Clustering Geolocation Data Intelligently in Python

We have taxi rank locations, and want to define key clusters of these taxis where we can build service stations for all taxis operating in that region.

Project Outline

In [3]:

```
import matplotlib
%matplotlib inline
%config InlineBackend.figure_format = 'svg'
import matplotlib.pyplot as plt
plt.style.use('ggplot')

import pandas as pd
import numpy as np

from tqdm import tqdm

from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score
from sklearn.datasets import make_blobs
from sklearn.neighbors import KNeighborsClassifier

from ipywidgets import interactive

from collections import defaultdict

#import hdbscan
import folium
import re


cols = ['#e6194b', '#3cb44b', '#ffe119', '#4363d8', '#f58231', '#911eb4',
        '#46f0f0', '#f032e6', '#bcf60c', '#fabebe', '#008080', '#e6beff',
        '#9a6324', '#fffac8', '#800000', '#aaffc3', '#808000', '#ffd8b1',
        '#000075', '#808080']*10
```

Task 1: Exploratory Data Analysis

In [4]:
```
1 df = pd.read_csv('Data/taxi_data.csv')
```

In [5]:
```
1 df.head()
```

Out[5]:

	LON	LAT	NAME
0	28.17858	-25.73882	11th Street Taxi Rank
1	28.17660	-25.73795	81 Bazaar Street Taxi Rank
2	27.83239	-26.53722	Adams Road Taxi Rank
3	28.12514	-26.26666	Alberton City Mall Taxi Rank
4	28.10144	-26.10567	Alexandra Main Taxi Rank

In [6]:
```
1 df.duplicated(subset=['LON', 'LAT']).values.any()
```

Out[6]: True

In [7]:
```
1 df.isna().values.any()
```

Out[7]: True

In [8]:
```
1 print(f'Before dropping NaNs and dupes\t:\tdf.shape = {df.shape}')
2 df.dropna(inplace=True)
3 df.drop_duplicates(subset=['LON', 'LAT'], keep='first', inplace=True)
4 print(f'After dropping NaNs and dupes\t:\tdf.shape = {df.shape}')
```

```
Before dropping NaNs and dupes  :       df.shape = (838, 3)
After dropping NaNs and dupes   :       df.shape = (823, 3)
```

In [9]:
```
1 df.head()
```

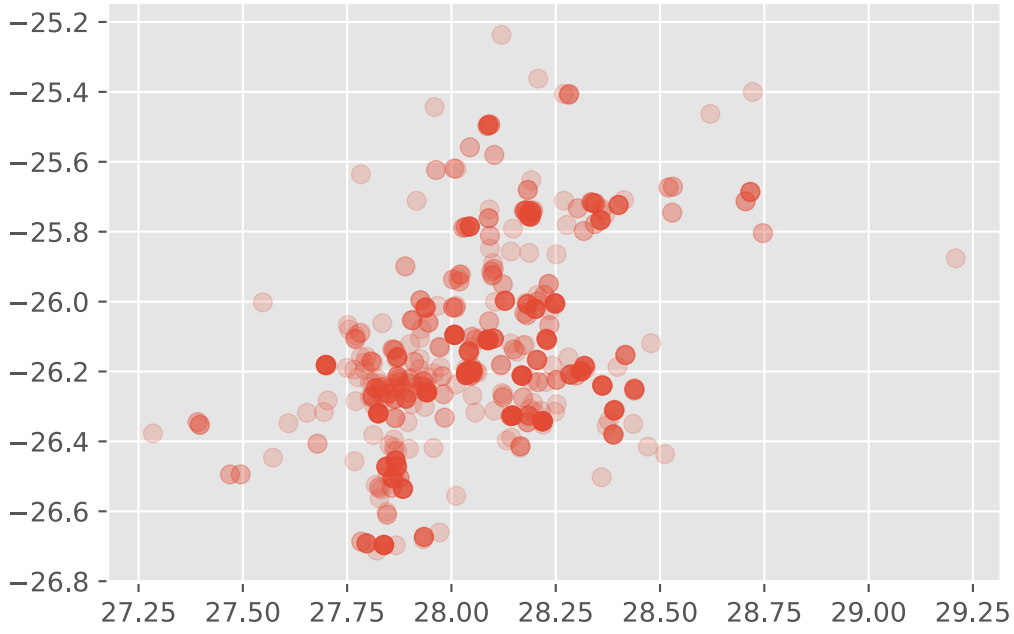
Out[9]:

