



```

from random import random
!pip install -U geopandas
import geopandas as gpd
import shapely
from shapely.geometry import *
from geopandas import GeoDataFrame
from sklearn.cluster import DBSCAN
from geopy.distance import great_circle
from shapely.geometry import MultiPoint
from pyproj import Proj, transform
import googlemaps

import warnings
warnings.simplefilter(action='ignore')

Python 3.8.10
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting geopandas
  Downloading geopandas-0.12.2-py3-none-any.whl (1.1 MB)
    1.1/1.1 MB 14.2 MB/s eta 0:00:00
Requirement already satisfied: shapely>=1.7 in /usr/local/lib/python3.8/dist-packages (from geopandas) (2.0.0)
Collecting pyproj>=2.6.1.post1
  Downloading pyproj-3.4.1-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (7.8 MB)
    7.8/7.8 MB 59.1 MB/s eta 0:00:00
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.8/dist-packages (from geopandas) (1.3.5)
Requirement already satisfied: packaging in /usr/local/lib/python3.8/dist-packages (from geopandas) (21.3)
Collecting fiona>=1.8
  Downloading Fiona-1.8.22-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (16.6 MB)
    16.6/16.6 MB 38.5 MB/s eta 0:00:00
Requirement already satisfied: attrs>=17 in /usr/local/lib/python3.8/dist-packages (from fiona>=1.8->geopandas) (22.2.0)
Requirement already satisfied: six>=1.7 in /usr/local/lib/python3.8/dist-packages (from fiona>=1.8->geopandas) (1.15.0)
Collecting cligj>=0.5
  Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Requirement already satisfied: click>=4.0 in /usr/local/lib/python3.8/dist-packages (from fiona>=1.8->geopandas) (7.1.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.8/dist-packages (from fiona>=1.8->geopandas) (2022.12.7)
Collecting munch
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Requirement already satisfied: setuptools in /usr/local/lib/python3.8/dist-packages (from fiona>=1.8->geopandas) (57.4.0)
Collecting click-plugins>=1.0
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=1.0.0->geopandas) (1
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=1.0.0->geopandas) (20
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=1.0.0->geop
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.8/dist-packages (from packaging->geopar
Installing collected packages: pyproj, munch, cligj, click-plugins, fiona, geopandas
Successfully installed click-plugins-1.1.1 cligj-0.7.2 fiona-1.8.22 geopandas-0.12.2 munch-2.5.0 pyproj-3.4.1

```

#roads.geojson

!gdown --id 1Z8KSaAUgy7ACVe8y43eoZHKgmSCEBgLK

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1Z8KSaAUgy7ACVe8y43eoZHKgmSCEBgLK
To: /content/roads.geojson
100% 217k/217k [00:00<00:00, 65.8MB/s]

```

#buildings.geojson

!gdown --id 1DraoZ15VjT_PKi43hNkAzYlxh9c_4tQ1

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1DraoZ15VjT\_PKi43hNkAzYlxh9c\_4tQ1
To: /content/buildings.geojson
100% 143k/143k [00:00<00:00, 82.2MB/s]

```

#Location and built environment variables.xlsx

!gdown --id 1ADRDAbj0bN8805bRb-B2T9FX40kJnrGn

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1ADRDAbj0bN8805bRb-B2T9FX40kJnrGn
To: /content/Location and built environment variables.xlsx
100% 29.1k/29.1k [00:00<00:00, 39.0MB/s]

```

#vic_establishments.shp

!gdown --id 1WTid3_clTG1Kmskm68hz1Mqw6WiBQIXB

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(

```

```

Downloading...
From: https://drive.google.com/uc?id=1WTid3\_clTG1KMskm68hz1Mqw6WiBQIXB
To: /content/vic_establishments.shp
100% 21.7k/21.7k [00:00<00:00, 29.4MB/s]

