DESARROLLO DE LABORATORIO 12 - ÍNDICES DEMOCRÁTICAS (Aplicación de Clusters)

In [1]:
```
#Importando librerías necesarias
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import os
from scipy.spatial.distance import pdist, squareform #Para hallar los pares de distancias y matriz
from scipy.cluster.hierarchy import linkage #Para utilizar los linkages
from scipy.cluster.hierarchy import dendrogram #Para el gráfico de dendograma
from sklearn.preprocessing import MinMaxScaler #Para escalamiento de datos - normalización
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import AgglomerativeClustering #Para métodos jerárquicos aglomerativos AGNES
from sklearn.metrics import silhouette_score #Para calcular métrica de silueta
from sklearn.metrics import calinski_harabasz_score #Para calcular métrica de CH
from sklearn.metrics import davies_bouldin_score #Para calcular métrica de DB
from sklearn.cluster import KMeans
#Just in Case
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Estableciendo directorio
os.chdir("D:\Social Data Consulting\Python for Data Science\data")
```

In [3]:
```
miArchivo='democracias_latam.sav'
df_democracia=pd.read_spss(miArchivo)
```

In [4]:
```
df_democracia.head()
```

Out[4]:

	tipoddem	pais	posicion	puntaj	ppelec	fdelgob	partpk	cultpk	libciv
0	Democracia plena	Costa Rica	25.0	8.04	9.58	8.21	6.11	6.88	9.41
1	Democracia plena	Uruguay	27.0	7.96	10.00	8.21	5.00	6.88	9.71
2	Democracia debil	Argentina	54.0	6.63	8.75	5.00	5.56	5.63	8.24
3	Democracia debil	Bolivia	81.0	5.98	8.33	5.71	4.44	3.75	7.65
4	Democracia debil	Brazil	42.0	7.38	9.58	7.86	4.44	5.63	9.41

In [5]:
```
df=df_democracia.iloc[:,4:]
```

In [6]:
```
df.head()
```

Out[6]:

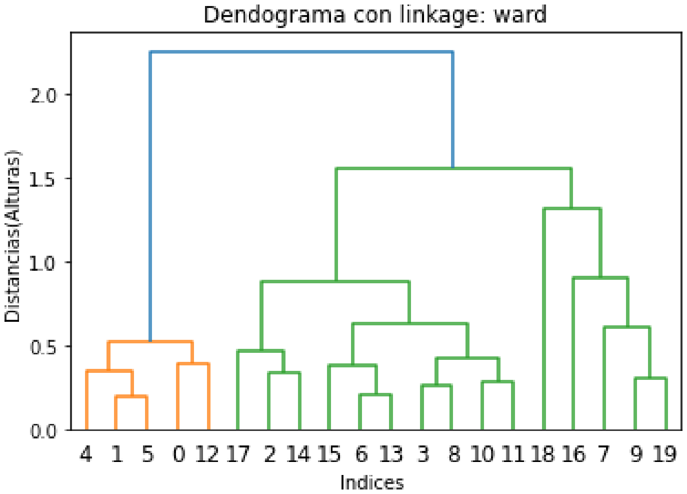
	ppelec	fdelgob	partpk	cultpk	libciv
0	9.58	8.21	6.11	6.88	9.41
1	10.00	8.21	5.00	6.88	9.71
2	8.75	5.00	5.56	5.63	8.24
3	8.33	5.71	4.44	3.75	7.65
4	9.58	7.86	4.44	5.63	9.41

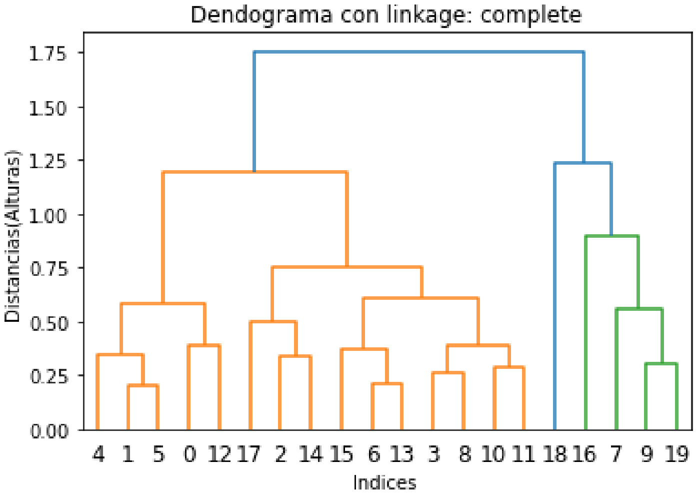
1.Número óptimo de clúster para cada una de las funciones de enlace.

