Maestría en Inteligencia Artificial Aplicada

Curso: Ciencia y Analitica de Datos

Tecnológico de Monterrey

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Equipo 170

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Reto - Entrega 1 - Limpieza, Analisis, Visualizaicon, Kmeans

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Enlace:

https://colab.research.google.com/drive/1Zac4x8CIagW34sWa1_TFJMv2LGlovfYh#scrollTo=ziy5VnXFxiqV

```
# Incluye aquí todos módulos, librerías y paquetes que requieras.

# Descargar Data Set
# ===============================
import requests, zipfile
from io import BytesIO

# Tratamiento de datos
# ===============================
import numpy as np
import pandas as pd

# Graficos
# ===============================
import seaborn as sns
import matplotlib.pyplot as plt

# Preprocesado y modelado
```

```
# ==============================
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder, StandardScaler
from sklearn.dummy import DummyRegressor
from sklearn.model_selection import RepeatedKFold
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer
from tabulate import tabulate
from sklearn.model_selection import GridSearchCV
from sklearn.inspection import permutation_importance
from sklearn.preprocessing import LabelEncoder

# Geopandas
# ==============================
! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes

import geopandas as gpd
from shapely.geometry import Point


# Kmeans
# ==============================
from sklearn.cluster import KMeans


# Mapa
# ==============================
import folium
```

```
Requirement already satisfied: folium in /usr/local/lib/python3.7/dist-packages (0.12
Requirement already satisfied: pyLDAvis in /usr/local/lib/python3.7/dist-packages (3.
Requirement already satisfied: descartes in /usr/local/lib/python3.7/dist-packages (1
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Requirement already satisfied: branca>=0.3.0 in /usr/local/lib/python3.7/dist-package
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Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/
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Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/python3.7
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.7/dist-packages
```

Eleccion de una base de datos

```
# Extraccion de la carpeta comprimida
url = "http://201.116.60.46/Datos_de_calidad_del_agua_de_5000_sitios_de_monitoreo.zip"
req = requests.get(url)
zipfile.ZipFile(BytesIO(req.content)).extractall()

# Lectura del csv como dataframe
path = "Datos_de_calidad_del_agua_2020/Datos_de_calidad_del_agua_de_sitios_de_monitoreo_de_ag
df=pd.read_csv(path, encoding="latin1")
```

```
# Datos de la calidad de aguas superficiales
df.head()
```

	CLAVE	SITIO	ORGANISMO_DE_CUENCA	ESTADO	MUNICIPIO
0	DLAGU6	POZO SAN GIL	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	ASIENTOS
1	DLAGU6516	POZO R013 CAÑADA HONDA	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	AGUASCALIENTES
2	DLAGU7	POZO COSIO	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	COSIO
3	DLAGU9	POZO EL SALITRILLO	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	RINCON DE ROMOS
4	DLBAJ107	RANCHO EL TECOLOTE	PENINSULA DE BAJA CALIFORNIA	BAJA CALIFORNIA SUR	LA PAZ

5 rows × 57 columns

Limpieza de los datos

```
# Se verifica la cantidad de datos nulos en cada columna
df.isna().sum()
```

```
CLAVE                   0
SITIO                   0
ORGANISMO_DE_CUENCA     0
ESTADO                  0
MUNICIPIO               0
ACUIFERO                0
SUBTIPO                 0
LONGITUD                0
LATITUD                 0
PERIODO                 0
ALC_mg/L                4
CALIDAD_ALC             4
CONDUCT_mS/cm           6
CALIDAD_CONDUC          6
SDT_mg/L             1068
SDT_M_mg/L              2
CALIDAD_SDT_ra          2
CALIDAD_SDT_salin       2
```

```
FLUORUROS_mg/L            0
CALIDAD_FLUO              0
DUR_mg/L                  1
CALIDAD_DUR               1
COLI_FEC_NMP/100_mL       0
CALIDAD_COLI_FEC          0
N_NO3_mg/L                1
CALIDAD_N_NO3             1
AS_TOT_mg/L               0
CALIDAD_AS                0
CD_TOT_mg/L               0
CALIDAD_CD                0
CR_TOT_mg/L               0
CALIDAD_CR                0
HG_TOT_mg/L               0
CALIDAD_HG                0
PB_TOT_mg/L               0
CALIDAD_PB                0
MN_TOT_mg/L               0
CALIDAD_MN                0
FE_TOT_mg/L               0
CALIDAD_FE                0
SEMAFORO                  0
CONTAMINANTES           434
CUMPLE_CON_ALC            0
CUMPLE_CON_COND           0
CUMPLE_CON_SDT_ra         0
CUMPLE_CON_SDT_salin      0
CUMPLE_CON_FLUO           0
CUMPLE_CON_DUR            0
CUMPLE_CON_CF             0
CUMPLE_CON_NO3            0
CUMPLE_CON_AS             0
CUMPLE_CON_CD             0
CUMPLE_CON_CR             0
CUMPLE_CON_HG             0
CUMPLE_CON_PB             0
CUMPLE_CON_MN             0
CUMPLE_CON_FE             0
dtype: int64
```

```
# Se descartan las columnas de CONTAMINANTES y SDT_mg/L ya que la mayor parte de sus datos so
df.drop(["CONTAMINANTES","SDT_mg/L"], inplace=True, axis=1)
```

Las demas columnas presentaban un 6 datos nulos como maximo, estos se pueden considerar despreciables, por lo que se procede a eliminarlos.

```
#Eliminamos los datos NaN
df.dropna(inplace = True)
```

```
#Se corrobora si quedo algún dato vacío, False = No hay datos nulos
df.isna().values.any()
```

```
False
```

Al analizar el set de datos, se puede inferir que los datos categoricos son dependientes de los datos numericos, es decir, hacen referencia a ellos, provocando asi una redundancia en los mismos, por lo tanto se procede a eliminar estas columnas y utilizar solo las numericas.

```
col_num = ['LONGITUD','LATITUD','ALC_mg/L','CONDUCT_mS/cm','SDT_M_mg/L','FLUORUROS_mg/L','DUR
           'N_NO3_mg/L','AS_TOT_mg/L','CD_TOT_mg/L','CR_TOT_mg/L','HG_TOT_mg/L','PB_TOT_mg/L'
df_new = df[col_num]
df_new.head()
```