```

```
#vic_establishments.shx
```

```
!gdown --id 1yxDQJzWoNCpEj-anUt2bp0kLExgF-2Wm
```

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1yxDQJzWoNCpEj-anUt2bp0kLExgF-2Wm
To: /content/vic_establishments.shx
100% 6.28k/6.28k [00:00<00:00, 9.15MB/s]

```

```
#vic_establishments.csv
```

```
!gdown --id 1ywVzPf0P67X1zPFKYKulH_1Fmmqdl28h
```

```

/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Option `--id` was deprecated in version 4.3.1 and
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1ywVzPf0P67X1zPFKYKulH\_1Fmmqdl28h
To: /content/vic_establishments.csv
100% 56.8k/56.8k [00:00<00:00, 55.6MB/s]

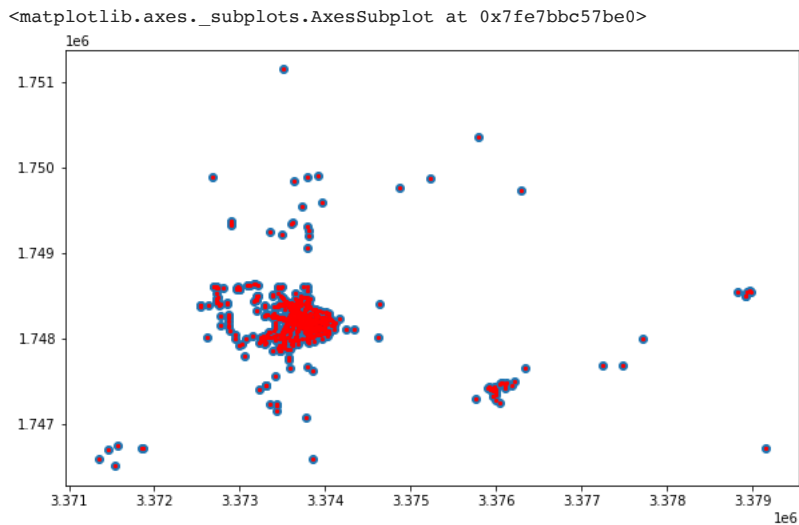
```

CLUSTER ANALYSIS FOR DISTANCES

```

vic = gpd.read_file("/content/vic_establishments.shx")
vic.plot(ax=vic.plot(figsize=(10, 6)), marker='o', color='red', markersize=5)

```



```
jorge = pd.read_csv('/content/vic_establishments.csv')
```

```
jorge
```

```

X          Y sid category subcategory      name      area
-----
inProj = Proj(init='epsg:3034')
outProj = Proj(init='epsg:4326')
x1,y1 = 3373168.48041169,1748433.54613485
x2,y2 = transform(inProj,outProj,x1,y1)
print(x2,y2)

2.2477862000000357 41.932068700000004
4  3.37316848041169  1.74843354613485  0  retail  supermarket  NaN  NaN

jorge['Lon'],jorge['Lat'] = transform(inProj,outProj,jorge['X'],jorge['Y'])

df_establishments = jorge.loc[(jorge['Lon'] > 2.252) & (jorge['Lon'] < 2.2585) &
                               (jorge['Lat'] > 41.927) & (jorge['Lat'] < 41.9315), ['Lon','Lat','category','subcategory','a
                               Claration

df_establishments
```

| | Lon | Lat | category | subcategory | area | |
|-----|----------|-----------|----------|-------------|--------|--|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | |
| 74 | 2.253181 | 41.927347 | retail | NaN | 906.0 | |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | |
| ... | ... | ... | ... | ... | ... | |
| 766 | 2.254810 | 41.930281 | services | NaN | 101.0 | |
| 767 | 2.252160 | 41.927119 | services | NaN | 454.0 | |
| 769 | 2.253838 | 41.927914 | services | NaN | 294.0 | |
| 770 | 2.253955 | 41.927728 | services | NaN | 435.0 | |
| 771 | 2.254725 | 41.927993 | services | NaN | 1235.0 | |

400 rows x 5 columns

