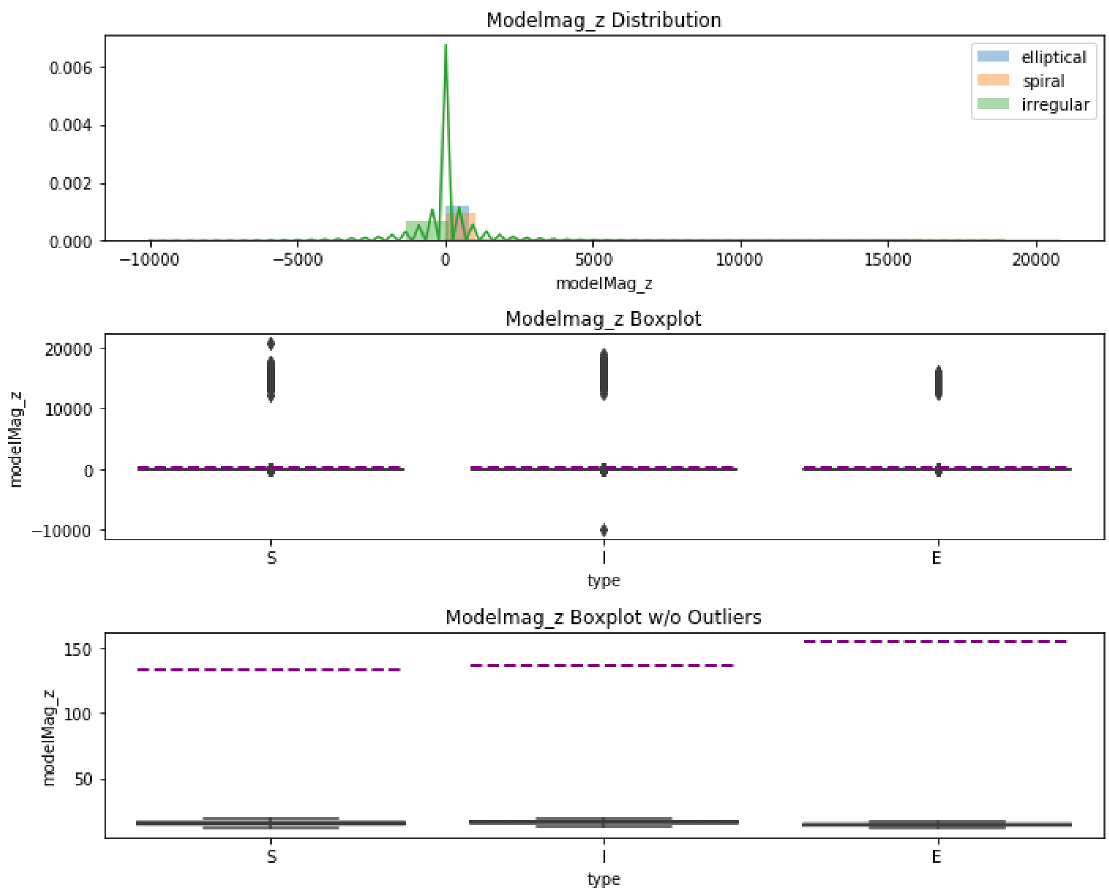
```
In [36]: for mag in ['modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i','modelMag_z']:
             plt.figure()
             exploratory_plots(data_cl, mag)
```


Modelmag_u Distribution
elliptical
spiral
irregular
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
−10000
−5000
0
5000
10000
15000
20000
25000
modelMag_u
Modelmag_u Boxplot
20000
10000
0
−10000
modelMag_u
S
I
E
type
Modelmag_u Boxplot w/o Outliers
200
150
100
50
modelMag_u
S
I
E
type


Modelmag_g Distribution
elliptical
spiral
irregular
0.003
0.002
0.001
0.000
−10000
−5000
0
5000
10000
15000
20000
modelMag_g
Modelmag_g Boxplot
20000
10000
0
−10000
modelMag_g
S
I
E
type
Modelmag_g Boxplot w/o Outliers
150
100
50
modelMag_g
S
I
E
type


Modelmag_r Distribution
elliptical
spiral
irregular
modelMag_r
Modelmag_r Boxplot
modelMag_r
type
S
I
E
Modelmag_r Boxplot w/o Outliers
modelMag_r
type

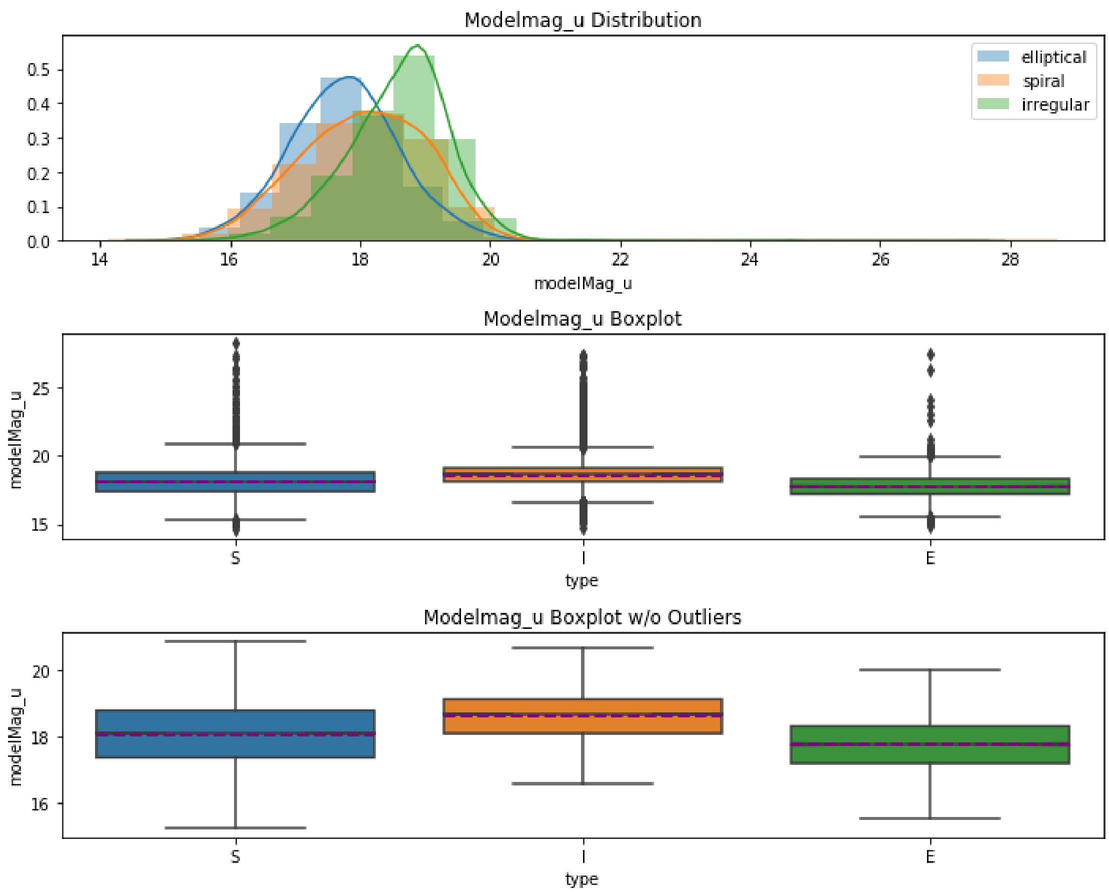

Modelmag_i Distribution
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
elliptical
spiral
irregular
0
5000
10000
15000
20000
25000
modelMag_i
Modelmag_i Boxplot
25000
20000
15000
10000
5000
0
modelMag_i
S
I
E
type
Modelmag_i Boxplot w/o Outliers
150
100
50
modelMag_i
S
I
E
type

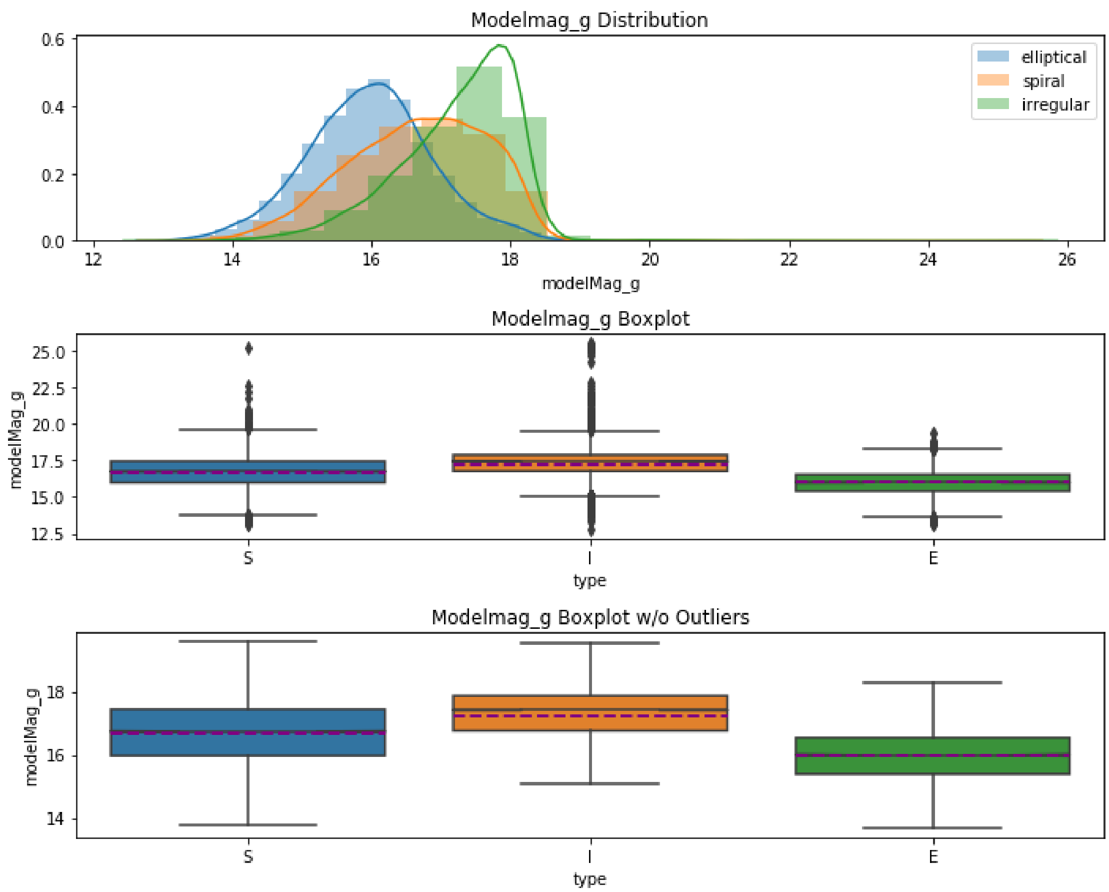


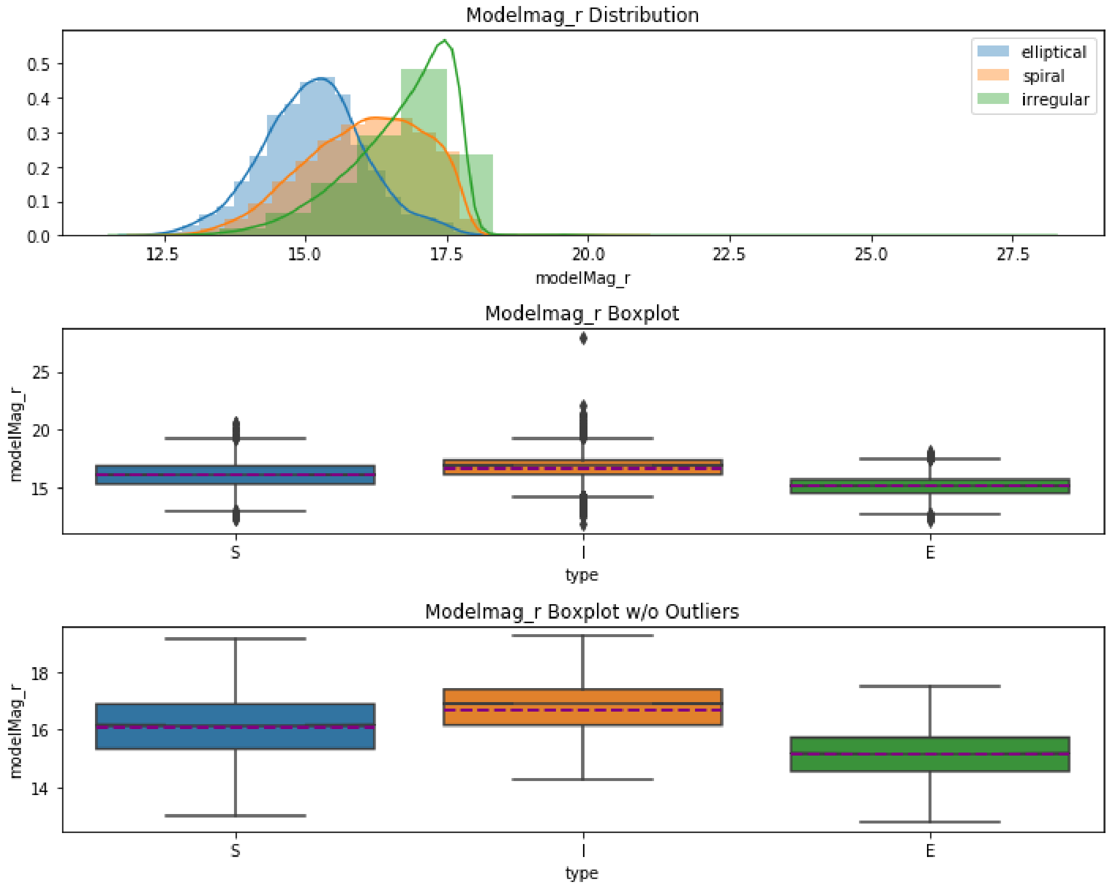

```
In [37]: mask_mag = ((abs(data_cl["modelMag_u"]) < 30) &
             (abs(data_cl["modelMag_g"] < 30)) &
             (abs(data_cl["modelMag_r"] < 30)) &
             (abs(data_cl["modelMag_i"] < 30)) &
             (abs(data_cl["modelMag_z"] < 30)))
         data_cl_mag = data_cl[mask_mag]
         data_cl_mag.shape
```

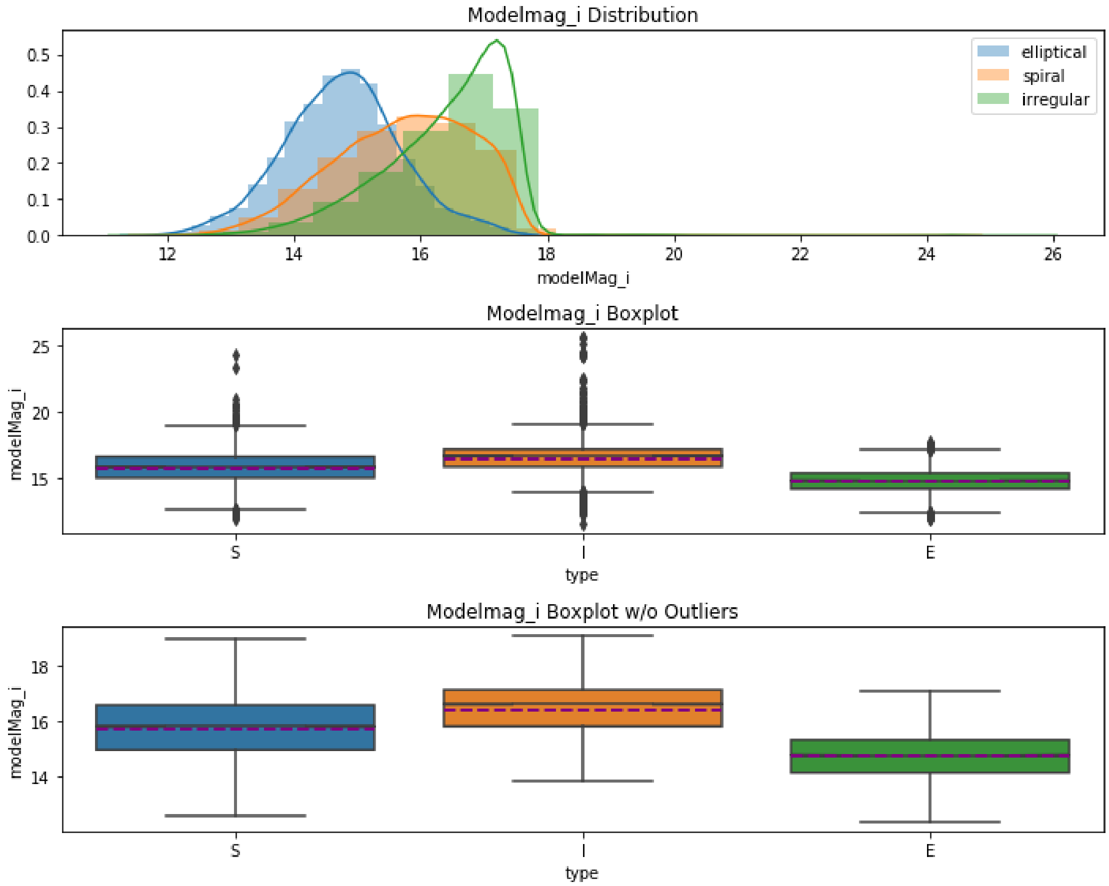
```
Out[37]: (55164, 14)
```

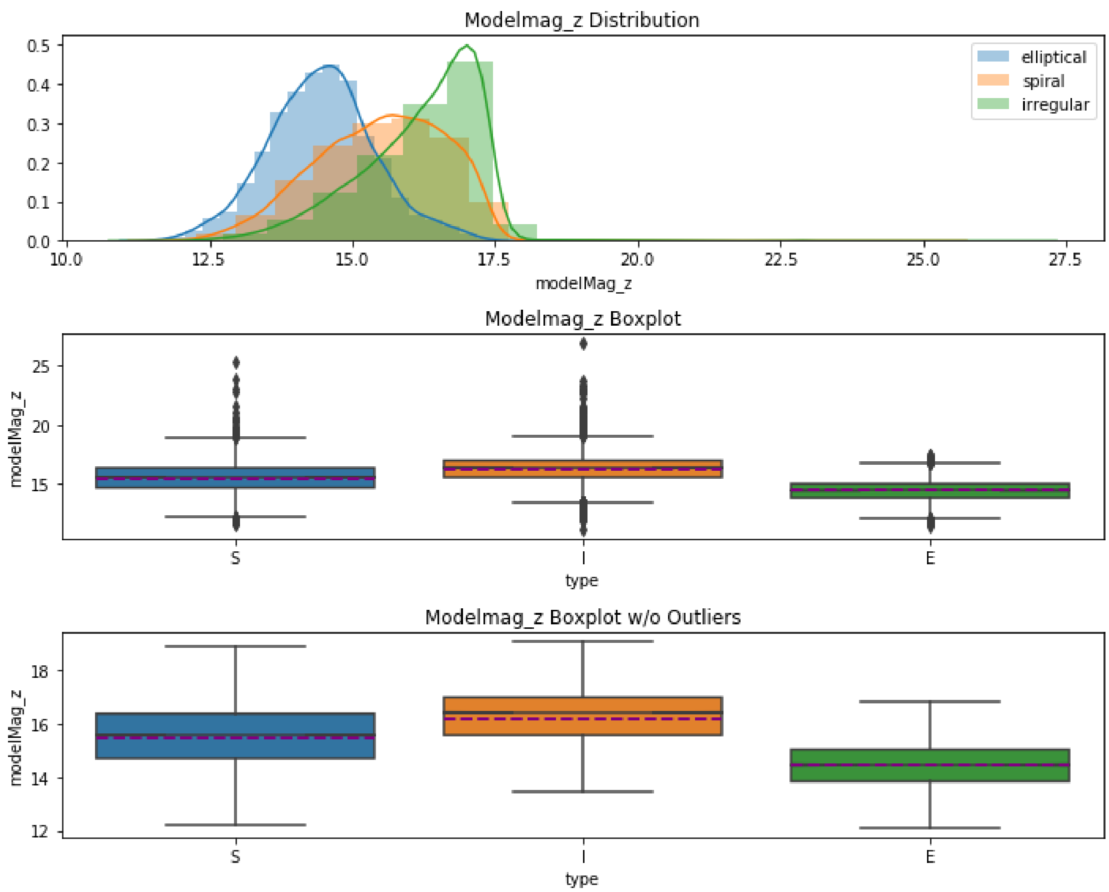
```
In [38]: for mag in ['modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i','modelMag_z']:
             plt.figure()
             exploratory_plots(data_cl_mag, mag)
```


Modelmag_u Distribution
elliptical
spiral
irregular
modelMag_u
Modelmag_u Boxplot
modelMag_u
type
S
I
E
Modelmag_u Boxplot w/o Outliers
modelMag_u
type
S
I
E


Modelmag_g Distribution
elliptical
spiral
irregular
0.0
0.2
0.4
0.6
12
14
16
18
20
22
24
26
modelMag_g
Modelmag_g Boxplot
modelMag_g
12.5
15.0
17.5
20.0
22.5
25.0
S
I
E
type
Modelmag_g Boxplot w/o Outliers
modelMag_g
14
16
18
S
I
E
type


Modelmag_r Distribution
elliptical
spiral
irregular
modelMag_r
Modelmag_r Boxplot
modelMag_r
type
Modelmag_r Boxplot w/o Outliers
modelMag_r
type


Modelmag_i Distribution
elliptical
spiral
irregular
0.0
0.1
0.2
0.3
0.4
0.5
12
14
16
18
20
22
24
26
modelMag_i
Modelmag_i Boxplot
modelMag_i
15
20
25
S
I
E
type
Modelmag_i Boxplot w/o Outliers
modelMag_i
14
16
18
S
I
E
type




```
In [39]: mask_no_outl = mask_color & mask_petro & mask_mag
         data_cl_no_outl = data_cl[mask_no_outl].copy()
         print(data_cl.shape)
         print(data_cl_no_outl.shape)
         print(data_cl_no_outl.shape[0]/data_cl.shape[0]*100)
```

```
(57681, 14)
(54764, 14)
94.94287547025884
```

Sacando los outliers, solo estoy descartando ~5000 de un total de ~57000. Aun no tengo el 95% de los datos. Por lo tanto acepto el descarte de esots datos

```
In [40]: data_cl_no_outl.head()
```

```
Out[40]:                               ra        dec  modelMag_u  modelMag_g  \
         objID
         1,23765119242489E+018  116.519097  39.886407    17.76235    16.72601
         1,23765149575578E+018  116.451900  41.421270    18.12179    16.26214
```

```
1,23767370611537E+018  115.946713  41.918877    18.57293    17.42053
1,2376737066523E+018   116.051943  42.287231    21.37438    19.77335
1,23765127349266E+018  117.287392  43.434782    19.18845    17.99682

                        modelMag_r  modelMag_i  modelMag_z  petroR90_r  \
objID
1,23765119242489E+018    16.33972    16.06614    15.90478    8.393773
1,23765149575578E+018    15.39272    14.97515    14.65105    9.674847
1,23767370611537E+018    17.01788    16.75617    16.70899   11.277470
1,2376737066523E+018     19.55791    20.35405    18.88184    1.539542
1,23765127349266E+018    17.51119    17.26241    17.09056   12.471450

                               z     Color  elliptical  spiral  uncertain type
objID
1,23765119242489E+018  0.041521 -1.422625           0       1          0    S
1,23765149575578E+018  0.040211 -2.729061           0       0          1    I
1,23767370611537E+018  0.024386 -1.555044           0       0          1    I
1,2376737066523E+018   0.039137 -1.816479           0       0          1    I
1,23765127349266E+018  0.042591 -1.677259           0       0          1    I
```

Elimino dataframes que no uso más

In [41]:
```
del data_cl_color
del data_cl_mag
del data_cl_petro
```

In [42]:
```
def num_type(row):
    if row["type"] == "I":
        return 1
    elif row["type"] == "S":
        return 2
    else:
        return 3
data_cl_no_outl["type_n"] = data_cl_no_outl.apply(num_type,axis=1)
data_cl["type_n"] = data_cl.apply(num_type,axis=1)
```

3 Clustering

In [43]:
```
from sklearn.cluster import DBSCAN, KMeans, MeanShift
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_samples, silhouette_score
from sklearn.preprocessing import StandardScaler
```

In [44]:
```
data_cl_no_outl.columns
```

Out[44]:
```
Index(['ra', 'dec', 'modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i',
       'modelMag_z', 'petroR90_r', 'z', 'Color', 'elliptical', 'spiral',
       'uncertain', 'type', 'type_n'],
      dtype='object')
```

3.1 Muestra Estratificada

```
In [45]: from sklearn.model_selection import StratifiedShuffleSplit

In [46]: sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=2411)

In [47]: data_cl_no_outl.columns

Out[47]: Index(['ra', 'dec', 'modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i',
               'modelMag_z', 'petroR90_r', 'z', 'Color', 'elliptical', 'spiral',
               'uncertain', 'type', 'type_n'],
              dtype='object')

In [48]: for train_idx, test_idx in sss.split(data_cl_no_outl, data_cl_no_outl["type_n"]):
             #strat_train_set = data_cl_no_outl.loc[train_idx]
             strat_test_set  = data_cl_no_outl.iloc[test_idx]
```

3.2 Análisis sin variables de ubicación y tipo

```
In [49]: pos_cols  = ["ra", "dec"]
         type_cols = ['elliptical', 'spiral', 'uncertain', 'type', 'type_n']
         data_clus_pos = strat_test_set.drop(type_cols, axis=1)
         data_clus_pos = StandardScaler().fit_transform(data_clus_pos)
         data_clus     = strat_test_set.drop(type_cols + pos_cols, axis=1)
         data_clus_cols = data_clus.columns
         data_clus     = pd.DataFrame(data=StandardScaler().fit_transform(data_clus),
                                      columns=data_clus_cols)

In [50]: def plot_silouette(silhouette_values, cluster_labels, silhouette_avg,
                            title="Visualizacion de los datos"):
             fig, ax1 = plt.subplots(1, 1)
             y_lower = 10
             n_clusters = len(np.unique(cluster_labels))
             for i in np.unique(cluster_labels):
                 # Aggregate the silhouette scores for samples belonging to
                 # cluster i, and sort them
                 ith_cluster_silhouette_values = silhouette_values[cluster_labels == i]
                 ith_cluster_silhouette_values.sort()
                 size_cluster_i = ith_cluster_silhouette_values.shape[0]
                 y_upper = y_lower + size_cluster_i
                 color   = cm.nipy_spectral(float(i) / n_clusters)
                 ax1.fill_betweenx(np.arange(y_lower, y_upper),
                                   0, ith_cluster_silhouette_values,
                                   facecolor=color, edgecolor=color, alpha=0.7)

                 # Label the silhouette plots with their cluster numbers at the middle
                 ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

                 # Compute the new y_lower for next plot
```

```
            y_lower = y_upper + 10  # 10 for the 0 samples

        ax1.set_title(title)
        # ax1.set_xlabel("espacio de la primera caracteristica")
        # ax1.set_ylabel("espacio de la segunda caracteristica")

        # The vertical line for average silhouette score of all the values
        ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

        ax1.set_yticks([])  # Clear the yaxis labels / ticks
        ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])
        plt.show()
```

Vamos a evaluar diferentes métodos de clustering. No todos ellos disponen de una métrica de **inercia** (ya que la misma se define para clusteres circulares). Por lo tanto para comparar los diferentes métodos vamos a usar gráficos de silueta.

