Clustering Cidades do Brasil

June 14, 2020

1 Análise de Agrupamento - Municípios Brasileiros (k-means)

In [1]:
```
# Carregando os módulos e pacotes
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

1.1 Descrição do dataset

In [ ]:
```
#FIELD        DESCRIPTION        UNIT
#CITY        Name of the City
#STATE        Name of the State
#CAPITAL        1 if Capital of State
#IBGE_RES_POP        Resident Population        -
#IBGE_RES_POP_BRAS        Resident Population Brazilian        -
#IBGE_RES_POP_ESTR        Redident Population Foreigners        -
#IBGE_DU        Domestic Units Total        -
#IBGE_DU_URBAN        Domestic Units Urban        -
#IBGE_DU_RURAL        Domestic Units Rural        -
#IBGE_POP        Resident Population Regular Urban Planning        -
#IBGE_1        Resident Population Regular Urban Planning - until 1 y.o        -
#IBGE_1-4        Resident Population Regular Urban Planning - from 1 to 4 y.o        -
#IBGE_5-9        Resident Population Regular Urban Planning - from 4 to 9 y.o        -
#IBGE_10-14        Resident Population Regular Urban Planning - from 10 to 14 y.o
#IBGE_15-59        Resident Population Regular Urban Planning - from 15 to 59 y.o
#IBGE_60+        Resident Population Regular Urban Planning - above 60 y.o        -
#IBGE_PLANTED_AREA        Planted Area (hectares)        1 hectare (1 hectare = 10,00
#IBGE_CROP_PRODUCTION_$        Crop Production        $ 1,000 reais
#IDHM Ranking        HDI Ranking        -
#IDHM        HDI Human Development Index        -
#IDHM_Renda        HDI GNI Index        -
#IDHM_Longevidade        HDI Life Expectancy index        -
#IDHM_Educacao        HDI Education index        -
#LONG        City Latitude        -
#LAT        City Longitude        -
#ALT        City Elevation (meters)        1 meter
#PAY_TV        PayTV users        -
```

```
#FIXED_PHONES        Fixed Fones (not cell phones) users        -
#AREA        City area (squared kilometers)        1 squared Kilometer (1 kilometer = 
#REGIAO_TUR        Turism Category Region        -
#CATEGORIA_TUR        Turism Category        -
#ESTIMATED_POP        Estimated Population        -
#RURAL_URBAN        Rural or Urban Tipology        -
#GVA_AGROPEC        Gross Added Value - Agropecuary        $ 1,000 reais
#GVA_INDUSTRY        Gross Added Value - Industry        $ 1,000 reais
#GVA_SERVICES        Gross Added Value - Services        $ 1,000 reais
#GVA_PUBLIC        Gross Added Value - Public Services        $ 1,000 reais
#GVA_TOTAL        Total Gross Added Value        $ 1,000 reais
#TAXES        Taxes        $ 1,000 reais
#GDP        Gross Domestic Product        $ 1,000 reais
#POP_GDP        Population        -
#GDP_CAPITA        Gross Domestic Product per capita        -
#MUN_EXPENDIT        Municipal expenditures - in reais        $ 1 real
#COMP_TOT        Total number of companies        -
#COMP_A        Number of Companies: Agriculture, livestock, forestry, fishing and aqua
#COMP_B        Number of Companies: Extractive industries        -
#COMP_C        Number of Companies: Industries of transformation        -
#COMP_D        Number of Companies: Electricity and gas        -
#COMP_E        Number of Companies: Water, sewage, waste management and decontaminatio
#COMP_F        Number of Companies: Construction        -
#COMP_G        "Number of Companies: Trade; repair of motor vehicles and motorcycles"
#COMP_H        Number of Companies: Transport, storage and mail        -
#COMP_I        Number of Companies: Accommodation and food        -
#COMP_J        Number of Companies: Information and communication        -
#COMP_K        Number of Companies: Financial, insurance and related services activiti
#COMP_L        Number of Companies: Real estate activities        -
#COMP_M        Number of Companies: Professional, scientific and technical activities
#COMP_N        Number of Companies: Administrative activities and complementary servic
#COMP_O        Number of Companies: Public administration, defense and social security
#COMP_P        Number of Companies: Education        -
#COMP_Q        Number of Companies: Human health and social services        -
#COMP_R        Number of Companies: Arts, culture, sport and recreation        -
#COMP_S        Number of Companies: Other service activities        -
#COMP_T        Number of Companies: Domestic services        -
#COMP_U        Number of Companies: International and other extraterritorial instituti
#HOTELS        Total number of hotels        -
#BEDS        Toal number of hotel beds        -
#Pr_Agencies        Total number of private bank agencies        -
#Pu_Agencies        Total number of public bank agencies        -
#Pr_Bank        Total number of private banks        -
#Pu_Bank        Total number of public banks        -
#Pr_Assets        Total amount of private bank assets        $ 1 real
#Pu_Assets        Total amount of public bank assets        $ 1 real
#Cars        Total number of cars        -
#Motorcycles        Total number of motorcycles, scooters, moped        -
```