```

df_south_establishments = df_establishments.loc[(df_establishments['Lon'] > 2.253) & (jorge['Lon'] < 2.260) &
                                                  (jorge['Lat'] > 41.927) & (jorge['Lat'] < 41.92937), ['Lon','Lat','category','subcategory','
df_south_establishments.index

Int64Index([ 74, 229, 322, 323, 325, 347, 348, 349, 350, 351, 396, 439, 441,
            473, 474, 475, 477, 478, 500, 501, 502, 505, 506, 513, 525, 526,
            527, 528, 529, 530, 531, 532, 533, 534, 535, 538, 553, 633, 655,
            656, 659, 662, 663, 664, 665, 666, 727, 764, 765, 769, 770, 771],
            dtype='int64')

df_establishments.drop(labels=df_south_establishments.index,axis=0,inplace=True)
```

df_establishments

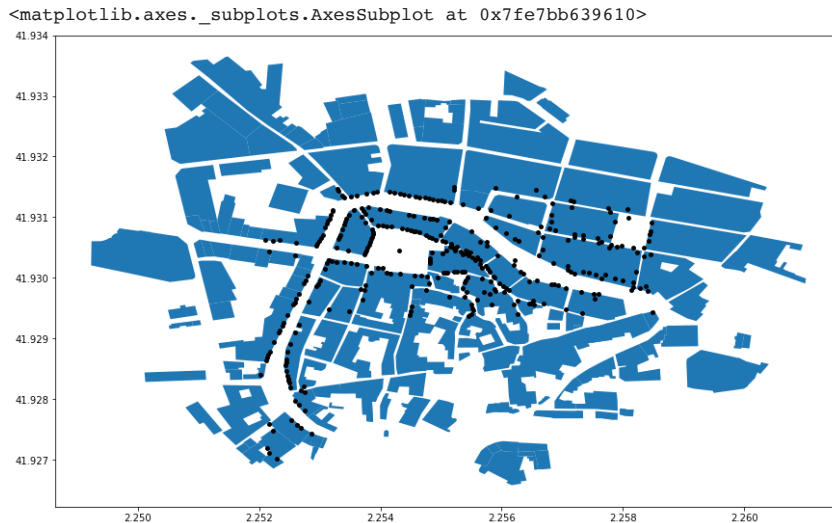
| | Lon | Lat | category | subcategory | area | |
|-----|----------|-----------|----------|-------------|-------|--|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | |
| 127 | 2.253853 | 41.930643 | retail | jewelry | 121.0 | |
| ... | ... | ... | ... | ... | ... | |
| 750 | 2.256840 | 41.931233 | services | NaN | 322.0 | |
| 751 | 2.256823 | 41.931045 | services | NaN | 322.0 | |
| 763 | 2.254482 | 41.929392 | services | NaN | 886.0 | |
| 766 | 2.254810 | 41.930281 | services | NaN | 101.0 | |
| 767 | 2.252160 | 41.927119 | services | NaN | 454.0 | |

348 rows x 5 columns

```

geometry = [Point(xy) for xy in zip(df_establishments['Lon'], df_establishments['Lat'])]
gdf = GeoDataFrame(df_establishments, geometry=geometry)
vic = gpd.read_file("/content/buildings.geojson")
gdf.plot(ax=vic.plot(figsize=(15, 9)), marker='o', color='black', markersize=15)

```



