DESARROLLO LABORATORIO 11

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import scipy.stats as stats #Para calculo de p-values, prob estadisticas
from sklearn.model_selection import train_test_split # Para particionamiento de datos
from sklearn.preprocessing import StandardScaler #Para estandarizacion
from sklearn.preprocessing import MinMaxScaler #Para normalizacion
from sklearn.metrics import euclidean_distances, silhouette_score #Para obtener valores de silueta
from sklearn.cluster import KMeans #Para utilizar el método KMeans
from sklearn.decomposition import PCA #para el analisis componentes principales
```

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

Obteniendo la data

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

Out[3]:

	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 [4]:
```
df_democracia.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   tipoddem  20 non-null     category
 1   pais      20 non-null     object
 2   posicion  20 non-null     float64
 3   puntaj    20 non-null     float64
 4   ppelec    20 non-null     float64
 5   fdelgob   20 non-null     float64
 6   partpk    20 non-null     float64
 7   cultpk    20 non-null     float64
 8   libciv    20 non-null     float64
dtypes: category(1), float64(7), object(1)
memory usage: 1.6+ KB
```

In [5]:
```
df=df_democracia.iloc[:,2:]
df.head()
```

Out[5]:

	posicion	puntaj	ppelec	fdelgob	partpk	cultpk	libciv
0	25.0	8.04	9.58	8.21	6.11	6.88	9.41
1	27.0	7.96	10.00	8.21	5.00	6.88	9.71
2	54.0	6.63	8.75	5.00	5.56	5.63	8.24
3	81.0	5.98	8.33	5.71	4.44	3.75	7.65
4	42.0	7.38	9.58	7.86	4.44	5.63	9.41

1.Número óptimo de clúster según método del codo y silueta aplicando kmeans.

In [6]:
```
#Instanciando un objeto de clase StandardScaler
sc=StandardScaler()
X_Std=sc.fit_transform(df)
```

In [7]:
```
X_Std[0:10]
```

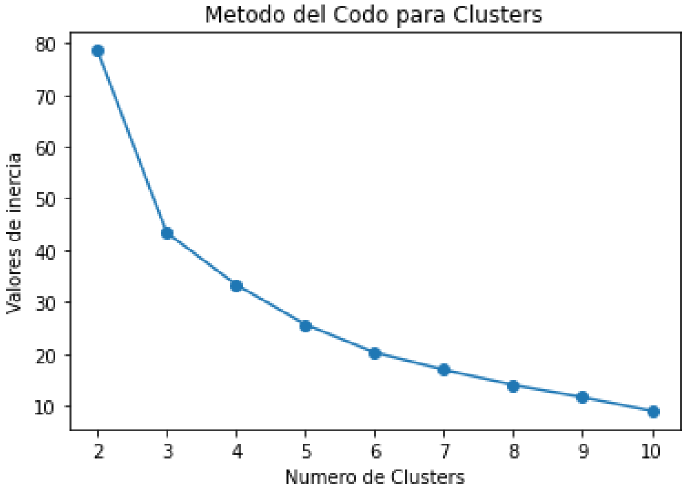
Out[7]:
```
array([[-1.66945207,  1.57474365,  0.71565194,  1.51011233,  1.61551782,
         1.80093364,  0.963626  ],
       [-1.59234112,  1.50298091,  0.94883566,  1.51011233,  0.44078819,
         1.80093364,  1.16055229],
       [-0.55134329,  0.30992534,  0.25483649, -0.44608645,  1.03344458,
         0.67647457,  0.19561345],
       [ 0.48965453, -0.27314693,  0.02165277, -0.01340697, -0.1518682 ,
        -1.01471186, -0.19167493],
       [-1.01400899,  0.98270103,  0.71565194,  1.29681962, -0.1518682 ,
         0.67647457,  0.963626  ],
       [-1.47667469,  1.44018851,  0.71565194,  1.94888588,  0.44078819,
         1.23420627,  1.16055229],
       [-0.05012212,  0.10360746,  0.48802021, -0.83610739,  0.44078819,
        -0.44798449,  0.77326391],
       [ 0.21976621, -0.13859179,  0.48802021, -0.87876593, -1.32659783,
         0.67647457,  0.19561345],
       [ 0.06554431, -0.05785871,  0.48802021, -0.18404113, -0.73394144,
        -0.44798449,  0.19561345],
       [ 0.33543263, -0.19241385,  0.25483649,  0.64475337, -1.90867107,
        -0.44798449, -0.19167493]])
```

KMEANS

Usando el metodo del codo para numero optimo de clusters

In [8]:
```
inercia=[]
for i in range(2,11):
    km=KMeans(n_clusters=i,
              init='k-means++',
              n_init=10,
              tol=0.0004,
              random_state=2020)
    km.fit(X_Std)
    inercia.append(km.inertia_)
```

In [9]:
```
plt.plot(range(2,11),inercia,marker='o')
plt.title('Metodo del Codo para Clusters')
plt.xlabel('Numero de Clusters')
plt.ylabel('Valores de inercia')
plt.show()
```

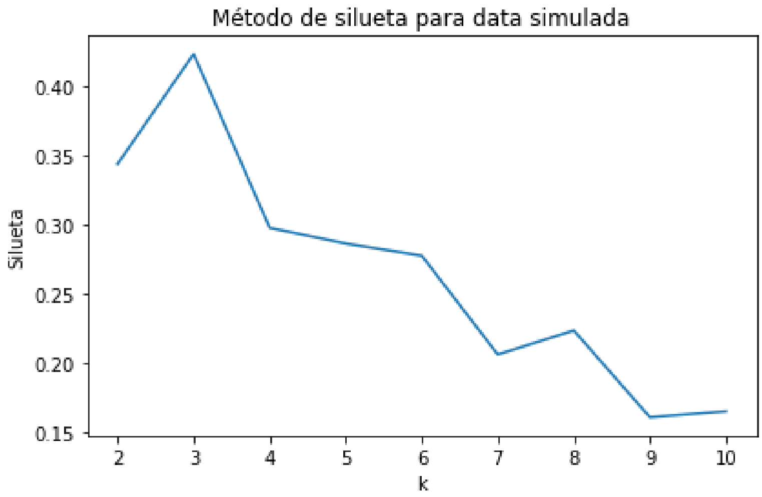