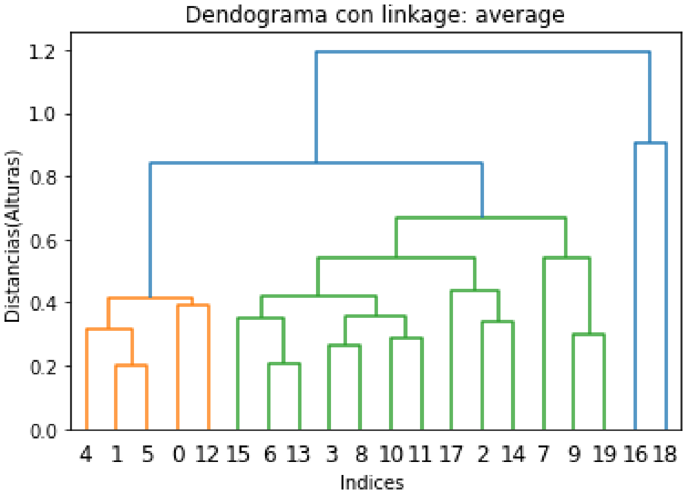
In [7]:
```
#Escalamiento de los datos
mms=MinMaxScaler()
x_mms=mms.fit_transform(df)
```

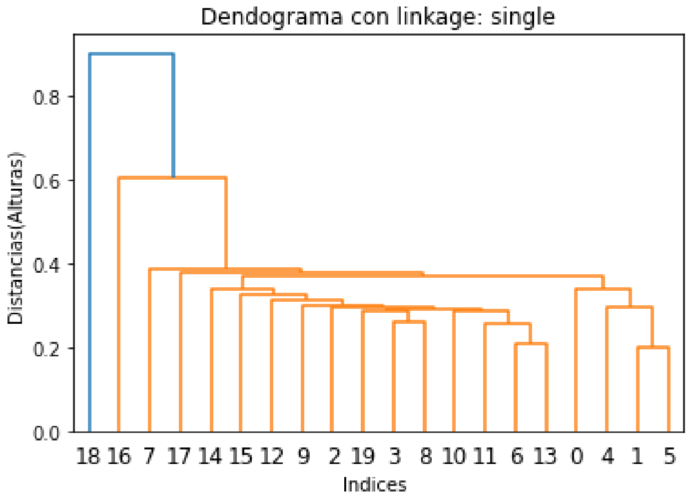
EVALUANDO NÚMERO OPTIMO DE CLUSTER POR CADA LINNKAGE CON DENDOGRAMA

In [8]:
```python
linkages=["ward","complete","average","single"]
clusters=[3,4,4,2]

for i in range(0,len(linkages)):
    clusters=linkage(x_mms,metric='euclidean',method=linkages[i])
    dendograma=dendrogram(clusters)
    plt.title('Dendograma con linkage: '+linkages[i])
    plt.xlabel('Indices ')
    plt.ylabel('Distancias(Alturas)')
    plt.show()
```