```

coords = df_establishments[['Lat', 'Lon']]
coords2 = coords.to_numpy()

```

```

def get_centermost_point(cluster):
    centroid = (MultiPoint(cluster).centroid.x, MultiPoint(cluster).centroid.y)
    centermost_point = min(cluster, key=lambda point: great_circle(point, centroid).m)
    return tuple(centermost_point)

def nearest_neigh(row, centroids):
    dist=np.inf
    nearest=0
    point=np.array([row['Lat'],row['Lon']])
    for idx,cent in centermost_points.items():
        dist0=np.linalg.norm(point-np.array(cent))
        if dist>dist0:
            dist=dist0
            nearest=idx
    return nearest

for k in [0.047]:
    kms_per_radian = 6371.0088
    epsilon = k / kms_per_radian
    db = DBSCAN(eps=epsilon, min_samples=1, algorithm='ball_tree', metric='manhattan').fit(np.radians(coords2))
    cluster_labels = db.labels_
    num_clusters = len(set(cluster_labels))
    clusters = pd.Series([coords2[cluster_labels == n] for n in range(num_clusters)])
    print('Number of clusters: {}'.format(num_clusters), 'Walking_distance: ',k)

    centermost_points = clusters.map(get_centermost_point)

    lats, lons = zip(*centermost_points)
    rep_points = pd.DataFrame({'lon':lons, 'lat':lats})
    rs = rep_points.apply(lambda row: df_establishments[(df_establishments['Lat']==row['lat']) &
                                                         (df_establishments['Lon']==row['lon'])].iloc[0], axis=1)

    fig, ax = plt.subplots(figsize=[10, 6])
    rs_scatter = ax.scatter(rs['Lon'], rs['Lat'], c='#99cc99', edgecolor='None', alpha=0.7, s=120)
    b_scatter = ax.scatter(df_establishments['Lon'], df_establishments['Lat'], c='k', alpha=0.9, s=3)
    ax.set_title('Full data set vs DBSCAN reduced set')
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')
    ax.legend([b_scatter, rs_scatter], ['Full set', 'Reduced set'], loc='upper right')
    plt.show()

    df_establishments['Cluster']=df_establishments.apply(lambda x: nearest_neigh(x,centermost_points),axis=1)
    geometryn = [Point(xy) for xy in zip(rs['Lon'], rs['Lat'])]

```

```
gdfn = GeoDataFrame(rs, geometry=geometryn)
gdfn.plot(ax=vic.plot(figsize=(15, 9)), marker='o', color='red', markersize=25)

geometryb = [Point(xy) for xy in zip(df_establishments['Lon'], df_establishments['Lat'])]
gdf3 = GeoDataFrame(df_establishments, geometry=geometryb)
gdf3.plot(ax=vic.plot(figsize=(15, 9)), marker='o', c=df_establishments['Cluster'], markersize=25, alpha=0.9, edgecolor='white')
```

Number of clusters: 5 Walking distance: 0.047

centermost_points

```
0 (41.930237000000005, 2.2548144000000017)
1 (41.927185399999997, 2.2521322000000016)
2 (41.929437299999995, 2.25849380000000347)
3 (41.931479100000003, 2.25589820000000665)
4 (41.931334999999998, 2.25625469999999493)
dtype: object
```

df_establishments

| | Lon | Lat | category | subcategory | area | geometry | Cluster |
|-----|----------|-----------|----------|-------------|-------|--------------------------|---------|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | POINT (2.25432 41.93045) | 0 |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | POINT (2.25654 41.92956) | 4 |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | POINT (2.25664 41.93085) | 4 |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | POINT (2.25302 41.93065) | 0 |
| 127 | 2.253853 | 41.930643 | retail | jewelry | 121.0 | POINT (2.25385 41.93064) | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 750 | 2.256840 | 41.931233 | services | NaN | 322.0 | POINT (2.25684 41.93123) | 4 |
| 751 | 2.256823 | 41.931045 | services | NaN | 322.0 | POINT (2.25682 41.93105) | 4 |

rs

| | Lon | Lat | category | subcategory | area | geometry |
|---|----------|-----------|----------|-------------|-------|--------------------------|
| 0 | 2.254814 | 41.930237 | retail | clothes | 101.0 | POINT (2.25481 41.93024) |
| 1 | 2.252132 | 41.927185 | food | pub | 454.0 | POINT (2.25213 41.92719) |
| 2 | 2.258494 | 41.929437 | food | bar | 412.0 | POINT (2.25849 41.92944) |
| 3 | 2.255898 | 41.931479 | retail | NaN | 584.0 | POINT (2.25590 41.93148) |
| 4 | 2.256255 | 41.931335 | retail | NaN | 722.0 | POINT (2.25625 41.93133) |

df_establishments.groupby('Cluster').count()

| | Lon | Lat | category | subcategory | area | geometry |
|---------|-----|-----|----------|-------------|------|----------|
| Cluster | | | | | | |
| 0 | 204 | 204 | 204 | 191 | 203 | 204 |
| 1 | 39 | 39 | 39 | 29 | 39 | 39 |
| 2 | 44 | 44 | 44 | 4 | 44 | 44 |
| 3 | 13 | 13 | 13 | 9 | 13 | 13 |
| 4 | 48 | 48 | 48 | 6 | 48 | 48 |