```
Obtenemos que el numero 3 es el numero de clusters optimo segun el metodo del codo
```

Usando el metodo de siluetas para numero optimo de clusters

In [10]:
```
silueta = [] #crear un objeto vacío tipo lista
for i in range(2,11):
    kmeans = KMeans(n_clusters = i,
                    init = 'k-means++',
                    max_iter = 300,
                    n_init = 10,
                    random_state = 2020)
    silueta.append(silhouette_score(X_Std, #datos
                                    kmeans.fit_predict(X_Std))) #etiquetas para cada observación
```

In [11]:
```
plt.plot(range(2, 11),
         silueta)
plt.ylabel("Silueta")
plt.xlabel("k")
plt.title("Método de silueta para data simulada")
plt.tight_layout()
plt.show()
```

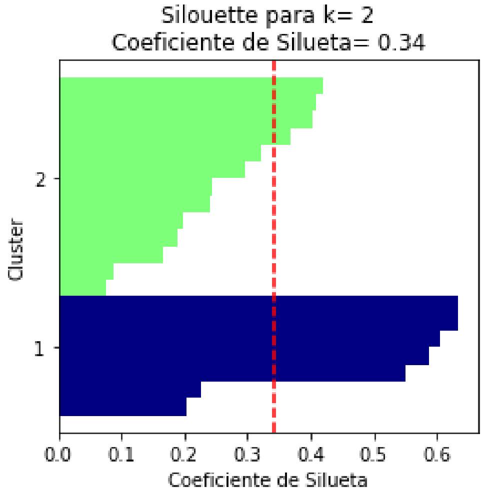


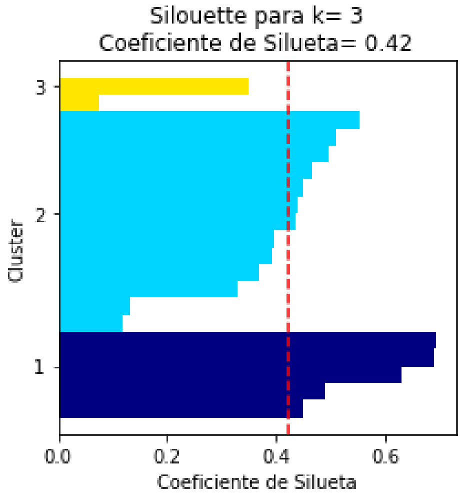
Segun metodo de siluetas el numero de clusters optimos a usar son 3

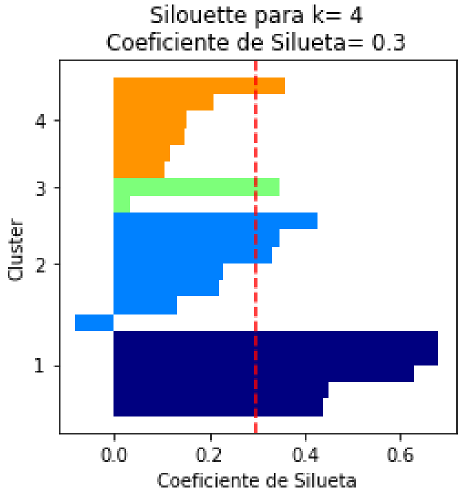
```
Gráfico de Silueta
```

In [12]:
```
import numpy as np
from matplotlib import cm
from sklearn.metrics import silhouette_samples
import matplotlib.pyplot as plt
import warnings