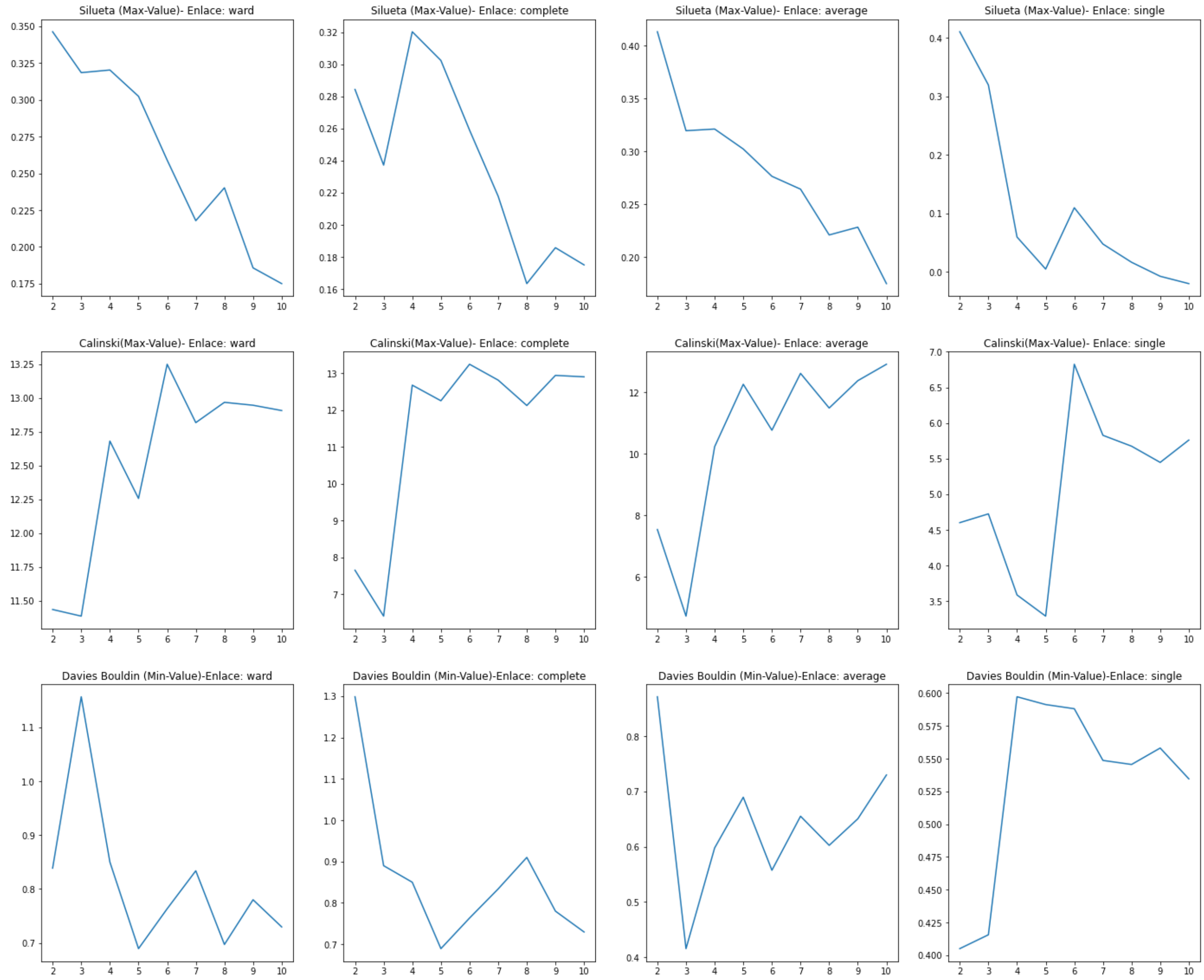






EVALUANDO NÚMERO OPTIMO DE CLUSTER POR CADA LINNKAGE CON OTROS CRITERIOS

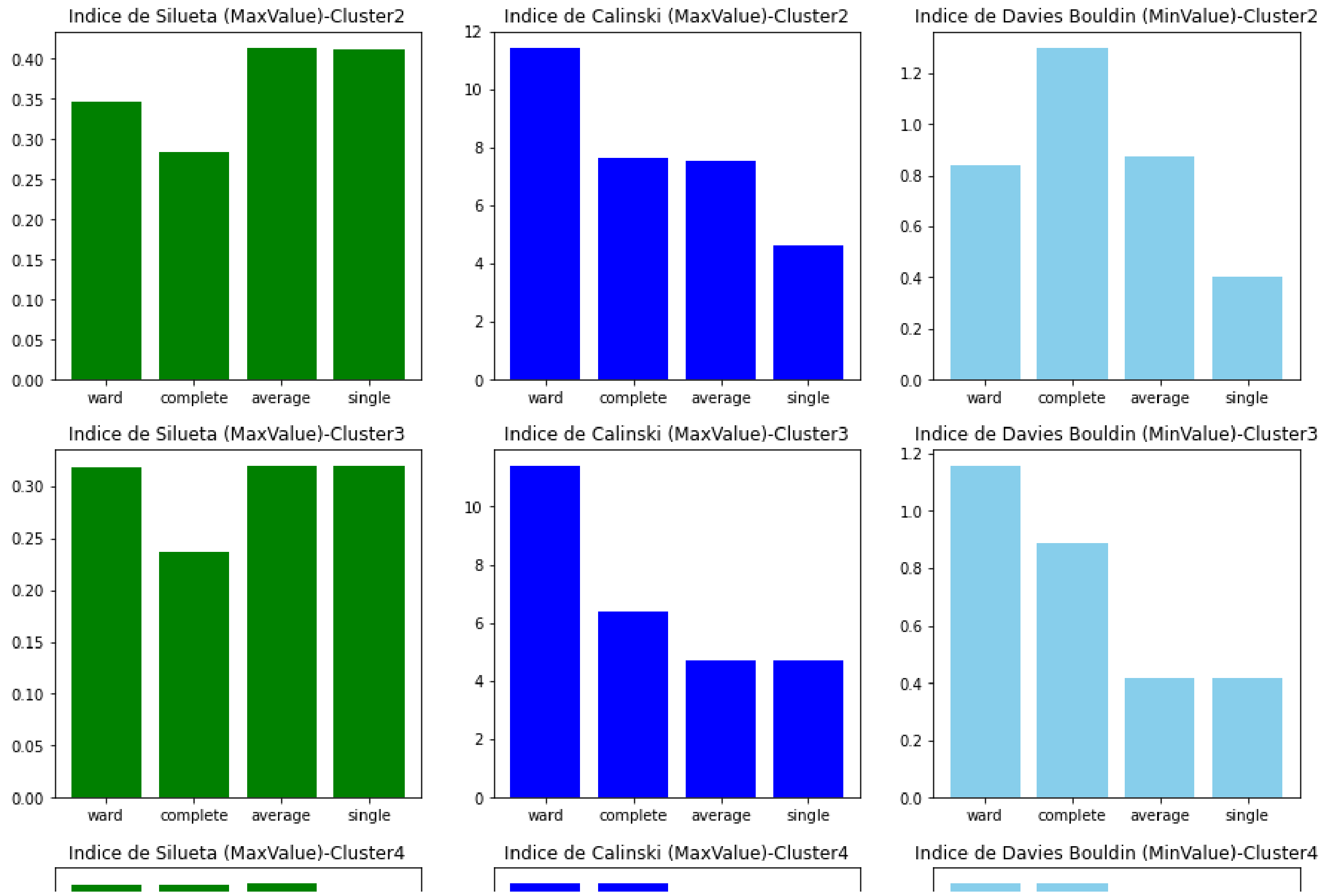
In [9]:
```
silueta=[]
calinski=[]
DB=[]
linkages=["ward","complete","average","single"]
fig, ax =plt.subplots(3,4)
fig.set_size_inches(24,20)
for a in range(len(linkages)):
    for i in range (2,11):
        hc=AgglomerativeClustering(n_clusters=i,affinity='euclidean',linkage=linkages[a])
        silueta.append(silhouette_score(x_mms,hc.fit_predict(x_mms)))
        calinski.append(calinski_harabasz_score(x_mms,hc.fit_predict(x_mms)))
        DB.append(davies_bouldin_score(x_mms,hc.fit_predict(x_mms)))

    ax[0][a].plot(range(2,11),silueta)
    ax[0][a].set_title("Silueta (Max-Value)- Enlace: "+ linkages[a])
    ax[1][a].plot(range(2,11),calinski)
    ax[1][a].set_title("Calinski(Max-Value)- Enlace: "+ linkages[a])
    ax[2][a].plot(range(2,11),DB)
    ax[2][a].set_title("Davies Bouldin (Min-Value)-Enlace: "+ linkages[a])
    silueta=[]
    calinski=[]
    DB=[]

plt.show()
```