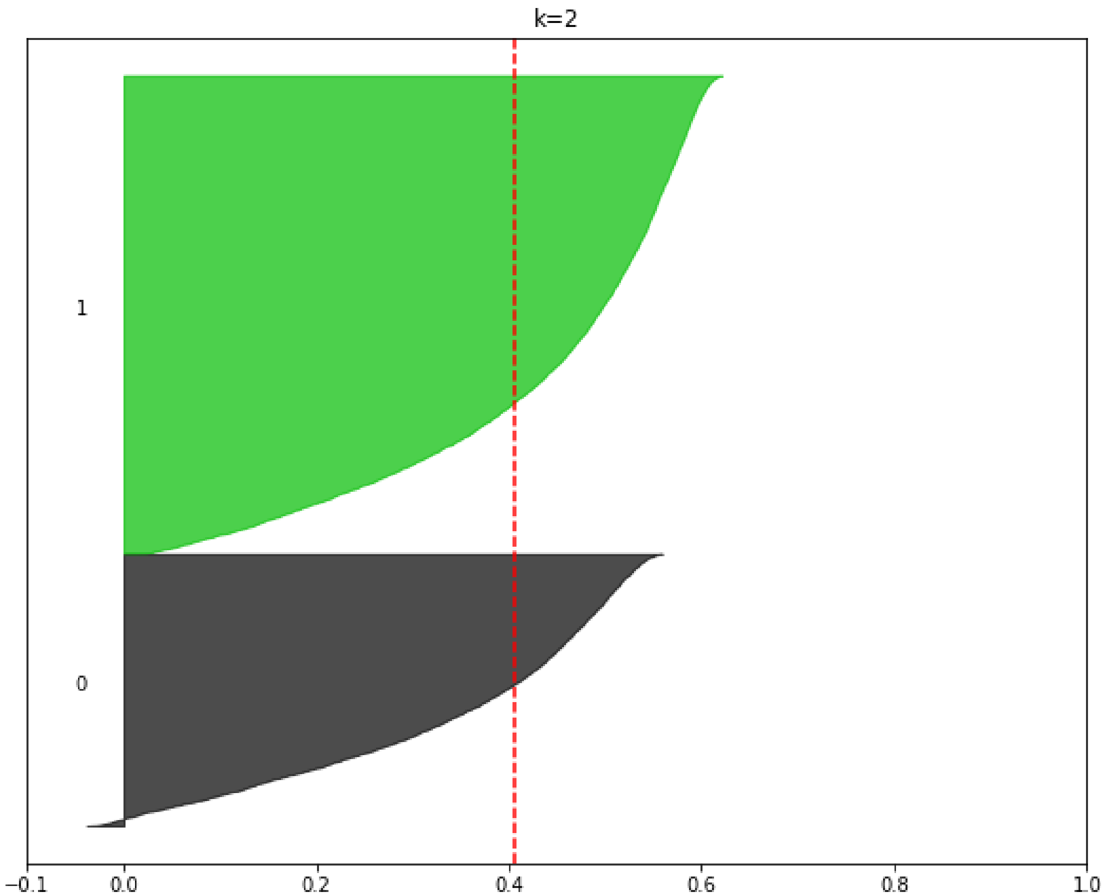
Al final de cada metodo haremos conclusiones parciales y una final antes de pasar a utilziar el mejor método junto con embeddings

3.2.1 K-Means

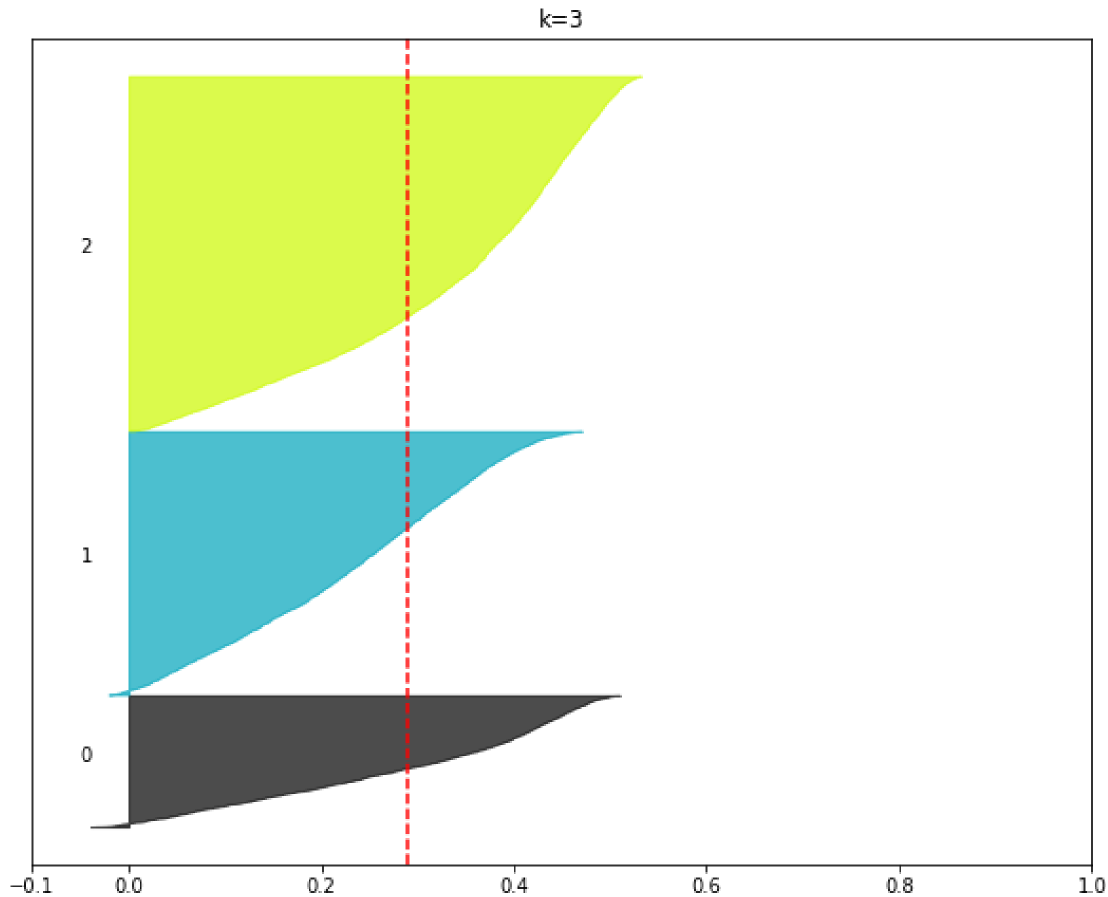
```
In [51]: range_n_clusters = [2, 3, 4, 5, 6]
         def serch_k_optimus(data_clus, range_n_clusters):
             sse ={}
             for n_clusters in range_n_clusters:
                 clusterer = KMeans(n_clusters=n_clusters, random_state=10, n_jobs=6)
                 print("Start fitting")
                 cluster_labels = clusterer.fit_predict(data_clus)
                 print("Stop fitting")
                 sse[n_clusters] = clusterer.inertia_

                 # The silhouette_score gives the average value for all the samples.
                 # This gives a perspective into the density and separation of the formed
                 # clusters
                 silhouette_avg = silhouette_score(data_clus, cluster_labels, random_state=352)
                 print("Para n_clusters =", n_clusters,
                       "El silhouette_score promedio es :", silhouette_avg)

                 # Compute the silhouette scores for each sample
                 sample_silhouette_values = silhouette_samples(data_clus, cluster_labels)

                 plot_silouette(sample_silhouette_values, cluster_labels,
                                silhouette_avg, title="k={}".format(n_clusters))
             return sse

In [52]: sse = serch_k_optimus(data_clus, range_n_clusters)
```

```
Start fitting
Stop fitting
```

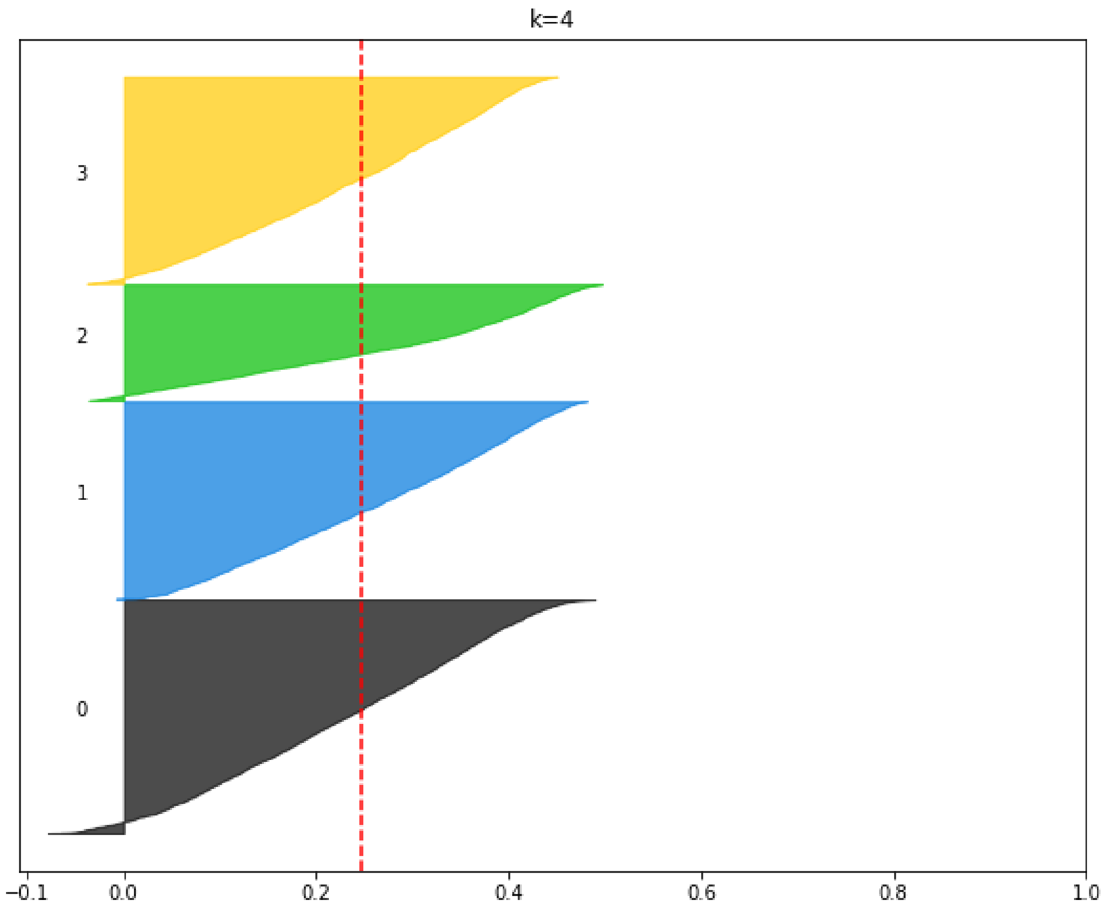
```
Para n_clusters = 2 El silhouette_score promedio es : 0.4066411598391905
```



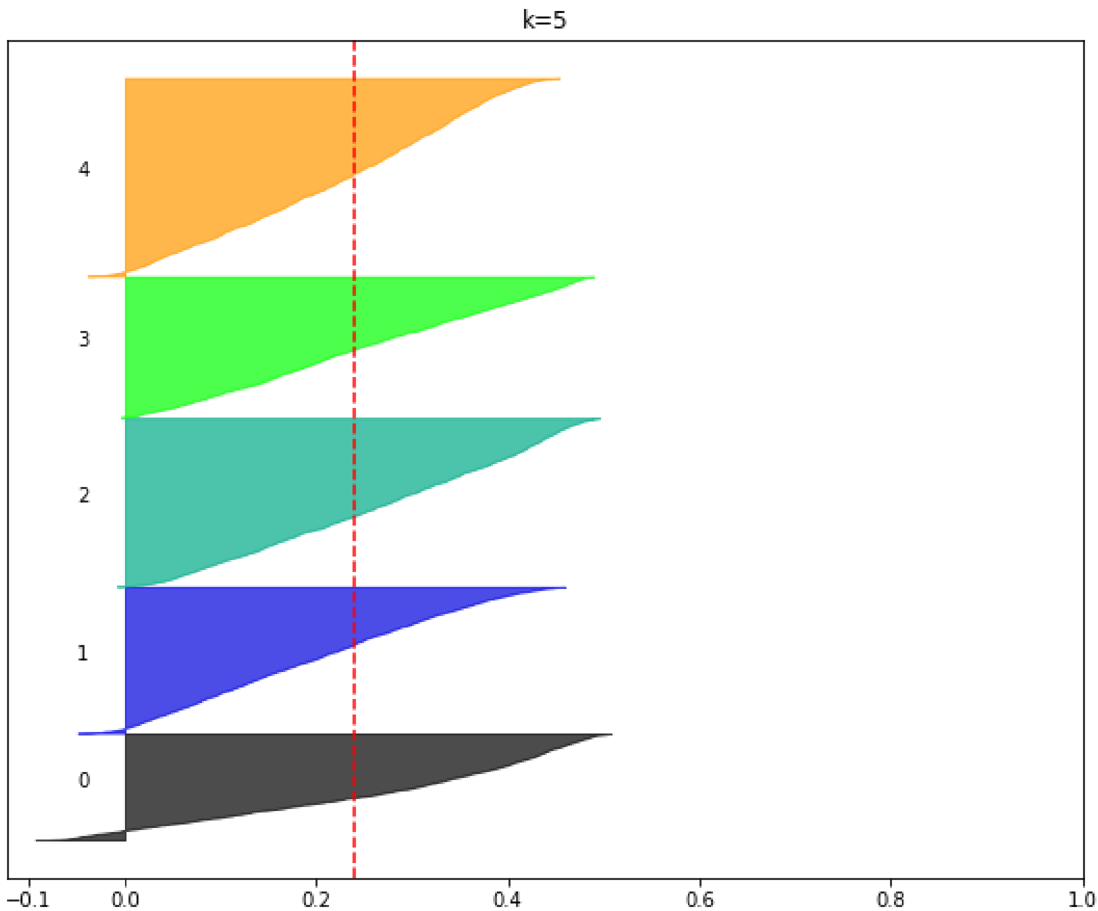

```
Start fitting
Stop fitting
Para n_clusters = 3 El silhouette_score promedio es : 0.29056193235326266
```



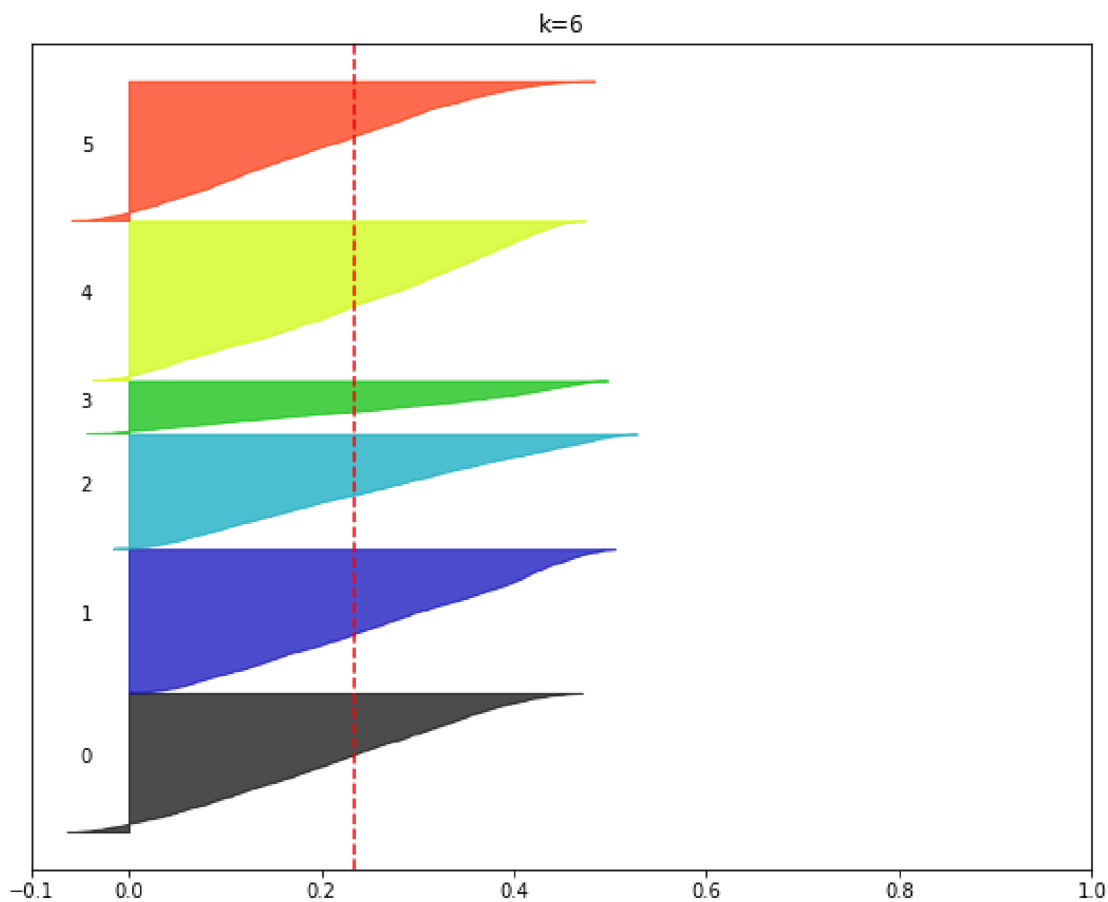

```
Start fitting
Stop fitting
Para n_clusters = 4 El silhouette_score promedio es : 0.24582779585518705
```



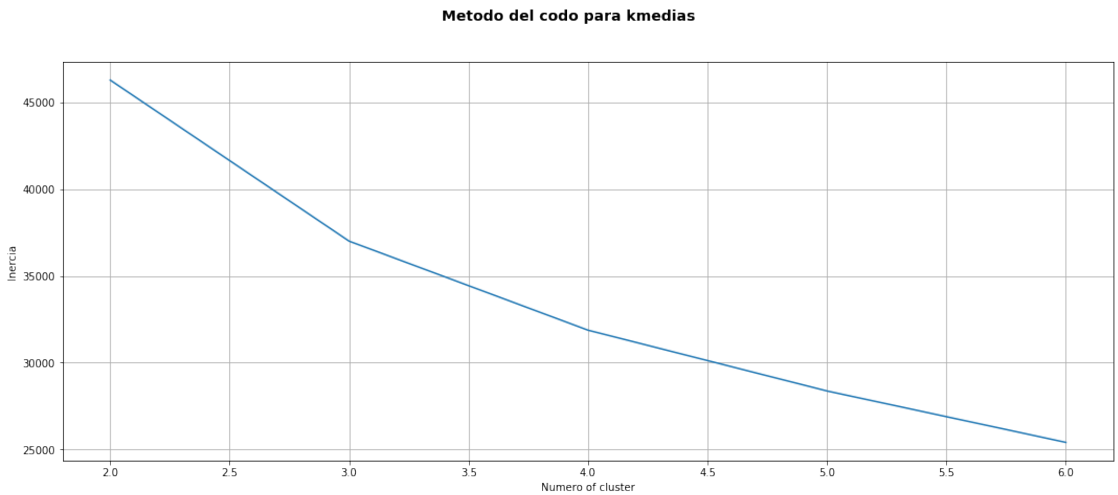

```
Start fitting
Stop fitting
Para n_clusters = 5 El silhouette_score promedio es : 0.23948166017902872
```




```
Start fitting
Stop fitting
Para n_clusters = 6 El silhouette_score promedio es : 0.23471891691017308
```




```
In [53]: fig, ax1 = plt.subplots(1, 1)
         fig.set_size_inches(18, 7)
         plt.suptitle(("Metodo del codo para kmedias "),
                      fontsize=14, fontweight='bold')
         ax1.plot(list(sse.keys()), list(sse.values()))
         ax1.set_xlabel("Numero of cluster")
         ax1.set_ylabel("Inercia")
         plt.grid()
```



De las siluetas, vemos que al incrementar el número de clusters el score promedio ba disminuyendo, lo que no es algo deseado. Pero, por otro lado vemos que con 2 clusters uno de ellos es mucho más grande que el otro, y que con k=3 o k=4 tenemos la mejor distribución en los tamaños.

Es importante notar que en ninguno de los clusters presenta colas negativas muy grandes, lo que indica que los clusters se estan separando bien.

K-Means CLustering si dispone de la métrica de **inercia** por lo que utilizamos el método del codo como segunda opinión a analísis de siluetas. Vemos que la pendiente cambia abruptamente en k=3 y un poco menos en k=4.

Por lo tanto, podemos decir que el número de clusters esta en k=3 o k=4. Vamos a ver más adelante que información podemos obtener utilizando embeddings

In [ ]:

3.2.2 DBScan

```
In [54]: from itertools import product
```

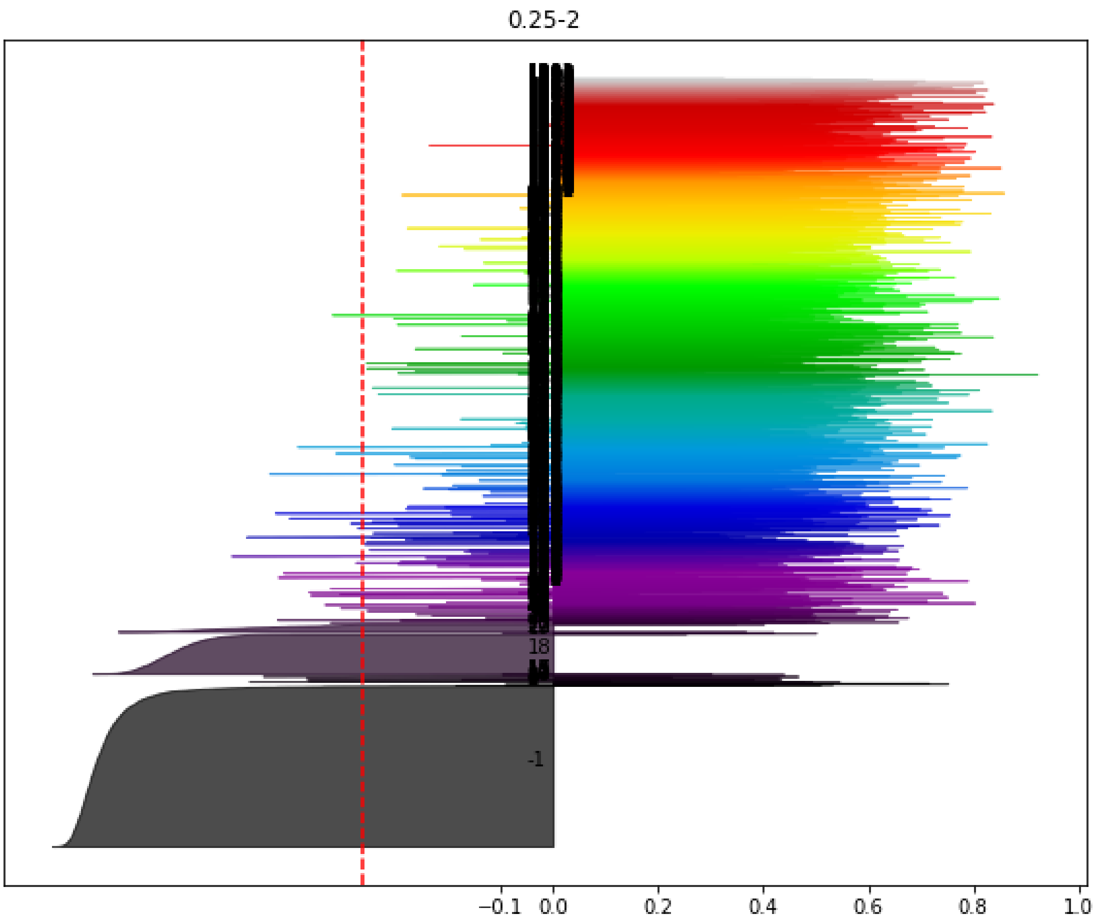
DBSCAN nos devuelve una etiqueta -1 para las muestras rudiosas. Por lo tanto, si tenemos un clustering con mucha de esas muestras lo descartamos

```
In [55]: n_min_samples = [2, 3, 4]
         n_eps         = [0.2, 0.25, 0.3, 0.35]
         noise_ratio_limit = 0.47
         def search_dbscan_optimus(data_clus, n_min_samples, n_eps, noise_ratio_limit):
             for min_samples, eps in product(n_min_samples, n_eps):
                 print("*"*80)
                 print("min_samples={} y eps={}".format(min_samples, eps))
                 print("*"*80)
                 dbscan_clusters = DBSCAN(eps=eps, min_samples=min_samples)
                 print("Start fitting")
                 cluster_labels = dbscan_clusters.fit_predict(data_clus, )
                 print("Stop fitting")
```

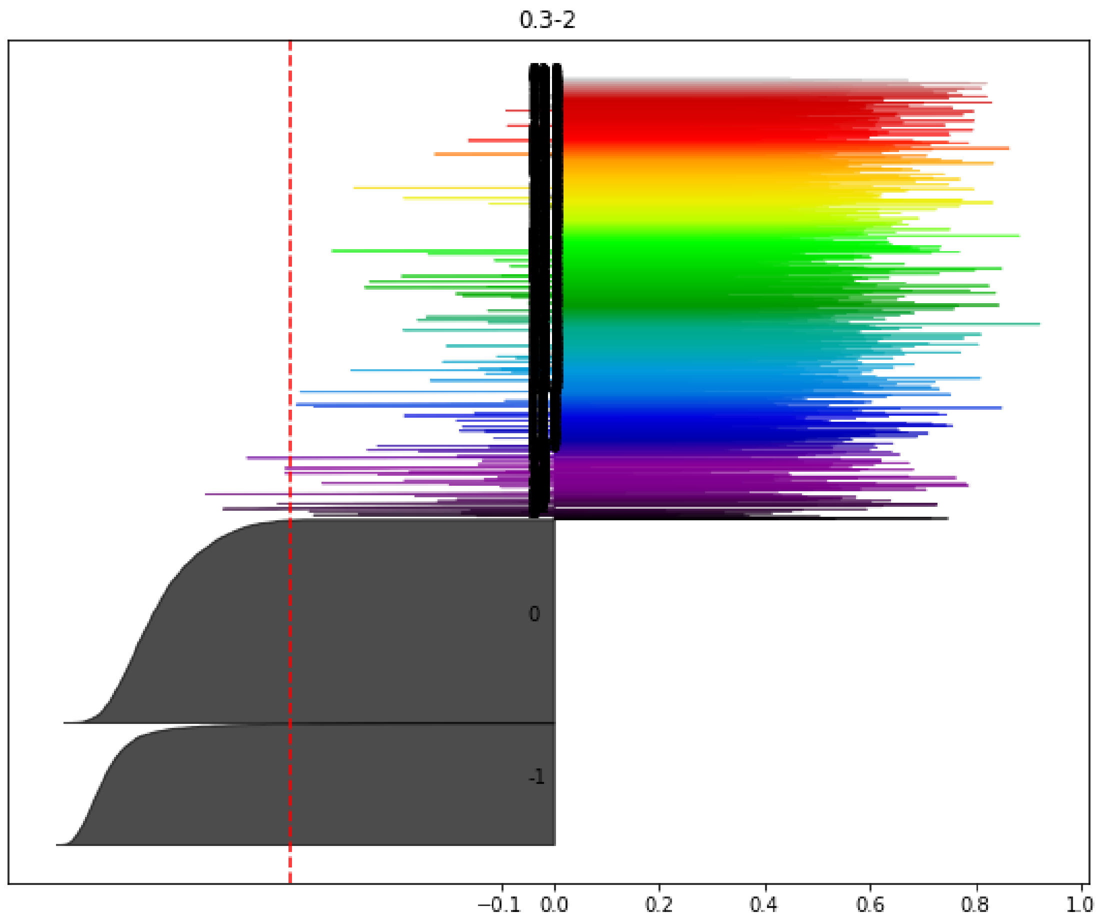
```
            noise_samples_ratio = sum(cluster_labels == -1) / len(cluster_labels)

            # The silhouette_score gives the average value for all the samples.
            # This gives a perspective into the density and separation of the formed
            # clusters
            if len(np.unique(cluster_labels)) > 1 and noise_samples_ratio<noise_ratio_limi
                silhouette_avg = silhouette_score(data_clus, cluster_labels,
                                                  random_state=352)
                print("El silhouette_score promedio es :", silhouette_avg)

                # Compute the silhouette scores for each sample
                sample_silhouette_values = silhouette_samples(data_clus,
                                                              cluster_labels)

                plot_silouette(sample_silhouette_values, cluster_labels,
                               silhouette_avg, title="{}-{}".format(eps, min_samples))
            elif len(np.unique(cluster_labels)) == 1:
                print("Solo 1 cluster identificado")
            elif noise_samples_ratio>=noise_ratio_limit:
                print("El cluster ruido es muy grande: {}".format(noise_samples_ratio))
```

```
In [56]: search_dbscan_optimus(data_clus, n_min_samples, n_eps, noise_ratio_limit)
```