warnings.filterwarnings('ignore')

plt.rcParams['figure.figsize'] = (14, 4)

def Grafico_de_silueta(X,n_cluster_list,init,n_init,max_iter,tol,semilla):
    cont=0
    for i in n_cluster_list:
        cont += 1
        plt.subplot(1, 4, cont)
        km = KMeans(n_clusters=i,
                    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)
        cluster_labels = np.unique(y_km) #valores de clúster
        n_clusters = cluster_labels.shape[0] #núnero de clústers
        silhouette_vals = silhouette_samples(X, y_km, metric='euclidean') #valores de silueta teni

        y_ax_lower, y_ax_upper = 0, 0
        yticks = [] #objeto tipo lista vacío
        for i, c in enumerate(cluster_labels):
            c_silhouette_vals = silhouette_vals[y_km == c] #valores de silueta cuando y_km toma el
            c_silhouette_vals.sort() #se ordenan de menor a mayor los valores de silueta
            y_ax_upper += len(c_silhouette_vals) #número de valores de silueta
            color = cm.jet(float(i) / km.n_clusters) # definir el color
            plt.barh(range(y_ax_lower, y_ax_upper), c_silhouette_vals, height=1.0,
                     edgecolor='none', color=color) #visualización de los valores de silueta para
            yticks.append((y_ax_lower + y_ax_upper) / 2.)
            y_ax_lower += len(c_silhouette_vals)
        silhouette_avg = np.mean(silhouette_vals)#media de los valores de silueta
        plt.axvline(silhouette_avg, color="red", linestyle="--") # mostrar una línea con los valor
        plt.yticks(yticks, cluster_labels + 1)
        plt.ylabel('Cluster')
        plt.xlabel('Coeficiente de Silueta')
        plt.title("Silouette para k= " + str(km.n_clusters) + "\n" + "Coeficiente de Silueta= "+st
        plt.tight_layout()
        plt.show()
```