```
from sklearn.cluster import KMeans
sum_sq_d = []
K = range(1,11)

for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(df_establishments[['Lon', 'Lat']])
    sum_sq_d.append(km.inertia_)

plt.figure(figsize=(8,6))

plt.plot(K, sum_sq_d, 'rx-.')

plt.xlabel('Number of Clusters, k', fontsize=12)
plt.xticks(range(1,11), fontsize=12)

plt.ylabel('Sum of Squared Distances', fontsize=12)
plt.xticks(fontsize=12)
```

```
plt.title('Elbow Method For Determining k', fontsize=16)

plt.show()
```

```
import sklearn
from sklearn.cluster import KMeans

k = 5

kmeans = KMeans(n_clusters=k, init='k-means++')
kmeans.fit(df_establishments[['Lon', 'Lat']])

labels = kmeans.predict(df_establishments[['Lon', 'Lat']],)

centroids = kmeans.cluster_centers_
df_establishments['Classification_Kmeans'] = pd.Series(labels, index=df_establishments.index)
```

```
centroids_df = pd.DataFrame(data=centroids,columns=['Lon','Lat'])
```

```
labels_centroids = kmeans.predict(centroids)
centroids_df['Coordinates'] = pd.Series(labels_centroids)
```

```
centroids_df
```

| | Lon | Lat | Coordinates | |
|---|----------|-----------|-------------|--|
| 0 | 2.254800 | 41.930691 | 0 | |
| 1 | 2.253376 | 41.930579 | 1 | |
| 2 | 2.255874 | 41.930122 | 2 | |
| 3 | 2.252444 | 41.928390 | 3 | |
| 4 | 2.257616 | 41.930380 | 4 | |

```
centroids
```

```
array([[ 2.2548      , 41.93069084],
       [ 2.2533762 , 41.93057923],
       [ 2.25587433, 41.93012186],
       [ 2.25244366, 41.92838953],
       [ 2.25761623, 41.9303803 ]])
```

```
df_establishments.groupby('Classification_Kmeans').count()
```

| | Lon | Lat | category | subcategory | area | geometry | Clus |
|-----------------------|-----|-----|----------|-------------|------|----------|------|
| Classification_Kmeans | | | | | | | |
| 0 | | 75 | 75 | 75 | 69 | 74 | 75 |
| 1 | | 87 | 87 | 87 | 81 | 87 | 87 |
| 2 | | 79 | 79 | 79 | 54 | 79 | 79 |
| 3 | | 41 | 41 | 41 | 31 | 41 | 41 |
| 4 | | 66 | 66 | 66 | 4 | 66 | 66 |