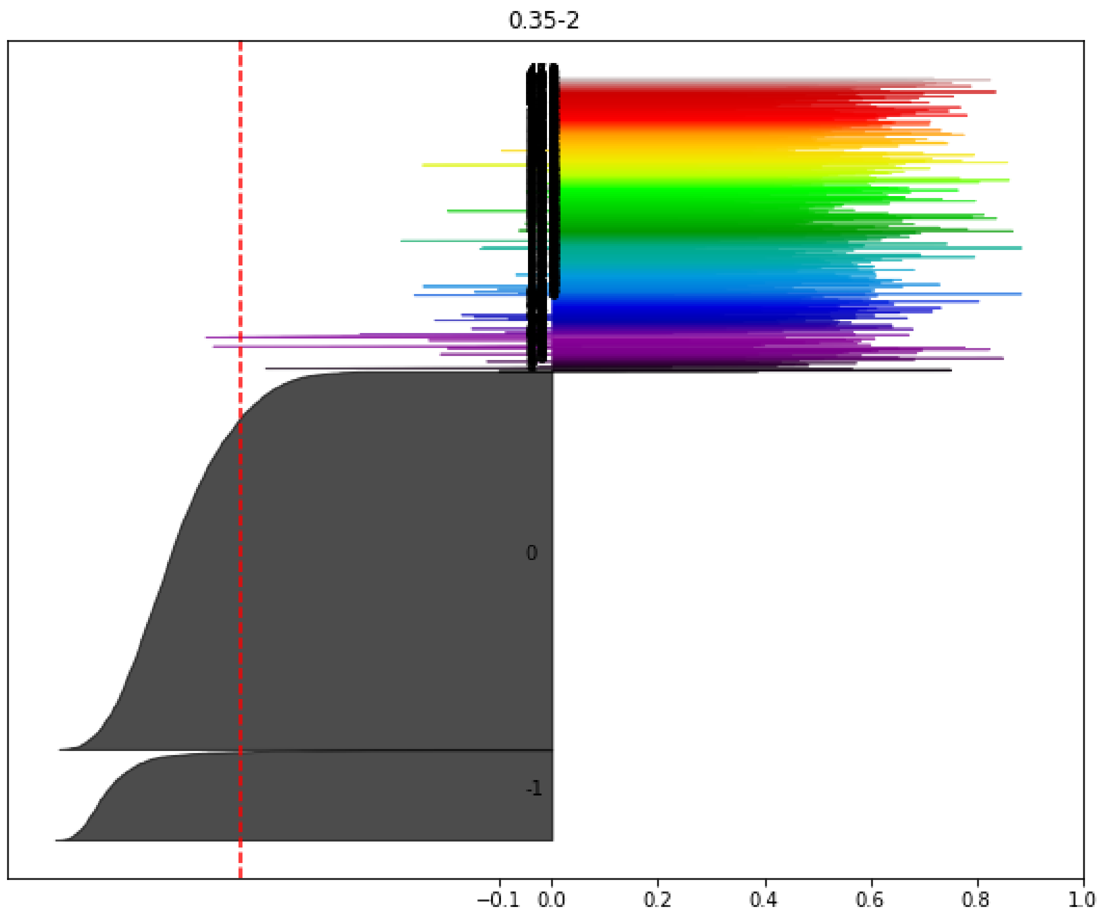
```
********************************************************************************
min_samples=2 y eps=0.2
********************************************************************************
Start fitting
Stop fitting
El cluster ruido es muy grande: 0.7028211448918105
********************************************************************************
min_samples=2 y eps=0.25
********************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.36139200343797445
```



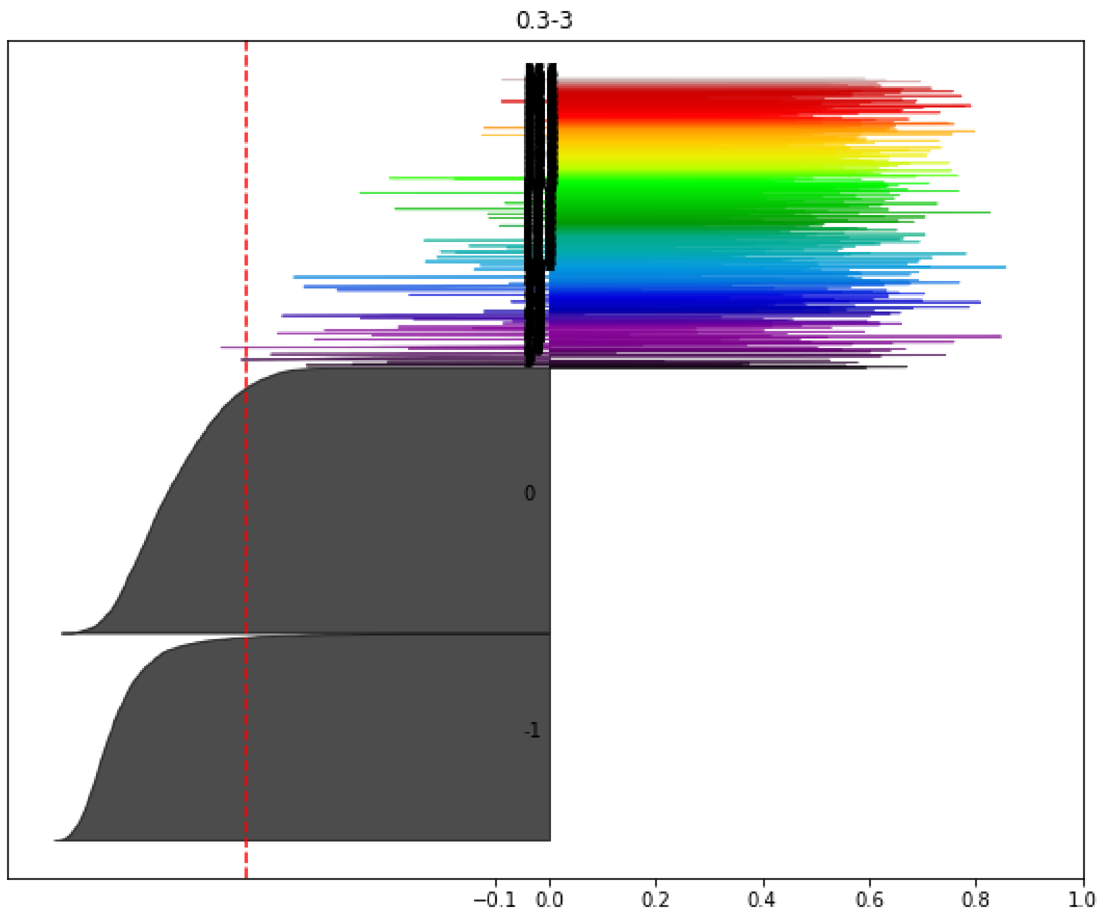

```
********************************************************************************
min_samples=2 y eps=0.3
********************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.4995462054677326
```



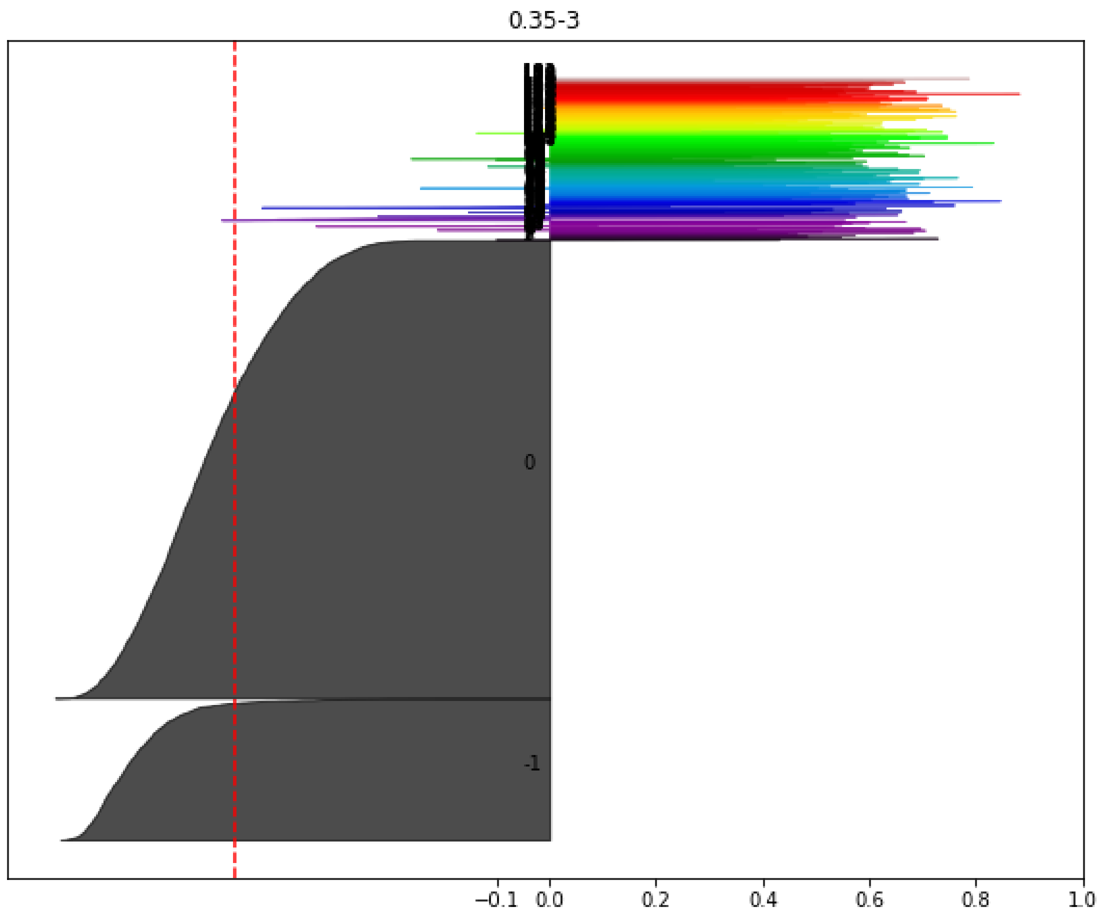

```
********************************************************************************
min_samples=2 y eps=0.35
********************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.586676658204438
```



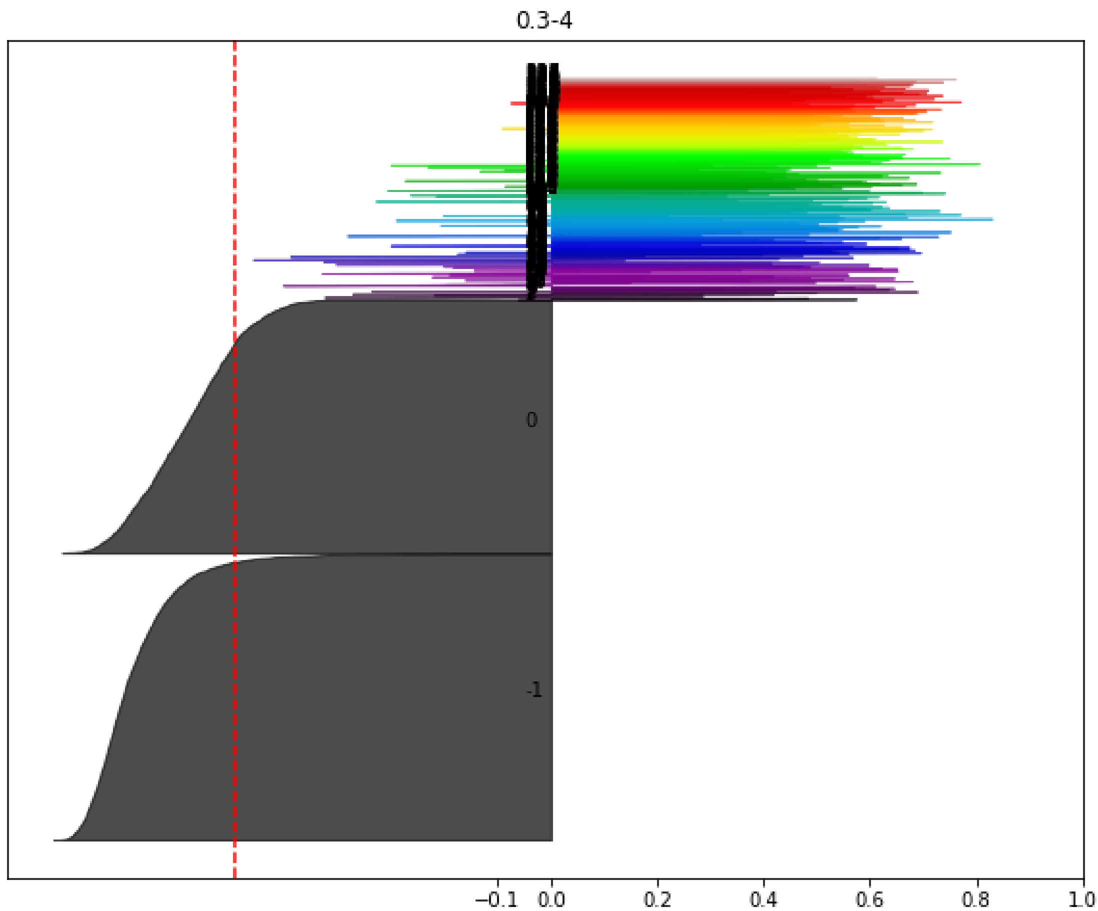

```
********************************************************************************
min_samples=3 y eps=0.2
********************************************************************************
Start fitting
Stop fitting
El cluster ruido es muy grande: 0.8483520496667579
********************************************************************************
min_samples=3 y eps=0.25
********************************************************************************
Start fitting
Stop fitting
El cluster ruido es muy grande: 0.600657354149548
********************************************************************************
min_samples=3 y eps=0.3
********************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.5662289748589515
```



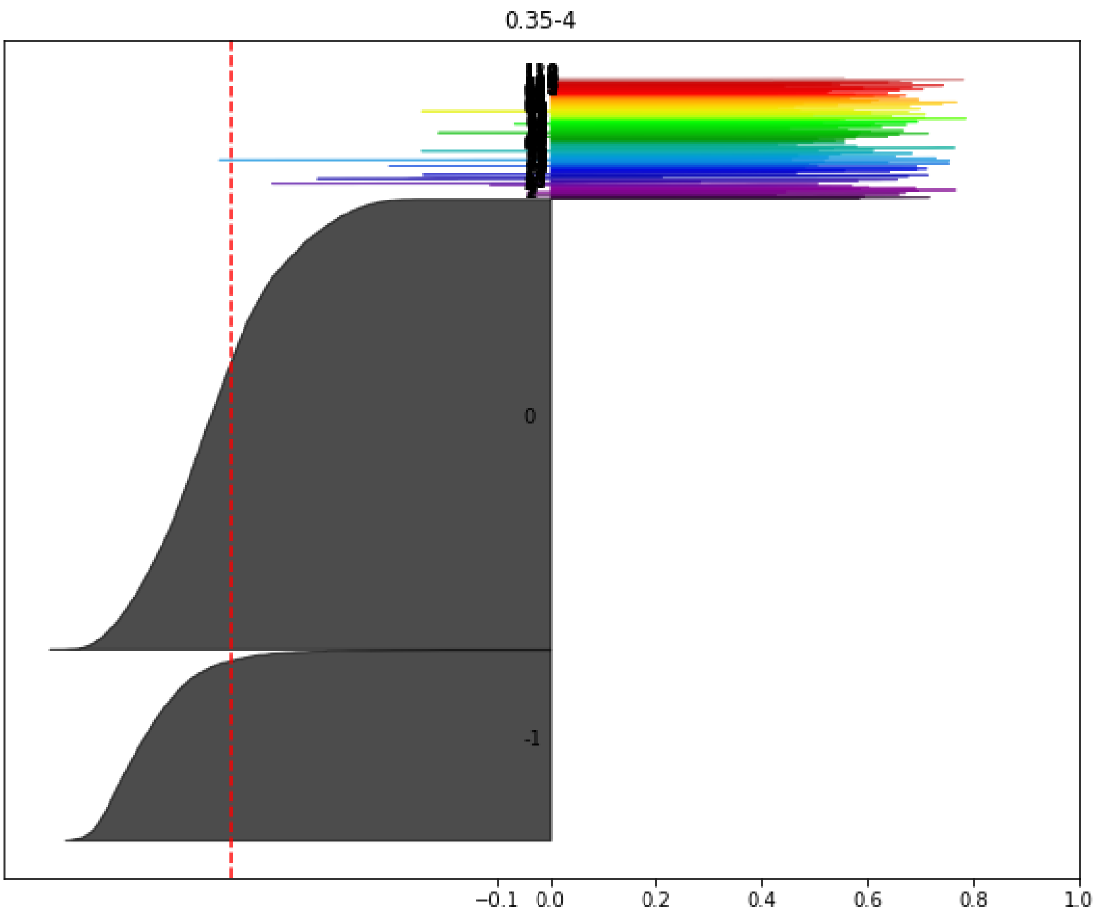

```
******************************************************************************
min_samples=3 y eps=0.35
******************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.589420630423244
```




```
******************************************************************************
min_samples=4 y eps=0.2
******************************************************************************
Start fitting
Stop fitting
El cluster ruido es muy grande: 0.942481511914544
******************************************************************************
min_samples=4 y eps=0.25
******************************************************************************
Start fitting
Stop fitting
El cluster ruido es muy grande: 0.7262850360631791
******************************************************************************
min_samples=4 y eps=0.3
******************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.5934888025417029
```




```
*******************************************************************************
min_samples=4 y eps=0.35
*******************************************************************************
Start fitting
Stop fitting
El silhouette_score promedio es : -0.6051385193556819
```



DBScan presenta en general muchos clusters y algunos de gran tamaño, por lo tanto no parece ser un buen algoritmo para este conjunto de datos

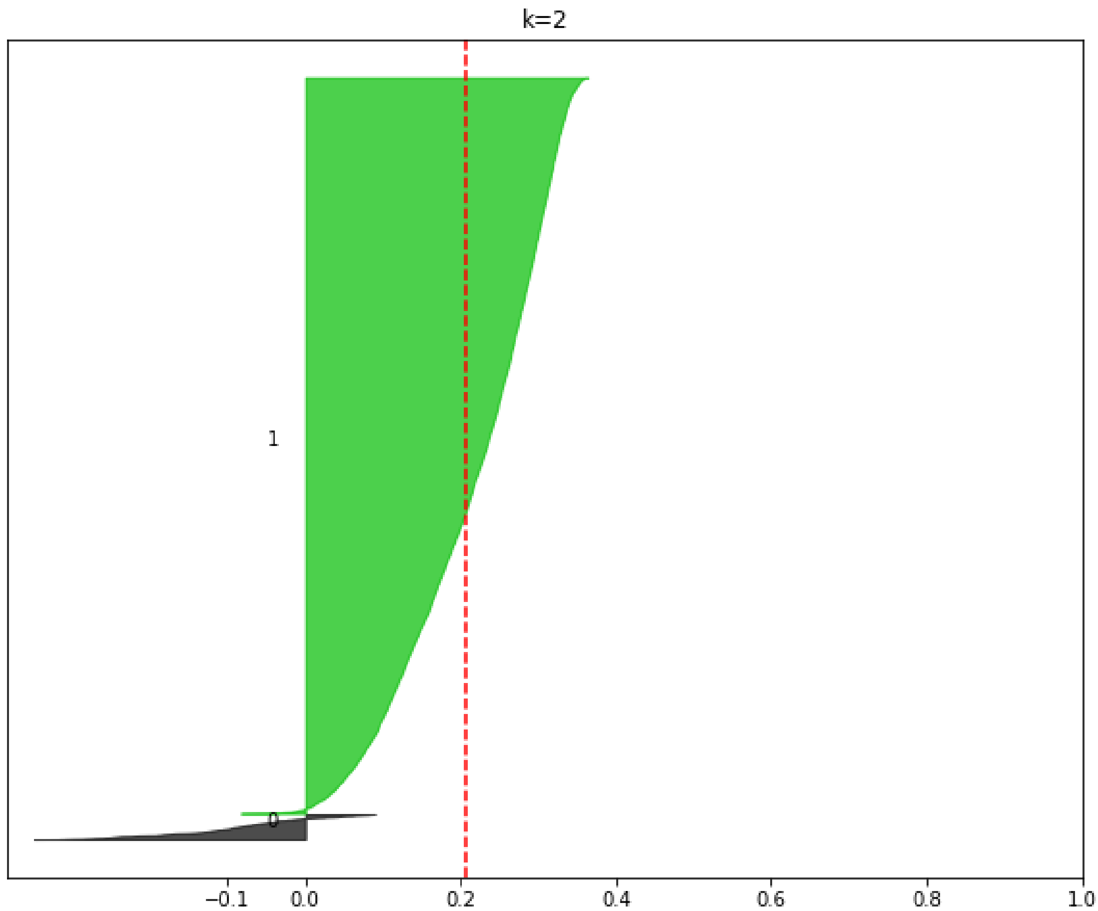
3.2.3 Gaussian Mixtures

```
In [57]: range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]

         def serch_gauss_optimus(data_clus, range_n_clusters):
             sse ={}
             for n_clusters in range_n_clusters:
                 clusterer = GaussianMixture(n_components=n_clusters, random_state=10)
                 print("Start fitting")
                 cluster_labels = clusterer.fit_predict(data_clus)
                 print("Stop fitting")
                 #sse[n_clusters] = clusterer.inertia_

                 # The silhouette_score gives the average value for all the samples.
                 # This gives a perspective into the density and separation of the formed
                 # clusters
```

```
            silhouette_avg = silhouette_score(data_clus, cluster_labels, random_state=352)
            print("Para n_clusters =", n_clusters,
                  "El silhouette_score promedio es :", silhouette_avg)

            # Compute the silhouette scores for each sample
            sample_silhouette_values = silhouette_samples(data_clus, cluster_labels)

            plot_silouette(sample_silhouette_values, cluster_labels,
                           silhouette_avg, title="k={}".format(n_clusters))
        return sse
```

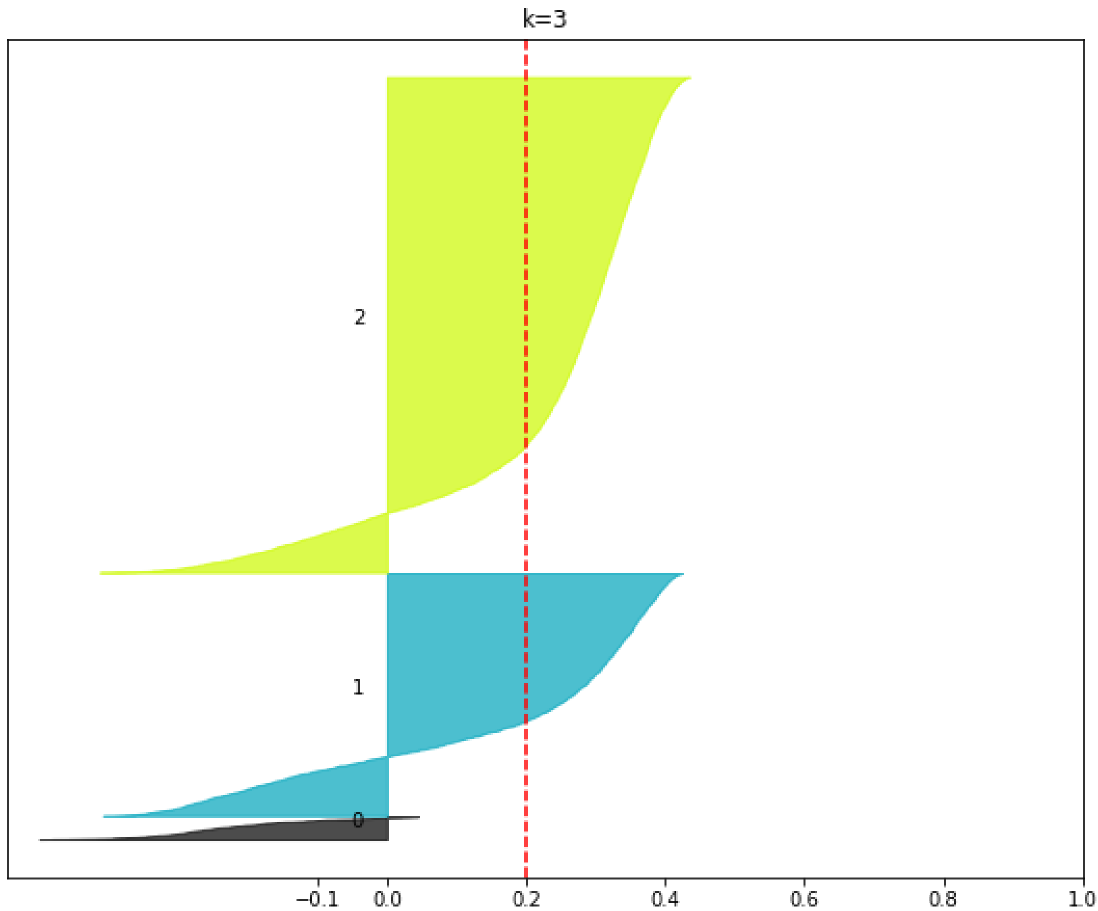
```
In [58]: sse = serch_gauss_optimus(data_clus, range_n_clusters)
```

```
Start fitting
Stop fitting
Para n_clusters = 2 El silhouette_score promedio es : 0.20575860629655854
```