```
In [13]: #Defino el numero de cluster en un array
n_cluster_list=[2,3,4]
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_silueta(X_Std,n_cluster_list,init,n_init,max_iter,tol,semilla)
```







El coeficiente de silueta es mayor cuando k=3

2.Data Frame donde se muestre la data incial y la etiqueta de clúster kmeans

In [15]:
```
#Creamos una instancia de K-Means
km=KMeans(n_clusters=3,# numero de clusters
          init='k-means++', #centroides iniciales
          n_init=10, #numero de veces que se ejecutará el algoritmo
          tol=0.0004,#tolerancia para declarar la convergencia
          random_state=2020)#semilla
```

In [16]:
```
#Obteniendo las etiquetas de clusters
y_km=km.fit_predict(X_Std)
y_km
```

Out[16]:
```
array([0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 2, 1, 2, 1])
```

In [17]:
```
df_democracia['cluster']=y_km
```

In [18]:
```
df_democracia.head()
```

Out[18]:

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

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

In [19]:
```
cov_mat = np.cov(df.T)
```

In [20]:
```
eigen_vals, eigen_vecs = np.linalg.eig(cov_mat)
```

In [21]:
```
print('\nEigenvalues \n%s' % eigen_vals)
```

```

Eigenvalues
[7.16360872e+02 2.08595367e+00 1.24738553e+00 3.49827463e-01
 2.49689736e-01 6.30611124e-02 4.56513700e-06]
```

In [22]:
```
(eigen_vals>1).sum() #CRITERIO DE KEISER , valor obtenido = 3
```

Out[22]:
```
3
```

In [23]:
```
pca = PCA() #función PCA() la guardamos en el objeto pca
df_pca = pca.fit_transform(df)
#fit_transform
pca.explained_variance_ratio_
```

Out[23]:
```
array([9.94452857e-01, 2.89572290e-03, 1.73162181e-03, 4.85630823e-04,
       3.46619534e-04, 8.75414973e-05, 6.33732761e-09])
```

PCA

In [24]:
```
pca=PCA(n_components=3)
x3comp=pca.fit_transform(X_Std)
print(x3comp)
```