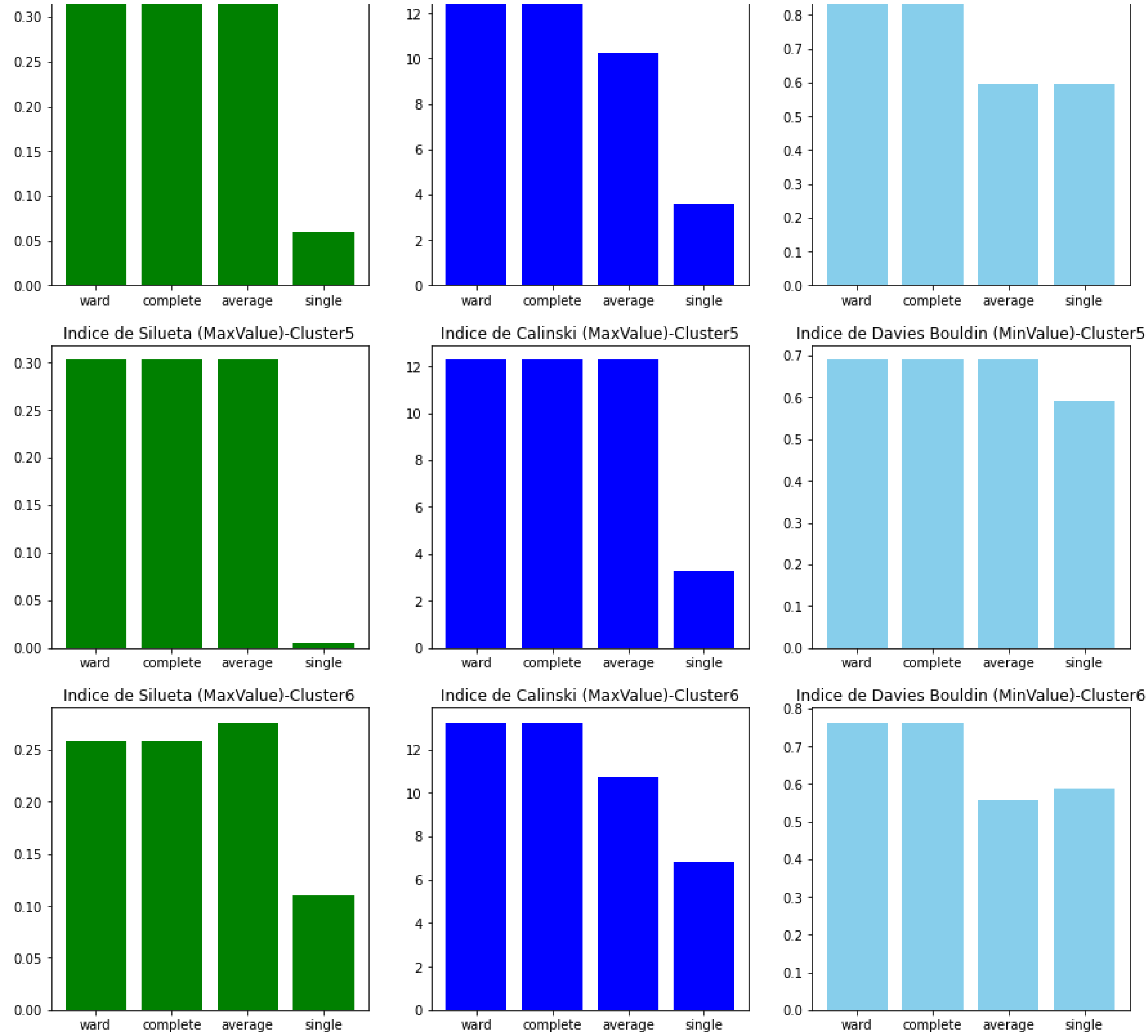


EVALUANDO LA VINCULACIÓN PARA K OPTIMO

In [10]:
```python
k_optimo=[2,3,4,5,6]
linkages=["ward","complete","average","single"]

fig, ax =plt.subplots(5,3)
fig.set_size_inches(15,25)
fig.suptitle("Gráficas para Vinculación Óptima")

silueta=[]
calinski=[]
DB=[]
for a in range(len(k_optimo)):
    for i in range(0,len(linkages)):
        hc=AgglomerativeClustering(n_clusters=k_optimo[a],affinity="euclidean",linkage=linkages[i]
        silueta.append(silhouette_score(x_mms,hc.fit_predict(x_mms)))
        calinski.append(calinski_harabasz_score(x_mms,hc.fit_predict(x_mms)))
        DB.append(davies_bouldin_score(x_mms,hc.fit_predict(x_mms)))

    #Acerca de gráficas
    ax[a][0].bar(linkages,silueta,color='green')
    ax[a][0].set_title("Indice de Silueta (MaxValue)-Cluster"+ str(k_optimo[a]))
    ax[a][1].bar(linkages,calinski,color='blue')
    ax[a][1].set_title("Indice de Calinski (MaxValue)-Cluster"+str(k_optimo[a]))
    ax[a][2].bar(linkages,DB,color='skyblue')
    ax[a][2].set_title("Indice de Davies Bouldin (MinValue)-Cluster"+str(k_optimo[a]))

    silueta=[]
    calinski=[]
    DB=[]

plt.show()
```

Gráficas para Vinculación Óptima





NUMERO DE CLUSTER ÓPTIMO PARA CADA LINKAGE ----- WARD: 3 --- COMPLETE: 4 --- AVERAGE: 4 --- SINGLE: 2

2.Data Frame donde se muestre la data incial y la etiqueta de clúster teniendo en cuenta como enlace "Ward", "average" y "complete". Considerar distancia coseno para "average" y "complete".

In [11]:
```
#Ward
agnes_ward=AgglomerativeClustering(n_clusters=3, affinity='euclidean',linkage='ward')
y_clust_ward=agnes_ward.fit_predict(x_mms)
y_clust_ward
```

Out[11]:
```
array([1, 1, 2, 2, 1, 1, 2, 0, 2, 0, 2, 2, 1, 2, 2, 2, 0, 2, 0, 0],
      dtype=int64)
```

In [12]:
```
#average
agnes_Avg=AgglomerativeClustering(n_clusters=4, affinity='cosine',linkage='average')
y_clust_average=agnes_Avg.fit_predict(x_mms)
y_clust_average
```

Out[12]:
```
array([0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 2, 1, 3, 0],
      dtype=int64)
```

In [13]:
```
#complete
agnes_complete=AgglomerativeClustering(n_clusters=4, affinity='cosine',linkage='complete')
y_clust_complete=agnes_complete.fit_predict(x_mms)
y_clust_complete
```

Out[13]:
```
array([0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 2, 1, 3, 0],
      dtype=int64)
```

In [14]:
```
df['Cluster_Ward']=y_clust_ward
df['Cluster_Complete']=y_clust_complete
df['Cluster_Average']=y_clust_average
df.head(20)
```

Out[14]:

	ppelec	fdelgob	partpk	cultpk	libciv	Cluster_Ward	Cluster_Complete	Cluster_Average
0	9.58	8.21	6.11	6.88	9.41	1	0	0
1	10.00	8.21	5.00	6.88	9.71	1	0	0
2	8.75	5.00	5.56	5.63	8.24	2	1	1
3	8.33	5.71	4.44	3.75	7.65	2	0	0
4	9.58	7.86	4.44	5.63	9.41	1	0	0
5	9.58	8.93	5.00	6.25	9.71	1	0	0
6	9.17	4.36	5.00	4.38	9.12	2	1	1
7	9.17	4.29	3.33	5.63	8.24	0	0	0
8	9.17	5.43	3.89	4.38	8.24	2	0	0
9	8.75	6.79	2.78	4.38	7.65	0	0	0
10	8.33	6.43	4.44	5.00	7.06	2	0	0
11	8.75	6.07	5.00	5.00	8.53	2	0	0
12	9.58	7.14	5.56	5.63	8.82	1	0	0
13	7.92	5.00	5.00	4.38	8.53	2	1	1
14	8.75	3.29	5.56	5.00	7.94	2	1	1
15	7.83	4.29	5.00	3.13	7.94	2	1	1
16	5.58	3.64	2.78	2.50	6.47	0	2	2
17	7.00	3.64	5.56	5.00	5.88	2	1	1
18	1.75	4.64	3.89	4.38	2.94	0	3	3
19	8.25	5.71	3.33	3.75	7.35	0	0	0

3.Realizando un análisis de componentes principales, visualizar las etiquetas predichas.