	LON	LAT	NAME
0	28.17858	-25.73882	11th Street Taxi Rank
1	28.17660	-25.73795	81 Bazaar Street Taxi Rank
2	27.83239	-26.53722	Adams Road Taxi Rank
3	28.12514	-26.26666	Alberton City Mall Taxi Rank
4	28.10144	-26.10567	Alexandra Main Taxi Rank

In [10]:
```
1 X = np.array(df[['LON', 'LAT']], dtype='float64')
```

In [11]:
```
1 plt.scatter(X[:,0], X[:,1], alpha=0.2, s=50)
```

Out[11]:
```
<matplotlib.collections.PathCollection at 0x21d2090b6a0>
```

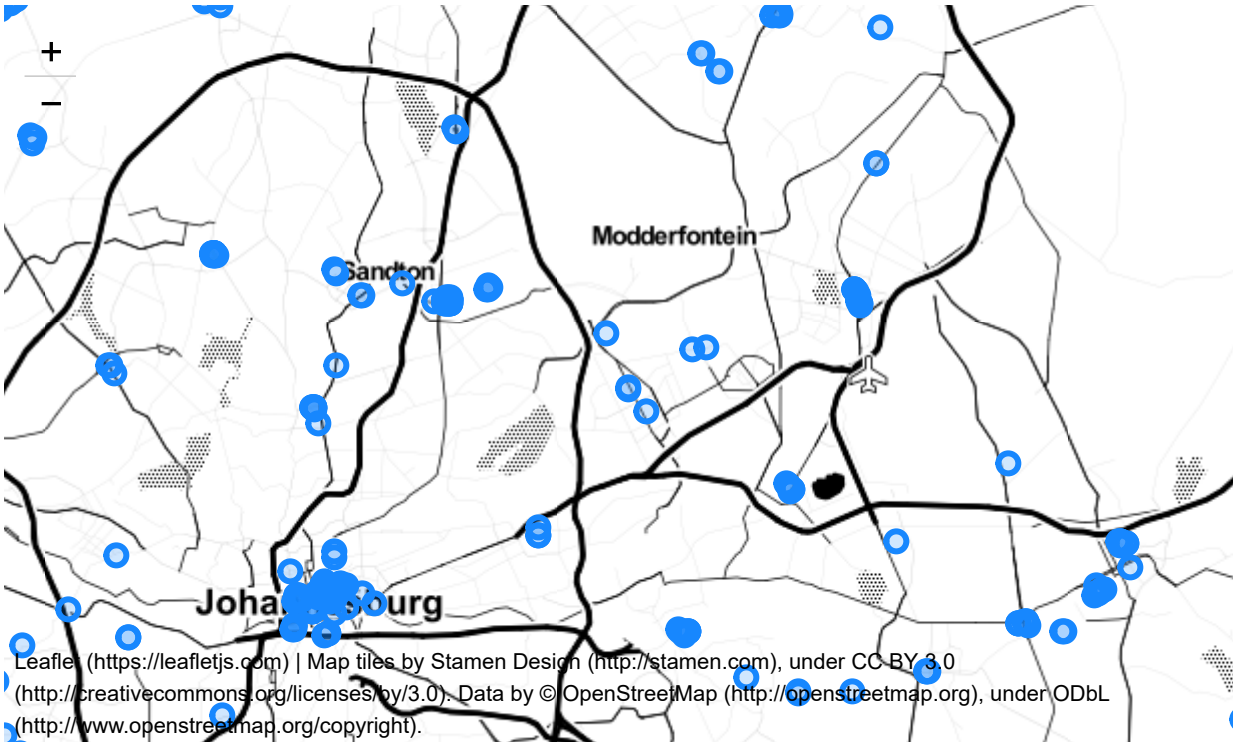


Task 2: Visualizing Geographical Data

In [12]:
```
1  m = folium.Map(location=[df.LAT.mean(), df.LON.mean()], zoom_start=9,
