main

Assignment_2_210018408 / Assignment_2_part_6.ipynb

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Part 6: K-Means – DBSCAN clustering

Mount drive

In [22]:

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

Task 1 Data Exploration: Load the Chicago parcels dataset using Pandas.

In [23]:

```
import numpy as np
import pandas as pd
import geopandas as gpd
```

In [24]:

```
chgo = gpd.read_file('/content/drive/MyDrive/Colab Notebooks/data/chicago_par
```

Task 2: Display the first few rows of the dataset. Investigate the available attributes and their data types.

In [25]:

```
chgo.head()
```

Out[25]:

	POLY_ID	ID	AREA	PIN_OLD	PIN	geometry
0	1	93	0.01	836300010	836300010	POLYGON ((1091182.694 1942890.287, 1091173.159...
1	2	94	0.00	836300011	836300011	POLYGON ((1092430.298 1943191.955, 1092463.452...
2	3	96	0.02	836300013	836300013	POLYGON ((1092323.996 1942962.61, 1092301.306 ...
3	4	95	0.01	836300012	836300012	POLYGON ((1092024.119 1942447.762, 1091997.19 ...
4	5	92	0.01	836300009	836300009	POLYGON ((1091970.533 1942338.191, 1091929.082...

In [26]:

```
chgo.shape
```

Out[26]:

```
(592521, 6)
```

In [27]:

```
chgo.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 592521 entries, 0 to 592520
Data columns (total 6 columns):
```

```
Data columns (total 6 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   POLY_ID   592521 non-null  int32
 1   ID        592521 non-null  int64
 2   AREA      592521 non-null  float64
 3   PIN_OLD   592521 non-null  int64
 4   PIN       592521 non-null  int64
 5   geometry  592521 non-null  geometry
dtypes: float64(1), geometry(1), int32(1), int64(3)
memory usage: 24.9 MB
```

Task 3: Create a map to visualize the spatial distribution of tax parcel polygons in Chicago. This is a dataset with more than a half millions of records, therefore if you use the traditional matplotlib or pandas you will reach the RAM limit of Colab, you need to use `lonboard` library and the SolidPolygonLayer layer to render polygons.

In [ ]:
```
pip install lonboard
```

In [29]:
```
from lonboard import Map, SolidPolygonLayer, viz
```

In [30]:
```
viz(chgo)
```

```
/usr/local/lib/python3.10/dist-packages/lonboard/_geoarrow/ops/reproject.py:10
7: UserWarning: Input being reprojected to EPSG:4326 CRS.
Lonboard is only able to render data in EPSG:4326 projection.
  warnings.warn(
Map(basemap_style=<CartoBasemap.DarkMatter: 'https://basemaps.cartocdn.com/gl/d
ark-matter-gl-style/style.json'…
```

Task 4 Correlation Analysis: Explore correlations between spatial attributes (latitude, longitude) and numerical attributes. Using the text cell, provide insights into any observed correlations.

There is limited data available within the Parcels file. Therefore there are not many correlations.

Task 5 K-Means Clustering: Implement K-Means clustering with different values of `n_clusters` .

In [ ]:
```
chgo.head()
```

In [32]:
```
gdf_chgo = chgo
```

In [ ]:
```
gdf_chgo.centroid
```

In [34]:
```
chgo["x"] = chgo.centroid.map(lambda p: p.x)
chgo["y"] = chgo.centroid.map(lambda p: p.y)
```

In [ ]:
```
gdf_chgo.head()
```

In [36]:
```
from sklearn.cluster import KMeans, DBSCAN
```

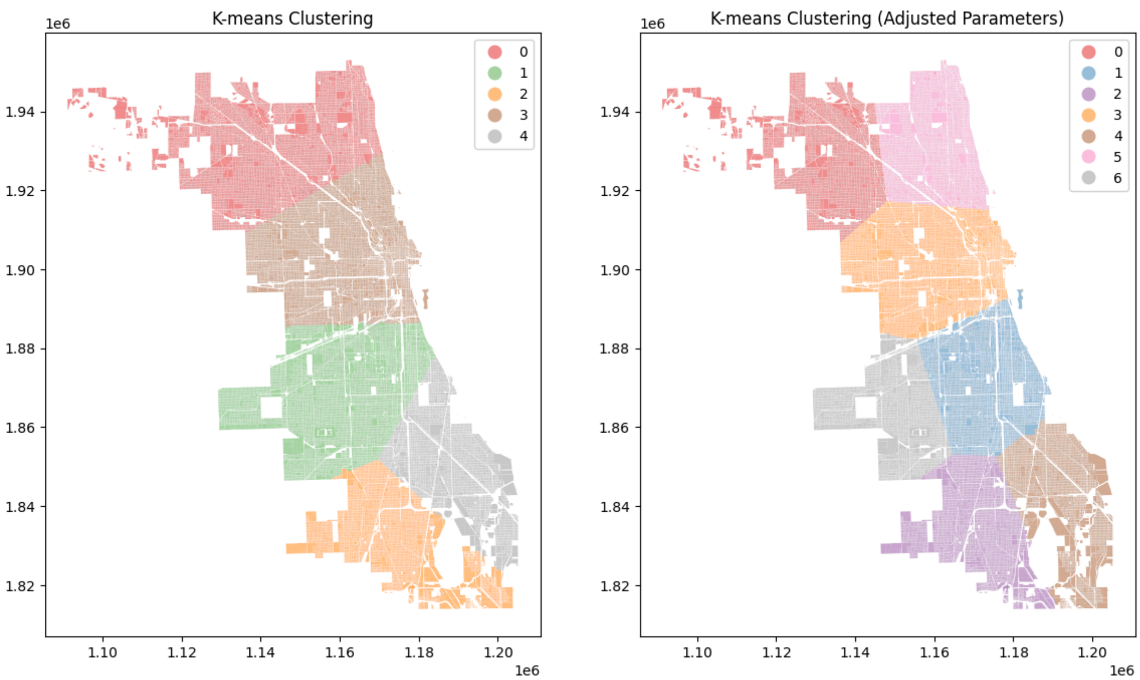
```python
import matplotlib.pyplot as plt
import shapely
import folium
import seaborn as sns
```

In [37]:
```python
# K-means clustering with some default parameters
kmeans = KMeans(n_clusters=5, random_state=42)
gdf_chgo['kmeans_cluster'] = kmeans.fit_predict(gdf_chgo[['x', 'y']])
```

In [38]:
```python
kmeans = KMeans(n_clusters=7, random_state=42)
gdf_chgo['kmeans_cluster_adjusted'] = kmeans.fit_predict(gdf_chgo[['x', 'y']]
```

Task 6: Visualize the clustering results for each value of `n_clusters`, using multiple lonboard maps, and customized colour ramps.

In [39]:
```python
# Visualize clustering results
fig1, axes = plt.subplots(1,2, figsize=(14, 8))
# K-means
gdf_chgo.plot(ax=axes[0], column='kmeans_cluster', categorical=True, legend=T
axes[0].set_title('K-means Clustering')


gdf_chgo.plot(ax=axes[1], column='kmeans_cluster_adjusted', categorical=True,
axes[1].set_title('K-means Clustering (Adjusted Parameters)')

plt.show(fig1)
```



Task 7: Evaluate the clustering results and choose an "optimal" value for `n_clusters`. Justify your choice in a markdown cell.

The clustering was different betweeen the different number of clusters.

Task 8 DBSCAN Clustering: Implement the DBSCAN method.

Experiment with different values of eps and `min_samples` in DBSCAN (at least three)

In [40]:

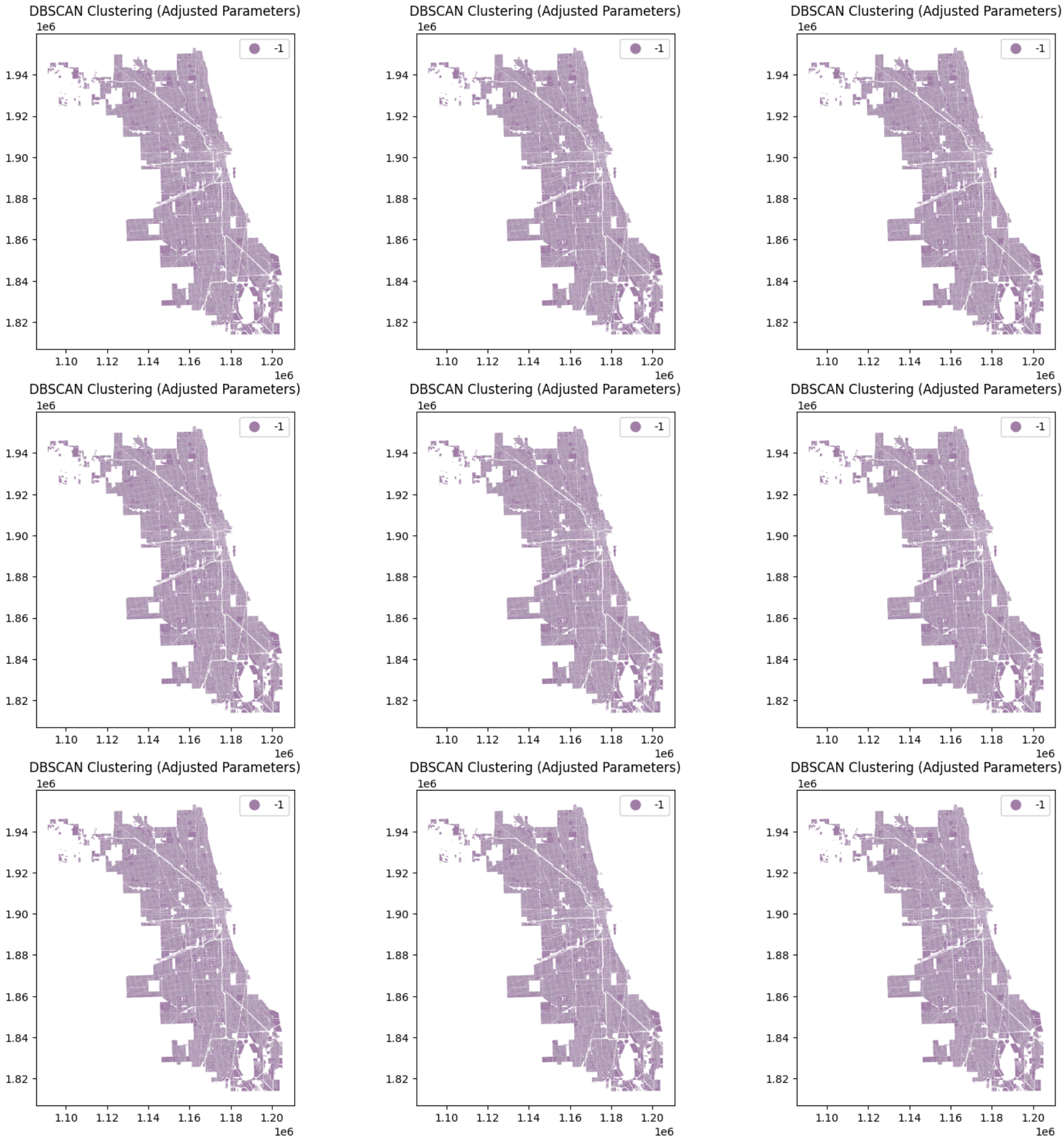
```
# DBSCAN clustering with adjusted parameters, recall what I have described ea
dbscan_adjusted = DBSCAN(eps=0.001, min_samples=5)
gdf_chgo['dbscan_cluster_adjusted_1'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=0.001, min_samples=25)
gdf_chgo['dbscan_cluster_adjusted_2'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=0.001, min_samples=50)
gdf_chgo['dbscan_cluster_adjusted_3'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=0.9, min_samples=5)
gdf_chgo['dbscan_cluster_adjusted_4'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=0.9, min_samples=25)
gdf_chgo['dbscan_cluster_adjusted_5'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=0.9, min_samples=50)
gdf_chgo['dbscan_cluster_adjusted_6'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=1.22, min_samples=5)
gdf_chgo['dbscan_cluster_adjusted_7'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=1.22, min_samples=25)
gdf_chgo['dbscan_cluster_adjusted_8'] = dbscan_adjusted.fit_predict(gdf_chgo[

dbscan_adjusted = DBSCAN(eps=1.22, min_samples=50)
gdf_chgo['dbscan_cluster_adjusted_9'] = dbscan_adjusted.fit_predict(gdf_chgo[
```

Task 9: Plot the clustering results for each combination of parameters. Therefore, you should create a plot matrix 3*3 (`min_samples` and `eps`)

In [41]:

```
fig2, axes = plt.subplots(3, 3, figsize=(18, 18))

gdf_chgo.plot(ax=axes[0, 0], column='dbscan_cluster_adjusted_1', categorical=
axes[0, 0].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[0, 1], column='dbscan_cluster_adjusted_2', categorical=
axes[0, 1].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[0, 2], column='dbscan_cluster_adjusted_3', categorical=
axes[0, 2].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[1, 0], column='dbscan_cluster_adjusted_4', categorical=
axes[1, 0].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[1, 1], column='dbscan_cluster_adjusted_5', categorical=
axes[1, 1].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[1, 2], column='dbscan_cluster_adjusted_6', categorical=
axes[1, 2].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[2, 0], column='dbscan_cluster_adjusted_7', categorical=
axes[2, 0].set_title('DBSCAN Clustering (Adjusted Parameters)')
```

```
gdf_chgo.plot(ax=axes[2, 1], column='dbscan_cluster_adjusted_8', categorical=
axes[2, 1].set_title('DBSCAN Clustering (Adjusted Parameters)')

gdf_chgo.plot(ax=axes[2, 2], column='dbscan_cluster_adjusted_9', categorical=
axes[2, 2].set_title('DBSCAN Clustering (Adjusted Parameters)')

plt.show(fig2)
```



Task 10: Using a text cell write your insights about the impact of modifying the `eps` and `min_samples` parameters, and finally recommend suitable values for `eps` and `min_samples` based on your analysis. **Note:** Consider the real-world implications of your findings, especially in the context of urban planning or data-driven decision-making.

Visually, there does not seem to be any changes in the map output when either of the parameters are changed.