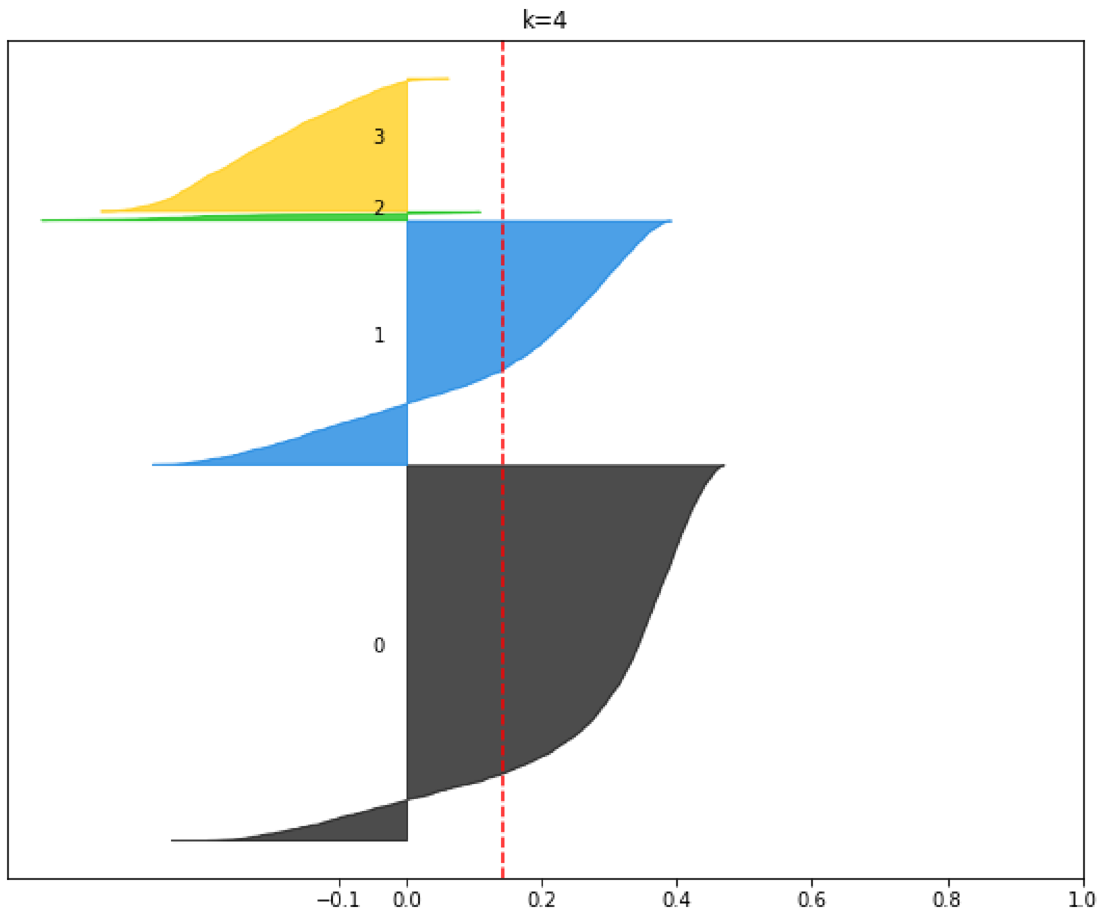



```
Start fitting
Stop fitting
```

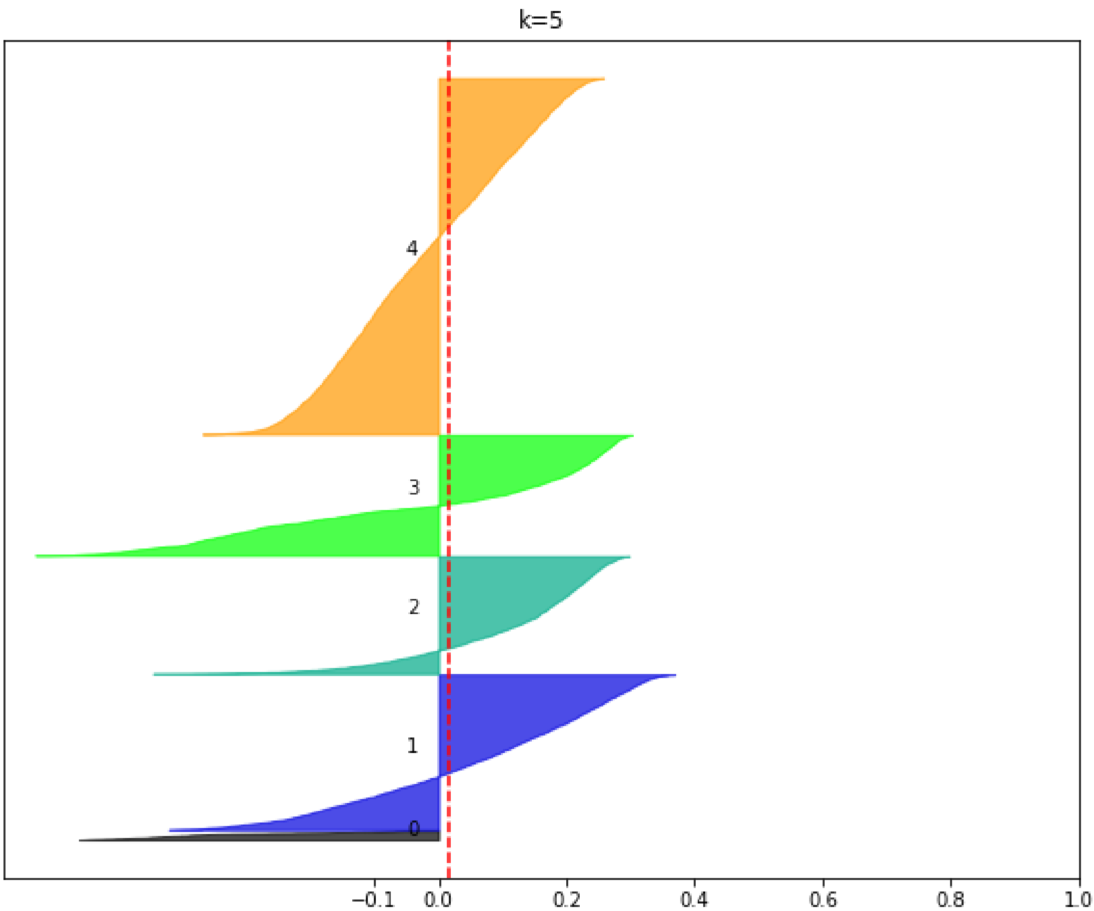
```
Para n_clusters = 3 El silhouette_score promedio es : 0.2001128160485019
```



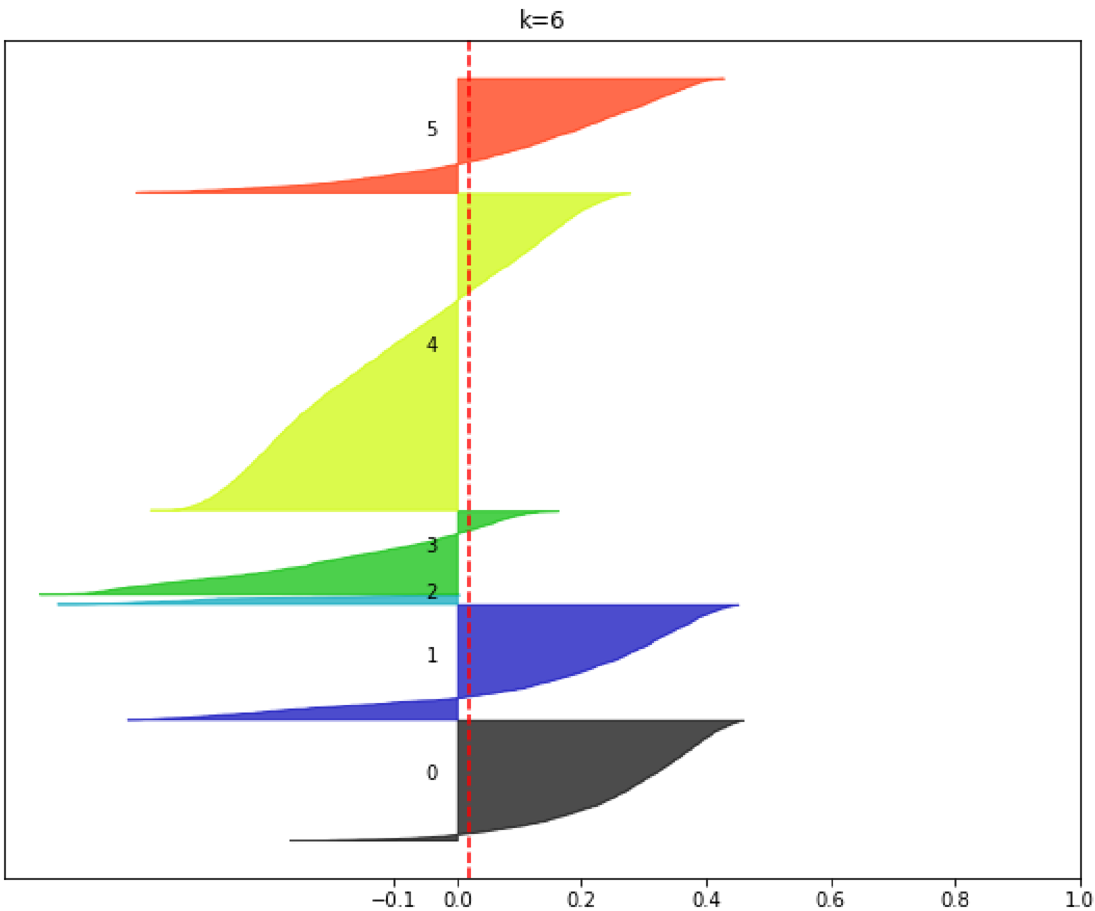

```
Start fitting
Stop fitting
Para n_clusters = 4 El silhouette_score promedio es : 0.1412729029900525
```



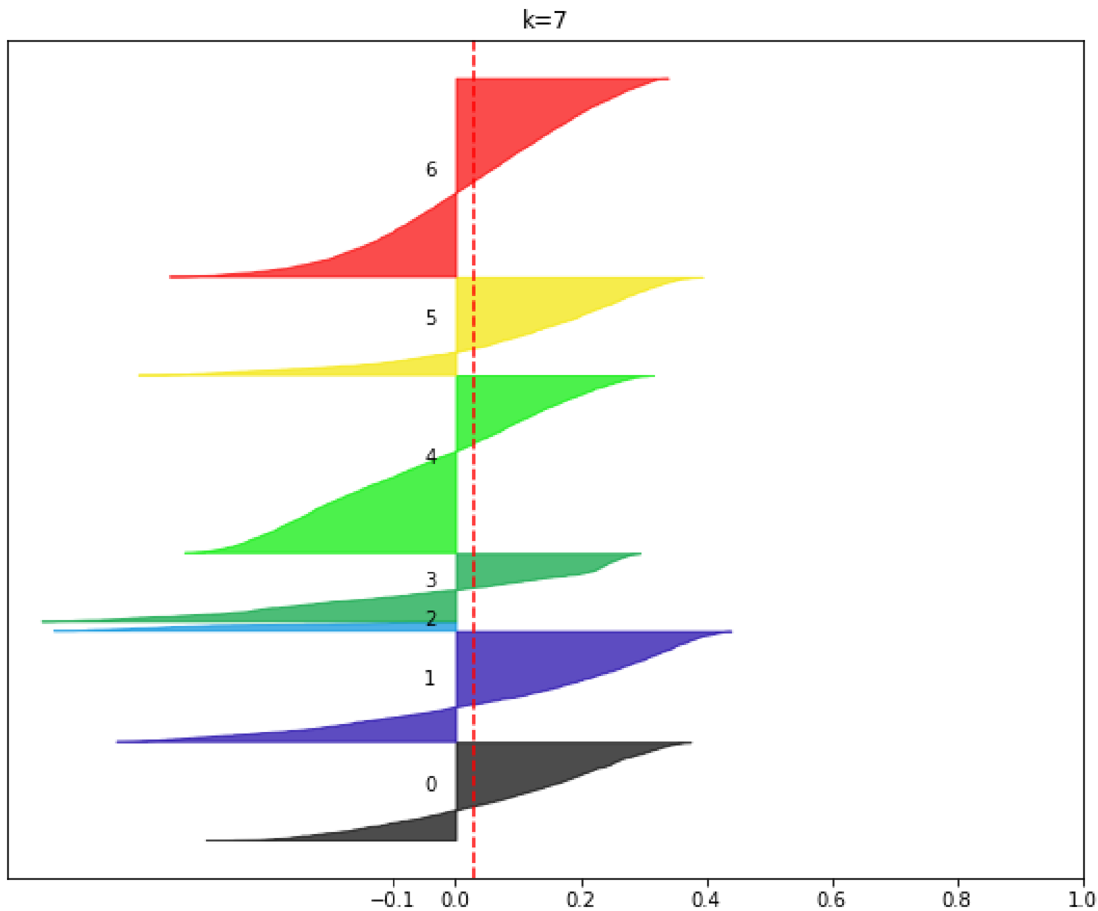

```
Start fitting
Stop fitting
Para n_clusters = 5 El silhouette_score promedio es : 0.016317813510311547
```



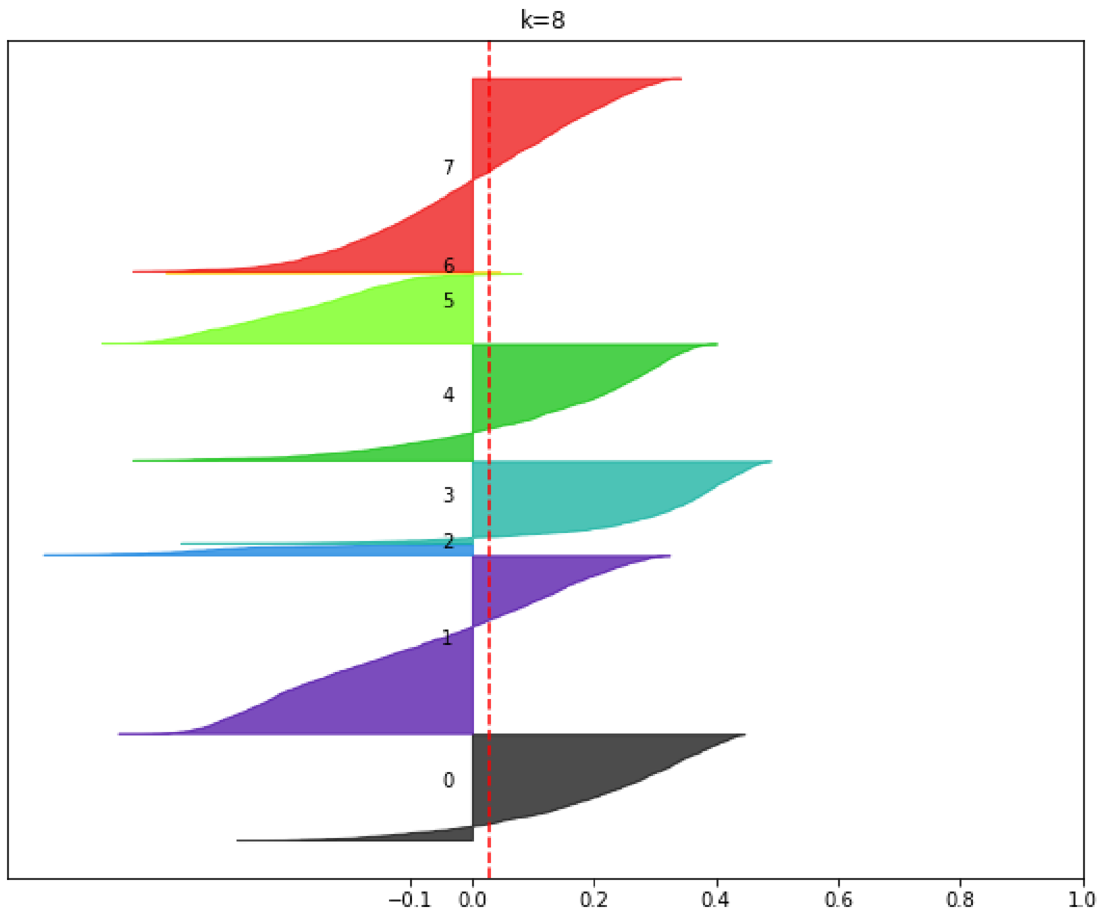

```
Start fitting
Stop fitting
Para n_clusters = 6 El silhouette_score promedio es : 0.018188289616214076
```



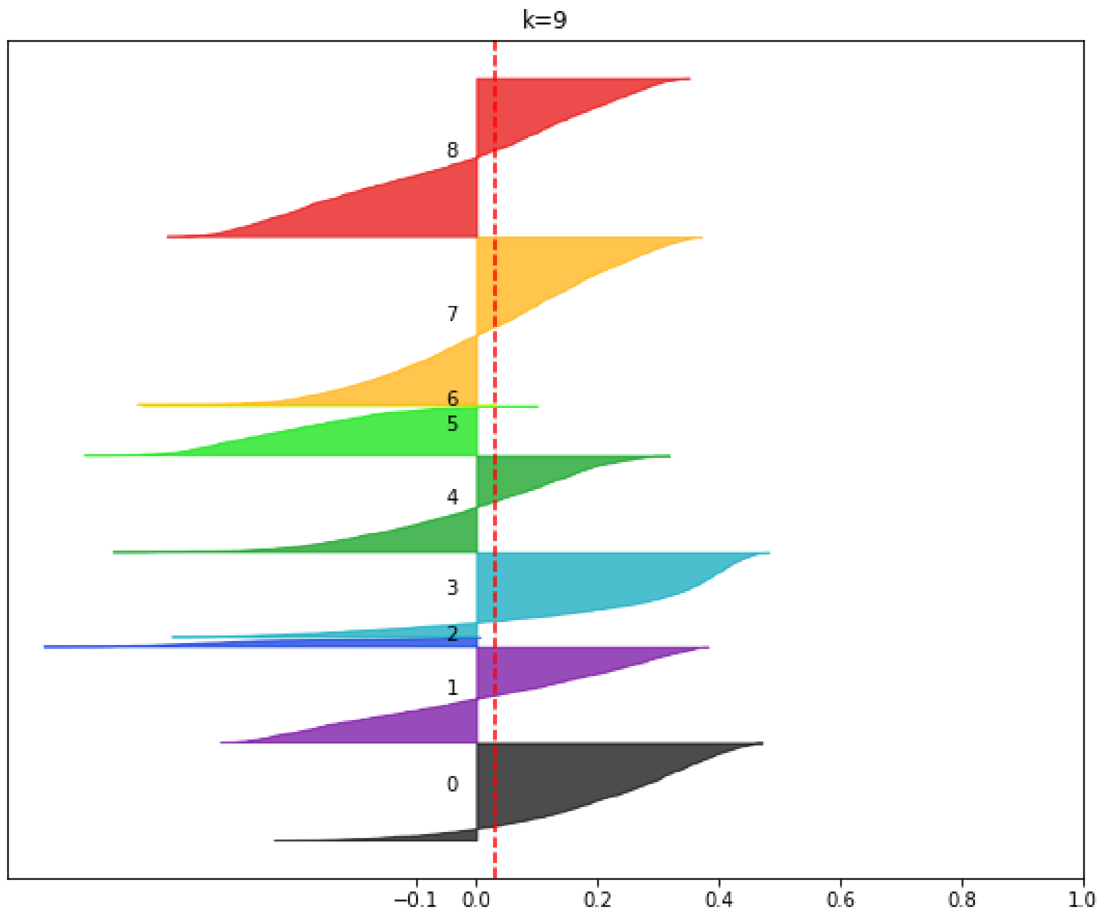

```
Start fitting
Stop fitting
Para n_clusters = 7 El silhouette_score promedio es : 0.028572093134639893
```



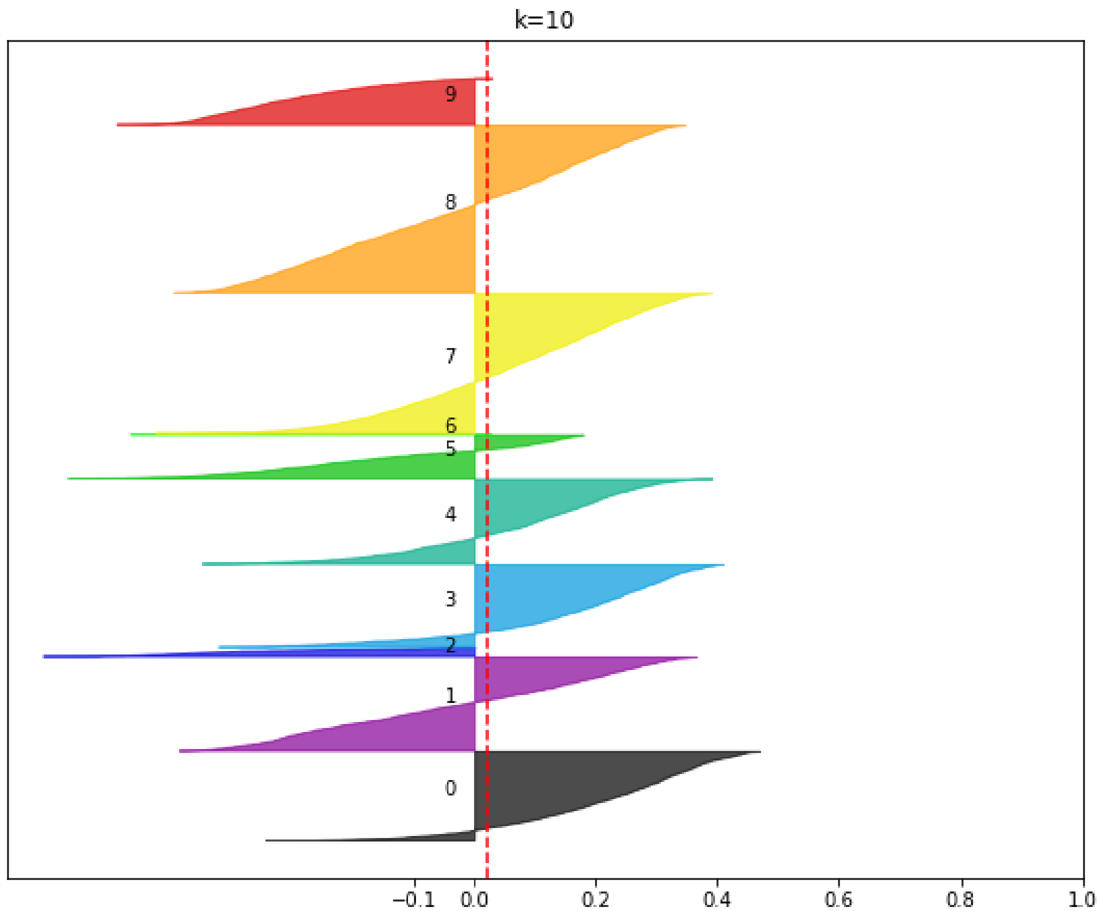

```
Start fitting
Stop fitting
Para n_clusters = 8 El silhouette_score promedio es : 0.029241794186039095
```




```
Start fitting
Stop fitting
Para n_clusters = 9 El silhouette_score promedio es : 0.03086141728984344
```




```
Start fitting
Stop fitting
Para n_clusters = 10 El silhouette_score promedio es : 0.02003784120983751
```



En este caso, el algoritmo Gaussian Mixture, presenta o clusters muy grandes o colas de valores negativos notorias en el analisis por siluetas, lo cual nos indica que hay mucha superposicion entre los clusters y no logra una buena separación

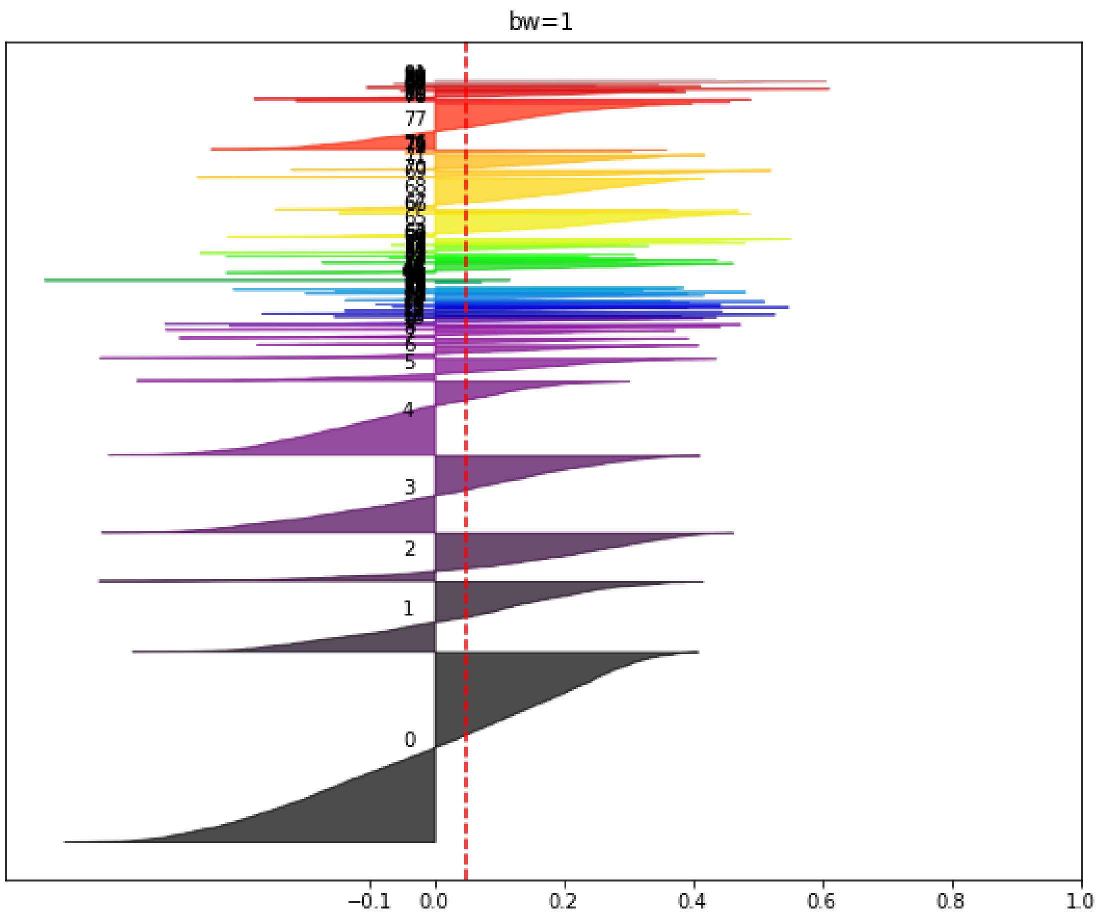
3.2.4 Mean Shift

```
In [59]: def serch_ms_optimus(data_clus, bandwidth):
             sse ={}
             for bw in bandwidth:
                 clusterer = MeanShift(bandwidth=bw, bin_seeding=True)
                 print("Start fitting")
                 cluster_labels = clusterer.fit_predict(data_clus)
                 print("Stop fitting")
                 #sse[n_clusters] = clusterer.inertia_

                 # The silhouette_score gives the average value for all the samples.
                 # This gives a perspective into the density and separation of the formed
                 # clusters
                 silhouette_avg = silhouette_score(data_clus, cluster_labels, random_state=352)
```

```
            print("Para bamdwith =", bw,
                  "El silhouette_score promedio es :", silhouette_avg)

            # Compute the silhouette scores for each sample
            sample_silhouette_values = silhouette_samples(data_clus, cluster_labels)

            plot_silouette(sample_silhouette_values, cluster_labels,
                           silhouette_avg, title="bw={}".format(bw))
        return sse
```