```
rs
```

| | Lon | Lat | category | subcategory | area | geometry |
|---|----------|-----------|----------|-------------|-------|--------------------------|
| 0 | 2.254814 | 41.930237 | retail | clothes | 101.0 | POINT (2.25481 41.93024) |
| 1 | 2.252132 | 41.927185 | food | pub | 454.0 | POINT (2.25213 41.92719) |
| 2 | 2.258494 | 41.929437 | food | bar | 412.0 | POINT (2.25849 41.92944) |
| 3 | 2.255898 | 41.931479 | retail | NaN | 584.0 | POINT (2.25590 41.93148) |
| 4 | 2.256255 | 41.931335 | retail | NaN | 722.0 | POINT (2.25625 41.93133) |

```
df_establishments
```


| | Lon | Lat | category | subcategory | area | geometry | Cluster | Class |
|-----|----------|-----------|----------|-------------|-------|--------------------------------|---------|-------|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | POINT (2.25432 41.93045) | 0 | |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | POINT (2.25654 41.92956) | 4 | |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | POINT (2.25664 41.93085) | 4 | |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | POINT (2.25302 41.93065) | 0 | |
| 127 | 2.253853 | 41.930643 | retail | jewelry | 121.0 | POINT (2.25385 41.93064) | 0 | |

```
geometryb = [Point(xy) for xy in zip(df_establishments['Lon'], df_establishments['Lat'])]
gdf3 = GeoDataFrame(df_establishments, geometry=geometryb)
gdf3.plot(ax=vic.plot(figsize=(15, 9)), marker='o',c=df_establishments['Classification_Kmeans'], markersize=25,alpha=0.9,edgecolor='red',facecolor='red')

geometryb = [Point(xy) for xy in zip(centroids_df['Lon'], centroids_df['Lat'])]
gdf3 = GeoDataFrame(centroids_df, geometry=geometryb)
gdf3.plot(ax=vic.plot(figsize=(15, 9)), marker='o', markersize=25,alpha=0.9,edgecolor='red',facecolor='red')
```

```
CENT_DBSCAN = {0:"2.254814,41.930237",1:"2.252132,41.927185",2:"2.258494,41.929437",
               3:"2.255898,41.931479",4:"2.256255,41.931335"}
CENT_KMEANS = {0:"2.25583343, 41.93008263",1:"2.25336722, 41.93056809",2:"2.2524401 , 41.9283593",
               3:"2.25756052, 41.93040757",4:"2.2548 , 41.93069084"}
```

```
df_establishments['Centr_DBSCAN'] = df_establishments['Cluster'].map(CENT_DBSCAN)
df_establishments['Centr_KMEANS'] = df_establishments['Classification_Kmeans'].map(CENT_KMEANS)
df_establishments['Coordinates'] = df_establishments['Lon'].map(str) + "," + df_establishments['Lat'].map(str)
df_establishments
```

| | Lon | Lat | category | subcategory | area | geometry | Cluster | Class |
|-----|----------|-----------|----------|-------------|-------|--------------------------------|---------|-------|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | POINT (2.25432 41.93045) | 0 | |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | POINT (2.25654 41.92956) | 4 | |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | POINT (2.25664 41.93085) | 4 | |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | POINT (2.25302 41.93065) | 0 | |
| 127 | 2.253853 | 41.930643 | retail | jewelry | 121.0 | POINT (2.25385 41.93064) | 0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |

```
#source https://www.linkedin.com/pulse/calculating-distances-using-python-google-maps-r%C3%A9gis-nisengwe?articleId=6625061973
API_key = 'XXX' #enter the key you got from Google. I put mine here

gmaps = googlemaps.Client(key=API_key)

df_establishments['DB_distance'] = df_establishments.apply(lambda row : gmaps.distance_matrix(row['Centr_DBSCAN'], row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)

df_establishments['KM_distance'] = df_establishments.apply(lambda row : gmaps.distance_matrix(row['Centr_KMEANS'], row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
```

```
df_establishments['DB_distance'].describe()

count    348.000000
mean      62.304598
std       48.222220
min        0.000000
25%       28.000000
50%       58.000000
75%       79.000000
max      267.000000
Name: DB_distance, dtype: float64
```