In [15]:
```
#Definimos nuestro dataframe a trabajar
df=df_democracia.iloc[:,4:]
```

In [16]:
```
#Instanciando un objeto de clase StandardScaler
sc=StandardScaler()
X_Std=sc.fit_transform(df)
```

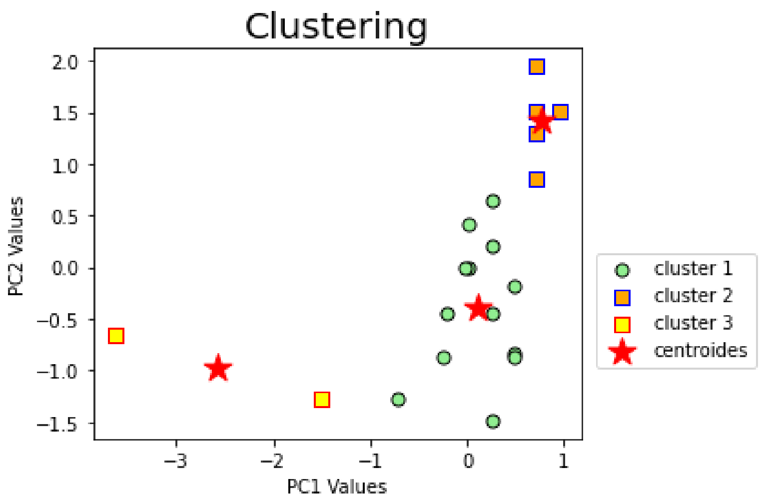
In [17]:
```
#Elijo 2 componentes
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca_data = pca.fit_transform(X_Std)
pca_data_df = pd.DataFrame(data = pca_data, columns = ['PC1 Values','PC2 Values'])
pca_data_df.head()
```

Out[17]:

	PC1 Values	PC2 Values
0	-2.840816	-1.021193
1	-2.673388	0.051207
2	-0.685006	-1.001818
3	0.611028	0.406915
4	-1.654792	0.714988

In [18]:
```
#Librerías a utilizar
import random

#Grafico_de_cluster
def Grafico_de_cluster(X,n_clusters,init,n_init,max_iter,semilla,tol,name_colors_c_list,name_color
    km = KMeans(n_clusters=n_clusters,
                init=init, #elija k observaciones (filas) para los centroides iniciales
                n_init=n_init, #número de veces que el algoritmo se ejecutará
                max_iter=max_iter,#número máximo de iteraciones para una ejecución
                tol=tol, #tolerancia para declarar convergencia
                random_state=semilla) #semilla
    y_km = km.fit_predict(X)
    for i in range(0,km.n_clusters):
            plt.scatter(X[y_km == i, 0], #primer clúster
                        X[y_km == i, 1],
                        s=50,
                        c=name_colors_c_list[i],#El color de los puntos
                        edgecolor=name_colors_edgecolor_list[i],#El punto de colors
                        marker=name_makers_list[random.randint(0,1)],#El tipo de representación
                        label='cluster '+str(i+1))
    plt.scatter(km.cluster_centers_[:, 0], km.cluster_centers_[:, 1],
                s=250, marker='*', c='red', label='centroides')
    plt.title('Clustering', fontsize=20)
    plt.xlabel('PC1 Values')
    plt.ylabel('PC2 Values')
    plt.legend(bbox_to_anchor=(1.01,0.5),loc=2)
    plt.tight_layout()
    plt.show()
```

In [19]:
```
#Defino el numero de cluster en un array
name_colors_c_list=['lightgreen','orange','yellow']#Defino el color de los puntos
name_colors_edgecolor_list=['black','blue','red']#Defino los puntos de color
name_makers_list=['s','o','v']#Defino el tipo de representación del punto
n_clusters=3 #Se define el numero de clusters
init='k-means++' #elija k observaciones (filas) para los centroides iniciales
n_init=10 #número de veces que el algoritmo se ejecutará
max_iter=300#número máximo de iteraciones para una ejecución
tol=1e-04 #tolerancia para declarar convergencia
semilla = 2020
Grafico_de_cluster(X_Std,n_clusters,init,n_init,max_iter,semilla,tol,name_colors_c_list,name_color
```



4.Teniendo en cuenta el enlace "ward" realizar un análisis clúster aglomerativo de k = 4 (k criterio de experto).