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L
0	-102.02210	22.20887	229.990	940.0	603.6	0.9766	213.732
1	-102.20075	21.99958	231.990	608.0	445.4	0.9298	185.0514
2	-102.28801	22.36685	204.920	532.0	342	1.8045	120.719
3	-102.29449	22.18435	327.000	686.0	478.6	1.1229	199.879
4	-110.24480	23.45138	309.885	1841.0	1179	0.2343	476.9872

```
# Se comprueba la cantidad de datos nulos por columna y su tipo de dato
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1054 entries, 0 to 1067
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   LONGITUD            1054 non-null   float64
 1   LATITUD             1054 non-null   float64
 2   ALC_mg/L            1054 non-null   float64
 3   CONDUCT_mS/cm       1054 non-null   float64
 4   SDT_M_mg/L          1054 non-null   object
 5   FLUORUROS_mg/L      1054 non-null   object
 6   DUR_mg/L            1054 non-null   object
 7   COLI_FEC_NMP/100_mL 1054 non-null   object
 8   N_NO3_mg/L          1054 non-null   object
 9   AS_TOT_mg/L         1054 non-null   object
 10  CD_TOT_mg/L         1054 non-null   object
 11  CR_TOT_mg/L         1054 non-null   object
 12  HG_TOT_mg/L         1054 non-null   object
 13  PB_TOT_mg/L         1054 non-null   object
 14  MN_TOT_mg/L         1054 non-null   object
 15  FE_TOT_mg/L         1054 non-null   object
 16  SEMAFORO            1054 non-null   object
dtypes: float64(4), object(13)
memory usage: 148.2+ KB
```

Se aprecia como en la mayor parte de las columnas son de tipo string (object) aunque son numericas, y esto se debe a que incluyen el simbolo <.

```
# Conversion de tipo de dato de la columna y eliminacion del <
col = ['ALC_mg/L','CONDUCT_mS/cm','SDT_M_mg/L','FLUORUROS_mg/L','DUR_mg/L','COLI_FEC_NMP/100_
       'AS_TOT_mg/L','CD_TOT_mg/L','CR_TOT_mg/L','HG_TOT_mg/L','PB_TOT_mg/L','MN_TOT_mg/L','F
for name in col:
  df_new[name] = df_new[name].astype(str)
  df_new[name] = df_new[name].replace("<","", regex=True)
  df_new[name]= df_new[name].astype(float)

df_new.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  """
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  import sys
```

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L	C
0	-102.02210	22.20887	229.990	940.0	603.6	0.9766	213.7320	
1	-102.20075	21.99958	231.990	608.0	445.4	0.9298	185.0514	
2	-102.28801	22.36685	204.920	532.0	342.0	1.8045	120.7190	
3	-102.29449	22.18435	327.000	686.0	478.6	1.1229	199.8790	
4	-110.24480	23.45138	309.885	1841.0	1179.0	0.2343	476.9872	

Se prosigue dividiendo este conjunto de datos en tres partes dependiendo de su categoria.

```
df_location = df_new[["LONGITUD","LATITUD"]] # Localizacion
df_sust = df_new.drop(["LONGITUD","LATITUD","SEMAFORO"], axis=1) # Sustancias contaminantes
y = pd.DataFrame(df_new["SEMAFORO"])# Semaforo
y
```

	SEMAFORO
0	Verde
1	Verde
2	Rojo
3	Verde
4	Rojo
...	...
1063	Rojo
1064	Rojo
1065	Rojo
1066	Verde
1067	Verde

1054 rows × 1 columns

Exploracion de los datos

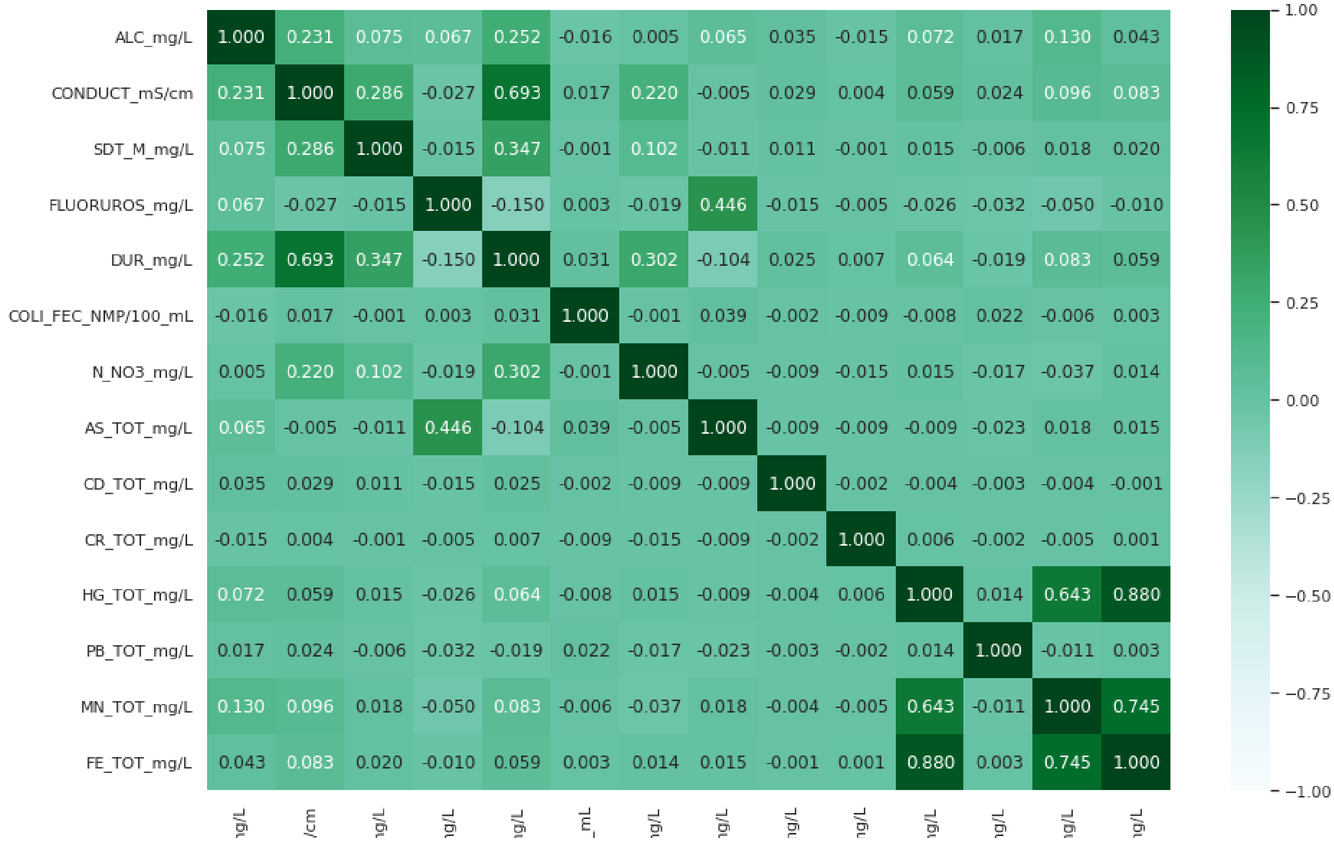
```
# Se exploran los datos estadisticos de las columnas de las sustancias contaminantes
df_sust.describe()
```