```
df_establishments[df_establishments['KM_distance']>75].count()

Lon          56
Lat          56
category     56
subcategory  31
area         56
geometry     56
Cluster      56
Classification_Kmeans  56
Centr_DBSCAN  56
Centr_KMEANS  56
Coordinates  56
DB_distance  56
KM_distance  56
dtype: int64
```

```
df_establishments[df_establishments['DB_distance']>75].count()
```

```
Lon          113
Lat          113
category     113
subcategory  79
area         113
geometry     113
Cluster      113
Classification_Kmeans 113
Centr_DBSCAN 113
Centr_KMEANS 113
Coordinates  113
DB_distance  113
KM_distance  113
dtype: int64
```

```
df_establishments.groupby(by='Cluster').agg({'area':'mean'})
```

| area | |
|---------|------------|
| Cluster | |
| 0 | 224.802956 |
| 1 | 292.692308 |
| 2 | 424.318182 |
| 3 | 386.230769 |
| 4 | 352.916667 |

```
df_establishments.groupby(by='Cluster').agg({'area':'std'})
```

| area | |
|---------|------------|
| Cluster | |
| 0 | 152.224758 |
| 1 | 129.033891 |
| 2 | 154.881766 |
| 3 | 153.049096 |
| 4 | 185.833354 |

```
df_establishments['Centr_KMEANS'].value_counts()
```

```
2.25336722, 41.93056809    88
2.2548      , 41.93069084    75
2.25583343, 41.93008263    75
2.25756052, 41.93040757    70
2.2524401 , 41.9283593     40
Name: Centr_KMEANS, dtype: int64
```

```
df_establishments.groupby(by='Classification_Kmeans').agg({'Classification_Kmeans':'count'})
```

| Classification_Kmeans | |
|-----------------------|----|
| Classification_Kmeans | |
| 0 | 75 |
| 1 | 88 |
| 2 | 40 |
| 3 | 70 |
| 4 | 75 |

```
df_establishments.groupby(by='Classification_Kmeans').agg({'area':'std'})
```

area

```
df_establishments.groupby(by='Classification Kmeans').agg({'area': 'mean'})
```

area

Classification_Kmeans

| | |
|---|------------|
| 0 | 229.026667 |
| 1 | 240.659091 |
| 2 | 293.250000 |
| 3 | 418.142857 |
| 4 | 247.648649 |

```
df establishments.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 348 entries, 64 to 767
Data columns (total 13 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Lon                                    348 non-null    float64
1   Lat                                    348 non-null    float64
2   category                              348 non-null    object
3   subcategory                           239 non-null    object
4   area                                  347 non-null    float64
5   geometry                              348 non-null    geometry
6   Cluster                               348 non-null    int64
7   Classification_Kmeans                 348 non-null    int32
8   Centr_DBSCAN                          348 non-null    object
9   Centr_KMEANS                          348 non-null    object
10  Coordinates                           348 non-null    object
11  DB_distance                           348 non-null    int64
12  KM_distance                           348 non-null    int64
dtypes: float64(3), geometry(1), int32(1), int64(3), object(5)
memory usage: 36.7+ KB
```

```
LZ1 = (2.257956913777889,41.92980661304041)
LZ2 = (2.2570145861240007,41.930074589359587)
LZ3 = (2.2562189136567667,41.930445169346633)
LZ4 = (2.255090232524026,41.93114375772215)
LZ5 = (2.2533523604093944,41.93103082640491)
LZ6 = (2.252704186417077,41.92960302034483)
LZ7 = (2.252546086056864,41.92928249137102)
LZ8 = (2.2527329960227007,41.9276266528334)
```