2                 tiles='Stamen Toner')
3
4  for _, row in df.iterrows():
5      folium.CircleMarker(
6          location=[row.LAT, row.LON],
7          radius=5,
8          popup=re.sub(r'[^a-zA-Z ]+', '', row.NAME),
9          color='#1787FE',
10         fill=True,
11         fill_colour='#1787FE'
12     ).add_to(m)
```

In [13]:
```
1 m
```

Out[13]:

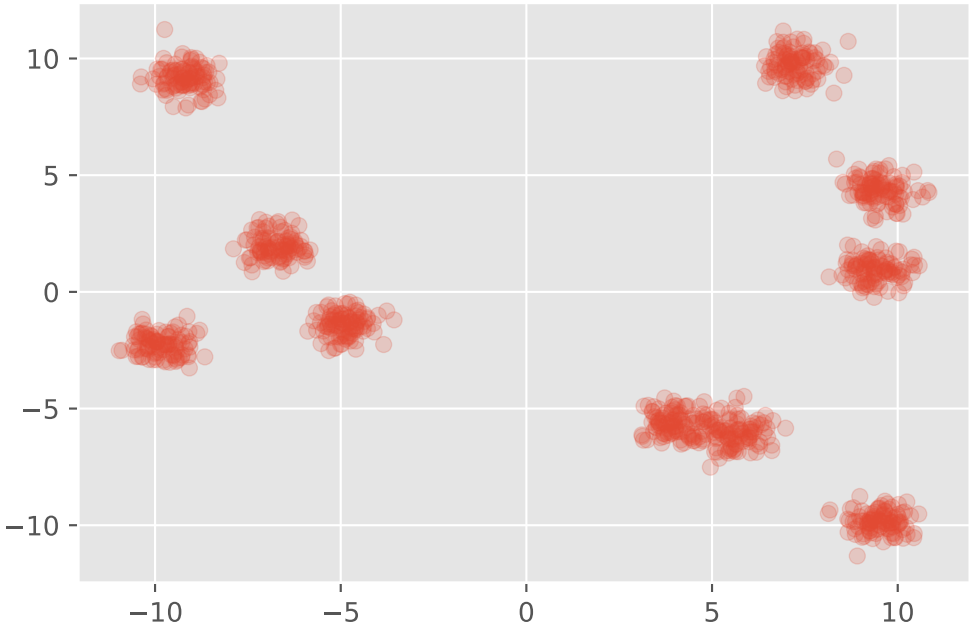


Task 3: Clustering Strength / Performance Metric

In [14]:
```
1 X_blobs, _ = make_blobs(n_samples=1000, centers=10, n_features=2,
2                         cluster_std=0.5, random_state=4)
```