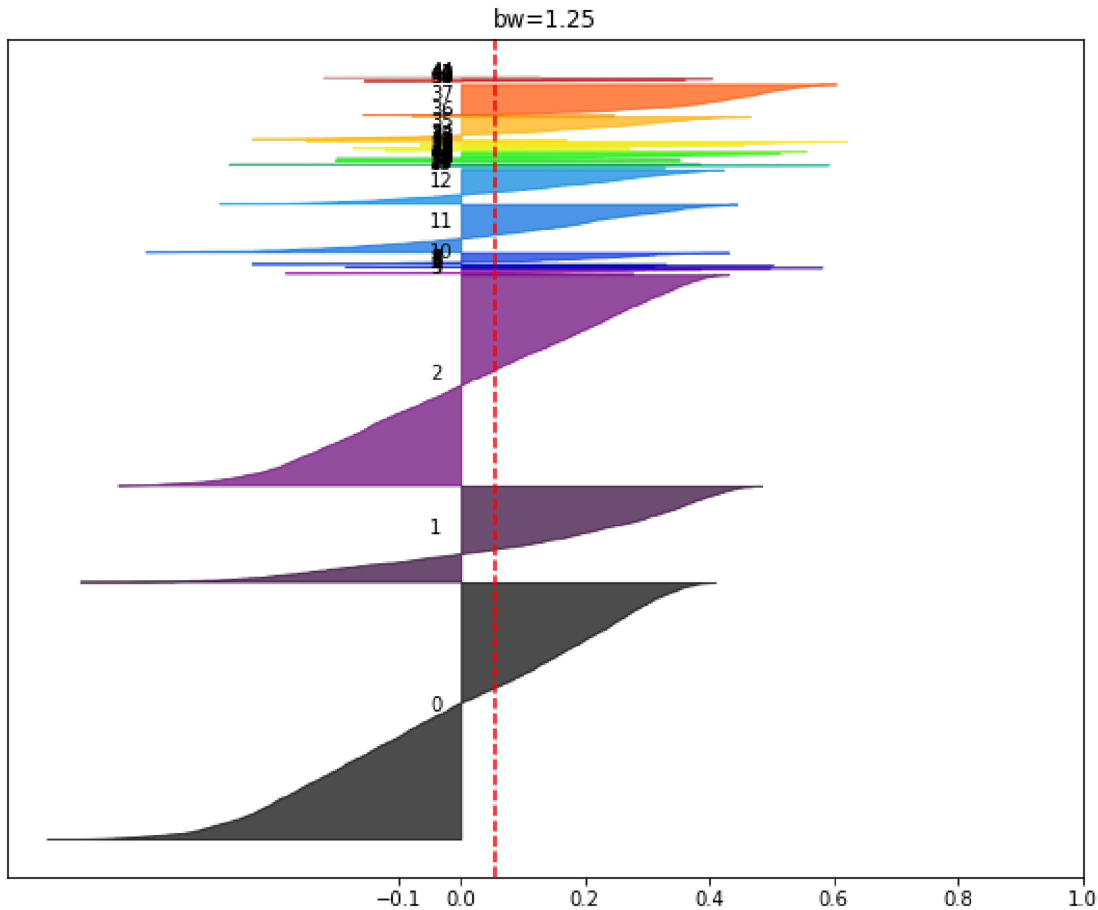
```
In [60]: bandwidth = [1, 1.25, 1.5, 1.75, 2]
         serch_ms_optimus(data_clus, bandwidth)
```

```
Start fitting
Stop fitting
Para bamdwith = 1 El silhouette_score promedio es : 0.048581508299265455
```

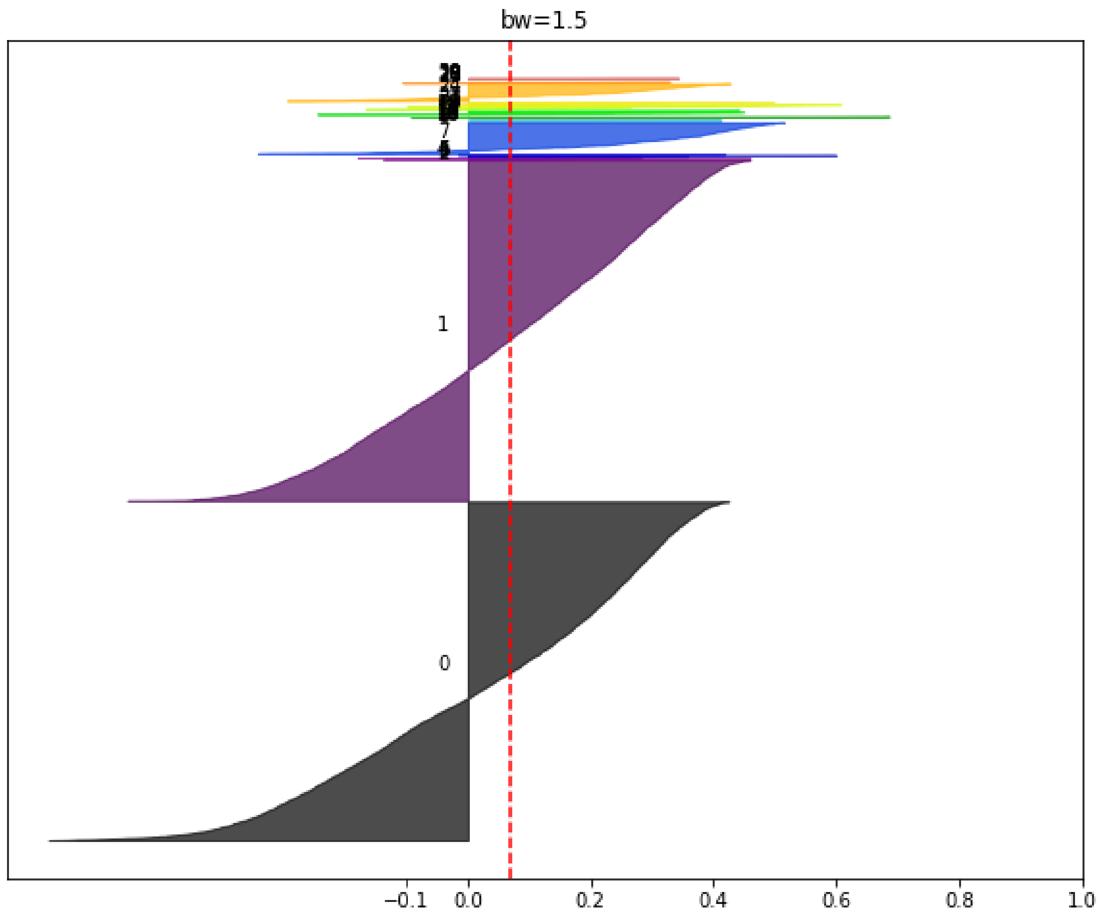



```
Start fitting
Stop fitting
```

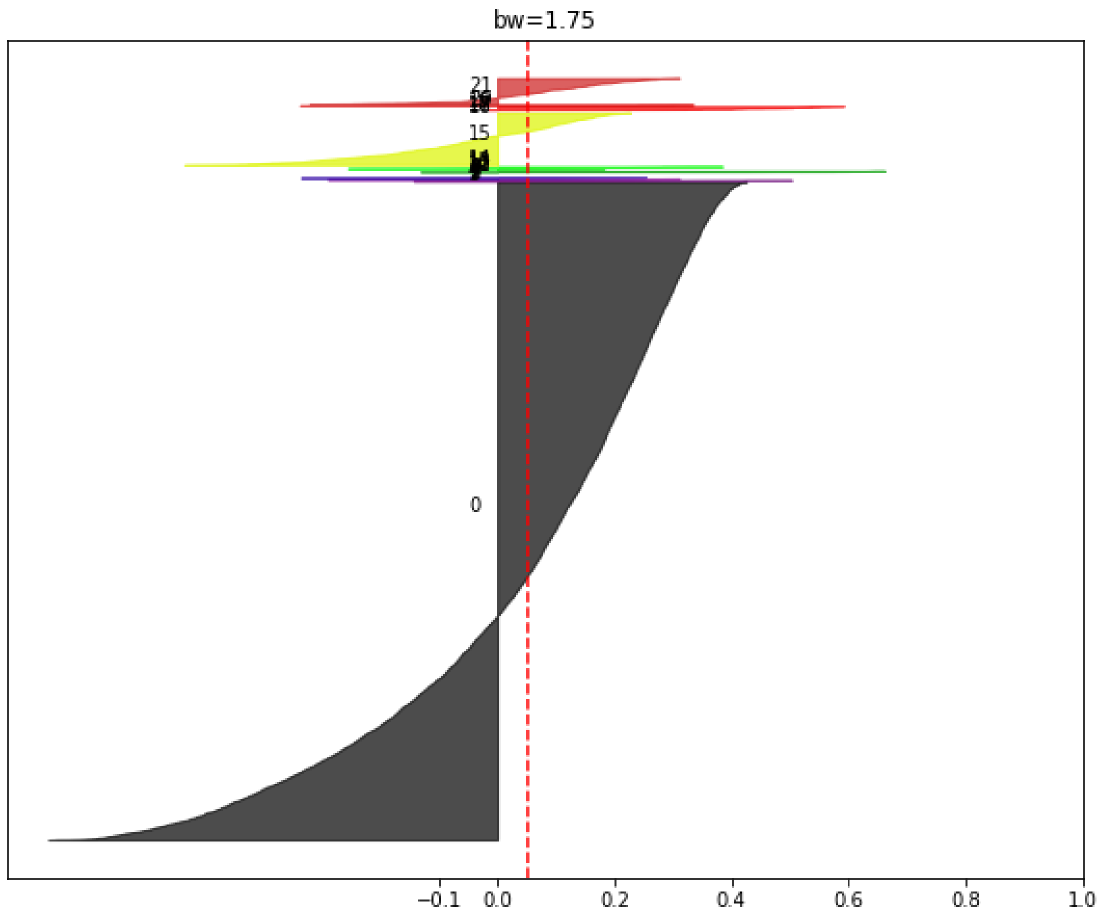
```
Para bamdwith = 1.25 El silhouette_score promedio es : 0.05561728357711319
```



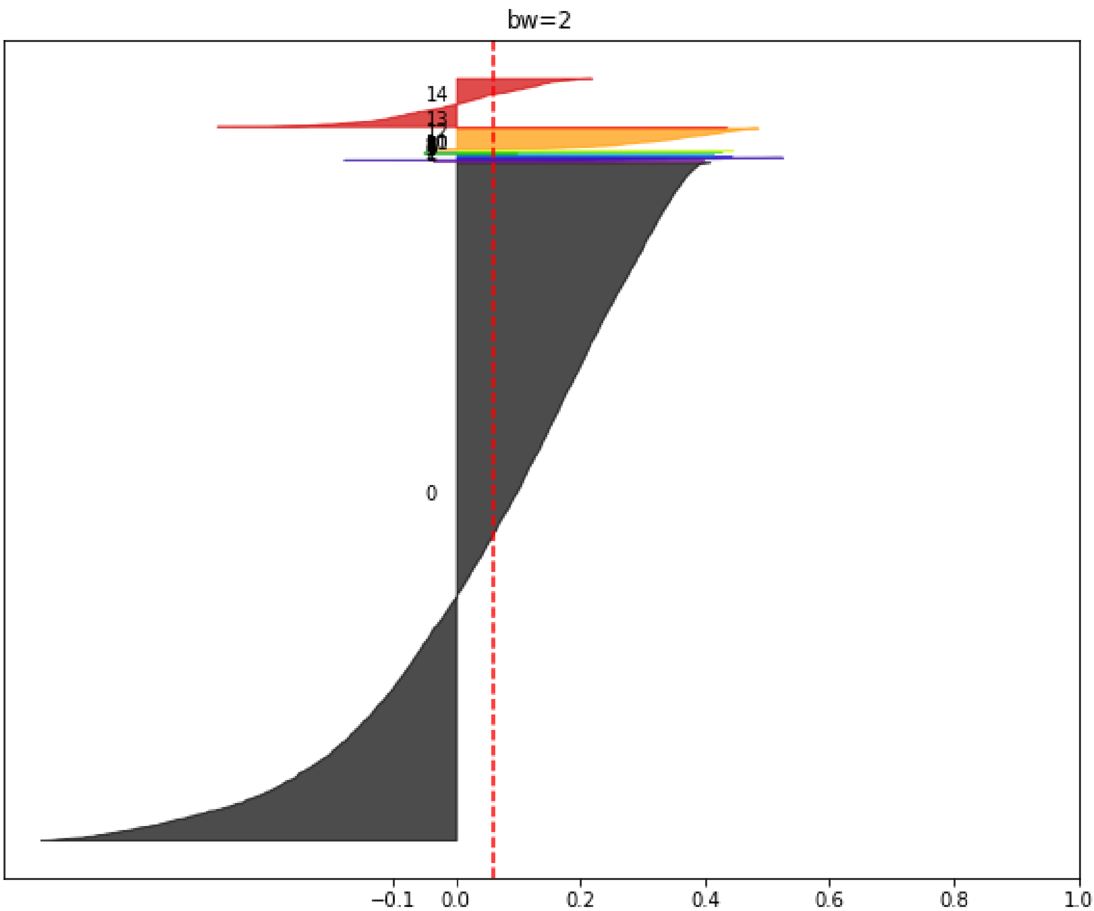

```
Start fitting
Stop fitting
Para bamdwith = 1.5 El silhouette_score promedio es : 0.06782756160766823
```




```
Start fitting
Stop fitting
Para bamdwith = 1.75 El silhouette_score promedio es : 0.05100630863782385
```




```
Start fitting
Stop fitting
Para bamdwith = 2 El silhouette_score promedio es : 0.05973664532286635
```



Out[60]: {}

En el analisis de silueta del algoritmo Mean Shift, se ven 2 problemas, muchos clusters y grandes colas negativas.

3.2.5 Conclusión

De todos los métodos analisados el que mejor resultados presento fue k-means con un k=3 o K=4. Vamos a utilizar esos 2 y vamos a aplicar diferentes embeddings para ver que podemos obtener desde ahí

4 Aplico K-means con k igual a 3 y 4

In [61]:
```
cluster_3 = KMeans(n_clusters=3, random_state=10, n_jobs=6)
cluster_labels_3 = cluster_3.fit_predict(data_clus)

cluster_4 = KMeans(n_clusters=4, random_state=531, n_jobs=6)
cluster_labels_4 = cluster_4.fit_predict(data_clus)
```

In [62]:
```
data_clus_k3 = data_clus.copy()
data_clus_k4 = data_clus.copy()
data_clus_k3["cluster_label"] = cluster_labels_3
data_clus_k4["cluster_label"] = cluster_labels_4
```

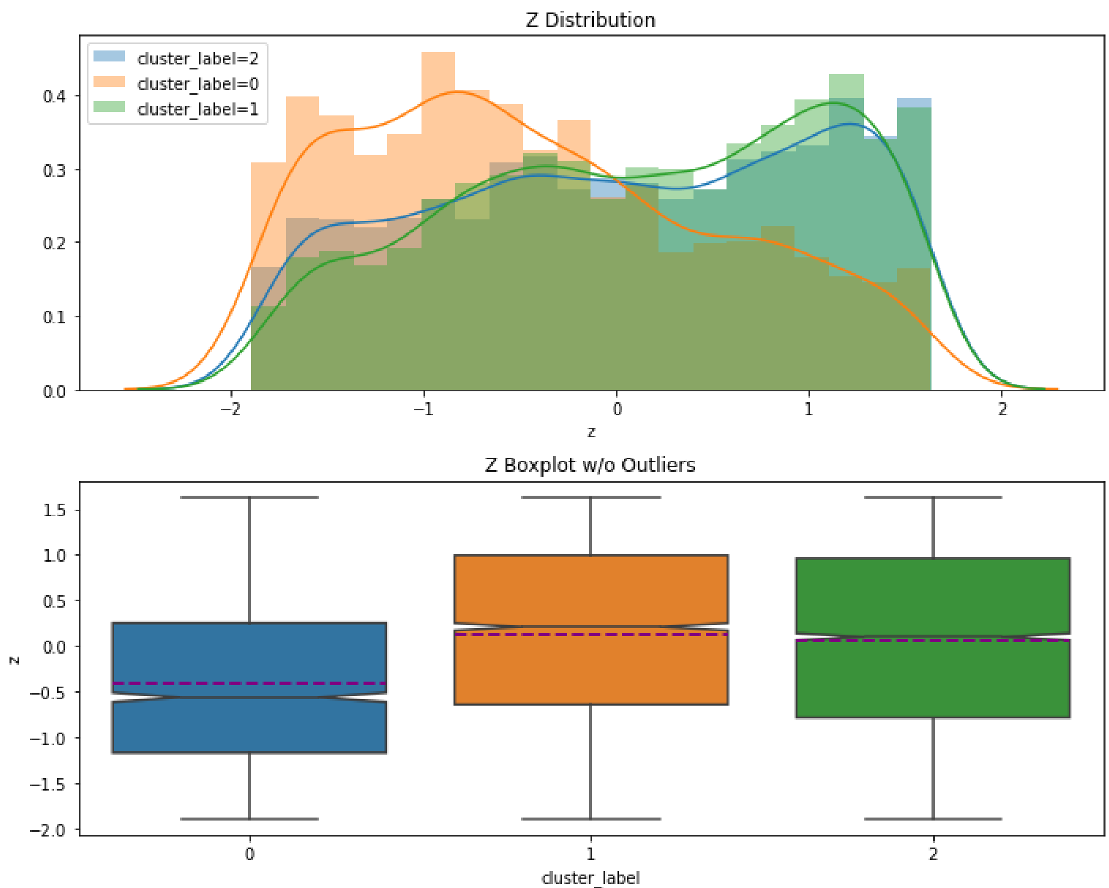
In [ ]:

4.1 Visualizacion segun cluster label

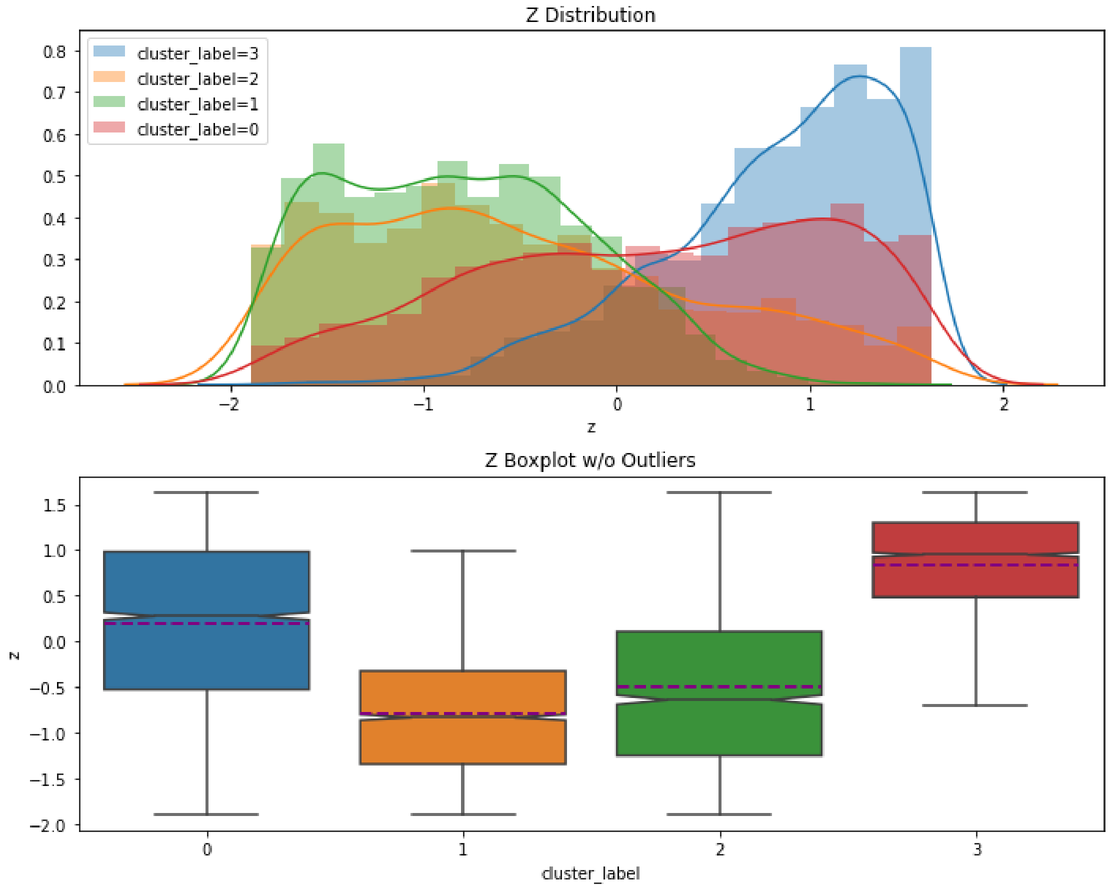
In [63]:
```
def distribution_per_label(df, col_name="", bins=20):
    plt.title(f"{col_name.capitalize()} Distribution")
    for kk in df["cluster_label"].unique():
        sns.distplot(df[df["cluster_label"] == kk][col_name],label=f"cluster_label={k
                     bins=bins)
    plt.legend()

def exploratory_plots_label(df, col_name=""):
    plt.subplot(2, 1, 1)
    distribution_per_label(df, col_name)
    plt.subplot(2, 1, 2)
    plt.title(f"{col_name.capitalize()} Boxplot w/o Outliers")
    sns.boxplot(x="cluster_label", y=col_name, data=df, showfliers=False, **box_params

    plt.tight_layout()
```

4.1.1 z

In [64]:
```
exploratory_plots_label(data_clus_k3, "z")
```

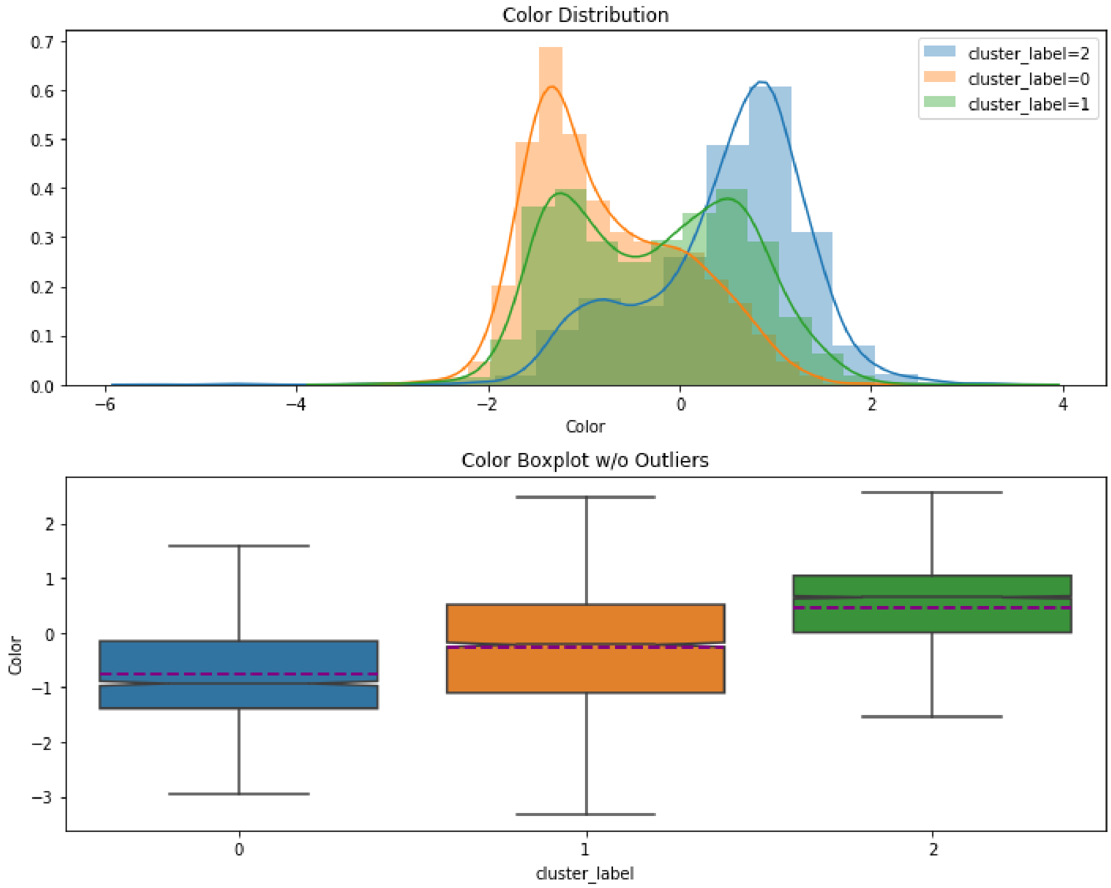



```
In [65]: exploratory_plots_label(data_clus_k4, "z")
```

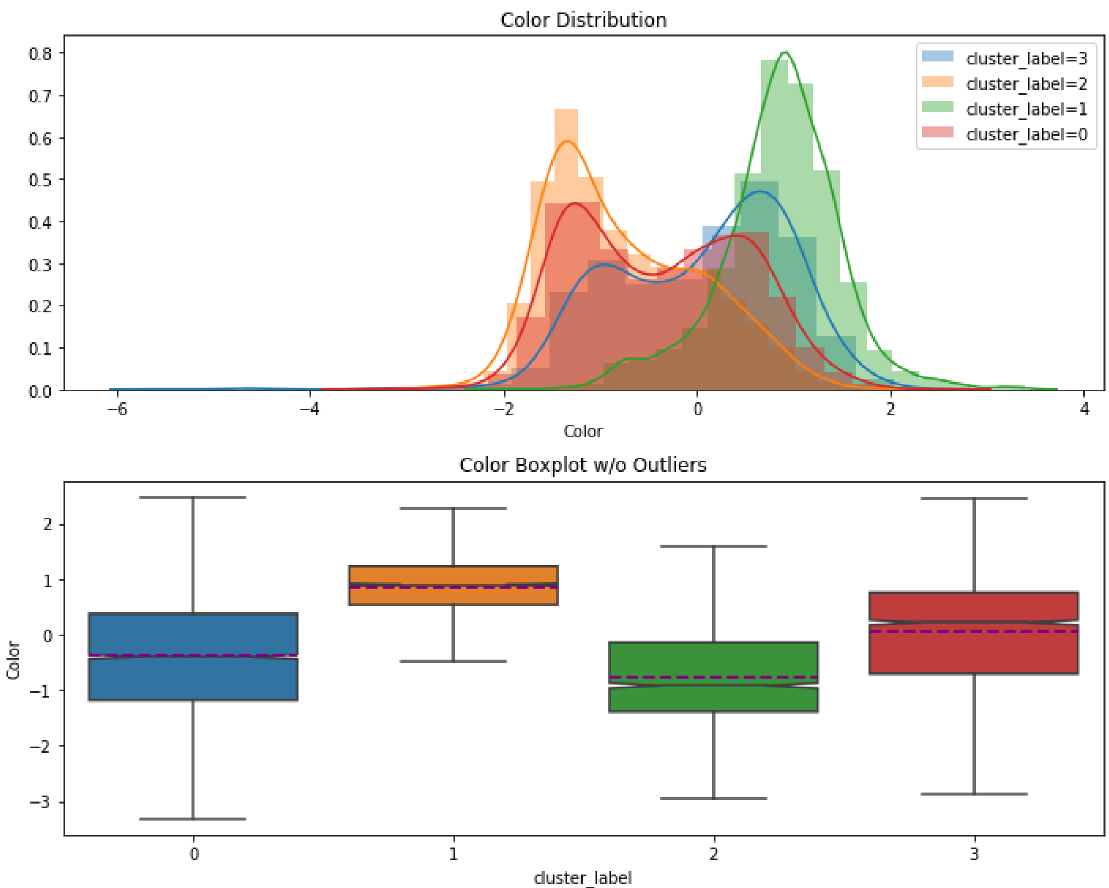


4.1.2 Color

```
In [66]: exploratory_plots_label(data_clus_k3, "Color")
```

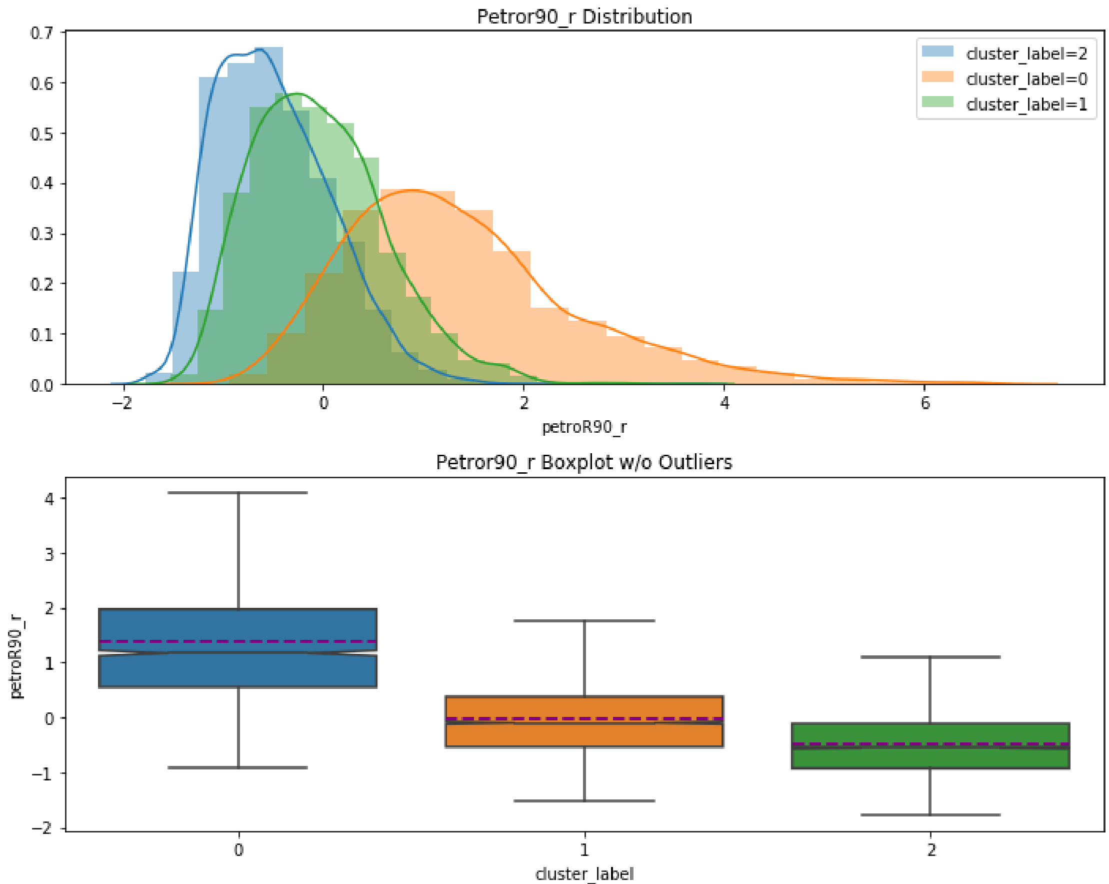



```
In [67]: exploratory_plots_label(data_clus_k4, "Color")
```