In [20]:
```
df.head()
```

Out[20]:

	ppelec	fdelgob	partpk	cultpk	libciv
0	9.58	8.21	6.11	6.88	9.41
1	10.00	8.21	5.00	6.88	9.71
2	8.75	5.00	5.56	5.63	8.24
3	8.33	5.71	4.44	3.75	7.65
4	9.58	7.86	4.44	5.63	9.41

In [21]:
```
#Instanciando un objeto de clase StandardScaler
X_mms=MinMaxScaler()
x_minMax=X_mms.fit_transform(df)
```

In [22]:
```
x_minMax
```

Out[22]:
```
array([[0.94909091, 0.87234043, 1.        , 1.        , 0.95568685],
       [1.        , 0.87234043, 0.66666667, 1.        , 1.        ],
       [0.84848485, 0.30319149, 0.83483483, 0.71461187, 0.78286558],
       [0.79757576, 0.42907801, 0.4984985 , 0.28538813, 0.6957164 ],
       [0.94909091, 0.81028369, 0.4984985 , 0.71461187, 0.95568685],
       [0.94909091, 1.        , 0.66666667, 0.85616438, 1.        ],
       [0.89939394, 0.18971631, 0.66666667, 0.42922374, 0.91285081],
       [0.89939394, 0.17730496, 0.16516517, 0.71461187, 0.78286558],
       [0.89939394, 0.37943262, 0.33333333, 0.42922374, 0.78286558],
       [0.84848485, 0.62056738, 0.        , 0.42922374, 0.6957164 ],
       [0.79757576, 0.55673759, 0.4984985 , 0.57077626, 0.60856721],
       [0.84848485, 0.4929078 , 0.66666667, 0.57077626, 0.82570162],
       [0.94909091, 0.68262411, 0.83483483, 0.71461187, 0.86853767],
       [0.74787879, 0.30319149, 0.66666667, 0.42922374, 0.82570162],
       [0.84848485, 0.        , 0.83483483, 0.57077626, 0.73855244],
       [0.7369697 , 0.17730496, 0.66666667, 0.14383562, 0.73855244],
       [0.46424242, 0.06205674, 0.        , 0.        , 0.52141802],
       [0.63636364, 0.06205674, 0.83483483, 0.57077626, 0.43426883],
       [0.        , 0.2393617 , 0.33333333, 0.42922374, 0.        ],
       [0.78787879, 0.42907801, 0.16516517, 0.28538813, 0.65140325]])
```

In [23]:
```
#Ward
agnes=AgglomerativeClustering(n_clusters=4, affinity='euclidean',linkage='ward')
y_clust_w=agnes.fit_predict(x_minMax)
y_clust_w
```

Out[23]:
```
array([1, 1, 2, 2, 1, 1, 2, 0, 2, 0, 2, 2, 1, 2, 2, 2, 0, 2, 3, 0],
      dtype=int64)
```

In [24]:
```
df['Cluster']=y_clust_w
df.head()
```

Out[24]:

	ppelec	fdelgob	partpk	cultpk	libciv	Cluster
0	9.58	8.21	6.11	6.88	9.41	1
1	10.00	8.21	5.00	6.88	9.71	1
2	8.75	5.00	5.56	5.63	8.24	2
3	8.33	5.71	4.44	3.75	7.65	2
4	9.58	7.86	4.44	5.63	9.41	1

In [25]:
```
#Graficando los clusters
plt.scatter(x_minMax[:,2], #valores eje X
            x_minMax[:,3], #valores eje Y
            c=y_clust_w,
            s=20)
plt.title('Grafico de Clusters')
plt.show()
```