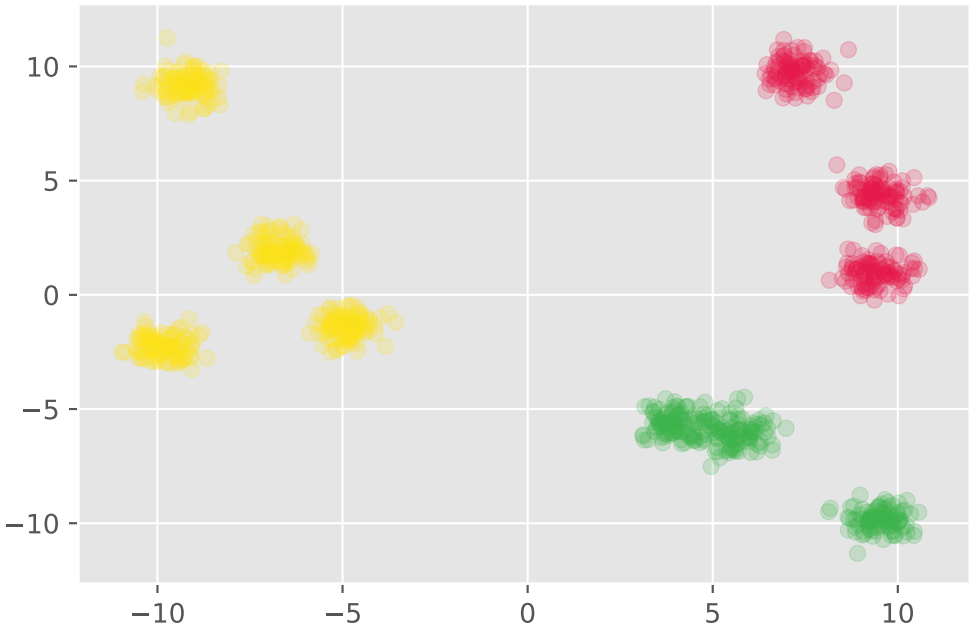
In [15]:
```
1 plt.scatter(X_blobs[:,0], X_blobs[:,1], alpha=0.2)
```

Out[15]:
```
<matplotlib.collections.PathCollection at 0x21d2147f320>
```



In [16]:
```
1 class_predictions = np.load('Data/sample_clusters.npy')
```

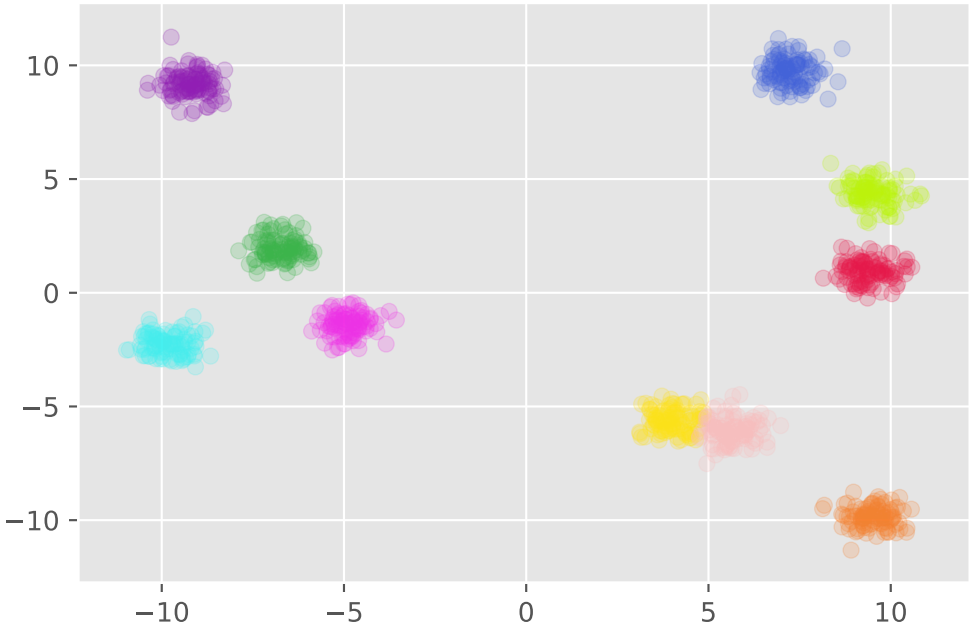
In [17]:
```
1 unique_clusters = np.unique(class_predictions)
2 for unique_cluster in unique_clusters:
3     X = X_blobs[class_predictions==unique_cluster]
4     plt.scatter(X[:,0], X[:,1], alpha=0.2, c=cols[unique_cluster])
```



In [18]:
```
silhouette_score(X_blobs, class_predictions)
```

Out[18]: 0.6657220862867241

In [19]:
```
class_predictions = np.load('Data/sample_clusters_improved.npy')
unique_clusters = np.unique(class_predictions)
for unique_cluster in unique_clusters:
    X = X_blobs[class_predictions==unique_cluster]
    plt.scatter(X[:,0], X[:,1], alpha=0.2, c=cols[unique_cluster])
```