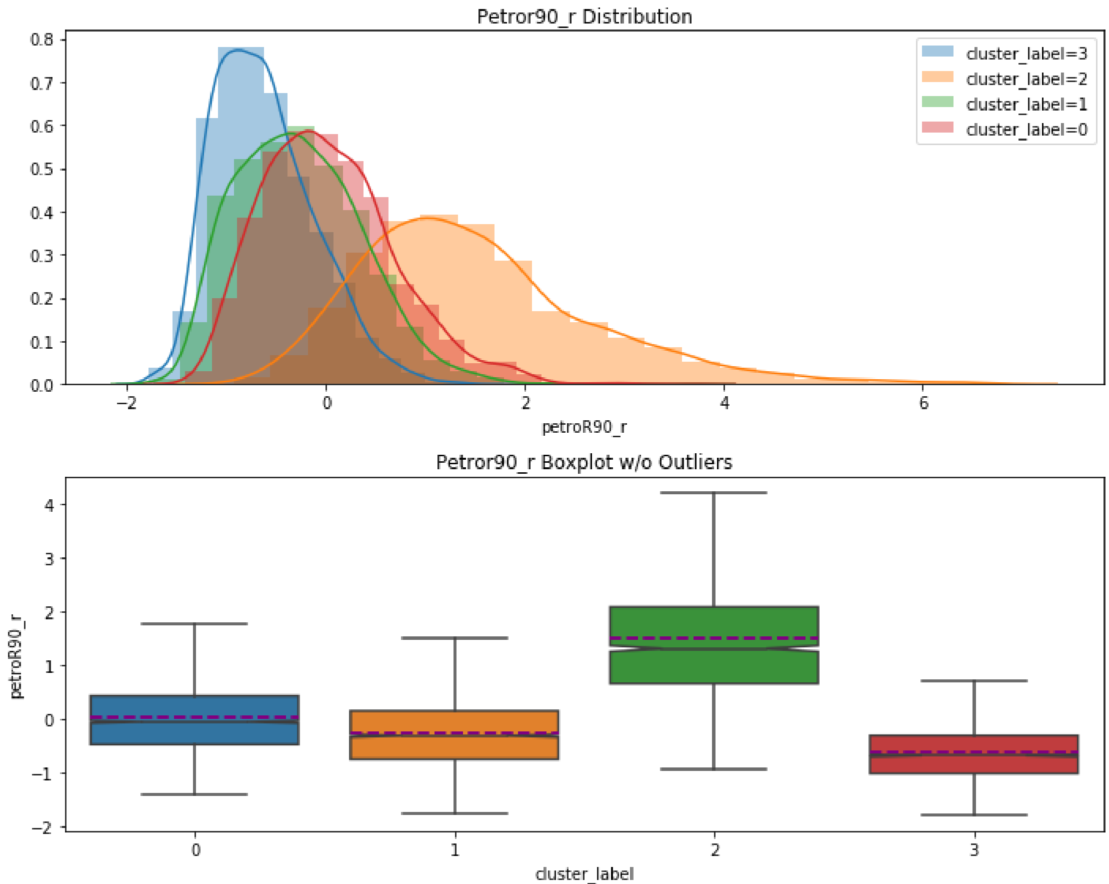


4.1.3 Petro R90

```
In [68]: exploratory_plots_label(data_clus_k3, "petroR90_r")
```



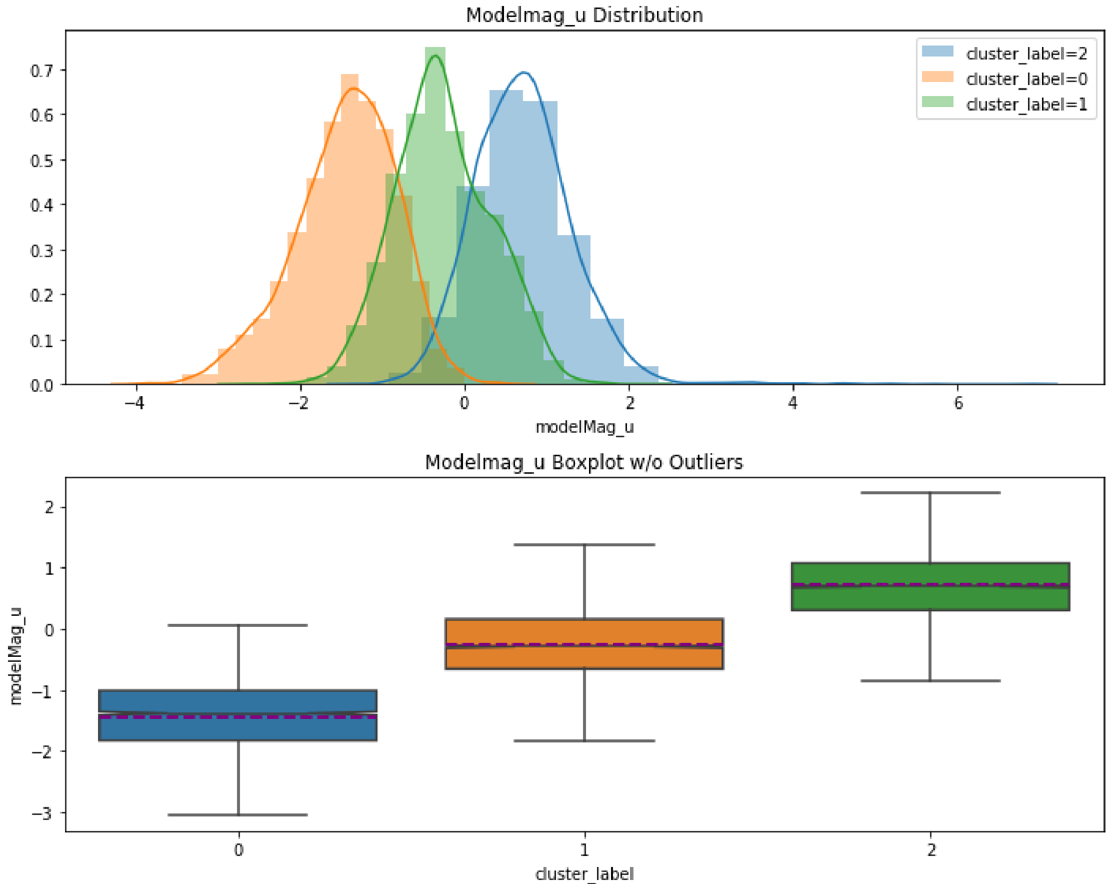

```
In [69]: exploratory_plots_label(data_clus_k4, "petroR90_r")
```

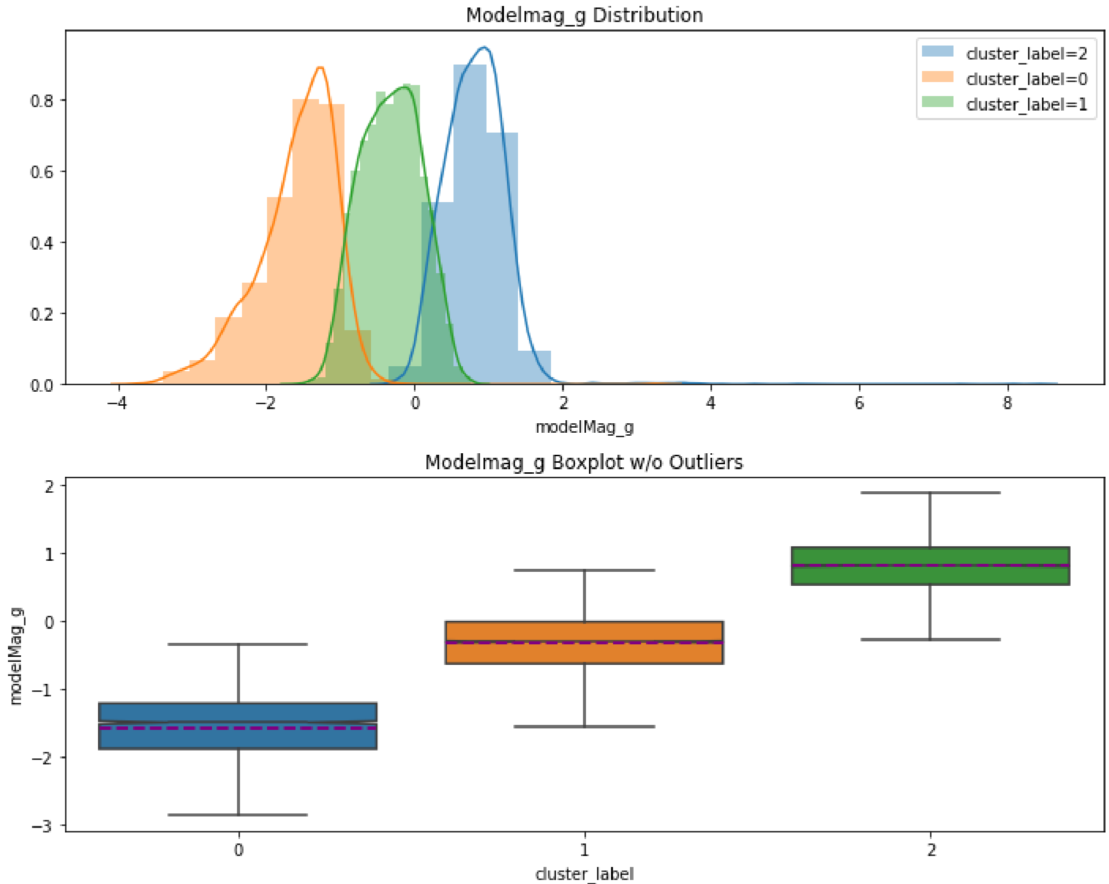


4.1.4 Mag Distributions

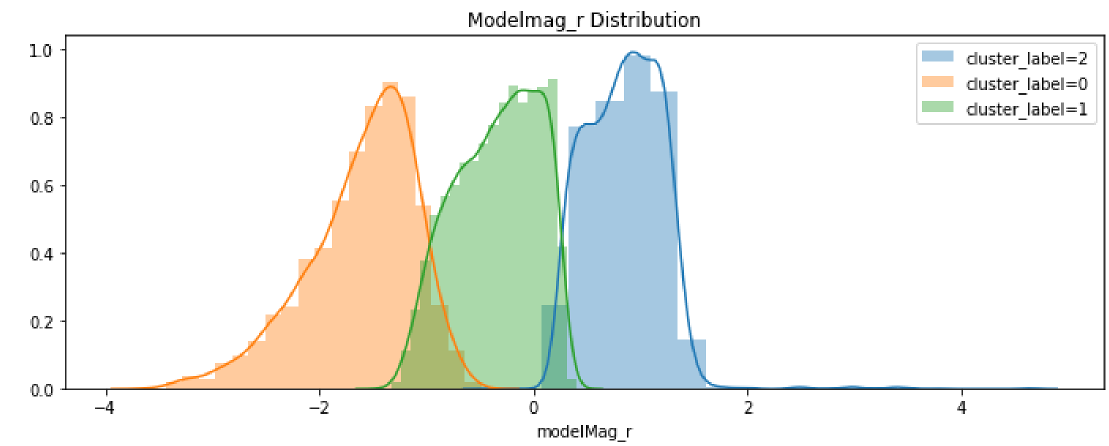
k = 3

```
In [70]: for mag in ['modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i','modelMag_z']:
             plt.figure()
             exploratory_plots_label(data_clus_k3, mag)
```

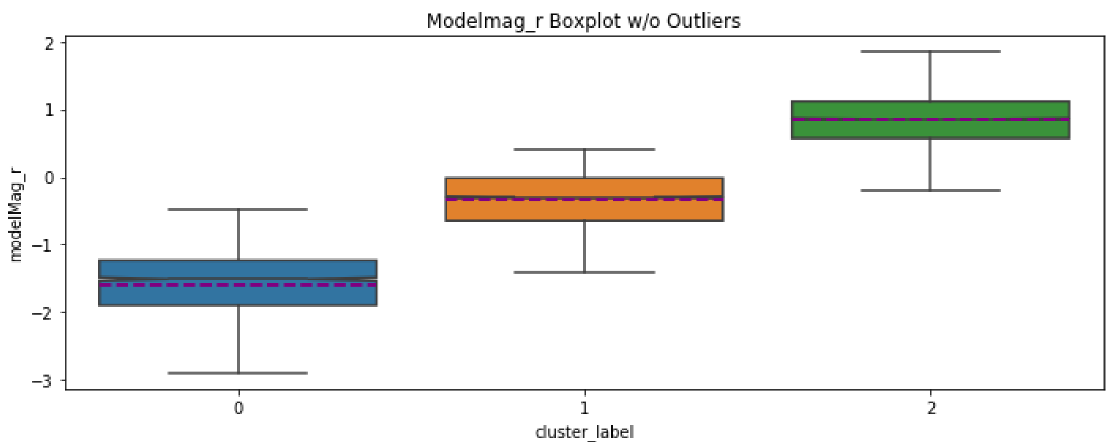

Modelmag_u Distribution
cluster_label=2
cluster_label=0
cluster_label=1
modelMag_u
Modelmag_u Boxplot w/o Outliers
modelMag_u
cluster_label



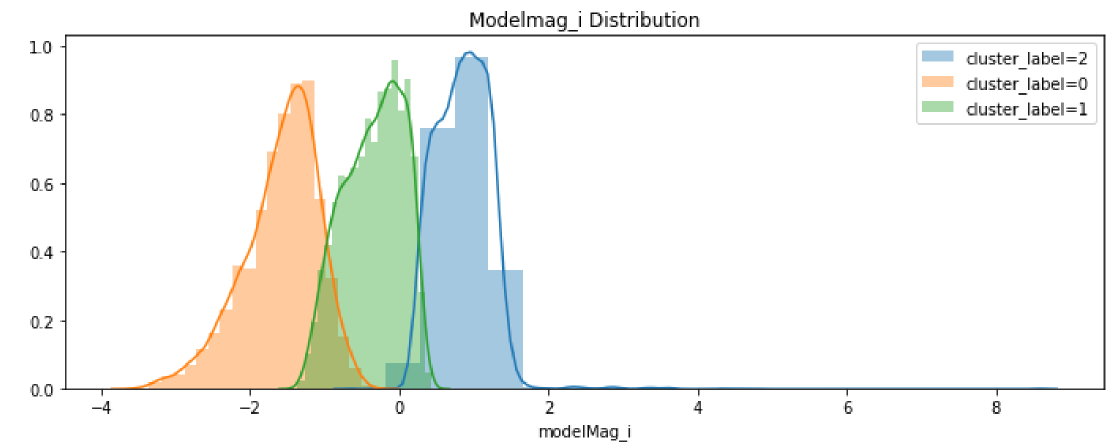
Modelmag_g Distribution
cluster_label=2
cluster_label=0
cluster_label=1
modelMag_g
Modelmag_g Boxplot w/o Outliers
modelMag_g
cluster_label



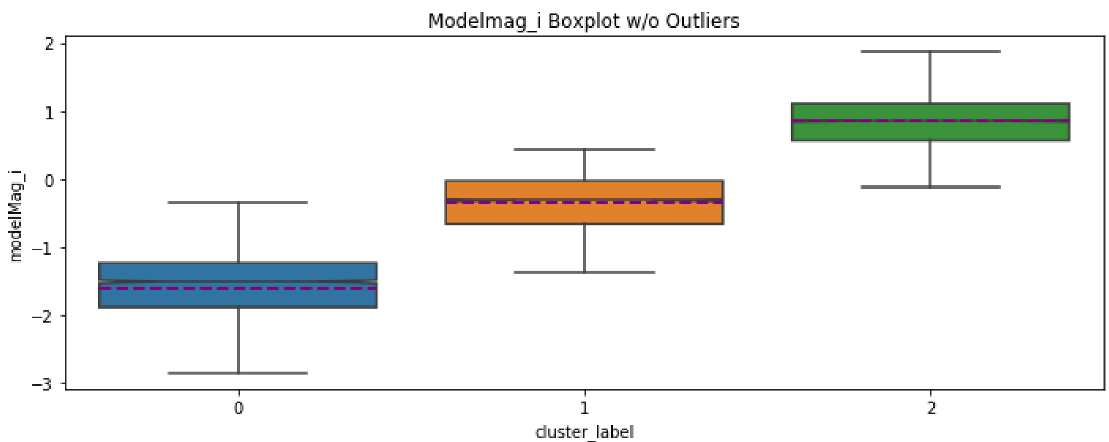
Modelmag_r Distribution
1.0
0.8
0.6
0.4
0.2
0.0
−4
−2
0
2
4
modelMag_r
cluster_label=2
cluster_label=0
cluster_label=1



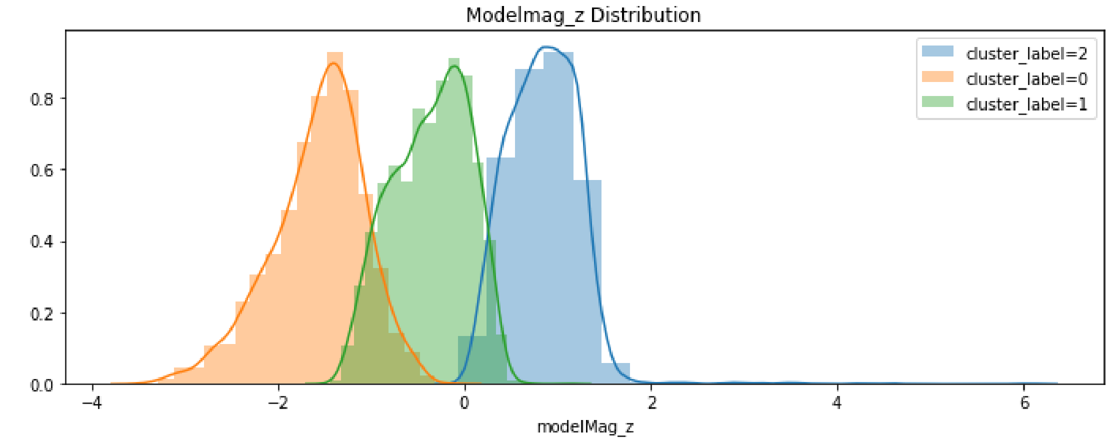
Modelmag_r Boxplot w/o Outliers
modelMag_r
2
1
0
−1
−2
−3
0
1
2
cluster_label

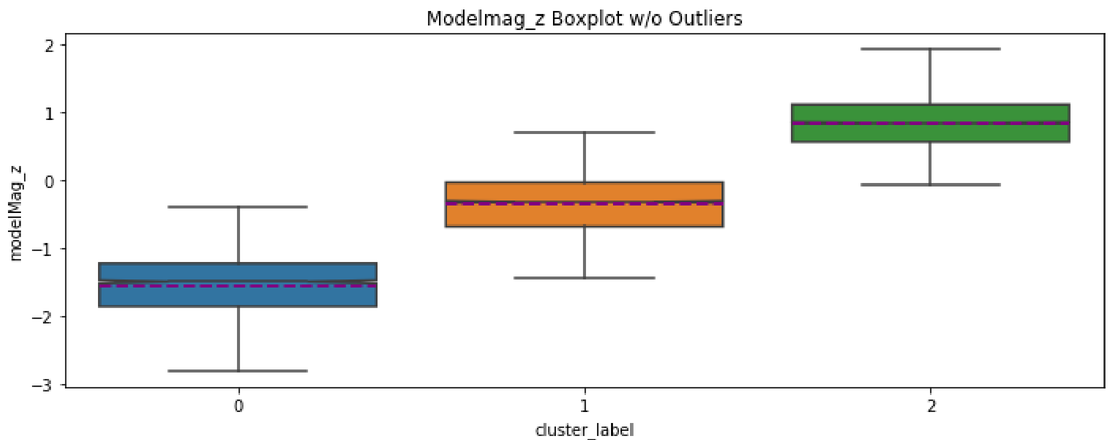


Modelmag_i Distribution
cluster_label=2
cluster_label=0
cluster_label=1
modelMag_i



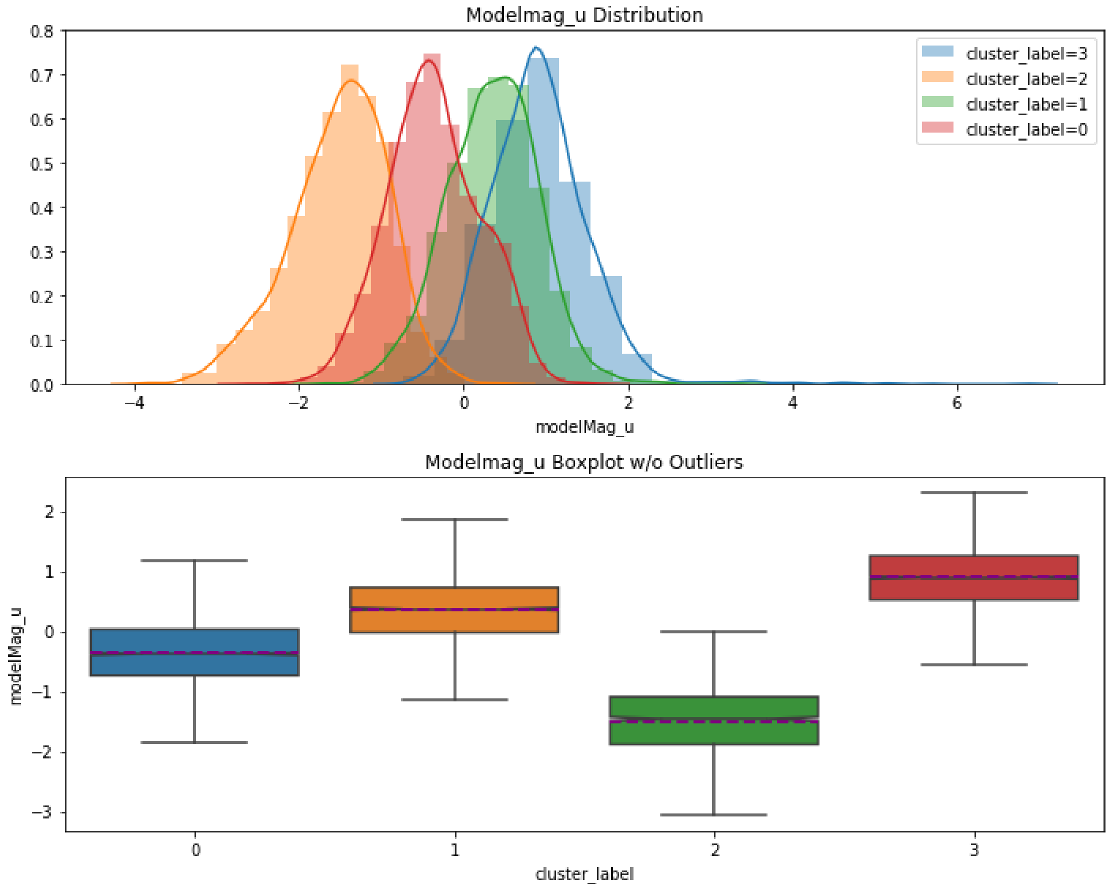
Modelmag_i Boxplot w/o Outliers
modelMag_i
cluster_label

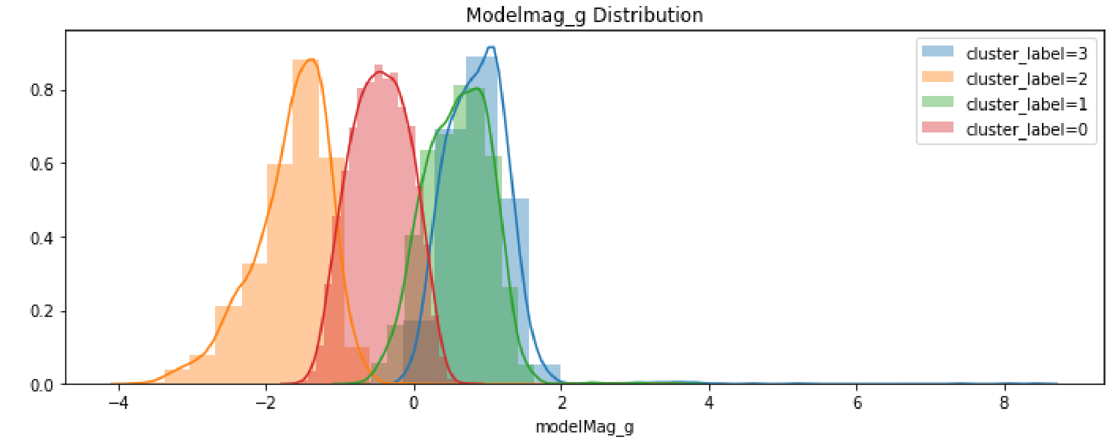




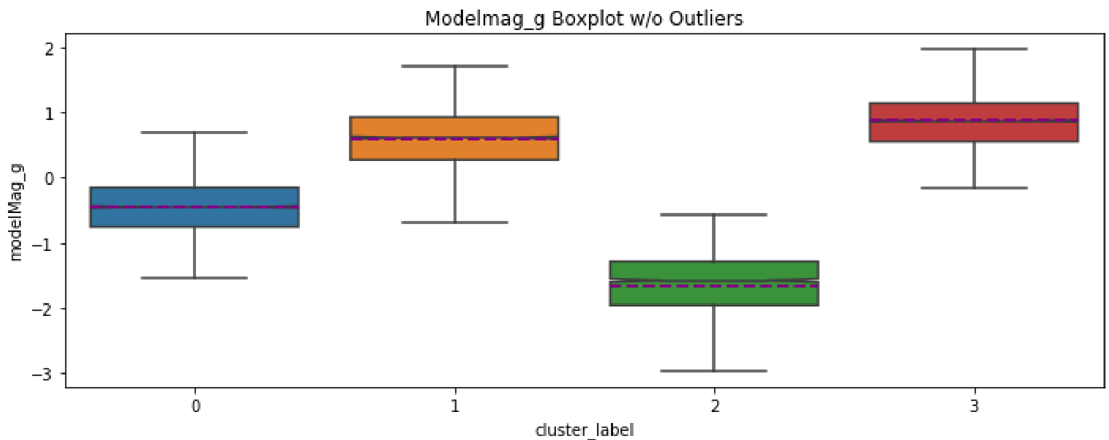
k = 4

```
In [71]: for mag in ['modelMag_u', 'modelMag_g', 'modelMag_r', 'modelMag_i','modelMag_z']:
             plt.figure()
             exploratory_plots_label(data_clus_k4, mag)
```