```
#Wheeled_tractor        Total number of wheeled tractors        -
#UBER        1 if UBER        -
#MAC        Total number of Mac Donalds stores        -
#WALLMART        Total number of Walmart Stores        -
#POST_OFFICES        Total number of post offices        -
```

In [2]:
```
# Carregando o dataset
cidades = pd.read_csv('BRAZIL_CITIES.csv', sep=';', thousands=',')
cidades.head()
```

Out[2]:
```
                  CITY STATE  CAPITAL  IBGE_RES_POP  IBGE_RES_POP_BRAS  \
0      Abadia De Goiás    GO        0        6876.0             6876.0
1  Abadia Dos Dourados    MG        0        6704.0             6704.0
2            Abadiânia    GO        0       15757.0            15609.0
3               Abaeté    MG        0       22690.0            22690.0
4           Abaetetuba    PA        0      141100.0           141040.0

   IBGE_RES_POP_ESTR  IBGE_DU  IBGE_DU_URBAN  IBGE_DU_RURAL  IBGE_POP  ...  \
0                0.0   2137.0         1546.0          591.0    5300.0  ...
1                0.0   2328.0         1481.0          847.0    4154.0  ...
2              148.0   4655.0         3233.0         1422.0   10656.0  ...
3                0.0   7694.0         6667.0         1027.0   18464.0  ...
4               60.0  31061.0        19057.0        12004.0   82956.0  ...

   Pu_Bank   Pr_Assets    Pu_Assets    Cars  Motorcycles  Wheeled_tractor  \
0      NaN         NaN          NaN  2158.0       1246.0              0.0
1      NaN         NaN          NaN  2227.0       1142.0              0.0
2      1.0  33724584.0   67091904.0  2838.0       1426.0              0.0
3      2.0  44974716.0  371922572.0  6928.0       2953.0              0.0
4      4.0  76181384.0  800078483.0  5277.0      25661.0              0.0

   UBER  MAC  WAL-MART  POST_OFFICES
0   NaN  NaN       NaN           1.0
1   NaN  NaN       NaN           1.0
2   NaN  NaN       NaN           3.0
3   NaN  NaN       NaN           4.0
4   NaN  NaN       NaN           2.0

[5 rows x 81 columns]
```

In [3]:
```
cidades.shape
```

Out[3]:
```
(5573, 81)
```

1.2 Pré-processamento

In [4]:
```
# Subconjunto do dataset
cidades2 = cidades[['IBGE_RES_POP', 'IBGE_DU_URBAN', 'IBGE_DU_RURAL', 'IBGE_1', 'IBGE_
                    'IBGE_10-14', 'IBGE_15-59','IBGE_60+', 'IBGE_PLANTED_AREA', 'IBGE_
```