In [20]:
```
silhouette_score(X_blobs, class_predictions)
```

Out[20]: 0.7473587799908298

Task 4: K-Means Clustering

In [21]:
```
X_blobs, _ = make_blobs(n_samples=1000, centers=50,
                        n_features=2, cluster_std=1, random_state=4)
```

In [22]:
```
data = defaultdict(dict)
for x in range(1,21):
    model = KMeans(n_clusters=3, random_state=17,
                   max_iter=x, n_init=1).fit(X_blobs)

    data[x]['class_predictions'] = model.predict(X_blobs)
    data[x]['centroids'] = model.cluster_centers_
    data[x]['unique_classes'] = np.unique(class_predictions)
```

In [23]:
```
def f(x):
    class_predictions = data[x]['class_predictions']
    centroids = data[x]['centroids']
    unique_classes = data[x]['unique_classes']

    for unique_class in unique_classes:
            plt.scatter(X_blobs[class_predictions==unique_class][:,0],
                        X_blobs[class_predictions==unique_class][:,1],
                        alpha=0.3, c=cols[unique_class])
    plt.scatter(centroids[:,0], centroids[:,1], s=200, c='#000000', marker='
    plt.ylim([-15,15]); plt.xlim([-15,15])
    plt.title('How K-Means Clusters')

interactive_plot = interactive(f, x=(1, 20))
output = interactive_plot.children[-1]
output.layout.height = '350px'
interactive_plot
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

In [24]:
```
X = np.array(df[['LON', 'LAT']], dtype='float64')
k = 70
model = KMeans(n_clusters=k, random_state=17).fit(X)
class_predictions = model.predict(X)
df[f'CLUSTER_kmeans{k}'] = class_predictions
```

In [25]:
```
df.head()
```

Out[25]:

	LON	LAT	NAME	CLUSTER_kmeans70
0	28.17858	-25.73882	11th Street Taxi Rank	1
1	28.17660	-25.73795	81 Bazaar Street Taxi Rank	1
2	27.83239	-26.53722	Adams Road Taxi Rank	9
3	28.12514	-26.26666	Alberton City Mall Taxi Rank	8
4	28.10144	-26.10567	Alexandra Main Taxi Rank	4

In [26]:

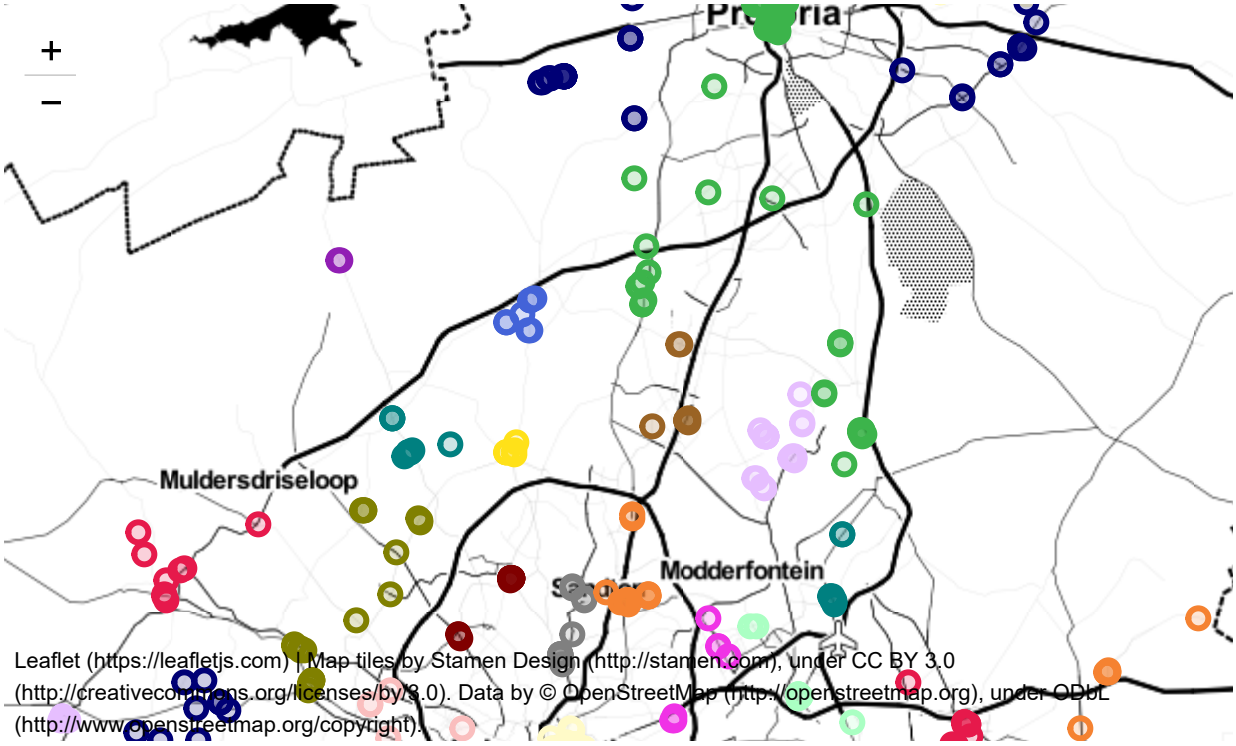
```
def create_map(df, cluster_column):
    m = folium.Map(location=[df.LAT.mean(), df.LON.mean()], zoom_start=9, ti