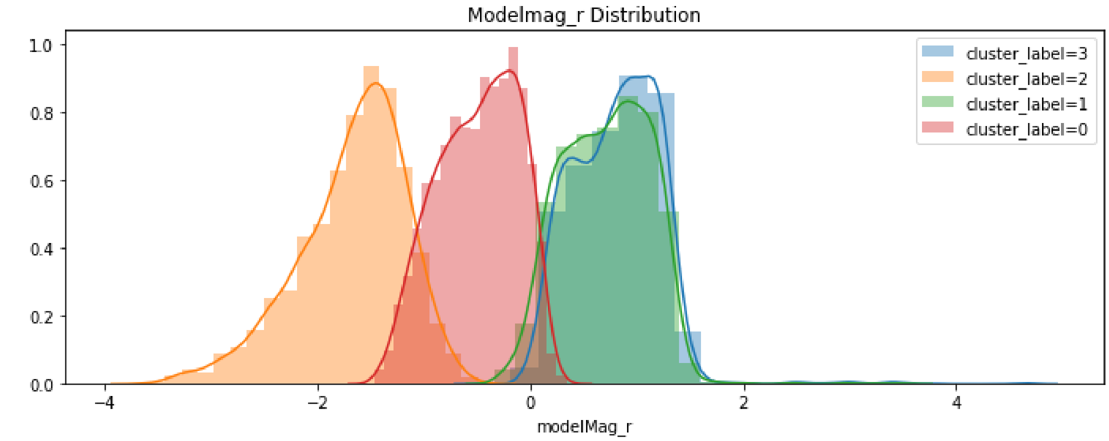

Modelmag_u Distribution
cluster_label=3
cluster_label=2
cluster_label=1
cluster_label=0
modelMag_u
Modelmag_u Boxplot w/o Outliers
modelMag_u
cluster_label

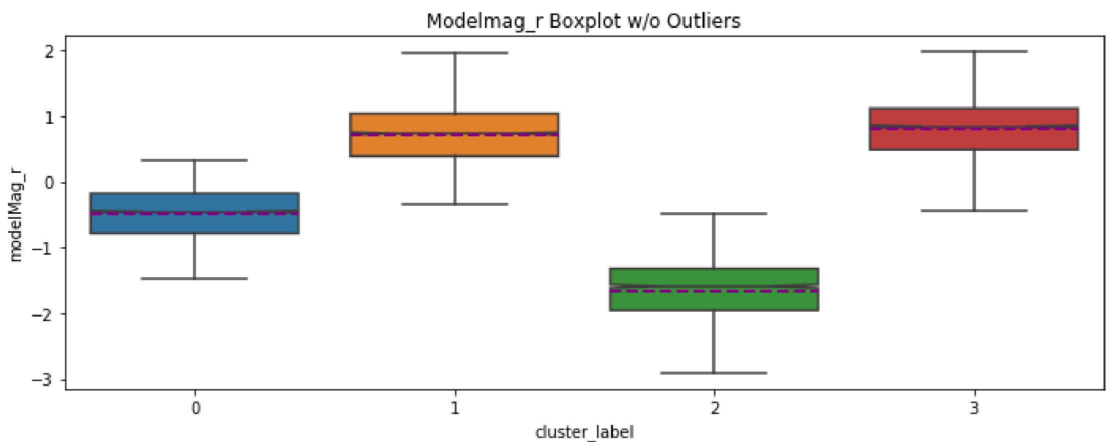


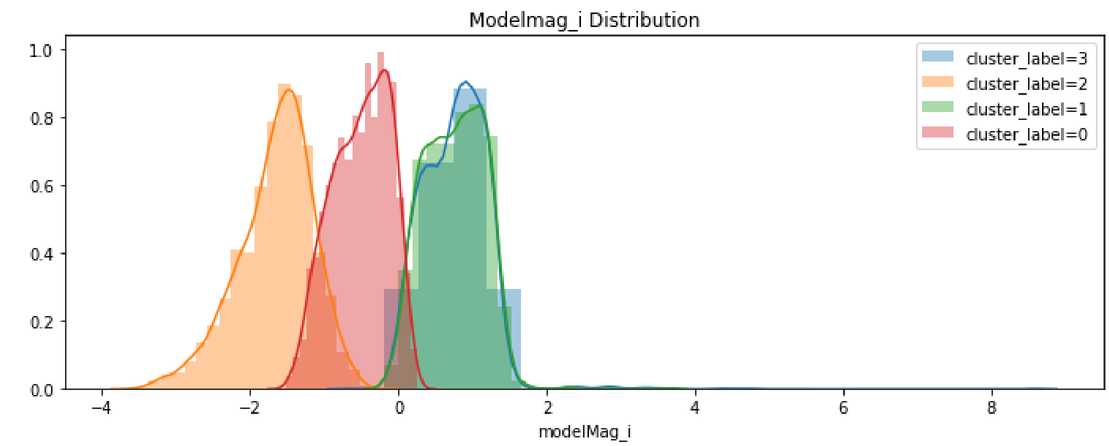
Modelmag_g Distribution
cluster_label=3
cluster_label=2
cluster_label=1
cluster_label=0
modelMag_g

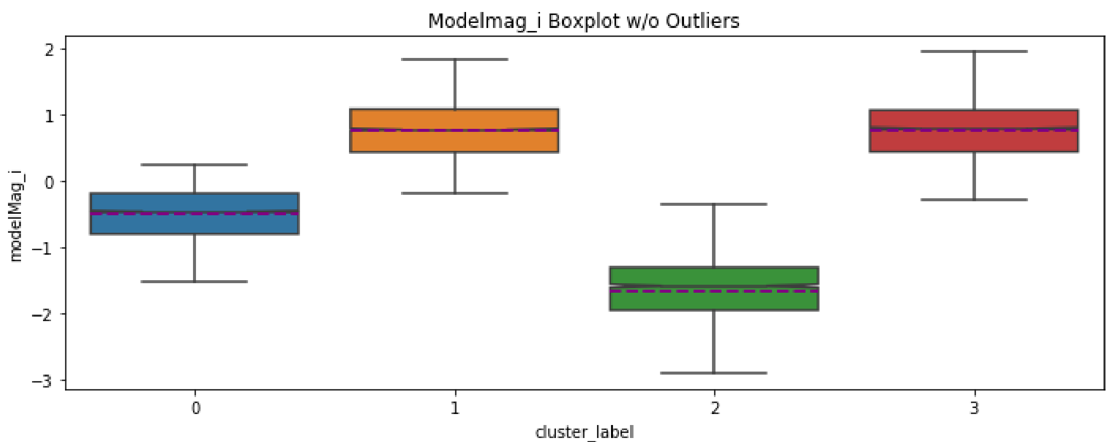


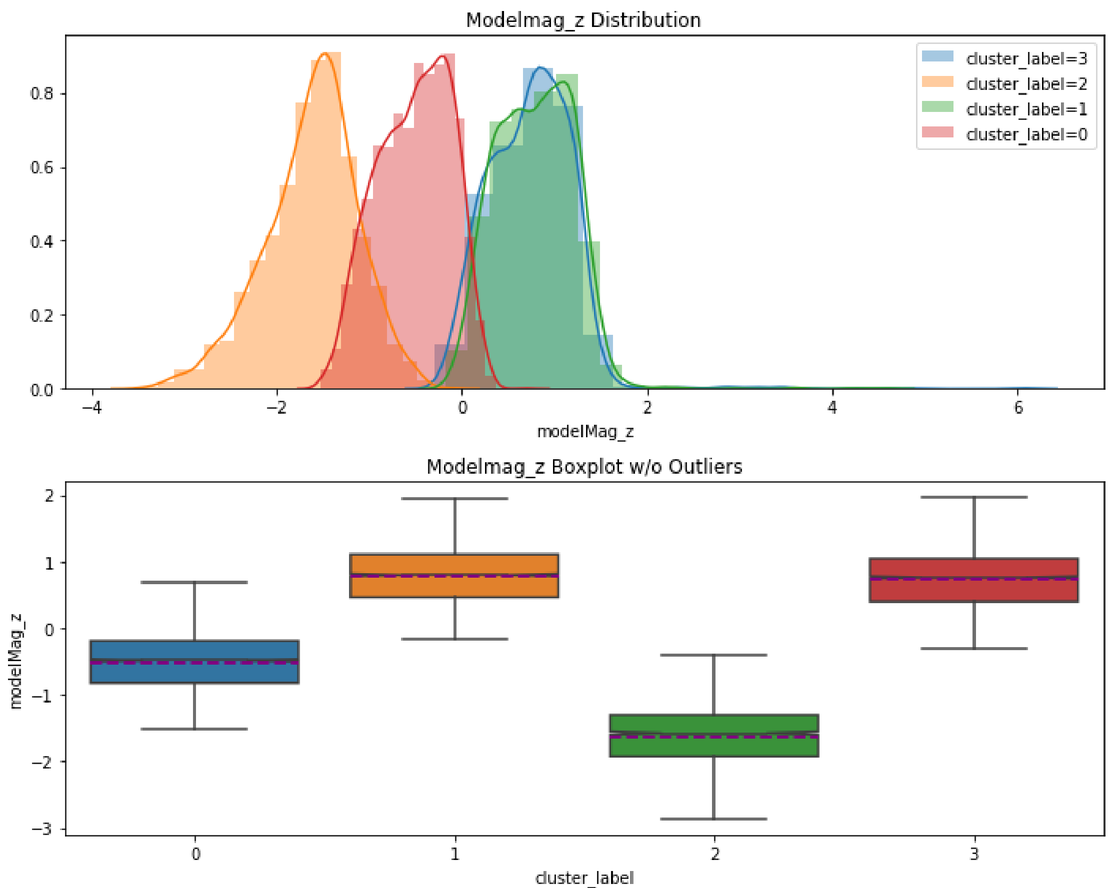
Modelmag_g Boxplot w/o Outliers
modelMag_g
cluster_label


Modelmag_r Distribution
cluster_label=3
cluster_label=2
cluster_label=1
cluster_label=0
1.0
0.8
0.6
0.4
0.2
0.0
−4
−2
0
2
4
modelMag_r


Modelmag_r Boxplot w/o Outliers
modelMag_r
2
1
0
−1
−2
−3
0
1
2
3
cluster_label


Modelmag_i Distribution
cluster_label=3
cluster_label=2
cluster_label=1
cluster_label=0
modelMag_i


Modelmag_i Boxplot w/o Outliers
modelMag_i
cluster_label



4.2 Conclusion

Al visualizar los datos de acuerdo al label, vemos que las diferentes clases tienen diferentes comportamientos en las distribuciones de los diferentes features.

En el caso de k=4 algunas features tienen distribuciones casi identticas para diferents valores de la etiqueta del cluster, lo que nos puede hacer pensar que k=4 sea medio grande, o que podemos probar agrupar esas etiquetas para crear un nuevo cluster.

Otras observación importante, es que estamos utilizando el **red shift** o **z** como feature de entrada a los algoritmos de cluster. Teniendo en cuenta el significado fisico de esa variable, nos parece que vale la pena realizar un analísis sin incluirla

5 Embeddings

```
In [72]: from sklearn.decomposition import PCA
         from sklearn.manifold import TSNE
```

5.1 Funciones útiles

```
In [73]: def print_title(title="", delimiter="*"):
             print(delimiter*80)
             print(title)
             print(delimiter*80)
```

```
In [87]: def plot_2d(pca, df, colname=""):
             from mpl_toolkits.mplot3d import Axes3D
             fig = plt.figure(figsize=(15,10))
             ax = fig.add_subplot(1,1,1)
             im = ax.scatter(pca[:,0],pca[:,1],
                             c=df[colname],cmap=plt.get_cmap("jet"),
                             alpha=0.5)
             ax.set_xlabel("Axis 1")
             ax.set_ylabel("Axis 2")
             fig.colorbar(im, ax=ax)
```

```
In [75]: def plot_3d(pca, df, colname=""):
             from mpl_toolkits.mplot3d import Axes3D
             fig = plt.figure(figsize=(15,10))
             for idx in range(1,5):
                 ax = fig.add_subplot(2,2,idx, projection='3d')
                 im = ax.scatter(pca[:,0],pca[:,1],pca[:,2],
                        c=df[colname],cmap=plt.get_cmap("jet"),
                       alpha=0.5)
                 ax.view_init(30, 45+90*idx)
                 ax.set_xlabel("Axis 1")
                 ax.set_ylabel("Axis 2")
                 ax.set_zlabel("Axis 3")
                 fig.colorbar(im, ax=ax)
```

5.2 PCA

```
In [84]: pca_3dim_k3 = PCA(n_components=3)
         pca_3dim_k4 = PCA(n_components=3)
         pca_2dim_k3 = PCA(n_components=2)
         pca_2dim_k4 = PCA(n_components=2)

         pca_std_k3 = pca_3dim_k3.fit_transform(data_clus_k3)
         pca_std_k4 = pca_3dim_k4.fit_transform(data_clus_k4)
         pca_std_k3_2d = pca_2dim_k3.fit_transform(data_clus_k3)
         pca_std_k4_2d = pca_2dim_k4.fit_transform(data_clus_k4)
```

```
In [94]: print_title("3D")
         print("k=3: ", pca_3dim_k3.explained_variance_ratio_, sum(pca_3dim_k3.explained_varia
         print("k=4: ", pca_3dim_k4.explained_variance_ratio_, sum(pca_3dim_k4.explained_varia
         print_title("2D")
         print("k=3: ", pca_2dim_k3.explained_variance_ratio_, sum(pca_2dim_k3.explained_varia
         print("k=4: ", pca_2dim_k4.explained_variance_ratio_, sum(pca_2dim_k4.explained_varia
```

```
********************************************************************************
3D
********************************************************************************
k=3:  [0.69203368 0.15264476 0.08601644] 0.9306948797217003
k=4:  [0.59477826 0.16607799 0.11293053] 0.8737867789226256
********************************************************************************
2D
********************************************************************************
k=3:  [0.69203368 0.15264476] 0.8446784397440101
k=4:  [0.59477826 0.16607799] 0.7608562504812656
```

In [78]:
```
axis_components_k3 = pd.DataFrame(index=data_clus_k3.columns, columns=["Ax1", "Ax2", "
                                  data=pca_3dim_k3.components_.T)
axis_components_k4 = pd.DataFrame(index=data_clus_k4.columns, columns=["Ax1", "Ax2", "
                                  data=pca_3dim_k4.components_.T)
```

In [79]:
```
axis_components_k3
```

Out[79]:

	Ax1	Ax2	Ax3
modelMag_u	0.361376	0.299015	0.358275
modelMag_g	0.401911	0.072165	0.139314
modelMag_r	0.408063	-0.047243	0.024284
modelMag_i	0.405632	-0.096221	-0.002434
modelMag_z	0.401969	-0.133200	-0.020805
petroR90_r	-0.299370	-0.205887	0.061313
z	0.069641	0.663901	-0.711502
Color	0.198885	-0.626176	-0.584090
cluster_label	0.284984	-0.029981	-0.006850

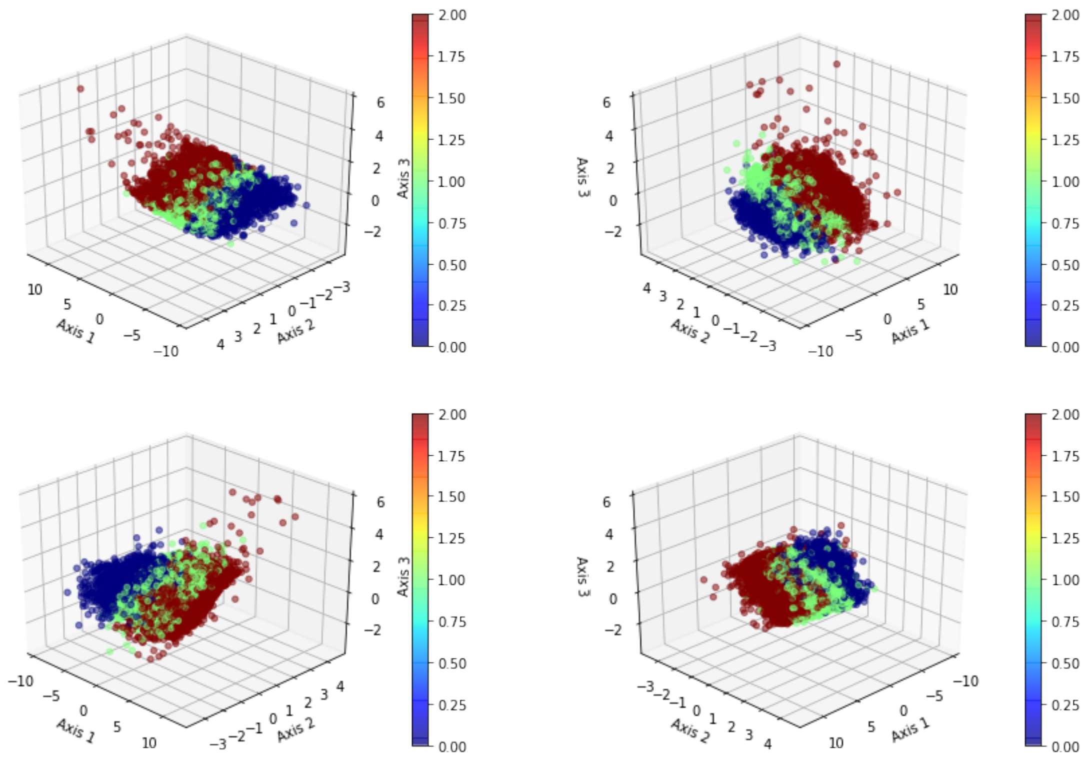
In [80]:
```
axis_components_k4
```

Out[80]:

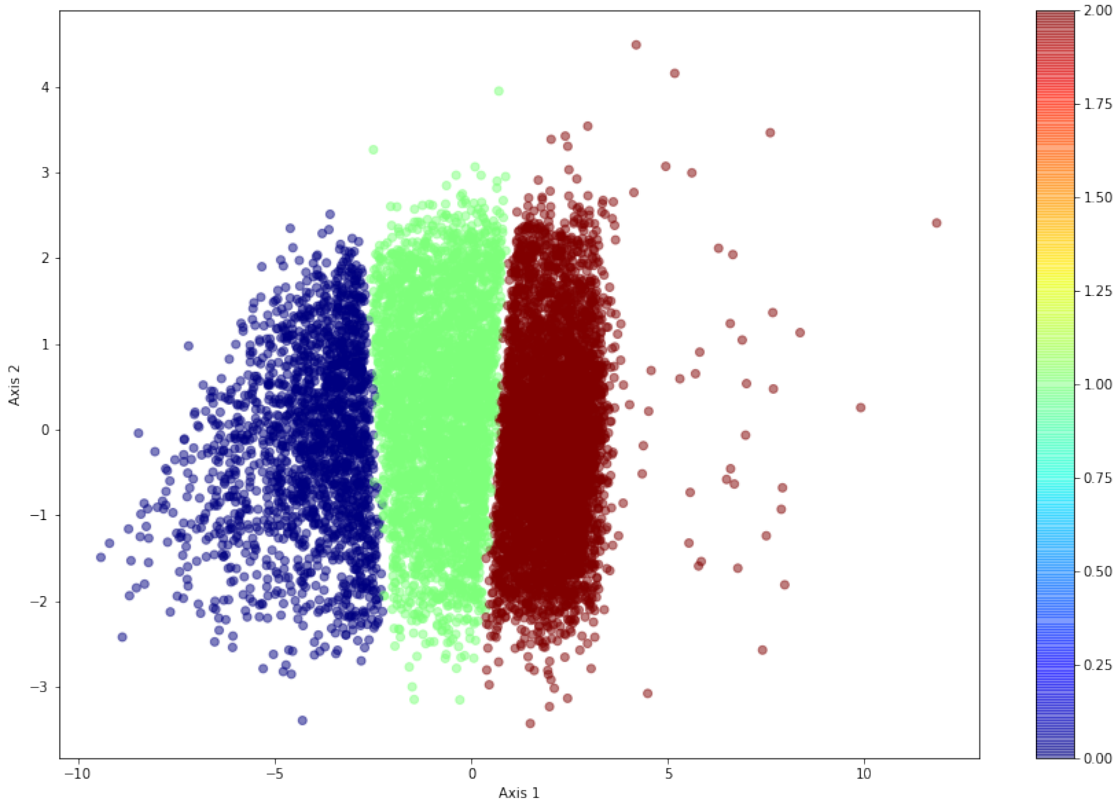
	Ax1	Ax2	Ax3
modelMag_u	0.374817	0.157210	-0.261143
modelMag_g	0.413677	-0.000135	-0.083288
modelMag_r	0.418378	-0.080137	0.012509
modelMag_i	0.415258	-0.113735	0.049567
modelMag_z	0.411074	-0.137192	0.080483
petroR90_r	-0.304501	0.013254	0.373324
z	0.083412	0.521203	-0.338203
Color	0.196293	-0.442827	0.487800
cluster_label	0.183612	0.684969	0.651211

5.2.1 k = 3

In [81]:
```
plot_3d(pca_std_k3, data_clus_k3, "cluster_label")
```

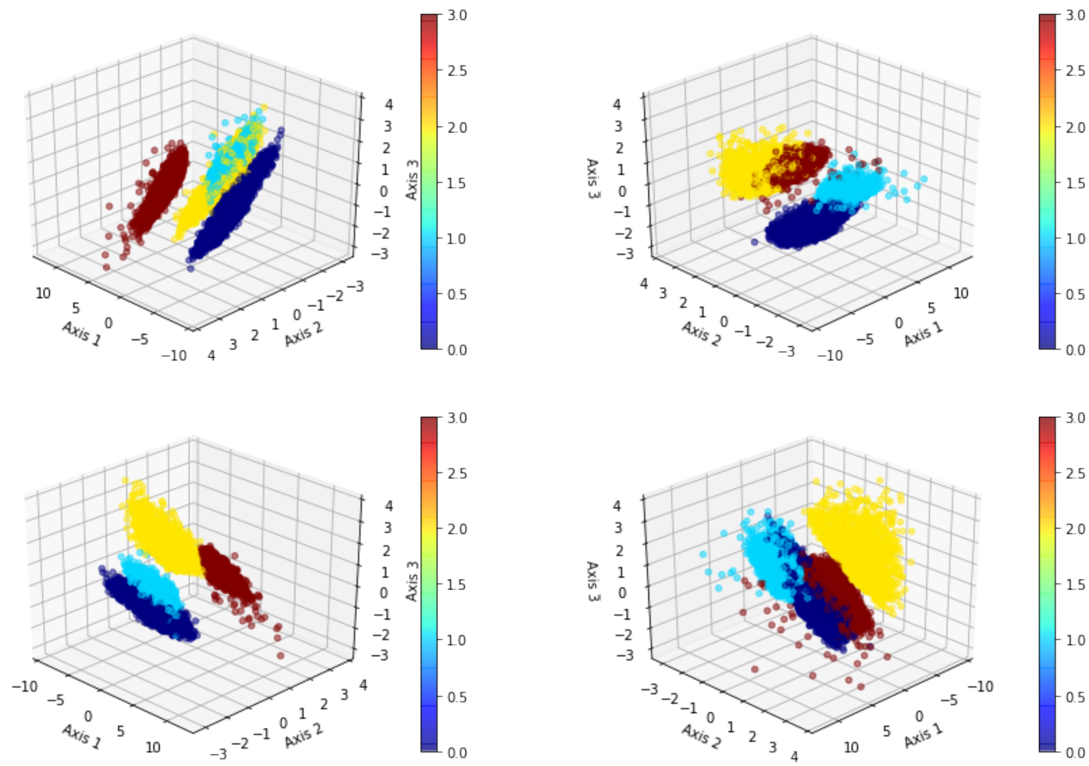



```
In [88]: plot_2d(pca_std_k3_2d, data_clus_k3, "cluster_label")
```

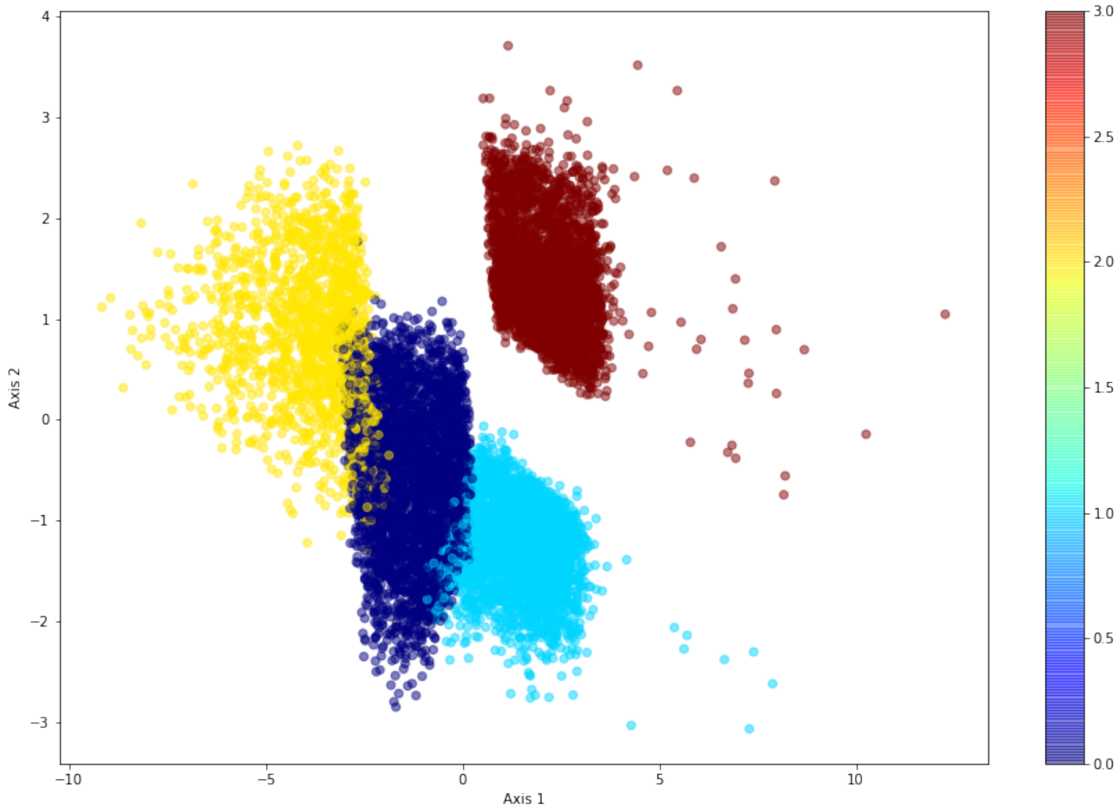


5.2.2 k = 4

```
In [86]: plot_3d(pca_std_k4, data_clus_k4, "cluster_label")
```



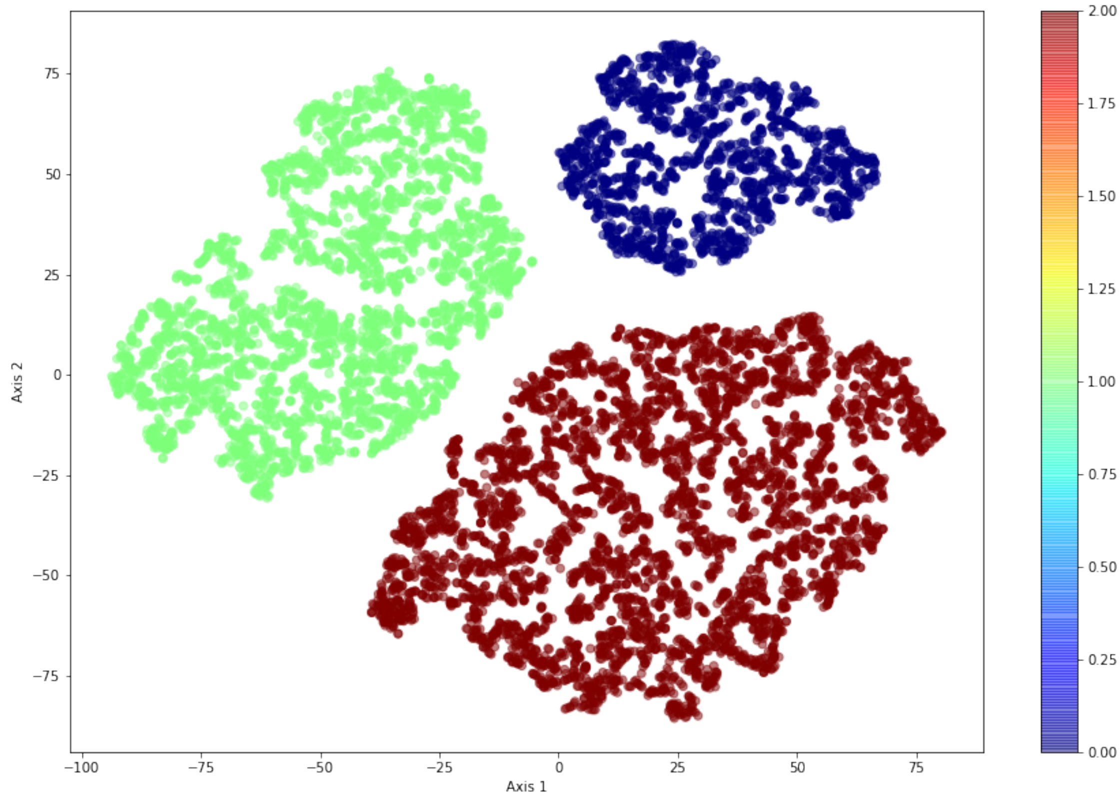

```
In [90]: plot_2d(pca_std_k4_2d, data_clus_k4, "cluster_label")
```