```
                          'IDHM', 'IDHM_Renda', 'IDHM_Longevidade', 'IDHM_Educacao',
                          'GDP_CAPITA', 'Cars','Motorcycles','Wheeled_tractor','LONG', 'LAT']
```

In [5]:
```
# Criando novas informações a partir das variáveis do dataset
IBGE_ate15=cidades2['IBGE_1']+cidades2['IBGE_1-4']+cidades2['IBGE_5-9']+cidades2['IBGE_
PercJovem=IBGE_ate15 / (IBGE_ate15 + cidades2['IBGE_15-59']+cidades2['IBGE_60+'])
PercIdoso=cidades2['IBGE_60+'] / (IBGE_ate15 + cidades2['IBGE_15-59']+cidades2['IBGE_60
PercCarros=cidades2['Cars'] / cidades2['IBGE_RES_POP']
PercMotos=cidades2['Motorcycles'] / cidades2['IBGE_RES_POP']
PercTratores=cidades2['Wheeled_tractor'] / cidades2['IBGE_RES_POP']
```

In [6]:
```
# Criando colunas no dataframe
cidades2.insert(18, 'PercJovem', PercJovem)
cidades2.insert(19, 'PercIdoso', PercIdoso)
cidades2.insert(20, 'PercCarros', PercCarros)
cidades2.insert(21, 'PercMotos', PercMotos)
cidades2.insert(22, 'PercTratores', PercTratores)
```

In [7]:
```
# Eliminando as colunas que não serão mais necessárias
cidades2=cidades2.drop(columns=['IBGE_1','IBGE_1-4','IBGE_5-9','IBGE_10-14','IBGE_15-59
                               'Cars','Motorcycles','Wheeled_tractor' ])
cidades2.head()
```

Out[7]:
```
   IBGE_RES_POP  IBGE_DU_URBAN  IBGE_DU_RURAL  IBGE_PLANTED_AREA  \
0        6876.0         1546.0          591.0              319.0
1        6704.0         1481.0          847.0             4479.0
2       15757.0         3233.0         1422.0            10307.0
3       22690.0         6667.0         1027.0             1862.0
4      141100.0        19057.0        12004.0            25200.0

   IBGE_CROP_PRODUCTION_$   IDHM  IDHM_Renda  IDHM_Longevidade  IDHM_Educacao  \
0                  1843.0  0.708       0.687             0.830          0.622
1                 18017.0  0.690       0.693             0.839          0.563
2                 33085.0  0.690       0.671             0.841          0.579
3                  7502.0  0.698       0.720             0.848          0.556
4                700872.0  0.628       0.579             0.798          0.537

   GDP_CAPITA  PercJovem  PercIdoso  PercCarros  PercMotos  PercTratores  \
0    20664.57   0.253208   0.078491    0.313845   0.181210           0.0
1    25591.70   0.206066   0.141791    0.332190   0.170346           0.0
2    15628.40   0.259947   0.092905    0.180110   0.090499           0.0
3    18250.42   0.206023   0.145201    0.305333   0.130145           0.0
4     8222.36   0.282608   0.072279    0.037399   0.181864           0.0

        LONG        LAT
0 -49.440548 -16.758812
1 -47.396832 -18.487565
2 -48.718812 -16.182672
```

```
3 -45.446191 -19.155848
4 -48.884404  -1.723470
```

```
In [8]: # Verificando a existência de dados missing
        cidades2.isnull().sum()
```

```
Out[8]: IBGE_RES_POP               8
        IBGE_DU_URBAN             10
        IBGE_DU_RURAL             81
        IBGE_PLANTED_AREA          3
        IBGE_CROP_PRODUCTION_$     3
        IDHM                       8
        IDHM_Renda                 8
        IDHM_Longevidade           8
        IDHM_Educacao              8
        GDP_CAPITA                 3
        PercJovem                  8
        PercIdoso                  8
        PercCarros                17
        PercMotos                 17
        PercTratores              17
        LONG                       9
        LAT                        9
        dtype: int64
```

```
In [9]: # Eliminando os dados missing
        cidades2.dropna(inplace=True)
```

```
In [10]: # Listando as variáveis sem as informações de LONG e LAT
         cidades2.iloc[:,:15].head()
```

```
Out[10]:    IBGE_RES_POP  IBGE_DU_URBAN  IBGE_DU_RURAL  IBGE_PLANTED_AREA  \
         0        6876.0         1546.0          591.0              319.0
         1        6704.0         1481.0          847.0             4479.0
         2       15757.0         3233.0         1422.0            10307.0
         3       22690.0         6667.0         1027.0             1862.0
         4      141100.0        19057.0        12004.0            25200.0

            IBGE_CROP_PRODUCTION_$   IDHM  IDHM_Renda  IDHM_Longevidade  IDHM_Educacao  \
         0                  1843.0  0.708       0.687             0.830          0.622
         1                 18017.0  0.690       0.693             0.839          0.563
         2                 33085.0  0.690       0.671             0.841          0.579
         3                  7502.0  0.698       0.720             0.848          0.556
         4                700872.0  0.628       0.579             0.798          0.537

            GDP_CAPITA  PercJovem  PercIdoso  PercCarros  PercMotos  PercTratores
         0    20664.57   0.253208   0.078491    0.313845   0.181210           0.0
         1    25591.70   0.206066   0.141791    0.332190   0.170346           0.0
         2    15628.40   0.259947   0.092905    0.180110   0.090499           0.0
```