	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L	COLI_FEC_NI
count	1054.000000	1054.000000	1054.000000	1054.000000	1054.000000	10
mean	234.695266	1142.726471	896.945797	1.078547	349.893584	3
std	111.147849	1248.990617	2765.757924	1.931204	360.960153	20
min	26.640000	110.000000	101.200000	0.200000	20.000000	
25%	164.257500	506.000000	338.050000	0.269475	121.512000	
50%	215.825000	820.000000	551.400000	0.506950	245.994450	
75%	292.930000	1328.000000	915.600000	1.142400	455.617200	
max	1650.000000	18577.000000	82170.000000	34.803300	3810.692200	241

```
# Grafico de cajas
sns.boxplot(data = df_sust, orient="h")
plt.show()
```


```
# Se visualiza la matriz de correlacion
corrs = df_sust.corr()
sns.set(rc = {'figure.figsize':(15,10)})
sns.heatmap(corrs, vmin = -1, vmax = 1, cmap = "BuGn", annot= True, fmt=".3f")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d876d410>
```




```
# Exploracion de la varianza
print('Varianza correspondiente a cada columna:')
print(df_sust.var())
print('\nTotal de varianza: ',sum(df_sust.var()))
print('\nProporcion de varianza de cada columna:')
print(np.round(df_sust.var()/sum(df_sust.var()),3)*100)
```

```
Varianza correspondiente a cada columna:
ALC_mg/L               1.235384e+04
CONDUCT_mS/cm          1.559978e+06
SDT_M_mg/L             7.649417e+06
FLUORUROS_mg/L         3.729549e+00
DUR_mg/L               1.302922e+05
COLI_FEC_NMP/100_mL    4.267140e+06
N_NO3_mg/L             7.019645e+01
AS_TOT_mg/L            1.228557e-03
CD_TOT_mg/L            8.102546e-07
CR_TOT_mg/L            2.415279e-02
HG_TOT_mg/L            2.206552e-07
PB_TOT_mg/L            1.073068e-05
MN_TOT_mg/L            1.435322e-01
FE_TOT_mg/L            3.107290e+01
dtype: float64

Total de varianza:  13619286.03779883

Proporcion de varianza de cada columna:
ALC_mg/L                0.1
CONDUCT_mS/cm          11.5
```

```
SDT_M_mg/L             56.2
FLUORUROS_mg/L          0.0
DUR_mg/L                1.0
COLI_FEC_NMP/100_mL    31.3
N_NO3_mg/L              0.0
AS_TOT_mg/L             0.0
CD_TOT_mg/L             0.0
CR_TOT_mg/L             0.0
HG_TOT_mg/L             0.0
PB_TOT_mg/L             0.0
MN_TOT_mg/L             0.0
FE_TOT_mg/L             0.0
dtype: float64
```

Segun su estadistica descriptiva y varianza, se aprecia como los valores entre columnas tienen diferentes escalas numericas, lo cual produce un alto indice de varianza. No nos podemos fiar de estos valores debido a las diferentes magnitudes que se presentan.

```
# Escalamiento de los datos
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df_sust)
scaled_df_sust = pd.DataFrame(scaled, columns=df_sust.columns)
scaled_df_sust.head()
```

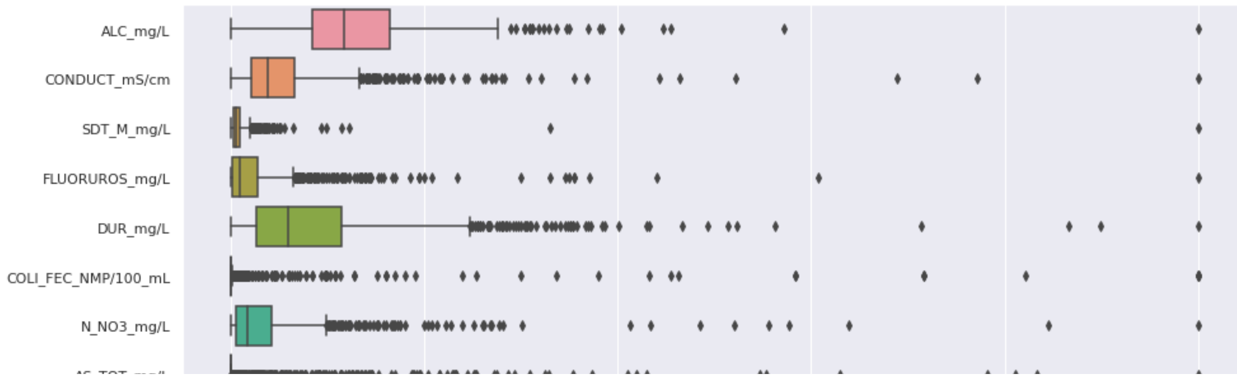
	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L	COLI_FEC_NMP/10(
0	0.125265	0.044945	0.006122	0.022443	0.051107	0.00(
1	0.126497	0.026967	0.004194	0.021090	0.043541	0.00(
2	0.109822	0.022852	0.002934	0.046368	0.026570	0.00(
3	0.185024	0.031191	0.004599	0.026671	0.047453	0.00(
4	0.174481	0.093735	0.013133	0.000991	0.120555	0.01

```
# Se explora nuevamente la varianza con los datos transformados
print('Varianza correspondiente a cada columna:')
print(scaled_df_sust.var())
print('\nTotal de varianza: ',sum(scaled_df_sust.var()))
print('\nProporcion de varianza de cada columna:')
print(np.round(scaled_df_sust.var()/sum(scaled_df_sust.var()),3)*100)
```

```
Varianza correspondiente a cada columna:
ALC_mg/L               0.004688
CONDUCT_mS/cm          0.004574
SDT_M_mg/L             0.001136
FLUORUROS_mg/L         0.003115
DUR_mg/L               0.009067
COLI_FEC_NMP/100_mL    0.007289
N_NO3_mg/L             0.004795
```

```
AS_TOT_mg/L            0.006283
CD_TOT_mg/L            0.000956
CR_TOT_mg/L            0.000967
HG_TOT_mg/L            0.001184
PB_TOT_mg/L            0.001863
MN_TOT_mg/L            0.001780
FE_TOT_mg/L            0.000974
dtype: float64

Total de varianza:  0.04867157843563119

Proporcion de varianza de cada columna:
ALC_mg/L                9.6
CONDUCT_mS/cm           9.4
SDT_M_mg/L              2.3
FLUORUROS_mg/L          6.4
DUR_mg/L               18.6
COLI_FEC_NMP/100_mL    15.0
N_NO3_mg/L              9.9
AS_TOT_mg/L            12.9
CD_TOT_mg/L             2.0
CR_TOT_mg/L             2.0
HG_TOT_mg/L             2.4
PB_TOT_mg/L             3.8
MN_TOT_mg/L             3.7
FE_TOT_mg/L             2.0
dtype: float64
```

```
# Grafico de cajas
sns.boxplot(data = scaled_df_sust, orient="h")
plt.show()
```




```
scaled_df_sust.describe() #Datos estadisticos de dataframe escalado
```

	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L	COLI_F
count	1054.000000	1054.000000	1054.000000	1054.000000	1054.000000	
mean	0.128163	0.055923	0.009696	0.025389	0.087027	
std	0.068468	0.067634	0.033700	0.055810	0.095223	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.084773	0.021444	0.002886	0.002008	0.026779	
50%	0.116539	0.038447	0.005486	0.008871	0.059618	
75%	0.164036	0.065955	0.009923	0.027234	0.114918	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

Aun transformando los datos, en el grafico de cajas puede notar como la distribucion de los lados en cada columna no es uniforme y presentad una cantidad grande de outliers.

Relacion entre la calidad del agua y su ubicacion geografica utilizando Kmeans

Mediante una gráfica de dispersión procedemos a visualizar las cordenadas de cada uno de los cuerpos de agua de la base de datos.

```
# Graficamos los cuerpos de agua segun sus coordenadas
df_location.plot.scatter('LONGITUD','LATITUD')
```

```
WARNING:matplotlib.axes._axes:*c* argument looks like a single numeric RGB or RGBA seque
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d829c210>
```


```
#Generamos dataframe con los datos de las coordendas
df_location
df_location["COORDENADAS"] = list(zip(df_location.LONGITUD, df_location.LATITUD))
df_location["COORDENADAS"] = df_location["COORDENADAS"].apply(Point)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  This is separate from the ipykernel package so we can avoid doing imports until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  after removing the cwd from sys.path.
```

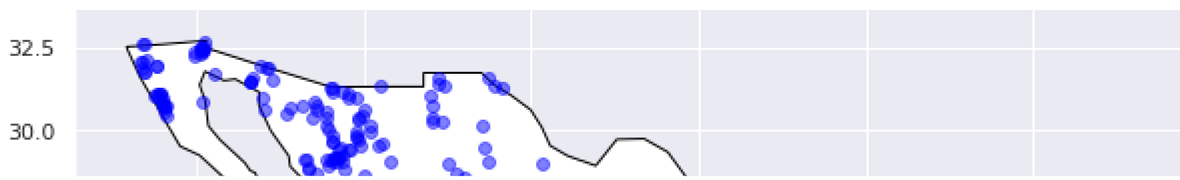
```
df_location.head() #Mostramos el dataframe generado con las coordenadas
```

	LONGITUD	LATITUD	COORDENADAS
0	-102.02210	22.20887	POINT (-102.0221 22.20887)
1	-102.20075	21.99958	POINT (-102.20075 21.99958)
2	-102.28801	22.36685	POINT (-102.28801 22.36685)
3	-102.29449	22.18435	POINT (-102.29449 22.18435)
4	-110.24480	23.45138	POINT (-110.2448 23.45138)

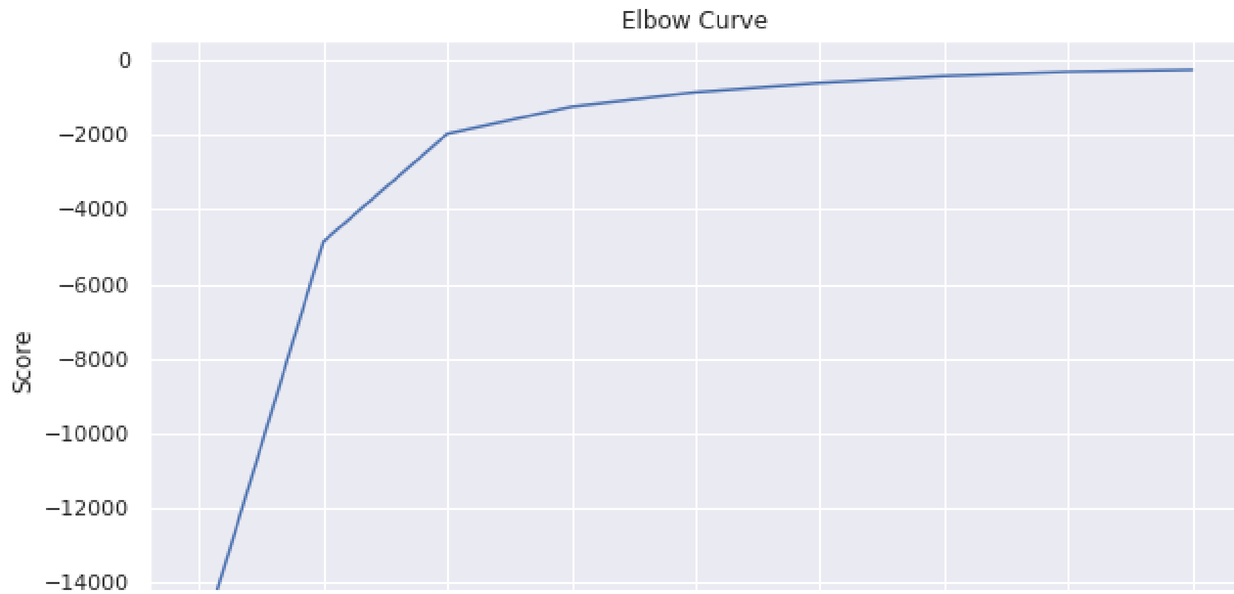
```
#Creamos Geodataframe
Mapa_Geo_Mex = gpd.GeoDataFrame(df_location, geometry="COORDENADAS")

world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))

world = world.set_index("iso_a3")
world.name.unique()
fig, gax = plt.subplots(figsize=(10,10))

world.query("name == 'Mexico'").plot(ax=gax, edgecolor='black',color='white')

gax.set_xlabel('LATITUD')
gax.set_ylabel('LONGITUD')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

#Graficamos mapa
Mapa_Geo_Mex.plot(ax=gax, color='Blue', alpha = 0.5)

#Mostramos dataframe generado
Mapa_Geo_Mex
```

	LONGITUD	LATITUD	COORDENADAS
0	-102.02210	22.20887	POINT (-102.02210 22.20887)
1	-102.20075	21.99958	POINT (-102.20075 21.99958)
2	-102.28801	22.36685	POINT (-102.28801 22.36685)
3	-102.29449	22.18435	POINT (-102.29449 22.18435)
4	-110.24480	23.45138	POINT (-110.24480 23.45138)
...	...	...	...
1063	-99.54191	24.76036	POINT (-99.54191 24.76036)
1064	-99.70099	24.78280	POINT (-99.70099 24.78280)
1065	-99.82249	25.55197	POINT (-99.82249 25.55197)
1066	-100.32683	24.80118	POINT (-100.32683 24.80118)
1067	-100.73302	25.09380	POINT (-100.73302 25.09380)

1054 rows × 3 columns




```
#Aplicamos Kmeans para generar la grafica de codo, que nos ayudara a determinar la cantidad d

#Definimos Kmeans usando las columnas de latitud y longitud
Cluster_num = range(1,10)
kmeans_cluster = [KMeans(n_clusters=i) for i in Cluster_num]
Y_axis = df_location[['LATITUD']]
X_axis = df_location[['LONGITUD']]
train_kmeans = [kmeans_cluster[i].fit(Y_axis).score(Y_axis) for i in range(len(kmeans_cluster

#Grafica de codo
plt.figure(figsize=(10,6))
plt.plot(Cluster_num, train_kmeans)
plt.xlabel('Number of Clusters')
plt.ylabel('Score')
plt.title('Elbow Curve')

#Mostramos grafica
plt.show()
```



Según la gráfica de codo podemos observar que el valor de clústeres adecuado es de 3, ya que a partir del cuarto se aprecia una tendecia de mantenerse constante.

Number of Clusters

```
#Generamos los 3 centroides de los clusters
X = df[['LONGITUD', 'LATITUD']]

#Usamos calculo de kmeans con 3 clusters
kmeans = KMeans(n_clusters=3).fit(X)

#Obtenemos centroides
centroids = kmeans.cluster_centers_

#Prediccion de kmeans
labels = kmeans.predict(X)

#Definimos dataframe con la informacion de los centroides de los clusters
df_centroids = pd.DataFrame(centroids)
df_centroids["Coordinates"] = list(zip(df_centroids[0], df_centroids[1]))
df_centroids["Coordinates"] = df_centroids["Coordinates"].apply(Point)

#creamos Geodataframe de los centroides
centroids_plot = gpd.GeoDataFrame(df_centroids, geometry="Coordinates")
centroids_plot
```

	0	1	Coordinates
0	-101.715581	22.271624	POINT (-101.71558 22.27162)
1	-90.698434	19.475165	POINT (-90.69843 19.47516)
2	-110.740896	28.420375	POINT (-110.74090 28.42038)

```
# Conteo de cuerpos de agua de acuerdo a su respectivo color de semaforo
```

```
df['SEMAFORO'].value_counts()
```

```
Verde       427
Rojo        382
Amarillo    245
Name: SEMAFORO, dtype: int64
```

```
#Agregamos la columna semaforo y numero de clsuter
Mapa_Geo_Mex['SEMAFORO']= y['SEMAFORO']
Mapa_Geo_Mex['CLUSTER'] = labels
Mapa_Geo_Mex
```