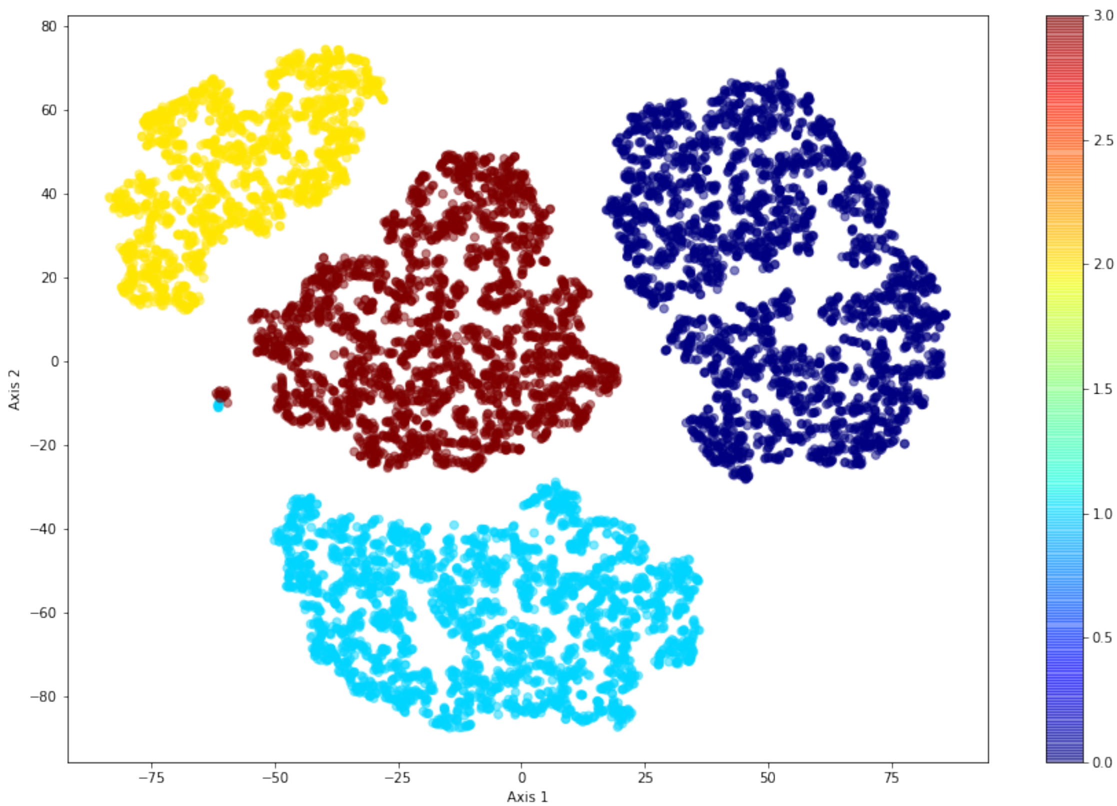
5.3 TSNE

In [91]:
```
tsne_2dim = TSNE(n_components=2, )
tsne_std_k3 = tsne_2dim.fit_transform(data_clus_k3)
tsne_std_k4 = tsne_2dim.fit_transform(data_clus_k4)
```

In [92]:
```
plot_2d(tsne_std_k3, data_clus_k3, "cluster_label")
```



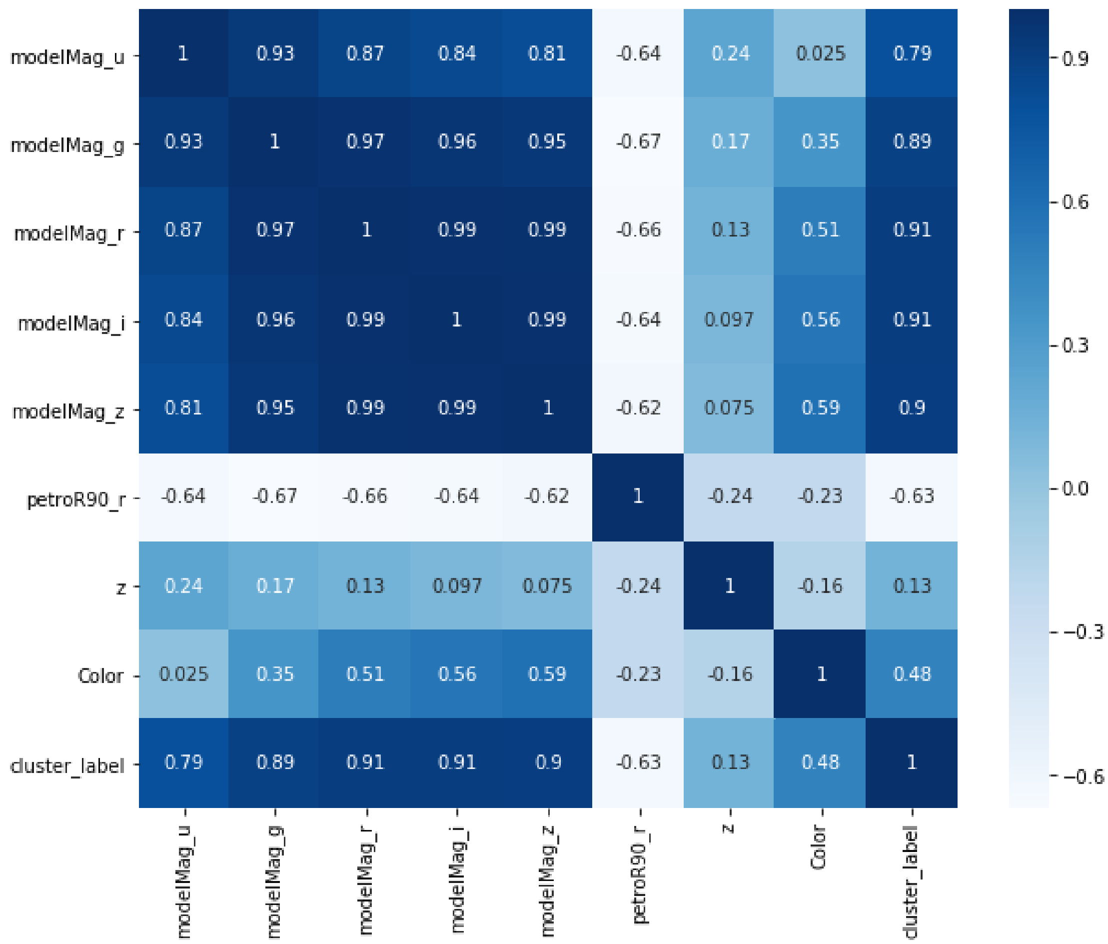

```
In [93]: plot_2d(tsne_std_k4, data_clus_k4, "cluster_label")
```



5.4 Correlación

```
In [95]: sns.heatmap(data_clus_k3.corr(), annot=True, cmap="Blues")
```

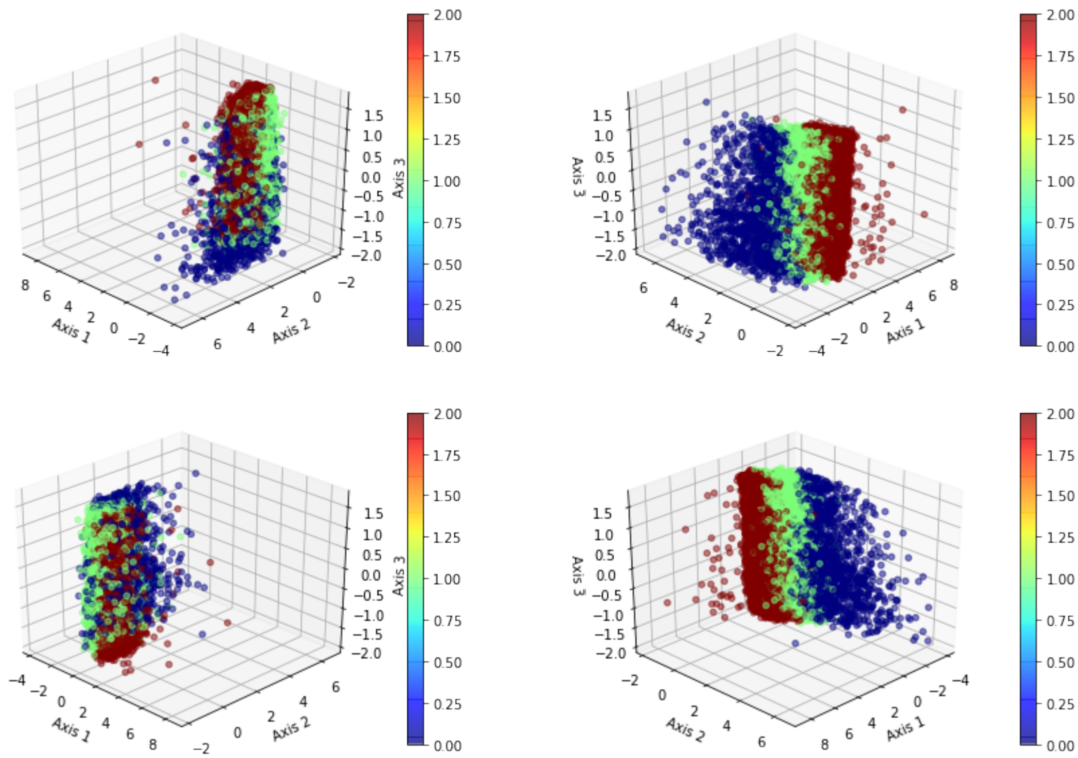
```
Out[95]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2082bdbe80>
```



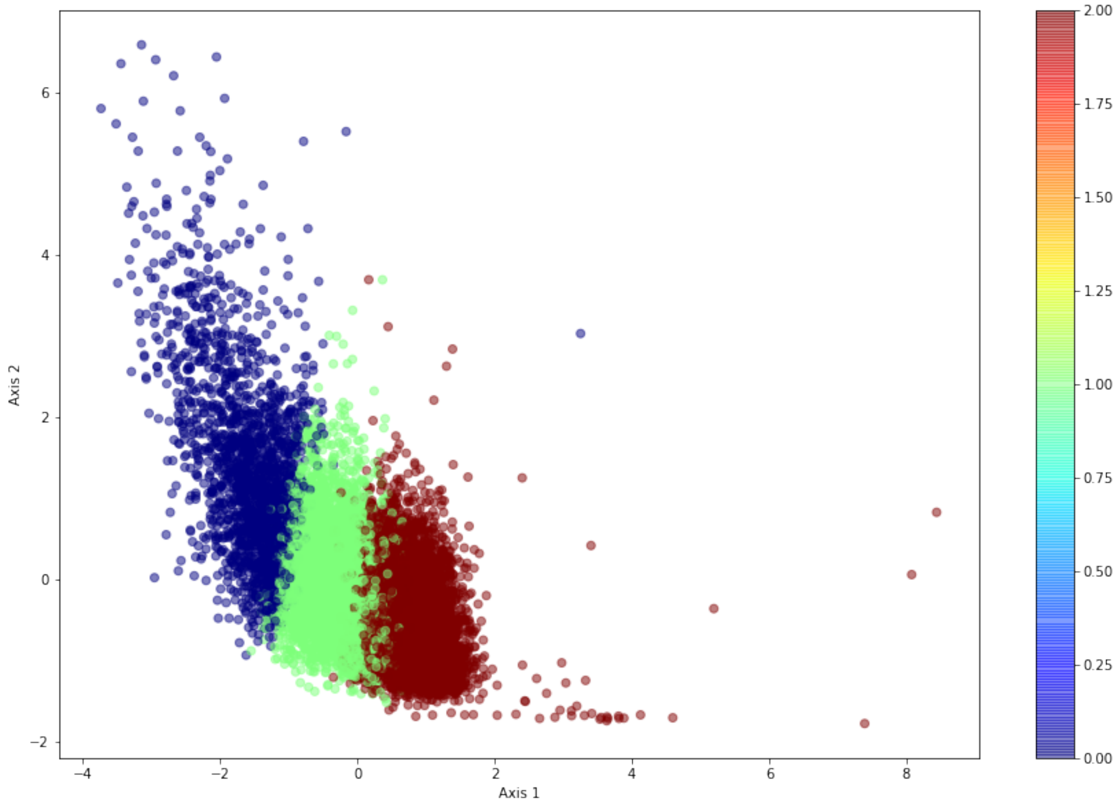
Vemos que los colores estan altamente correlacionados entre ellos, siendo **modelMag_g** el que parece tener más correlación con el resto. Ademas tiene buena correlacion con el label asignado por el cluster, por lo tanto esta es una de las features que vamos a utilziar para graficar.

Luego, las otras 2 columnas que vamos a utilizar son **petroR90_r** y **z**, ya uqe color sigue teniendo cierta correlacion con modelMag_g

```
In [96]: plot_3d(data_clus_k3[["modelMag_g", "petroR90_r", "z"]].values,
                 data_clus_k3, "cluster_label")
```

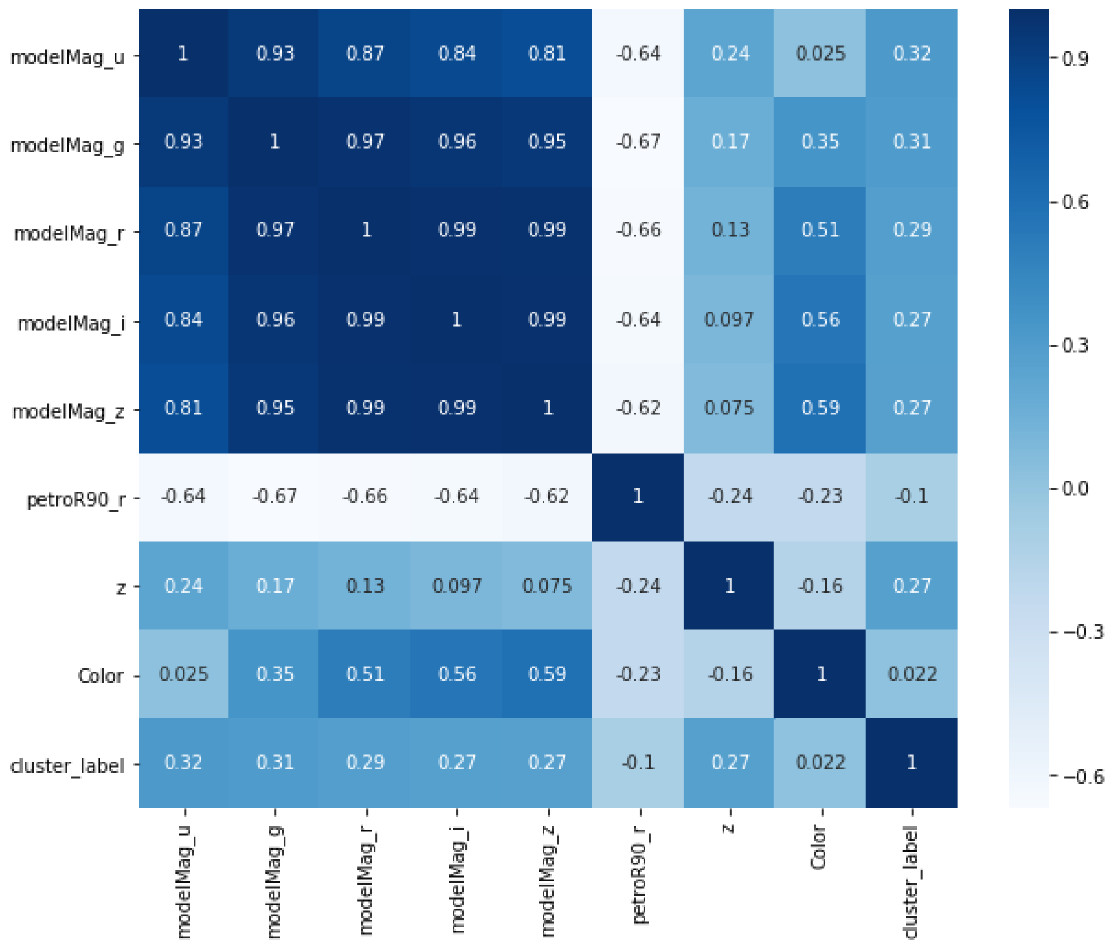



```
In [98]: plot_2d(data_clus_k3[["modelMag_g", "petroR90_r"]].values,
                 data_clus_k3, "cluster_label")
```



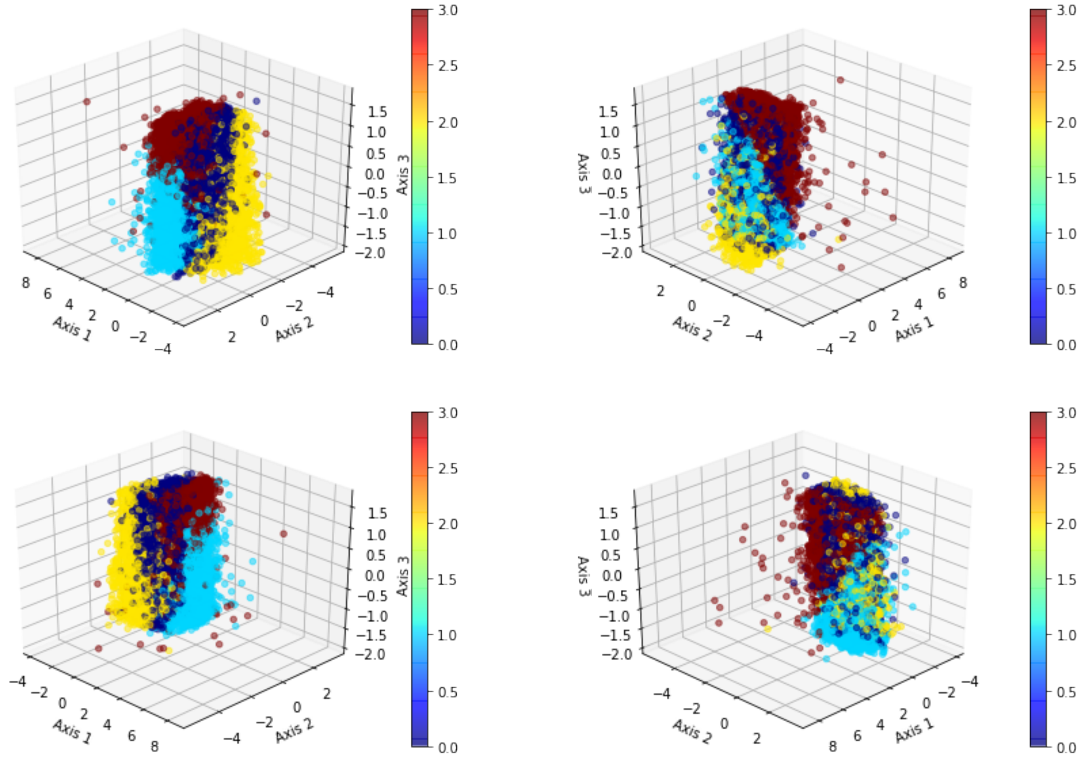

```
In [97]: sns.heatmap(data_clus_k4.corr(), annot=True, cmap="Blues")
```

```
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x7f209029fa58>
```

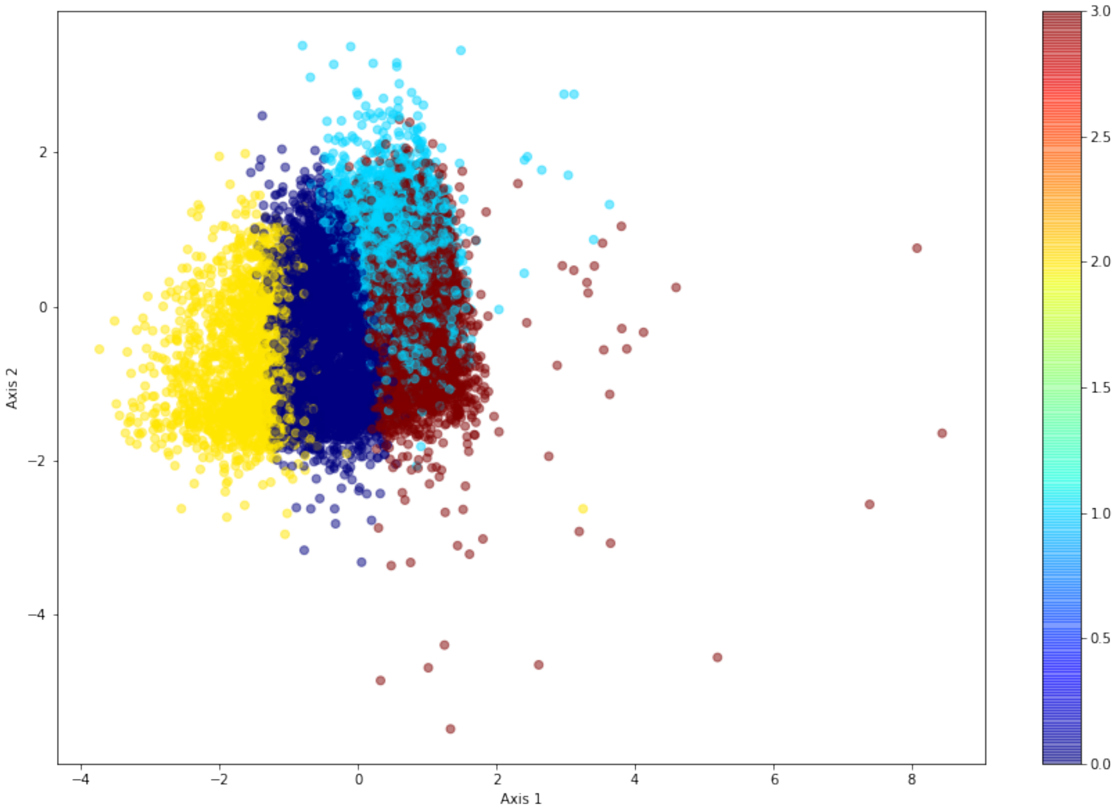


En este caso nos quedamos con las variables: * modelMag_g * z * Color

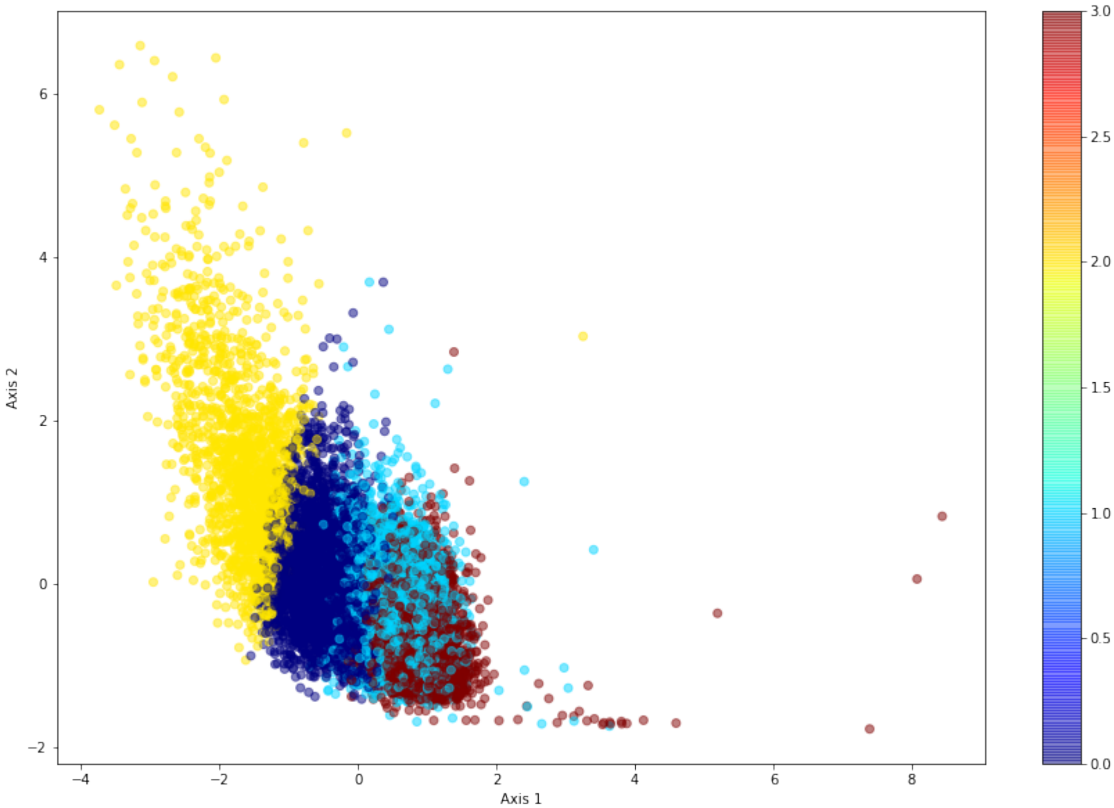
```
In [99]: plot_3d(data_clus_k4[["modelMag_g", "Color", "z"]].values,
                 data_clus_k4, "cluster_label")
```




```
In [100]: plot_2d(data_clus_k4[["modelMag_g", "Color"]].values,
                  data_clus_k4, "cluster_label")
```




```
In [102]: plot_2d(data_clus_k4[["modelMag_g", "petroR90_r"]].values,
              data_clus_k4, "cluster_label")
```




```
In [ ]:
```