```
[[-3.64980323 -1.0459456   0.62098365]
 [-3.4605844   0.02665836  0.80917447]
 [-0.90456118 -1.00955    -0.49184929]
 [ 0.81276625  0.41620338 -0.32732093]
 [-2.18315486  0.70104232  0.55119876]
 [-3.23620064  0.2395192   0.96268794]
 [-0.22541715  0.01838136 -1.35365289]
 [ 0.27527053  0.85478459 -0.18717334]
 [ 0.19555624  0.91920759 -0.34981498]
 [ 0.62712097  1.84035651  0.78254867]
 [ 0.10024913  0.00622807  0.57728124]
 [-0.88212933 -0.14322429 -0.17530993]
 [-2.12903053 -0.45581414  0.03906855]
 [ 0.22530902 -0.24484069 -0.67022931]
 [ 0.29413542 -1.09950572 -1.37031569]
 [ 1.51353156 -0.08559126 -1.27707018]
 [ 4.15904403  1.18237874 -0.16677905]
 [ 1.70947429 -1.78646006 -0.35209168]
 [ 5.30481247 -1.6108831   2.26582604]
 [ 1.45361139  1.27705476  0.11283796]]
```

In [25]:
```
df_x=pd.DataFrame(x3comp,columns=['PC1','PC2','PC3'])
df_x['Cluster']=y_km
df_x.head(10)
```

Out[25]:

	PC1	PC2	PC3	Cluster
0	-3.649803	-1.045946	0.620984	0
1	-3.460584	0.026658	0.809174	0
2	-0.904561	-1.009550	-0.491849	1
3	0.812766	0.416203	-0.327321	1
4	-2.183155	0.701042	0.551199	0
5	-3.236201	0.239519	0.962688	0
6	-0.225417	0.018381	-1.353653	1
7	0.275271	0.854785	-0.187173	1
8	0.195556	0.919208	-0.349815	1
9	0.627121	1.840357	0.782549	1

4.Teniendo en cuenta el método de k-means realizar un análisis clúster de k = 4 (k criterio de experto) y agregar la etiqueta a la data inicial.

In [26]:
```
#Creamos una instancia de K-Means
km=KMeans(n_clusters=4,# numero de clusters
          init='k-means++', #centroides iniciales
          n_init=10, #numero de veces que se ejecutará el algoritmo
          tol=0.0004,#tolerancia para declarar la convergencia
          random_state=2020)#semilla
```

In [27]:
```
#Obteniendo las etiquetas de clusters
y_km=km.fit_predict(X_Std)
y_km
```

Out[27]:
```
array([0, 0, 3, 1, 0, 0, 3, 1, 1, 1, 1, 1, 0, 3, 3, 3, 2, 3, 2, 1])
```

In [28]:
```
df_democracia['Cluster-4']=y_km
```

In [29]:
```
df_democracia.head()
```

Out[29]:

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

5.Perfilamiento del modelo k-means según el óptimo de clúster.

In [31]:
```
#Creamos una instancia de K-Means
km=KMeans(n_clusters=3,# numero de clusters (NÚMERO OPTIMO DE CLUSTERS)
         init='k-means++', #centroides iniciales
         n_init=10, #numero de veces que se ejecutará el algoritmo
         tol=0.0004,#tolerancia para declarar la convergencia
         random_state=2020)#semilla
```

In [32]:
```
#Obteniendo las etiquetas de clusters
y_km=km.fit_predict(X_Std)
y_km
```

Out[32]:
```
array([0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 2, 1, 2, 1])
```

In [33]:
```
y_kmeans=pd.DataFrame(y_km,columns=['cluster_label'])
y_kmeans.head()
```

Out[33]:

	cluster_label
0	0
1	0
2	1
3	1
4	0

In [34]:
```
x_df=pd.DataFrame(df,columns=df.columns)
x_df
```

Out[34]:

	posicion	puntaj	ppelec	fdelgob	partpk	cultpk	libciv
0	25.0	8.04	9.58	8.21	6.11	6.88	9.41
1	27.0	7.96	10.00	8.21	5.00	6.88	9.71
2	54.0	6.63	8.75	5.00	5.56	5.63	8.24
3	81.0	5.98	8.33	5.71	4.44	3.75	7.65
4	42.0	7.38	9.58	7.86	4.44	5.63	9.41
5	30.0	7.89	9.58	8.93	5.00	6.25	9.71
6	67.0	6.40	9.17	4.36	5.00	4.38	9.12
7	74.0	6.13	9.17	4.29	3.33	5.63	8.24
8	70.0	6.22	9.17	5.43	3.89	4.38	8.24
9	77.0	6.07	8.75	6.79	2.78	4.38	7.65
10	69.0	6.25	8.33	6.43	4.44	5.00	7.06
11	53.0	6.67	8.75	6.07	5.00	5.00	8.53
12	44.0	7.35	9.58	7.14	5.56	5.63	8.82
13	71.0	6.16	7.92	5.00	5.00	4.38	8.53
14	75.0	6.11	8.75	3.29	5.56	5.00	7.94
15	92.0	5.64	7.83	4.29	5.00	3.13	7.94
16	109.0	4.19	5.58	3.64	2.78	2.50	6.47
17	93.0	5.42	7.00	3.64	5.56	5.00	5.88
18	124.0	3.52	1.75	4.64	3.89	4.38	2.94
19	89.0	5.68	8.25	5.71	3.33	3.75	7.35

In [35]:
```
datafinal=pd.concat([x_df,y_kmeans],axis=1)
datafinal.head()
```

Out[35]:

	posicion	puntaj	ppelec	fdelgob	partpk	cultpk	libciv	cluster_label
0	25.0	8.04	9.58	8.21	6.11	6.88	9.41	0
1	27.0	7.96	10.00	8.21	5.00	6.88	9.71	0
2	54.0	6.63	8.75	5.00	5.56	5.63	8.24	1
3	81.0	5.98	8.33	5.71	4.44	3.75	7.65	1
4	42.0	7.38	9.58	7.86	4.44	5.63	9.41	0

In [36]:
```
#Trabajando la media por clusters
cluster_means=datafinal.groupby(['cluster_label']).mean().round(1)
cluster_means
```

Out[36]:

	posicion	puntaj	ppelec	fdelgob	partpk	cultpk	libciv
cluster_label							
0	33.6	7.7	9.7	8.1	5.2	6.3	9.4
1	74.2	6.1	8.5	5.1	4.5	4.6	7.9
2	116.5	3.9	3.7	4.1	3.3	3.4	4.7