	LONGITUD	LATITUD	COORDENADAS	SEMAFORO	CLUSTER
0	-102.02210	22.20887	POINT (-102.02210 22.20887)	Verde	0
1	-102.20075	21.99958	POINT (-102.20075 21.99958)	Verde	0
2	-102.28801	22.36685	POINT (-102.28801 22.36685)	Rojo	0
3	-102.29449	22.18435	POINT (-102.29449 22.18435)	Verde	0
4	-110.24480	23.45138	POINT (-110.24480 23.45138)	Rojo	2
...	...	...	...	...	...
1063	-99.54191	24.76036	POINT (-99.54191 24.76036)	Rojo	0
1064	-99.70099	24.78280	POINT (-99.70099 24.78280)	Rojo	0
1065	-99.82249	25.55197	POINT (-99.82249 25.55197)	Rojo	0
1066	-100.32683	24.80118	POINT (-100.32683 24.80118)	Verde	0
1067	-100.73302	25.09380	POINT (-100.73302 25.09380)	Verde	0

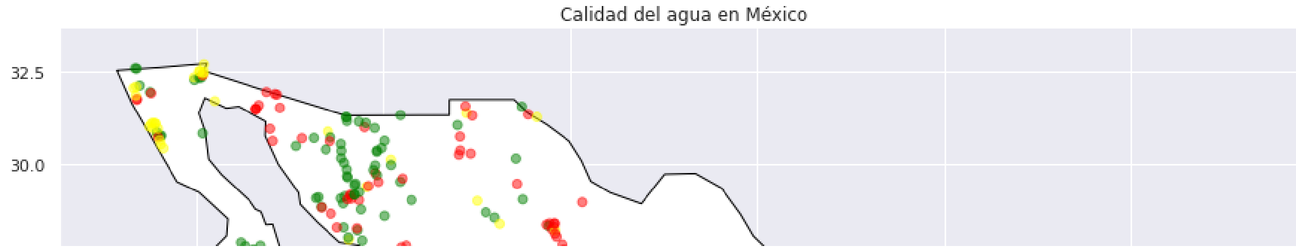
1054 rows × 5 columns

```
#Cambiamos el nombre del color a ingles
Mapa_Geo_Mex['SEMAFORO_Plot'] = Mapa_Geo_Mex['SEMAFORO'].replace(to_replace = "Verde", value
Mapa_Geo_Mex['SEMAFORO_Plot'].replace(to_replace = "Rojo", value = "red", inplace=True)
Mapa_Geo_Mex['SEMAFORO_Plot'].replace(to_replace = "Amarillo", value = "yellow", inplace=True

labels_semaforo = Mapa_Geo_Mex['SEMAFORO_Plot'].tolist()
Mapa_Geo_Mex['SEMAFORO_Plot']
```

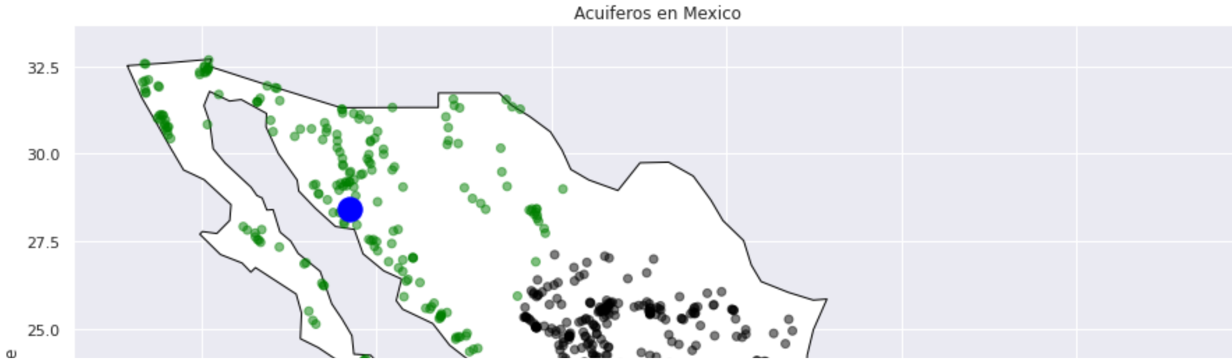
```
0       green
1       green
2         red
3       green
4         red
        ...
1063      red
1064      red
1065      red
```

```
1066    green
1067    green
Name: SEMAFORO_Plot, Length: 1054, dtype: object
```

```
#Graficamos el mapa con los colores de semaforo individual de cada cuerpo de agua
fig, gax = plt.subplots(figsize=(15,10))

colores = ['green','yellow','red']

color_asig = []

for j in range(0,1054):
  color_asig.append(labels_semaforo[j])

world.query("name == 'Mexico'").plot(ax = gax, edgecolor='black', color='white')

Mapa_Geo_Mex.plot(ax=gax, color=color_asig, alpha = 0.5, legend=True)

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Calidad del agua en México')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```

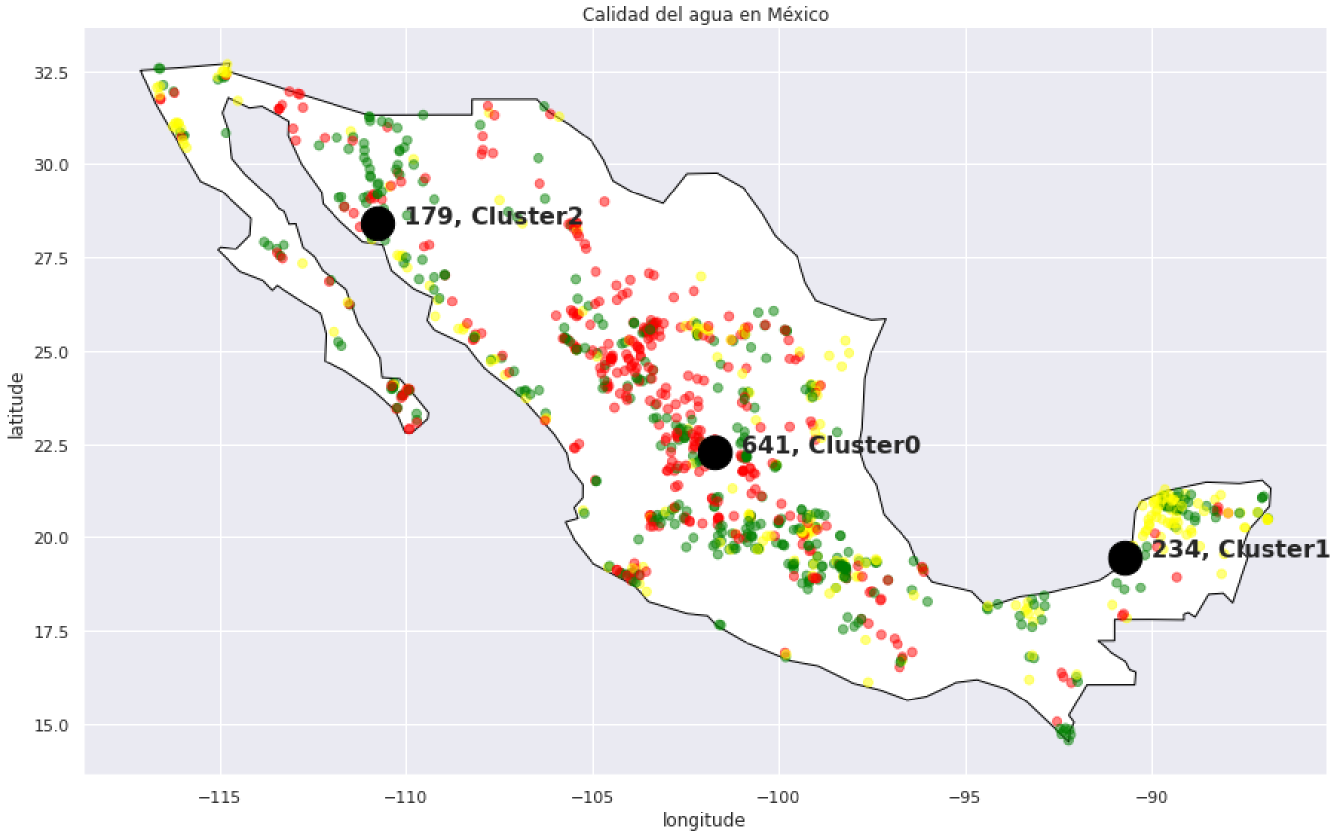



```
#Graficamos los clusters
fig, gax = plt.subplots(figsize=(15,10))
colores = ['black','purple','green']
color_asig = []

for row in labels:
  color_asig.append(colores[row])

#Definimos parametros de grafica
world.query("name == 'Mexico'").plot(ax = gax, edgecolor='black', color='white')

Mapa_Geo_Mex.plot(ax=gax, color=color_asig, alpha = 0.5)
centroids_plot.plot(ax=gax, color='blue', alpha = 1, markersize = 300)

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Acuiferos en Mexico')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```



Resultados de agrupamiento de latitudes y longitudes con Kmeans en el mapa de Mexico


```
#Graficamos el mapa con los clusters y los colores de semaforo individual de cada cuerpo de a
fig, gax = plt.subplots(figsize=(15,10))

colores = ['green','yellow','red']

color_asig = []

for j in range(0,1054):
  color_asig.append(labels_semaforo[j])

world.query("name == 'Mexico'").plot(ax = gax, edgecolor='black', color='white')

Mapa_Geo_Mex.plot(ax=gax, color=color_asig, alpha = 0.5, legend=True)

plt.scatter(centroids[:, 0], centroids[:, 1], c='black', s=500, alpha=1)

list_names_regions = ["Cluster0", "Cluster1", "Cluster2"]
list_stores_cluster = pd.DataFrame(labels).value_counts().to_list()
for i, txt in enumerate(list_stores_cluster):
    plt.annotate(str(txt)+ ", " + list_names_regions[i], (centroids[i,0], centroids[i,1]), xy

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Calidad del agua en México')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```

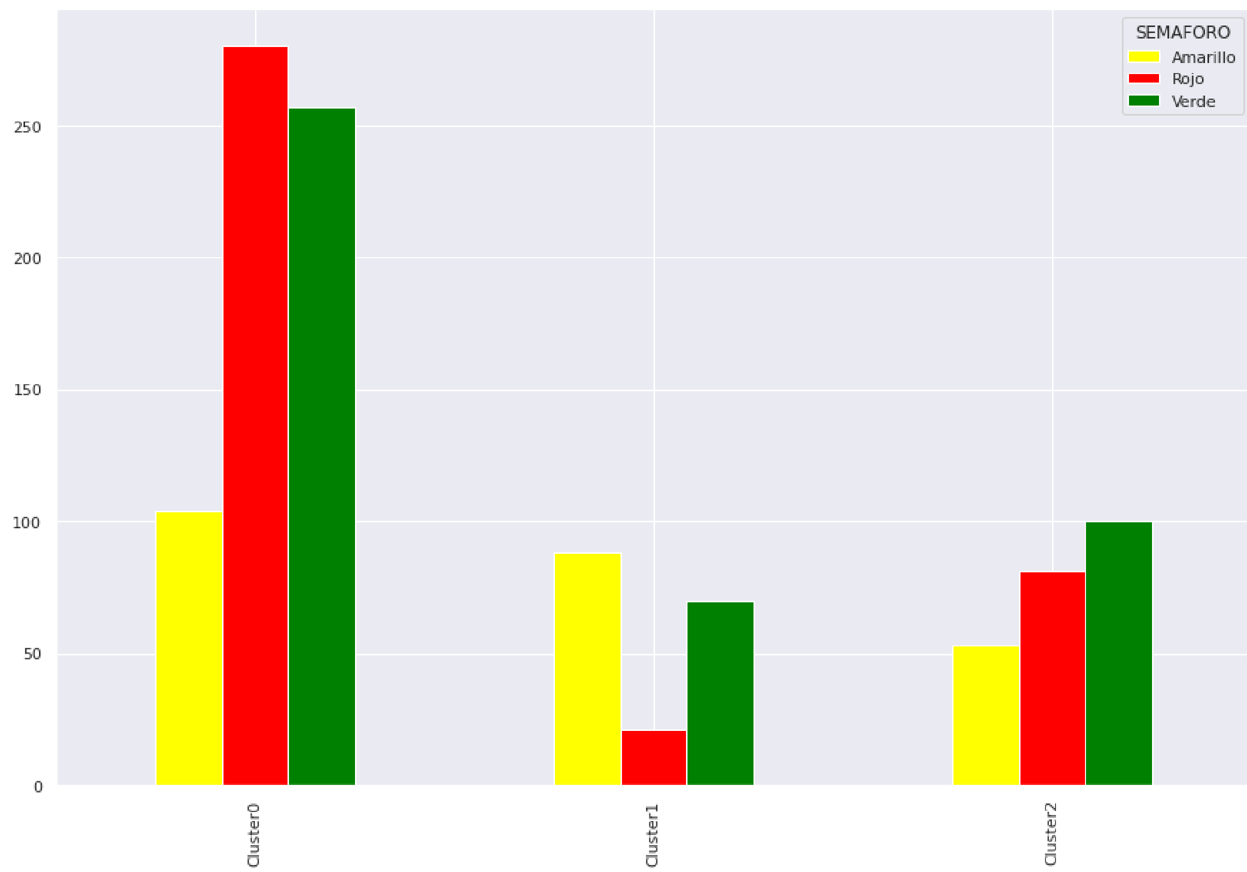