```
df_establishments['LZ1'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ1, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ2'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ2, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ3'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ3, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ4'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ4, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ5'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ5, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ6'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ6, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ7'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ7, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
df_establishments['LZ8'] = df_establishments.apply(lambda row : gmaps.distance_matrix(LZ8, row['Coordinates'],
mode="walking")["rows"][0]["elements"][0]["distance"]["value"], axis = 1)
```

df establishments

| | Lon | Lat | category | subcategory | area | geometry | Cluster | Classification_Kmeans | Centr_DBSCAN | Cent |
|-----|----------|-----------|----------|-------------|-------|--------------------------------|---------|-----------------------|--------------------|---------------|
| 64 | 2.254315 | 41.930450 | retail | marketplace | NaN | POINT (2.25432 41.93045) | 0 | 2 | 2.254814,41.930237 | 2.25485771,41 |
| 85 | 2.256540 | 41.929556 | retail | convenience | 134.0 | POINT (2.25654 41.92956) | 4 | 1 | 2.256255,41.931335 | 2.25583706,41 |
| 121 | 2.256639 | 41.930846 | retail | supermarket | 722.0 | POINT (2.25664 41.93085) | 4 | 4 | 2.256255,41.931335 | 2.25754692,4 |
| 126 | 2.253023 | 41.930651 | retail | jewelry | 228.0 | POINT (2.25302 41.93065) | 0 | 0 | 2.254814,41.930237 | 2.25339331,41 |
| 127 | 2.253853 | 41.930643 | retail | jewelry | 121.0 | POINT (2.25385 41.93064) | 0 | 0 | 2.254814,41.930237 | 2.25339331,41 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 750 | 2.256840 | 41.931233 | services | NaN | 322.0 | POINT (2.25684 41.93123) | 4 | 4 | 2.256255,41.931335 | 2.25754692,4 |
| 751 | 2.256823 | 41.931045 | services | NaN | 322.0 | POINT (2.25682 41.93105) | 4 | 4 | 2.256255,41.931335 | 2.25754692,4 |

```
from google.colab import files
df_establishments.to_excel('df_establishments.xls')
files.download('df_establishments.xls')
```

41.93028)

```
df_establishments.columns
```

```
Index(['Lon', 'Lat', 'category', 'subcategory', 'area', 'geometry', 'Cluster',
      'Classification_Kmeans', 'Centr_DBSCAN', 'Centr_KMEANS', 'Coordinates',
      'DB_distance', 'KM_distance', 'LZ1', 'LZ2', 'LZ3', 'LZ4', 'LZ5', 'LZ6',
      'LZ7', 'LZ8'],
      dtype='object')
```

```
ftg = df_establishments[['category', 'subcategory', 'area', 'Cluster',
      'Classification_Kmeans', 'LZ1', 'LZ4', 'LZ5', 'LZ6', 'LZ8']]
```

| | category | subcategory | area | Cluster | Classification_Kmeans | LZ1 | LZ4 | LZ5 |
|-----|----------|-------------|-------|---------|-----------------------|-----|-----|-----|
| 64 | retail | marketplace | NaN | 0 | 2 | 230 | 115 | 28 |
| 85 | retail | convenience | 134.0 | 4 | 4 | 130 | 15 | 128 |
| 121 | retail | supermarket | 722.0 | 4 | 0 | 19 | 96 | 239 |
| 126 | retail | jewelry | 228.0 | 0 | 1 | 287 | 173 | 30 |
| 127 | retail | jewelry | 121.0 | 0 | 1 | 250 | 136 | 8 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 750 | services | NaN | 322.0 | 4 | 0 | 28 | 142 | 285 |
| 751 | services | NaN | 322.0 | 4 | 0 | 11 | 126 | 269 |
| 763 | services | NaN | 886.0 | 0 | 2 | 287 | 173 | 30 |
| 766 | services | NaN | 101.0 | 0 | 2 | 205 | 91 | 53 |
| 767 | services | NaN | 454.0 | 1 | 3 | 642 | 528 | 384 |

348 rows x 10 columns