```
3    18250.42   0.206023   0.145201    0.305333   0.130145            0.0
4     8222.36   0.282608   0.072279    0.037399   0.181864            0.0
```

In [11]:
```python
# Padronização dos dados (mesma escala) - Não normalizar os dados de LONG e LAT
from sklearn.preprocessing import MinMaxScaler
pad=MinMaxScaler()
cidades2_pad=pd.DataFrame(pad.fit_transform(cidades2.iloc[:,:15]),columns=cidades2.col
```

1.3 Criando o modelo

In [12]:
```python
# Criando o modelo com 3 clusters (grupos)
km = KMeans(n_clusters=3, random_state=123)
km.fit(cidades2_pad)
```

Out[12]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=123, tol=0.0001, verbose=0)
```

In [13]:
```python
# Verificando o array de grupos
grupos = km.labels_
grupos
```

Out[13]:
```
array([1, 1, 0, ..., 1, 2, 1])
```

In [14]:
```python
# Criando uma coluna com a informação do grupo (dataset cidades2)
cidades2['Grupo']=km.labels_
cidades2.head()
```

Out[14]:
```
   IBGE_RES_POP  IBGE_DU_URBAN  IBGE_DU_RURAL  IBGE_PLANTED_AREA  \
0        6876.0         1546.0          591.0              319.0
1        6704.0         1481.0          847.0             4479.0
2       15757.0         3233.0         1422.0            10307.0
3       22690.0         6667.0         1027.0             1862.0
4      141100.0        19057.0        12004.0            25200.0

   IBGE_CROP_PRODUCTION_$   IDHM  IDHM_Renda  IDHM_Longevidade  IDHM_Educacao  \
0                  1843.0  0.708       0.687             0.830          0.622
1                 18017.0  0.690       0.693             0.839          0.563
2                 33085.0  0.690       0.671             0.841          0.579
3                  7502.0  0.698       0.720             0.848          0.556
4                700872.0  0.628       0.579             0.798          0.537

   GDP_CAPITA  PercJovem  PercIdoso  PercCarros  PercMotos  PercTratores  \
0    20664.57   0.253208   0.078491    0.313845   0.181210            0.0
1    25591.70   0.206066   0.141791    0.332190   0.170346            0.0
2    15628.40   0.259947   0.092905    0.180110   0.090499            0.0
3    18250.42   0.206023   0.145201    0.305333   0.130145            0.0
4     8222.36   0.282608   0.072279    0.037399   0.181864            0.0
```

```
        LONG        LAT  Grupo
0 -49.440548 -16.758812      1
1 -47.396832 -18.487565      1
2 -48.718812 -16.182672      0
3 -45.446191 -19.155848      1
4 -48.884404  -1.723470      2
```

In [15]:
```
# Lista com os nomes das colunas do dataset
colunas = list(cidades2.columns)
colunas
```

Out[15]:
```
['IBGE_RES_POP',
 'IBGE_DU_URBAN',
 'IBGE_DU_RURAL',
 'IBGE_PLANTED_AREA',
 'IBGE_CROP_PRODUCTION_$',
 'IDHM',
 'IDHM_Renda',
 'IDHM_Longevidade',
 'IDHM_Educacao',
 'GDP_CAPITA',
 'PercJovem',
 'PercIdoso',
 'PercCarros',
 'PercMotos',
 'PercTratores',
 'LONG',
 'LAT',
 'Grupo']
```

In [16]:
```
# Eliminando as colunas LONG e LAT da lista
del colunas[15:17]
colunas
```

Out[16]:
```
['IBGE_RES_POP',
 'IBGE_DU_URBAN',
 'IBGE_DU_RURAL',
 'IBGE_PLANTED_AREA',
 'IBGE_CROP_PRODUCTION_$',
 'IDHM',
 'IDHM_Renda',
 'IDHM_Longevidade',
 'IDHM_Educacao',
 'GDP_CAPITA',
 'PercJovem',
 'PercIdoso',
 'PercCarros',
 'PercMotos',
```

```
 'PercTratores',
 'Grupo']
```

In [17]:
```
# Analisando a média dos valores (variáveis) por grupo
cidades2.groupby('Grupo')[colunas].mean()
```

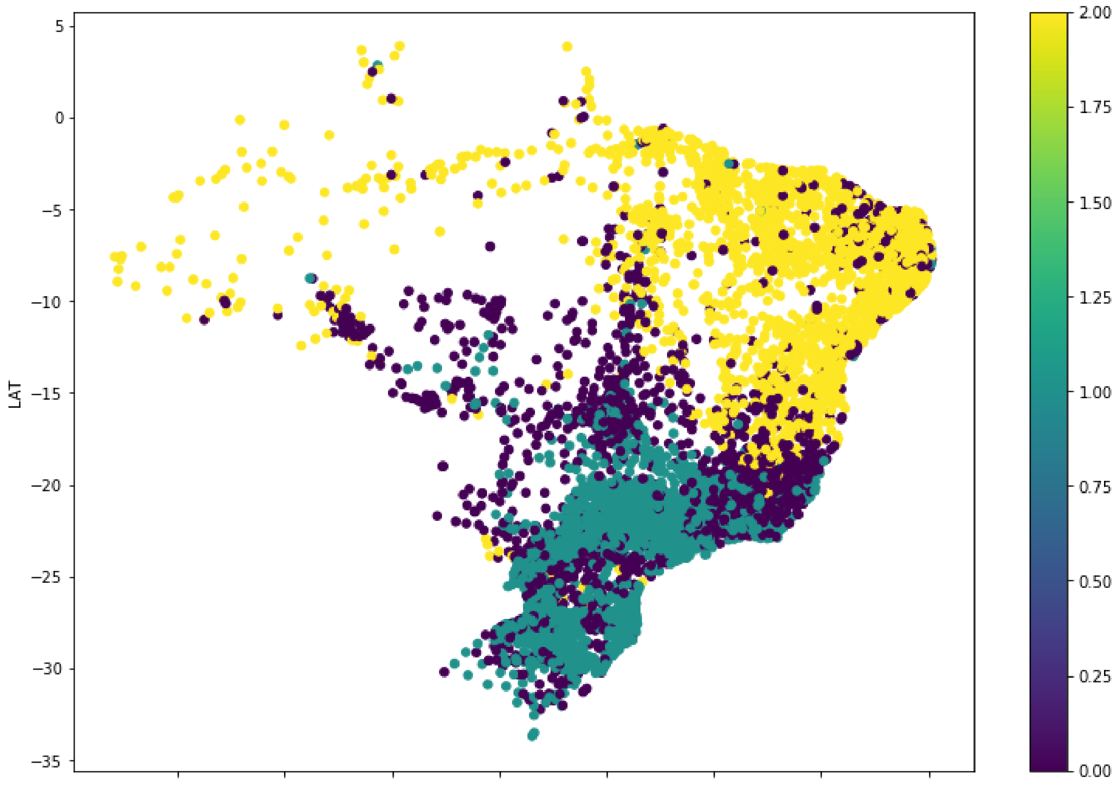
Out[17]:
```
        IBGE_RES_POP  IBGE_DU_URBAN  IBGE_DU_RURAL  IBGE_PLANTED_AREA  \
Grupo
0       24574.120700    5772.390869    1384.644153       16717.431520
1       47689.408488   13935.555968    1045.154377       21094.781963
2       16548.833333    2382.790791    1920.435435        6089.496997

        IBGE_CROP_PRODUCTION_$      IDHM  IDHM_Renda  IDHM_Longevidade  \
Grupo
0                 61793.317073  0.666799    0.653308          0.811064
1                 92380.730504  0.733362    0.724618          0.842634
2                 22683.133133  0.580120    0.554194          0.753945

        IDHM_Educacao    GDP_CAPITA  PercJovem  PercIdoso  PercCarros  \
Grupo
0            0.561225  20902.545866   0.246000   0.118460    0.188544
1            0.647730  32860.607088   0.211139   0.133895    0.367211
2            0.469755   9581.140280   0.288054   0.108915    0.055183

        PercMotos  PercTratores  Grupo
Grupo
0        0.164690      0.000075      0
1        0.150215      0.000329      1
2        0.116343      0.000012      2
```

In [18]:
```
# Verificando a quantidade de municípios por grupo
cidades2['Grupo'].value_counts()
```

Out[18]:
```
2    1998
1    1885
0    1599
Name: Grupo, dtype: int64
```

In [19]:
```
# Visualizando os grupos no mapa
cidades2.plot(kind='scatter', x='LONG', y='LAT', c=grupos, colormap='viridis', s=30, 
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ccec11d0>
```




```
In [ ]:
```