```
#Determinamos la moda de cada cluster
mode_list=[]

for i in range(0,3):
  df_cluster = pd.DataFrame()
  df_cluster = Mapa_Geo_Mex[Mapa_Geo_Mex.CLUSTER == i].copy()
  moda = df_cluster['SEMAFORO'].mode()[0]
  mode_list.append(moda)

len(mode_list)


centroids_plot['MODA'] = mode_list
centroids_plot
```

	0	1	Coordinates	MODA
0	-101.715581	22.271624	POINT (-101.71558 22.27162)	Rojo
1	-90.698434	19.475165	POINT (-90.69843 19.47516)	Amarillo
2	-110.740896	28.420375	POINT (-110.74090 28.42038)	Verde

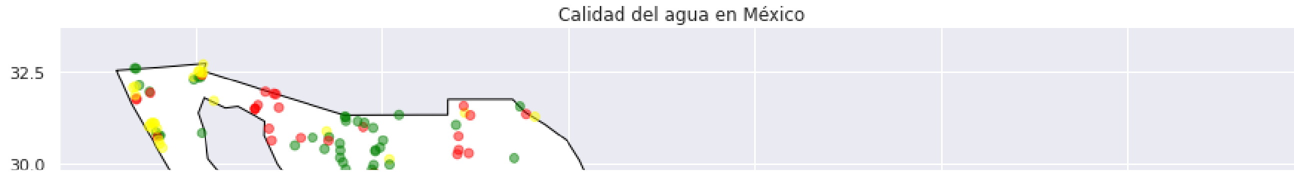
```
#Relizamos el conteo de cada color de semaforo de cada uno de los clusters
Mapa_Geo_Mex["Cluster"] = labels
clusters_dict = {}
for i in range(3):
  if "Cluster"+str(i) not in clusters_dict:
      clusters_dict["Cluster"+str(i)] = []
  clusters_dict["Cluster"+str(i)] = Mapa_Geo_Mex[Mapa_Geo_Mex["Cluster"] == i].groupby(by="SE

#Graficamos el conteo de las clases de cada cluster
Cluster_Semaforo = pd.DataFrame(clusters_dict)
Cluster_Semaforo.transpose().plot.bar(color={"Amarillo": "yellow", "Rojo": "red", "Verde": "g
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d7b540d0>
```




```
#Graficamos los clusters con sus color de semaforo basado en la moda
fig, gax = plt.subplots(figsize=(15,10))

colores = ['green','yellow','red']
```

```
color_asig = []

for j in range(0,1054):
  color_asig.append(labels_semaforo[j])

world.query("name == 'Mexico'").plot(ax = gax, edgecolor='black', color='white')

Mapa_Geo_Mex.plot(ax=gax, color=color_asig, alpha = 0.5, legend=True)

plt.scatter(centroids[:, 0], centroids[:, 1], c=["red", "yellow", "green"], s=500, alpha=1)

list_names_regions = ["Cluster0", "Cluster1", "Cluster2"]
list_stores_cluster = pd.DataFrame(labels).value_counts().to_list()
for i, txt in enumerate(list_stores_cluster):
    plt.annotate(str(txt)+ ", " + list_names_regions[i], (centroids[i,0], centroids[i,1]), xy

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Calidad del agua en México')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```



CONCLUSIONES

Gracias a este ejercicio hemos descubierto datos interesantes sobre la calidad del agua en el país, asi como su relación con su ubicación geográfica.

Gracias al uso de Kmeans hemos podido determinar los conjuntos o zonas de cuerpos de agua asi como su relación basada en su calidad. Notamos y concluimos que la mejor calidad de agua basada en la moda de los conjuntos o clusters es la que se encuentra en la zona noroeste, mientras que la peor calidad de agua la ubicamos en el centro del país. En la parte sur de México observamos que la categoría dominante es la amarilla.

Ahora bien si prestamos atención a la grafica de barras notamos que aunque la moda del cluster noroeste es verde, hay una cantidad similar de cuerpos de agua con semáforo rojo, lo que nos indica que en proporción estan casi parejos. Siguiendo esa tónica, podríamos considerar que la zona que menos semáforos rojos tiene es la zona sur (cluster1)

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