    for _, row in df.iterrows():

        if row[cluster_column] == -1:
            cluster_colour = '#000000'
        else:
            cluster_colour = cols[row[cluster_column]]

        folium.CircleMarker(
            location= [row['LAT'], row['LON']],
            radius=5,
            popup= row[cluster_column],
            color=cluster_colour,
            fill=True,
            fill_color=cluster_colour
        ).add_to(m)

    return m

m = create_map(df, 'CLUSTER_kmeans70')
print(f'K={k}')
print(f'Silhouette Score: {silhouette_score(X, class_predictions)}')

m.save('kmeans_70.html')
```

```
K=70
Silhouette Score: 0.6527069281188838
```

In [27]:

```
m
```

Out[27]:



In [28]:
```
best_silhouette, best_k = -1, 0

for k in tqdm(range(2, 100)):
    model = KMeans(n_clusters=k, random_state=1).fit(X)
    class_predictions = model.predict(X)

    curr_silhouette = silhouette_score(X, class_predictions)
    if curr_silhouette > best_silhouette:
        best_k = k
        best_silhouette = curr_silhouette

print(f'K={best_k}')
print(f'Silhouette Score: {best_silhouette}')
```

```
100%|██████████| 98/98 [00:24<00:00,  1.73it/s]


K=99
Silhouette Score: 0.7084996241477046
```

Task 5: DBSCAN

Density-Based Spatial Clustering of Applications with Noise

In [29]:
```
# code for indexing out certain values
dummy = np.array([-1, -1, -1, 2, 3, 4, 5, -1])

new = np.array([(counter+2)*x if x==-1 else x for counter, x in enumerate(du
```

In [30]:
```
model = DBSCAN(eps=0.01, min_samples=5).fit(X)
class_predictions = model.labels_

df['CLUSTERS_DBSCAN'] = class_predictions
```

In [31]:
```
m = create_map(df, 'CLUSTERS_DBSCAN')


print(f'Number of clusters found: {len(np.unique(class_predictions))}')
print(f'Number of outliers found: {len(class_predictions[class_predictions==
print(f'Silhouette ignoring outliers: {silhouette_score(X[class_predictions!

no_outliers = 0
no_outliers = np.array([(counter+2)*x if x==-1 else x for counter, x in enum
print(f'Silhouette outliers as singletons: {silhouette_score(X, no_outliers)
```

```
Number of clusters found: 51
Number of outliers found: 289
Silhouette ignoring outliers: 0.9232138250288208
Silhouette outliers as singletons: 0.5667489350583482
```

In [32]:
```
m
```

Out[32]: